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Review

Toward Modern Pesticide Use Reduction Strategies in Advancing Precision Agriculture: A Bibliometric Review

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Abstract

Precision agriculture technologies (PATs) are revolutionizing the agricultural sector by minimizing the reliance on plant protection products (PPPs) in crop management. This approach integrates a broad range of advanced solutions employed to help farmers in optimizing PPP application, while minimizing input and maintaining effective crop protection. These technologies include sensors, drones, robotics, variable rate systems, and artificial intelligence (AI) tools that support site-specific pesticide applications. The objective of this review was to perform a bibliometric analysis to identify scientific trends and gaps in this field. The analysis was conducted using Scopus and Web of Science databases for the period of 2015–2024, by applying a data filtering process to ensure a clean and reliable dataset. The methodology involved citation, co-authorship, co-citation, and co-occurrence analysis. VOSviewer software (version 1.6.20) was used to generate maps and assess global research developments. Results identified AI, sensor, and data processing categories as the most central and interconnected scientific topics, emphasizing their vital role in the evolution of precision spraying technology. Bibliometric analysis highlighted that China, the United States, and India were the most productive countries, with strong collaborations within Europe. The co-occurrence and co-citation analyses revealed increasing interdisciplinarity and the integration of AI tools across various technologies. These findings help identify key experts and research leaders in the precision agriculture domain, thus underscoring the shift toward a more sustainable, data-driven, and synergistic approach in crop protection.

Keywords: agrochemical products; digital farming; pesticide reduction; site-specific application; environmental impact; VOSviewer; correlation analysis

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1. Introduction

1.1. Importance of Sustainable Plant Protection

In the modern agricultural scenario, the efficient and precise application of plant protection products (PPPs) holds a fundamental role in ensuring productivity and crop health, as well as meeting the global demand for food production [1,2]. The intensification of agricultural systems, driven by the necessity to sustain a growing population, has significantly increased the reliance on PPP usage to protect crops from pests and diseases [3]. However, the indiscriminate use of these compounds can pose several risks to overall biodiversity, threatening both agricultural sustainability and food security [4,5]. To cope with these challenges, there is a pressing need to optimize PPP application technology, ensuring the efficacy and efficiency of treatment, while safeguarding the surrounding environment (e.g., drift, evaporation, and run-off) and maximizing operator safety (ingestion, inhalation, and dermal exposure) [6,7]. While traditional agricultural approaches, like integrated pest management (IPM) [8], are widely adopted by farmers to contain the PPP usage, advanced precision agriculture technologies (PATs) are increasingly becoming a notable cornerstone for contributing to agricultural sustainability in modern agriculture [9–16].

Precision agriculture (PA) represents an agricultural management strategy that collects data from technology and high-tech equipment to manage resource utilization and comprehend the variability in space and time. Unlike conventional farming, which applies inputs uniformly without considering the variability across the field—resulting in unnecessary waste of resources such as water, fertilizers, and pesticides—PA enables the site-specific application of inputs to optimize crop yields while enhancing both environmental and economic benefits. In this context, PA plays a pivotal role in reducing the use of plant protection products (PPPs) by applying them only where and when needed, thereby limiting excessive applications and contributing to more sustainable crop protection [17,18].

1.2. Core Technologies in Advancing PA

Advancements in the context of PA, including sensor-based application systems [19,20], unmanned aerial vehicle (UAV) technology [21,22], robot platforms [23,24], variable-rate technologies (VRTs) [25,26], remote sensing (RS) [27–29], and AI-driven decision support tools [30,31], offer promising solutions to enhance the accuracy of phytosanitary treatment. By integrating these innovations, the PPP application process can be optimized to reduce input without compromising crop protection.

Among these application technologies, sensors can provide useful data for crop and soil monitoring and can be applied on UAVs, sprayers, or directly located in contact with the ground or crop. Several researchers showed that the adoption of sensor technologies can effectively predict crop yields and implement a precise management strategy, allowing farmers to collect multiple data on soil humidity, temperature, and nutrient levels [32–36]. For example, soil humidity sensors can provide real-time data on the soil water content that is crucial to optimize irrigation and ensure that pesticides are applied under optimal conditions [37].

In this framework, it is worth recalling the work conducted by Reyns et al. [38], which highlighted the central role of sensors in PA as early as the 90s. In particular, they analyzed the first developments of yield and moisture sensors introduced in the years 80s and 90s, examining the evolutions through patents and commercial solutions and concluding with the state of the art in the early 2000s. Such work set the basis for the adoption of modern sensor-based approaches, today extended to UAVs and sprayers.

RS has been widely used in PA to detect, from a distance, the physical–chemical properties of crop plant tissue or soil. The main key point of RS is to produce spatially varied data for taking reasonable decisions for agricultural operations. Additionally, red–green–blue (RGB), multispectral, and hyperspectral cameras have shown great potentiality in detecting biotic stresses in crops, facilitating real-time monitoring and precise management responses [28,39–42]. Mulla et al. [42] reviewed 25 years of remote sensing applications (1987–2012) in PA, focusing on how advances in sensors, platforms (satellites, UAVs), and processing methods have improved crop monitoring and site-specific management. Moreover, they emphasized remaining gaps in scaling methods from experimental to operational levels, integrating multi-source data, and addressing variability in crops, soils, and environments to achieve site-specific agricultural practices. Huang et al. [43] reviewed applications of agricultural remote sensing for big data management and processing, addressing the challenges of handling vast and complex remote sensing data to enable an effective decision-making in agricultural operations. A more recent study was carried out by Sishodia et al. [39], which provided an overview of remote sensing systems, techniques, and vegetation indices during the years 2015–2020 with applications in irrigation, nutrient, disease, and pest management.

Rapid advancements in agricultural robots and automated machinery have gained great opportunities for improving farming practices and supporting human labor. Automated machinery are mobile robots that can efficiently perform repetitive tasks, such as weeding, planting, and harvesting [44]. Adamides and Edan [45] provided a comprehensive overview on human–robot collaboration (HRC), focusing on their applications in agricultural settings. Particularly, they focused on 27 studies published from 2001 to 2022, categorizing them on task type (e.g., spraying, harvesting), collaboration level, interaction modalities, system architecture, and evaluation methods. This enabled a critical assessment of the evolution of these technologies within the context of smart agriculture. Similarly, Vasconez et al. [46] provided a general description of the potentiality of human–robot interaction in many agricultural activities. A smart sprayer system was developed by Cantelli et al. [47] for autonomous spraying operation. This versatile robotic platform made use of the prescription map to activate the sprayer unit and to determine the precise dosage of the applied mixture.

1.3. Applications of PA-Based Technologies

The precise PPP application enables increasing the amount of product that should reach the target and result in a considerable reduction in the quantities used. In this way, the dose is released only where effectively needed. Over the years, many technologies and successful applications oriented to this purpose have significantly improved the effectiveness and sustainability of PPP applications [48–50]. Research has proposed the development and implementation of innovative VRTs [51–54]. Sawyer [55] laid the conceptual framework for the VRT, especially in the context of fertilizer application, remarking that one of the prerequisites for its success is the capability to accurately and reliably interpret within-field variation. Pulse-width modulation (PWM) technology plays a great role in obtaining variable-rate spray without altering the operating pressure and ensuring uniform droplet size [56]. Salcedo et al. [57] studied three PWM spray configurations (a manually controlled PWM system producing constant-rate application, a laser-guided PWM-controlled intelligent system producing variable-rate application, and the same laser-guided configuration with disabled PWM producing constant-rate application). Results showed that the PWM control valve improved the uniformity of the distribution of spray deposition and coverage, representing the most efficient method to save chemical products and reduce environmental concerns. Wen et al. [58] developed a PWM spray system to achieve an accurate change in the flow rate according to the prescription maps previously obtained. Results demonstrated the effectiveness of the system in rapidly adjusting the flow rate based on the prescription map and maintaining uniform droplet deposition. A field experiment using a VRT-based sprayer equipped with ultrasonic sensors was carried out by Salas et al. [59]. Authors compared the new prototype, in terms of spray deposition and leaf coverage, against two representative sprayers for pest control. This study demonstrated that the variable-rate equipment improved spray deposition and coverage compared to conventional systems, resulting in greater saving in terms of sprayed mixture.

The advent of electrostatic nozzles has enabled greater efficiency and precision in the application of PPPs [60,61]. These nozzles are capable of charging droplets through a high-voltage electrostatic generator, so improving their adhesion to crop surfaces and then minimizing drift. Research demonstrated the improved deposition efficiency of electrostatic spraying compared to conventional hydraulic spraying, particularly in dense canopies. For example, Zhou et al. [62] employed an air-assisted electrostatic nozzle to obtain the best performance in terms of droplet size and deposition. Findings showed that the electrostatic spraying system had a good atomization effect and chargeability with a voltage of 3000–5000-V at an air pressure of 0.1 MPa and liquid flow rate of 0.2 L/min. This study could highlight technical references for the optimization of operating parameters of the electrostatic nozzle. An experimental comparative evaluation of electrostatic hand-held spraying equipment and a conventional hand-held sprayer was conducted in a greenhouse pepper crop by Sánchez-Hermosilla et al. [63]. Authors revealed that the electrostatic equipment increased plant deposition by 1.48 times that of the conventional one, resulting in reduction in application rate by 48%. Concerning the ground losses, it was noted that using the electrostatic spraying equipment implied less pollution to the ground by 36% compared to the reference application. A study by Pascuzzi and Cerruto [64] on a pergola-trained ("tendone") vineyard showed that the activation of the electrostatic system produced a significant increase in the mean foliar deposit only on the lower layer of the canopy (+50%, statistically significant), while it had no effect on the upper layer (+12%, not significant). The integration of electrostatic spraying systems with PWM technology would be capable of optimizing the PPP application in terms of reduction in pesticide use while improving surface coverage and reducing drift. This behavior offers the dual benefits of precise flow rate control via PWM and enhanced adhesion on the target via electrostatic spraying, which contributes to overall environmental impact. Furthermore, using these technologies, especially in regions where environmental regulations are becoming stricter, their synergy not only improves spraying effectiveness but also helps meet regulatory standards.

In the last few years, AI has enhanced the sector of PA by applying advanced algorithms to conduct in-depth analysis of agricultural data, as well as to allow for more accurate predictions regarding pest infestations and diseases. AI can extend the capability of traditional agricultural practices by building predictive models and algorithms to support decision-making procedures [65]. For example, Dhillon et al. [66] utilized random forest regression models to improve the yields of winter wheat and oilseed rape based on satellite and climate data. By integrating a light use efficiency (LUE) model, they demonstrated that the combined approach improved prediction model accuracy.

1.4. Research Questions and Review Structure

Although previous studies have delved into specific technologies within the PA, they often tend to provide fragmented information, lacking a comprehensive analysis that integrates the broader background of various technologies and practices. Therefore, the main objective of this bibliometric review was to address the following research questions:

RQ1: How have PATs for agrochemical reduction evolved over the past 10 years?

RQ2: How have PATs for agrochemical reduction impacted across the globe?

RQ3: Who are the most influent authors and scholars within the field of PATs, and which journals have been selected for publication?

RQ4: What is the relative contribution of individual PAT for agrochemical reduction to the overall development of precision agriculture?

This review article follows an organized structure to investigate the broad domain of PATs aimed at reducing agrochemical use. In detail, Section 1 introduces the background of PA, emphasizing the importance of adopting these technologies in reducing the PPP application while enhancing the effectiveness of phytosanitary treatment. Section 2 describes the materials, data sources, and bibliometric methods used for the data analysis and research methodology. Section 3 presents the main results and their implications for the research trends. Finally, a summary of the overall findings and outlined directions for future research is presented in Section 4.

2. Materials and Methods

2.1. Bibliometric Analysis

The approach used for the study was grounded in a bibliometric review of the existing literature related to the modern pesticide use reduction strategies in the context of PA. Bibliometric reviews are systematic analyses of the scientific literature that employ quantitative methods to evaluate research trends, influential authors, institutional collaborations, and the evolution of specific research fields. By using this approach, the findings contribute to research by providing a comprehensive perspective of scientific progress, while also systematically exploring the current knowledge base and facilitating evidence-based decision-making in research strategy and policy [67].

This review employed citation analysis along with co-authorship, co-citation, and co-occurrence analysis, which enriched the examination of structural aspects and future directions. Citation analysis was used to assess the impact of articles on the citations received by a publication, allowing them to map the influence of scientific contributions. Co-authorship analysis investigated the collaboration networks and intentions among authors and their affiliations. This method allowed identifying scientific partnerships and the geographical distribution of research efforts. Co-citation analysis examined how frequently two or more papers were cited together in later to evaluate the relatedness among these documents. Co-occurrence analysis measured the frequency of keywords appearing together in published articles, thus exploring inherent connections and core research topics.

The bibliometric analysis was conducted using VOSviewer software, version 1.6.20 [68], chosen for its intuitive interface and effective visualization of scientific trends. Thresholds applied in the VOSviewer maps were not based on theoretical or statistical models but were adopted following common practice in bibliometric studies to balance graphical readability and dataset completeness [67,68].

2.2. Data Collection

A literature search, conducted in March 2025, served as the basis for a bibliometric analysis aimed at identifying innovative PATs for reducing agrochemical use. To ensure an exhaustive analysis and reflect the current growth on the topic, a bibliometric literature review from the past 10 years (2015–2024) was conducted using the two leading academic databases Scopus and Web of Science (WoS) [69,70]. The choice of these databases was due to their extensive coverage of scientific content, which provides comprehensive access to worldwide prestigious research. To restrict the number of papers published, this review established specific selection criteria. The search was confined to the title, abstract, and keywords. Additionally, only journal articles were included. The selection process was restricted to publications in English language to enhance accessibility and comprehension among the academic community.

2.3. Search Methodology

The selection of articles was based on a combination of targeted keywords related to the thematic field of investigation, grouped into two main categories:

- Precision agriculture (PA)-related terms: This set included keywords pertaining to the domain of precision farming, also incorporating synonymous and equivalent terms to ensure a broad and relevant dataset.

- Plant protection product (PPP)-related terms: This set included keywords referring to agrochemical products and related terminology, thereby ensuring that the selected works addressed this specific area.

To refine the results, a search strategy was applied methodologically to include all relevant terminological variants without compromising precision. Boolean operators such as "AND" and "OR" were used to restrict or broaden the search to documents containing all specified terms. The asterisk "*" was used as a wildcard character to replace multiple characters, allowing retrieval of word variants. Words enclosed within double quotation marks ("") ensured an exact sequence match, thereby excluding irrelevant results. Additionally, parentheses were used to control the order of operations in Boolean expressions, ensuring proper interpretation of the query. Figure 1 shows the diagram of the search methodology employed for the construction of the main search strings in Scopus and Web of Science (WoS).

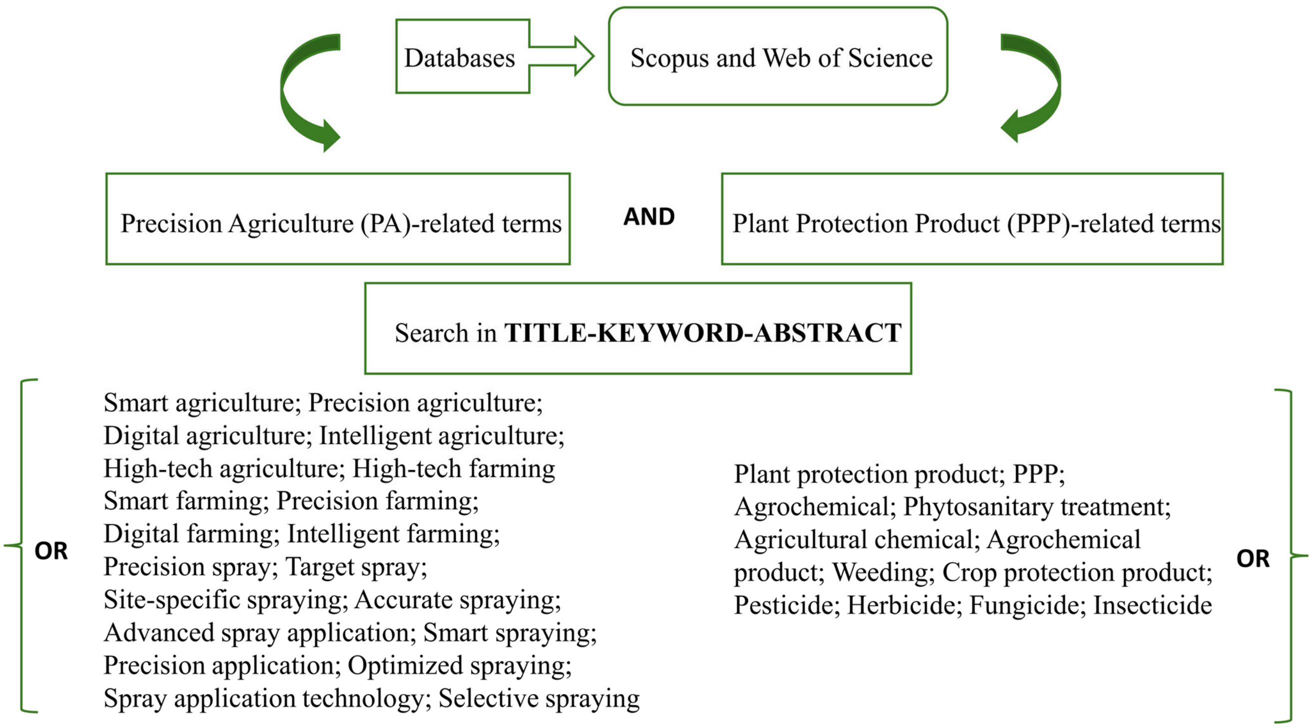

Figure 1. Diagram of the search methodology employed in Scopus and Web of Science.

Subsequently, the search results were categorized into seven specific technological areas: VRT, drones, robots, PWM systems, data processing, sensors, and AI. This classification enabled an in-depth analysis of the diverse applications of PATs, making it possible to identify trends across the various technologies involved in digital farming. Table 1 lists the specific keywords used in the categorization process. Categorization was conducted by querying the title, abstract, and keyword fields of the records.

2.4. Dataset Analysis

After data collection was completed, search results from each database were exported as ".xlsx" files and then merged considering the common fields. To ensure metadata consistency, titles and author's name were standardized, by making all the characters lowercase and by eliminating any unnecessary spaces or hyphens. This step was crucial in preventing inconsistencies that could interfere with automated analysis. A deduplication step was performed by cross-checking key fields (title, year, DOI) to eliminate redundant publications, resulting in a unified and duplicate-free dataset. This ensured accuracy and facilitated subsequent analysis.

Table 1. Keywords used for each sub-category in the categorization process.

Sub-Category (Topic)	Specific Keywords
Variable-Rate Technology (VRT)	Variable rate; VRT; patch spray; variable spray; variable application; variable-rate spraying; VRS; controlled-rate spray; adaptive spray; variable-rate strategy; variable-rate technology; spraying system; sprayer automation; variable pesticide application; microdose spray; spot spray
Drone	UAV; drone; agricultural drone; aerial pesticide application; agricultural UAV sprayer; unmanned aerial vehicles; UASS; RPAS; aerial robot; copter; aerial application
Robot	UGV; robot spray; autonomous vehicle; agricultural robotics; unmanned ground vehicle; agri-robot; field robot; weeding robot; smart robotic; autonomous system; agrobot; robot; ugrobot; robot system; mobile robot; electrical robot
Pulse-Width Modulation (PWM)	PWM; solenoid valve; control valve; pulse-width modulation; electronic valve; intermittent valve
Data Processing (DP)	GIS; geographic information system; DSS; decision support system; spatial decision support system; prescription map; vigor map; weed mapping; map; GNSS; GPS; quantum geographic information system; QGIS; Machine vision; computer vision; decision-making; segmentation; image processing
Sensor	Remote sensing; remote sensor; satellite; proximal sensor; proximal sensing; sensor; lidar; radar; ultrasonic; multispectral camera; thermal camera; hyperspectral camera; flow sensor; pressure sensor; hygrometer; anemometer; temperature sensor; biosensor; RGB; sensitive detection; stereo vision; camera; pulsed thermography; hyperspectral imaging; digital twin
Artificial Intelligence (AI)	AI; IoT; internet of things; artificial intelligence; machine learning; ML; deep learning; DL; neural network; CNN; YOLO; algorithm

Figure 2 illustrates the flow diagram of the selection process, based on the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines [71,72].

A total of 4828 records were initially identified through database searches in Scopus (3088) and Web of Science (1740). The application of selection criteria in terms of temporal range (2015–2024), language (English), and document type (journal article) led to excluding 2782 records, resulting in 2046 articles. The final screening phase (duplicate removal) resulted in the exclusion of 779 records, leaving 1267 studies. The eligibility criterion, which involved the exclusion of review papers classified as article by databases or unrelated to the main topic, resulted in the removal of 152 records, leaving 1115 articles for inclusion in the quantitative analysis. The final 1115 records were classified according to the topics reported in Table 1. Uncategorized records were named "General topic" to indicate a broader discussion not focused on a particular technology. This category included studies on advanced irrigation and fertigation systems, where IoT sensors, NIR spectroscopy, and machine learning algorithms help optimize water and nutrient use; environmental sustainability and resource management, aiming at reducing chemical input and improving soil and water quality; smart agricultural management strategies, improving efficiency and competitiveness of farms; use of nanotechnologies in agriculture, raising concerns about pollution and the need for proper regulations; climate and environmental factors, where precision agriculture helps in monitoring and adapting to climate change, increasing crop resilience; and consumer behavior and economic systems, showing how sustainable agricultural practices influence market trends and environmental awareness.

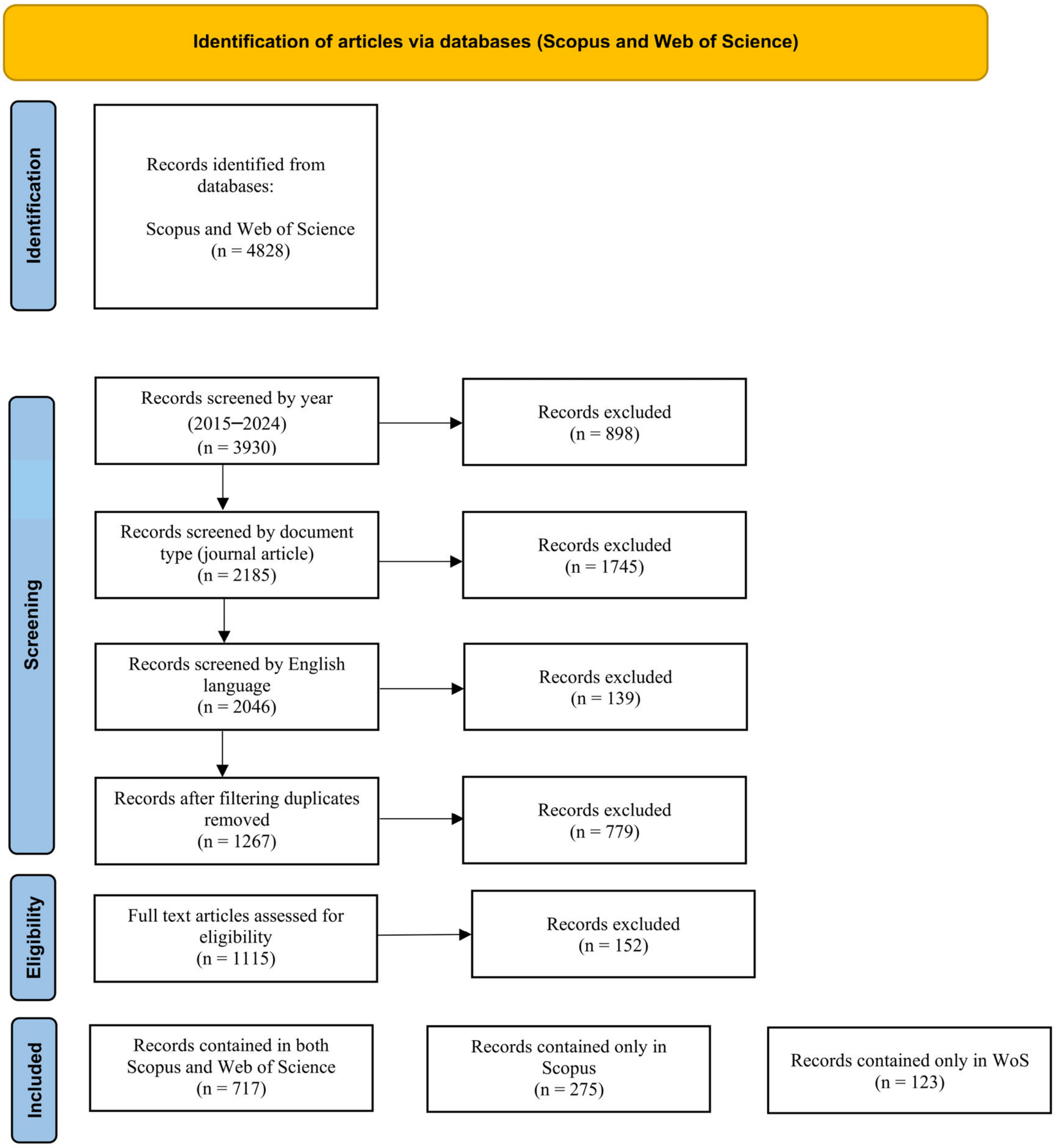

Figure 2. PRISMA-based flow chart diagram.

An ad hoc Python code was developed to perform the categorization process (version 3.12.11, Google Colaboratory). In several instances, a single study was assigned to more than one of the predefined topics, reflecting its multidisciplinary content. This approach enabled the calculation of the relative weight of each topic within the entire dataset, providing a quantitative measure of their significance and interconnections across different research domains. The relative weight of each topic was determined as the percentage of papers addressing that subject. The interconnections among topics were assessed through correlation coefficients computed from the annual distribution of papers over the analyzed decade. Through this methodological approach, a clean, coherent, and organized dataset was obtained.

Dataset analysis and graphic representations were carried out within the RStudio environment (version 4.4.2) [73], utilizing the R language [74] and the Tidyverse packages [75].

3. Results

3.1. Annual Scientific Production

The year-wise production (2015–2024) of research articles related to the adoption of precision agriculture technologies for plant protection products (PAT-PPPs) is shown in Figure 3. In the initial phase, particularly in 2015, the scientific output was sporadic, with only 19 documents published, followed by a marked year-on-year increase. The evident growth highlights incremental attention from the global scientific community toward PAT-PPPs in the last decade. The increase in publication output was negligible between 2018 and 2019, but it became more consistent from 2019 onward. In 2024, a total of 260 articles were published, with an increase of 61 with respect to 2023. This rapid growth can likely be attributed to the proliferation of research driven by technological advancements in agriculture.

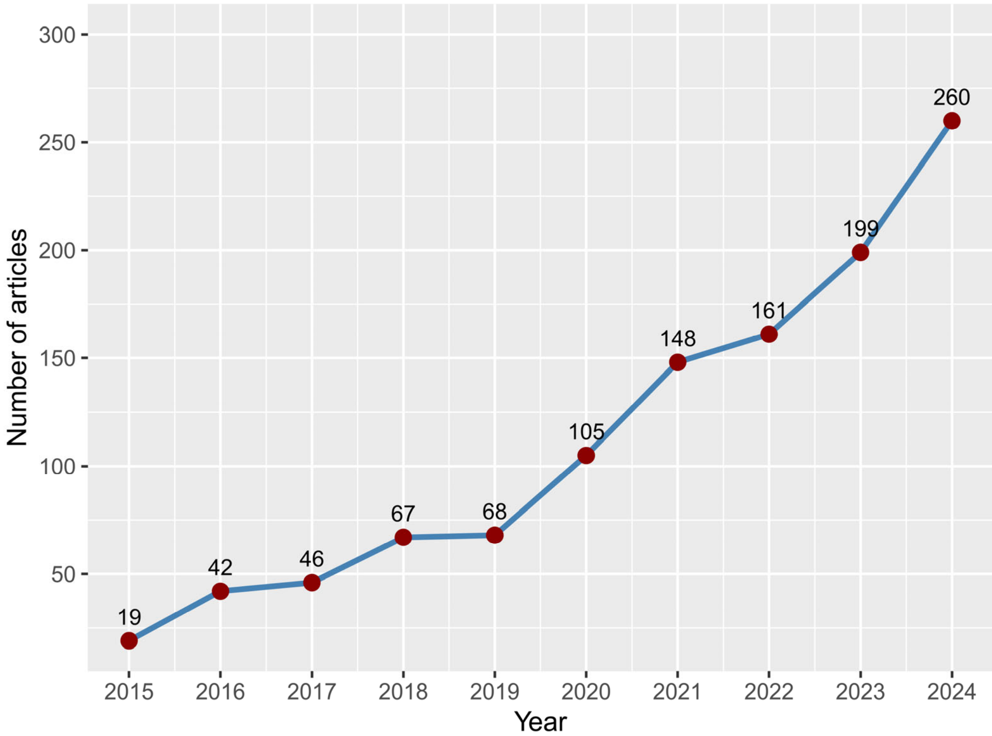

Figure 3. Number of articles published in each year (2015–2024).

This rapid expansion also indicates that research on pesticide reduction through PATs is not only gaining momentum but is increasingly perceived as a strategic response to global challenges such as food security, environmental protection, and regulatory restrictions on pesticide use. Overall, the acceleration in academic productivity after 2019 implies both technological readiness (e.g., maturation of artificial intelligence and UAVs) and heightened policy pressures in favor of sustainable farming.

This trend also reflects a growing consolidation of the research community around practical solutions for reducing agrochemical inputs. The steady increase in publications signals not only the maturation of specific technologies, but also the recognition of pesticide reduction as a central research priority in precision agriculture. Importantly, the observed growth highlights both areas of intense activity (e.g., UAV-based spraying, AI-driven monitoring) and emerging gaps where further exploration is needed (e.g., integration of novel sensor technologies or robotics). Such dynamics provide useful guidance for aligning future research agendas and policy initiatives with the most promising strategies for sustainable farming.

3.2. Scientific Publications and Co-Authorship Analysis

Figure 4 illustrates the global distribution of published articles in the research field investigated in this review, originating from a total of 102 countries. To enhance readability, the figure includes only countries with more than three published articles, representing 56 countries in total. China emerged as the leading contributor with 241 documents, followed by the United States (195). India also played a prominent role, ranking third with 131 documents. A secondary cluster comprised several European countries, including Germany (92), Italy (84), and Spain (66), all showing relatively comparable values.

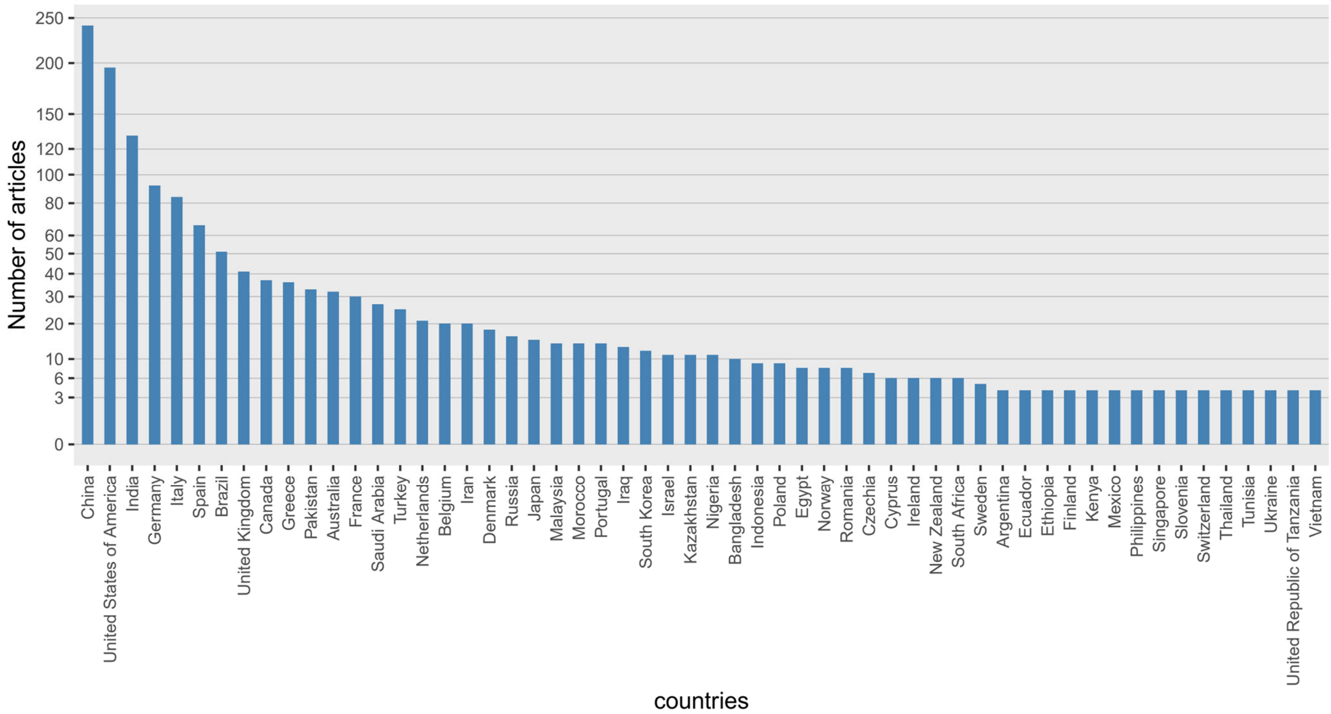

Figure 4. Country or region distribution of publications.

This pattern suggests a clear stratification, with a dominant leader (China), two prominent contributors (the United States and India), a cohesive European segment, and a more heterogeneous spread across the remaining countries.

The stratified structure of contributions suggests a dual dynamic: on the one hand, leadership by China, the United States, and India points to strong investment capacity and research infrastructures; on the other side, the European countries show the importance of common regional collaboration and policy-driven research agendas (e.g., Farm-to-Fork strategy). This contrast may imply that while major extended countries in terms of territorial surface drive production volume and innovation, the European cluster advances through coordinated and policy-aligned research.

Figure 5 presents a co-authorship network map generated by VOSviewer software, highlighting the international scientific collaboration landscape in the PAT-PPP research domain. For this map, the parameter “Minimum number of documents of a country” was set to 5; out of 102 countries, 41 met this threshold and were included in the mapping. Each node represents a country, and the color-coded cluster indicates groups of countries with regional research communities or thematic synergies. The connecting lines represent co-authorship links, with thicker lines denoting stronger collaborations. Strong partnerships are evident within European countries, particularly Germany, Italy, Spain, France, the United Kingdom, and Greece. This underscores a robust interconnection, indicating a high level of joint research activity and well-established scientific partnerships in this field.

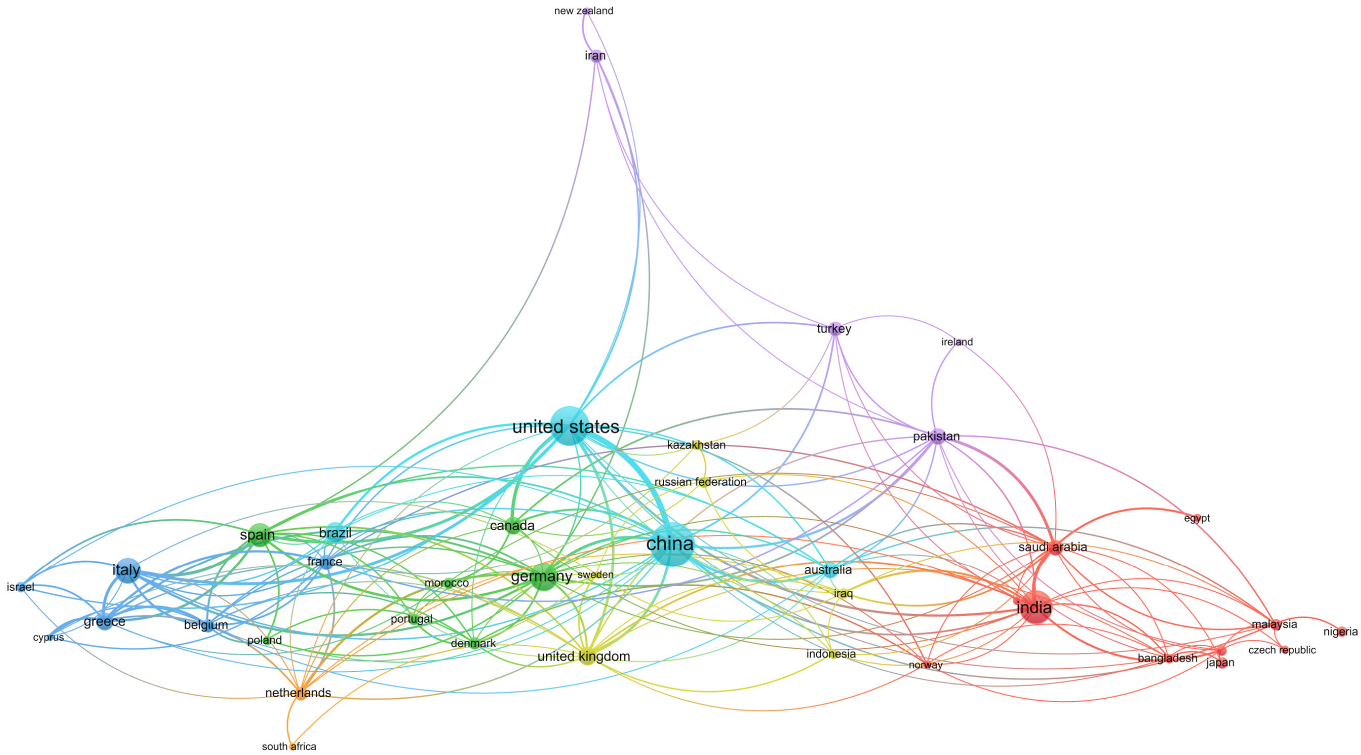

Figure 5. Network visualization based on co-authorship analysis by country or region. Colors identify clusters of countries with stronger collaborative links.

China, the United States, and India, leading with their high levels of scientific productivity, here indicated by their large node sizes, also show extensive collaboration with other countries. In addition, countries such as Iran, Saudi Arabia, and Brazil show rising integration into the international research network, although with fewer strong ties compared to the major countries.

The strong intra-European collaboration may reflect the effectiveness of EU-funded programs in fostering cross-border projects. Such networks may accelerate the transfer of technology, ensuring that PATs can be rapidly implemented in various farming systems. Conversely, the more fragmented collaborations in some countries may imply the need for greater integration into global research networks to avoid geographical disparities in technology adoption.

Analysis of the co-authorship network reveals structural patterns that can shape the dissemination of pesticide reduction strategies. Strong collaborative ties are likely to facilitate the transfer and implementation of PATs across diverse farming systems. These findings offer insights for guiding future research collaborations and informing policy measures to enhance the effectiveness of precision agriculture in reducing pesticide use.

3.3. Most Prolific Authors

Figure 6 illustrates the production analysis, indicating the top 25 authors in the PAT-PPP research field, ranked by the number of scientific articles published.

Overall, the dataset revealed that 4530 authors were involved in the bibliographic production analysis within this field, with an average of 4.06 authors per document. Among the most prolific contributors, Heping Zhu stands out with 20 publications, followed by Roland Gerhards with 16, and Yubin Lan with 12. Several notable authors have published between 8 and 10 articles, indicating relevant contributions in the field. Authors with 5 to 7 publications constitute a significant portion of the active research community. Identifying these leading authors is not intended as a mere tally, but rather as a way to highlight the key contributors who drive research in this field, revealing established research groups and collaborative hubs that play a central role in advancing Precision Agricultural Technologies aimed at reducing agrochemical use.

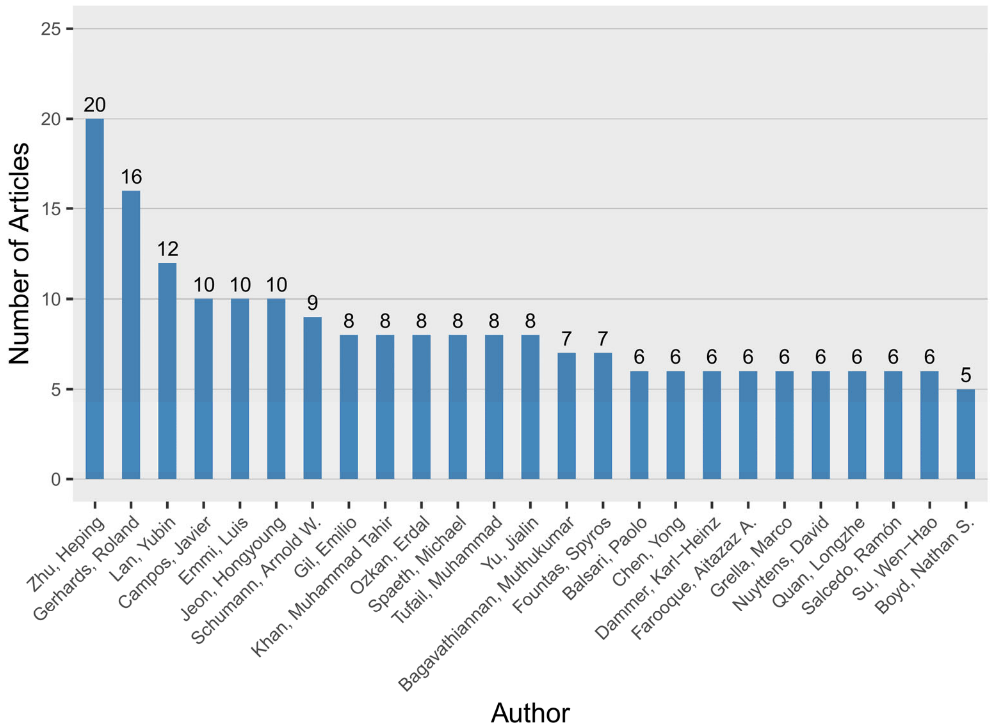

Figure 6. Number of scientific articles published by the most productive authors.

These results reflect the varied presence of researchers from different geographic and institutional backgrounds, playing a central role in shaping the current knowledge. The presence of a relatively small number of productive authors may indicate the formation of a specialized research core. This trend may help consolidate expertise and accelerate the innovation degree in a specific area, but it also suggests poor dependence with leading research groups that work in advancing PA around the globe. On the other hand, a broader diversification of these contributors may enhance resilience and widen the scope of research across the PA scenario.

3.4. Co-Occurrence Analysis

The keyword co-occurrence network visualization is shown in Figure 7, representing the occurrence of keywords across the analyzed literature. The color gradient from blue to yellow highlights the chronological development of keywords. The parameter "Minimum number of occurrences of a keyword" was set to 8; of the 3085 keywords identified, 67 met this threshold and were included in the analysis.

Based exclusively on author-provided keywords, the co-occurrence analysis identified seven distinct thematic clusters. At the center of the map, the word "precision agriculture" emerged as the main interconnected node, underlining its central role on this research area. Closely associated terms included "machine learning", "deep learning", and "computer vision", indicating a strong focus on AI-driven approaches. Emerging keywords like "semantic segmentation" and "yolo"-related terms (e.g., "yolov3", "yolov5", "yolov8") reflected innovation in image-based analysis, suggesting that the field is moving toward the integration of computer science and precision agriculture. Importantly, the coexistence of terms like "pesticide", "agrochemicals", and "drift" indicated that traditional concerns remained relevant, reinforcing the dual trajectory of this field: consolidating environmental safety while embracing innovative technologies.

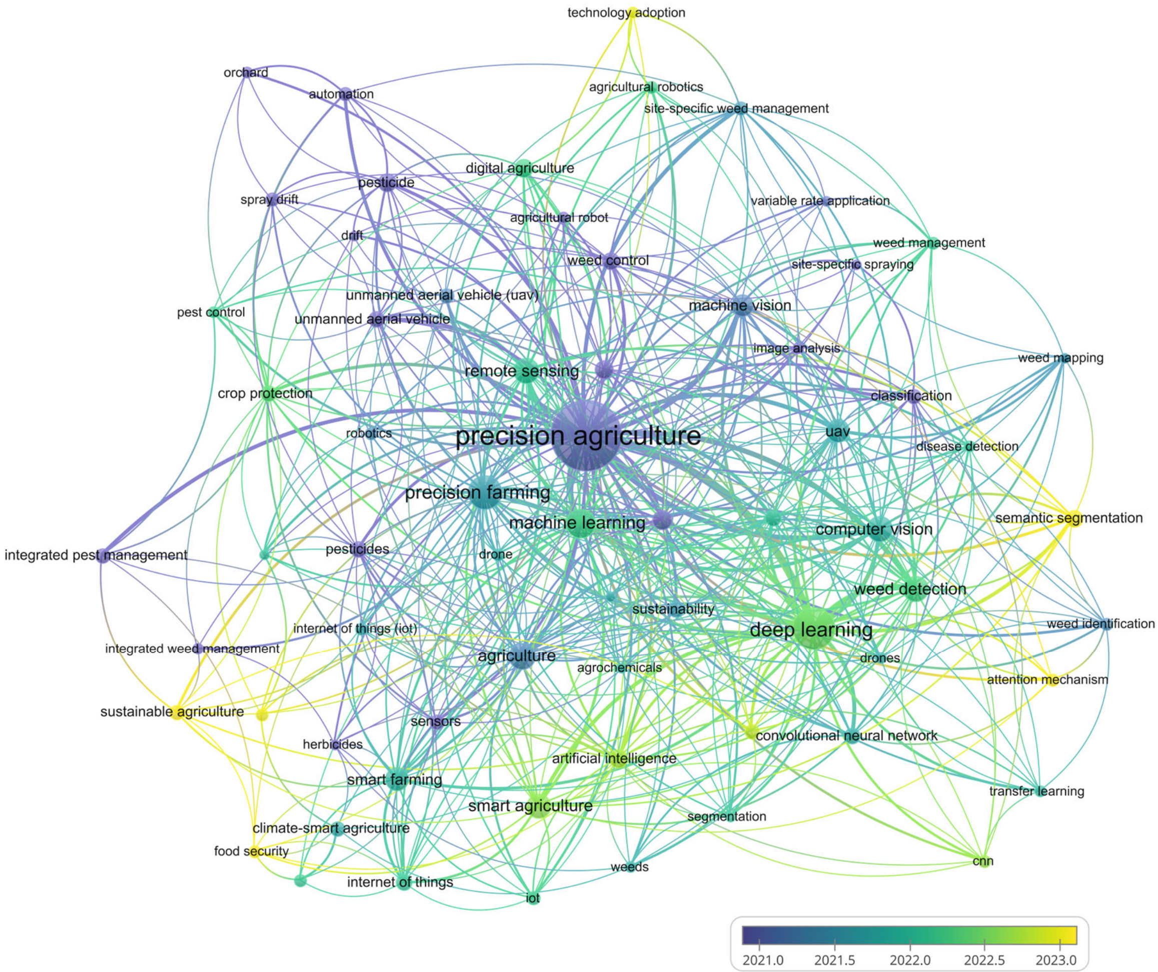

Figure 7. Network visualization based on keyword co-occurrence analysis of publications from 2015 to 2024. Only keywords occurring at least 8 times are displayed, highlighting terms predominantly from 2021–2023.

This output underscores current trends and evolving thematic orientations in the field, addressing agricultural and environmental sustainability goals, technological innovation, and climate resilience. The observed co-occurrence patterns not only reflect current research focus but also provide insights for practical applications and future studies. The prominence of AI-driven terms suggests that technological innovation is increasingly leveraged to enhance precision in pesticide application. Simultaneously, the persistence of keywords related to agrochemicals and environmental safety indicates ongoing attention to sustainability challenges. These findings highlight the integration of technological and environmental priorities and can guide future research, fostering the development of solutions that combine innovation with environmental stewardship.

3.5. Number of Articles in Journals

To assess source influence, the number of articles published in specific journals was considered in the analysis, as shown in Figure 8. This tree map provides a visual representation of the distribution of publications across different journal sources. Each rectangle area is proportional to the percentage of publications from that journal.

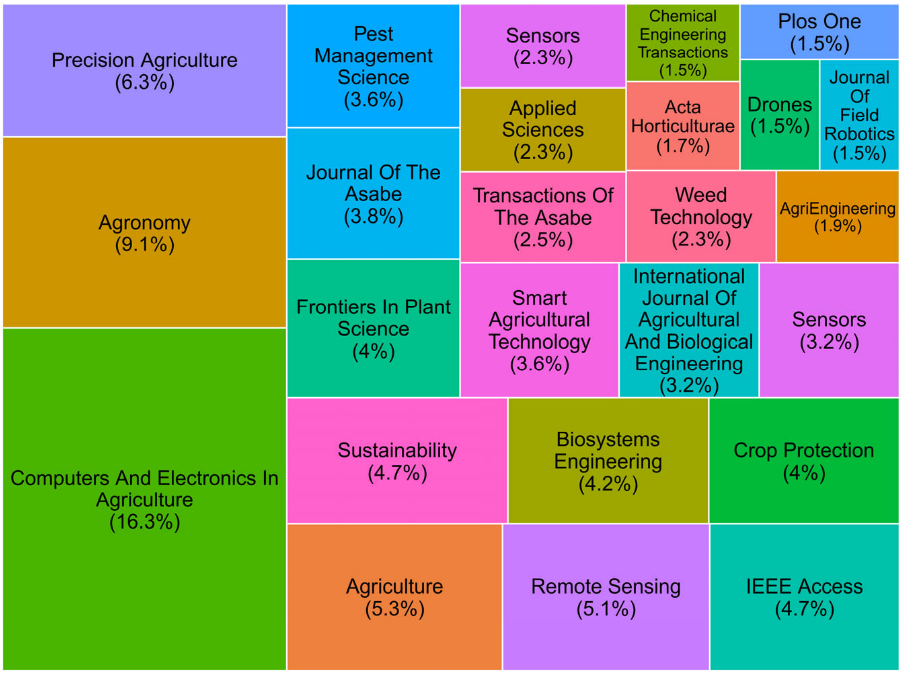

Figure 8. Tree map of top 25 journals.

In general terms, 451 journals were involved in this bibliometric study, but, in this analysis, only the top 25 were considered, for a total of 473 scientific articles. The dominant journal was found to be *Computers and electronics in agriculture* (77 documents) from Elsevier, followed by *Agronomy* from MDPI (43 documents) and *Precision Agriculture* from Springer (30 documents). These journals served as primary outlets for dissemination in the research area (Figure 8). Smaller but relevant percentages (from 3.6% to 5.3%) were represented by the *Pest Management Science*, *Smart Agricultural Technology, Journal of The Asabe, Frontiers in Plant Science, Crop Protection, Biosystems Engineering, IEEE Access, Sustainability*, *Remote Sensing*, and *Agriculture* journals, which addressed advancements in the PA sector.

The variety of journals highlights the multidisciplinary nature of the research, with contributions originating from diverse areas within the agricultural research landscape and related technological fields.

The distribution of publications across these journals not only highlights the multidisciplinary nature of the field but also reflects the focal points of research dissemination. Journals such as *Computers and Electronics in Agriculture* and *Precision Agriculture* emphasize technological and methodological innovation, whereas journals like *Pest Management Science* and *Crop Protection* maintain a strong focus on agrochemical management and environmental safety. This pattern indicates that research on PATs for pesticide reduction is situated at the intersection of precision agriculture, technology development, and sustainability-oriented agronomy. Recognizing these primary outlets can guide researchers in selecting appropriate venues for publication and facilitate knowledge transfer to practitioners and policymakers seeking to implement effective pesticide reduction strategies.

3.6. Co-Citation Analysis

Figure 9 shows the author co-citation analysis, visually indicating how frequently authors are jointly cited. The parameter "Minimum number of citations of an author" was set to 70. Out of 69,199 authors, 132 met this threshold and were included in the analysis. The network visualization was derived only from Scopus-indexed documents, as WoS did not provide the bibliographic information required to perform the co-citation analysis in VOSviewer. Each node represents individual authors, with its size proportional to the co-citation frequency. The connecting lines indicate co-citation relationships among authors and authors within the same cluster are more frequently co-cited with each other.

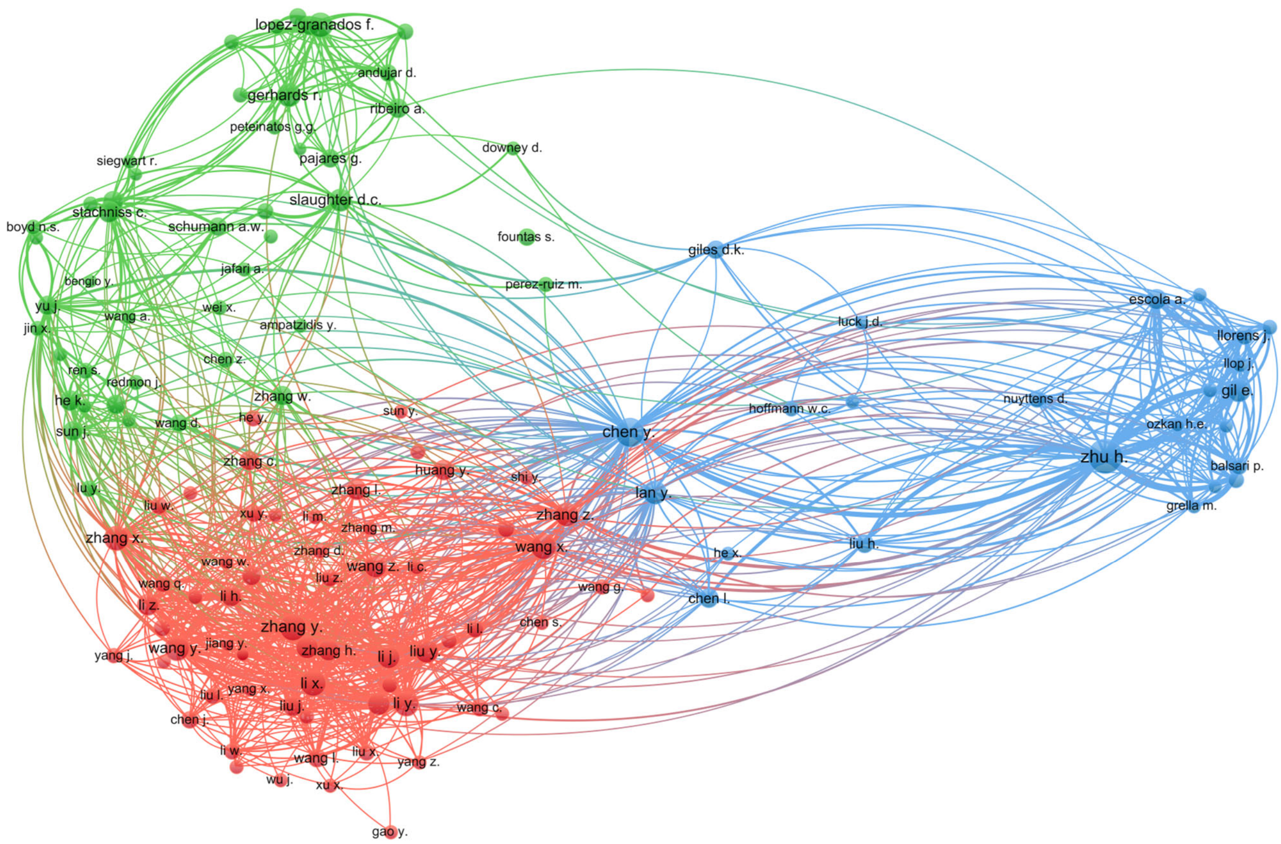

Figure 9. Network visualization based on co-citation analysis by authors. Colors identify clusters of authors who are frequently co-cited.

Overall, the network analysis yielded three main clusters (red, green, and blue), suggesting that there were three distinct groups of influential authors who were cited together within their respective node. Two main authors, Chen Y. and Zhu H., appeared to be prominent contributors due to their large node size and connections to multiple clusters. Notably, the red cluster predominantly was composed of authors from Asian institutions, reflecting a strong focus on computer vision, deep learning, and the broader use of artificial intelligence in agricultural contexts. This suggests a growing integration of advanced computational methods into precision agriculture. The green cluster was centered around weed management technologies, agricultural robotics, and advanced geospatial mapping techniques, revealing a methodological focus on automation and spatial decision support systems. Conversely, the blue cluster was closely associated with precision spraying, agrochemical application, and the use of drones and sensor systems for crop protection. This group reflected a consolidated research interest in optimizing field operations and minimizing environmental impact through technological innovation. Collectively, these clusters highlighted a diversifying yet interconnected research landscape within the field. The presence of distinct but complementary clusters implies that the domain is not dominated by a single paradigm but rather is moving toward an integrated ecosystem of innovation areas, contributing to a specific stage of PPP use reduction.

These co-citation patterns not only reveal the intellectual structure of the field but also provide guidance for future research directions by highlighting potential collaborations across thematic areas. The identification of influential author clusters can inform both researchers and policymakers, suggesting where efforts in technological innovation, field optimization, and pesticide reduction strategies may be most effectively focused.

3.7. Quantitative Distribution of Topics

The pie chart in Figure 10 illustrates the percentage distribution of research topics over the 10-year period. Each segment represents a specific technology or approach within the PAT-PPP field. Since articles could be assigned to multiple topics, the total number of topic occurrences (2056) exceeds the number of articles. Consequently, the percentages were calculated based on the total number of topic assignments rather than the number of articles.

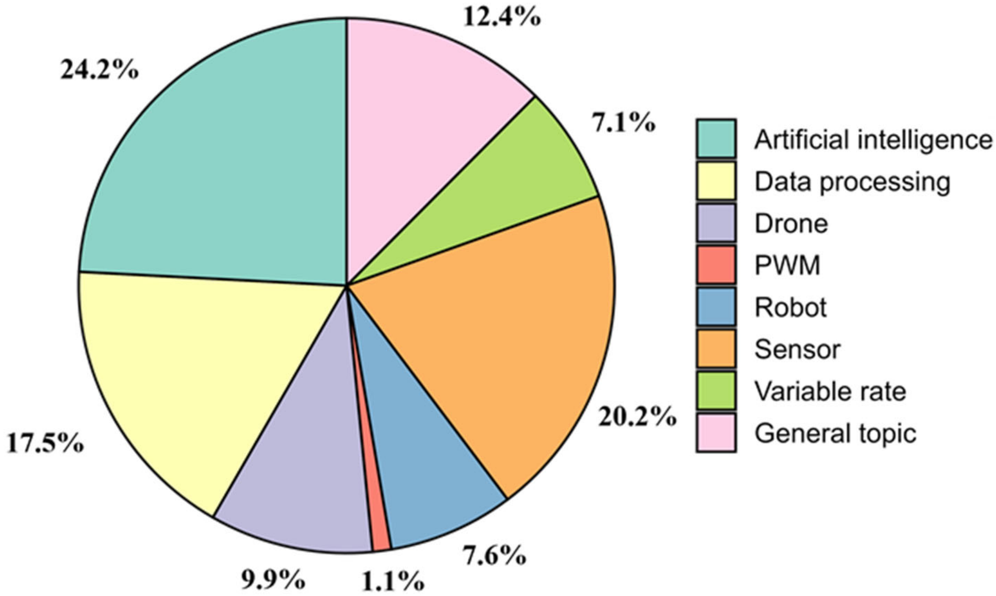

Figure 10. Percentage distribution of each sub-category.

The largest segment was dedicated to "artificial intelligence", accounting for 497 documents. This was followed by "sensor" and "data processing", which represented significant areas of focus, with 415 and 360 documents, respectively. Their predominance, together representing more than half of the dataset, underscores their pivotal role in shaping the future of pesticide reduction strategies. This reflects the growing reliance on data-driven decision-making, where sensors generate reliable field information, and data processing tools translate it into actionable insights. The remaining segments suggested a broader variety of less-represented topics, reflecting a diversification in research directions. For instance, categories such as "variable rate" and "PWM" reveal underexplored niches with untapped potential. This behavior may imply that, while the field is moving toward digital and smart approaches, there is still needed to further integrate these technologies into AI-based frameworks to achieve more effective and sustainable crop protection.

Table 2 reports the classification of documents across topics. Approximately 23.0% of documents did not focus on specific technology (General topic), while 25.5% of the papers were assigned to a single topic, indicating a predominant focus on core technologies. Notably, 51.5% of papers were associated with between two and six of the specific technology topics, reflecting the frequent overlap and integration of approaches. This highlights the multidisciplinary nature of the field and the tendency of research to combine multiple technological strategies for the reduction in pesticide use.

Table 2. Classification of the papers per number of topics.

Number of Topics Per Document	Number of Documents	Percentage of Total
General topic	256	23.0
One topic	284	25.5
Two topics	308	27.6
Three topics	181	16.2
Four topics	75	6.7
Five topics	9	0.8
Six topics	2	0.2
Total	1115	100

Figure 11 shows the percentage distribution of the scientific articles by number of topics (from 1 to 6) associated with each of the eight thematic sub-categories (topics). The analysis revealed a moderate but consistent pattern of interdisciplinarity of articles within each area.

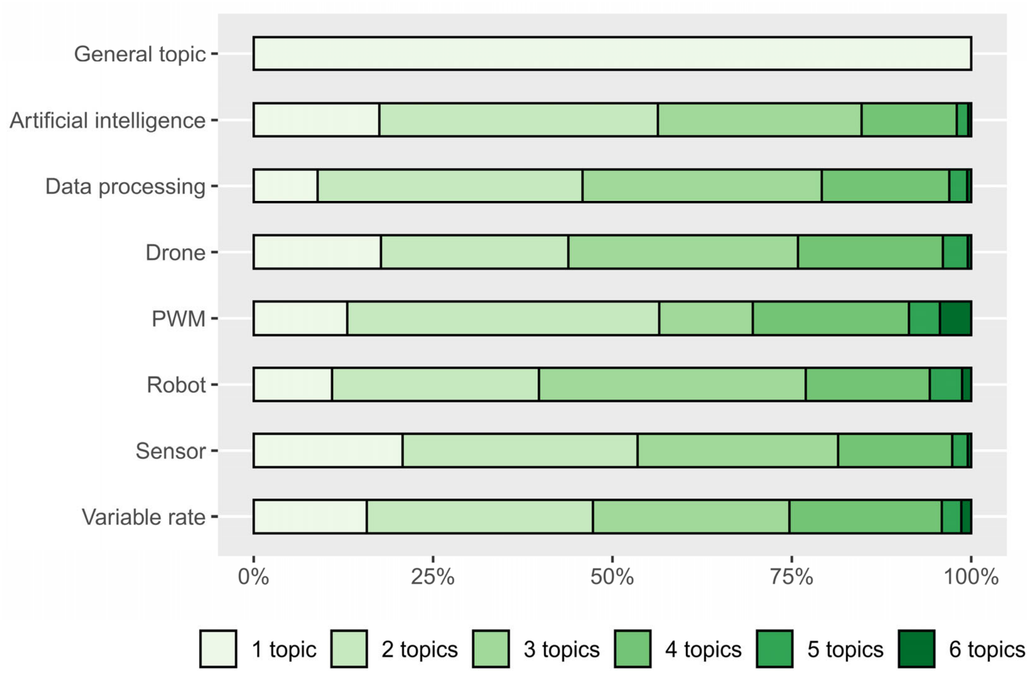

Figure 11. Percentage distribution by number of topics.

The "general topic" category consisted exclusively of articles with a single topic assigned, reflecting its broad and unspecific nature. In contrast, the more specific categories showed a wider distribution across multiple topics, indicating a greater degree of thematic overlap. Notably, the "PWM" category stood out for having the highest percentage of articles with two topics (43.5%), alongside substantial proportions of articles with four (21.7%), five (4.4%), and six topics (4.4%). This suggested that PWM-related studies were frequently integrated with other technological areas. Similarly, the "robot" category exhibited the highest proportion of articles with three topics (37.2%) and non-negligible values for two (28.8%) and four topics (17.3%), emphasizing its interdisciplinary character. The "artificial intelligence" and "data processing" categories also displayed considerable multidisciplinarity, with a great share of articles categorized under two to four topics, representing over 80.0% combined in both cases. This output suggested their widespread applicability across various research areas. Lastly, the "sensor", "drone", and "variable rate" categories showed a moderate-to-high level of interconnection with other categories, though to a somewhat lesser extent than the aforementioned ones.

In this context, it was important to investigate how papers addressing two or more technologies were thematically related. Although the majority of works focused on a single topic, a significant portion explored combinations of different technologies. For this reason, the relationships between individual topics were analyzed. In Table 3, each row reports the number of papers already assigned to a given topic and the percentage of those papers also dealing with other topics. The "general topic" category was not included in the table as it embraced a broader discussion not focused on a specific technology and showed no interaction between topics. This analysis provided insights into the structure of the research sample and allowed for the identification of the degree of interdisciplinary interaction.

Table 3. Interactions between topics.

Topic	Number of Documents	Percentage of Papers of a Topic Dealing with Other Topics						
		VRT	Drone	Robot	PWM	DP	Sensor	AI
Variable-Rate Technology (VRT)	141	100	11	9	7	23	26	24
Drone	199	8	100	7	0	22	31	32
Robot	149	8	8	100	1	27	22	34
Pulse-Width Modulation (PWM)	23	44	0	5	100	15	28	8
Data Processing (DP)	345	9	12	12	1	100	26	39
Sensor	398	11	17	10	2	26	100	34
Artificial Intelligence (AI)	497	8	15	14	0	33	29	100

In the topic network, the "artificial intelligence" and "sensor" categories emerged as central hubs, frequently connecting with other technologies. They also showed a strong association with "robot" and "drone" classes, highlighting the growing focus on smart automation and intelligent aerial systems in agricultural research. The "sensor" topic played a crucial role in supplying data to AI models and was commonly integrated into drone systems and data processing applications. The "variable-rate technology" and "pulse-width modulation" categories formed a distinct sub-cluster focused on smart dosing control. "Data processing" was closely linked with the "drone" topic, reinforcing their role as key tools for data acquisition. Although the "artificial intelligence" class connected with several topics, not all AI-related works were directly linked to the "robot" or "drone" topics. This indicated its broader applicability across diverse agricultural domains.

3.8. Time Distribution of Topics

The bar chart of Figure 12 illustrates the annual distribution of scientific articles by year (2015–2024), categorized by research topics. As a general trend, there was evident upward growth in the total number of publications over the years, with a significant surge from 2020 onwards. The number of studies more than doubled between 2020 and 2024, highlighting the growing interest and investment in PAT-PPT.

"Artificial intelligence" and "sensor" consistently dominated the thematic landscape, reflecting their centrality across PAT-PPP applications. The "data processing" category also expanded over time, highlighting its foundational role in handling large-scale collected data and field monitoring. The "drone" and "robot" classes showed a noticeable growth starting from around 2020. In particular, they saw a sharp increase in 2023–2024, reflecting their growing role in aerial monitoring and adoption to autonomous operations in agriculture. Conversely, the "pulse-width modulation" and "variable-rate technology" categories appeared sporadically and in a relatively small number of articles. Their niche presence could suggest either a mature field with limited novelty or underexplored areas with potential prominence for further research.

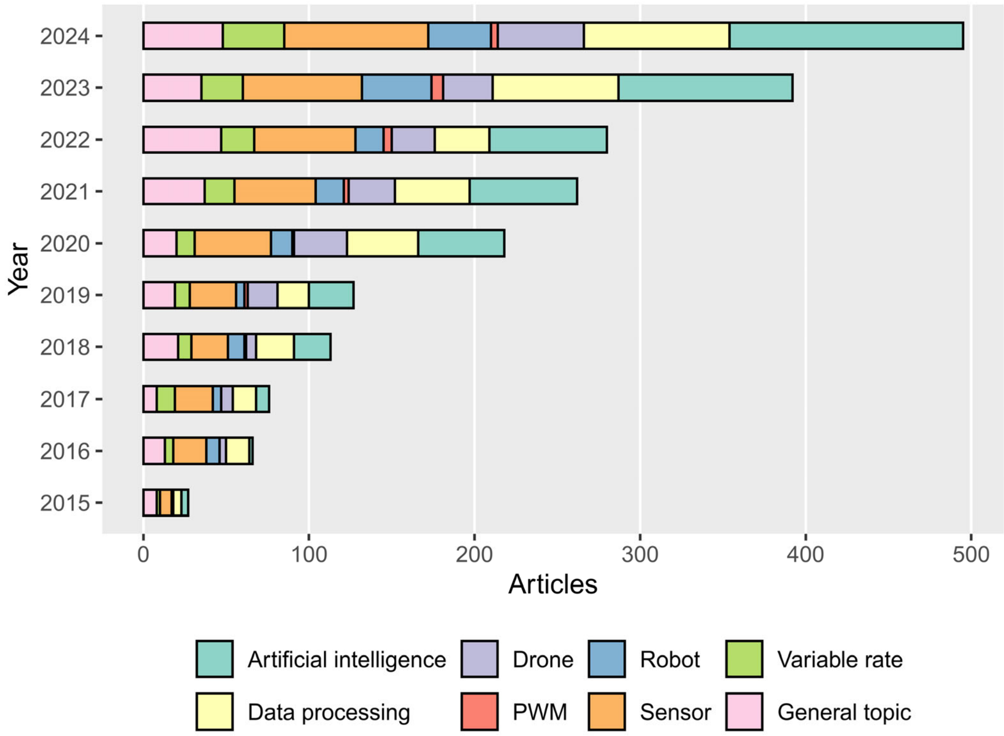

Figure 12. Time distribution of the topic by number of articles.

Figure 13 displays the temporal trend in the percentage of research articles categorized by topic from 2015 to 2024. For each year, percentage values represent the proportion of articles addressing a given topic with respect to the total number of articles published in that year. Importantly, the sum of annual percentages exceeds 100% due to topic overlaps, as an individual paper can be assigned to multiple topics. This perspective allowed for the analysis of topic dominance and shifting research priorities over time, regardless of the absolute number of studies. The most dominant trend was related to articles falling in "artificial intelligence", which surpassed most other categories and peaked above 50% in 2024. This rise confirmed its versatility in different tasks such as automation, prediction, and decision-making. Both the "drone" and "robot" domains showed interesting trends. In fact, although in lower percentage, robot systems showed a slight upward trend post 2021, indicating rising adoption in field applications for labor reduction. On the other hand, UAV-based systems increased sharply up to 2020 but then stabilized around 20%. Notably, the "general topic" class started with a percentage higher than 40% in 2015, following a decline in early years, probably due to the scholars' interest in adopting more specialized and technology-specific research.

Figure 14 depicts the yearly percentage distribution of documents by considering the number of assigned topic labels. Most notably, documents with a single topic remained prevalent but declined modestly over time, ranging from 32.6% in 2017 to 21.1% in 2022, and stabilizing around 25.4% in 2024. This shift suggested a gradual move away from monodisciplinary research. In contrast, articles tagged with two or three topics increased steadily, underscoring a clear tendency toward moderate interdisciplinarity. In particular, the proportion of two-topic documents peaked in 2017 (34.8%) and remained high in 2024 (31.9%), while three-topic articles reached their maximum in 2023 (20.6%), more than tripling the 2015 total (5.3%). A notable peak was observed in 2020, where articles dealing with four topics increased to 16.2%, reflecting targeted efforts with high thematic integration. Articles with five and six topics remained marginal over time, appearing sporadically in recent years. The "general topic" category, while dominant in 2015 (42.1%), showed a substantial decrease over the years, dropping to 18.5% in 2024.

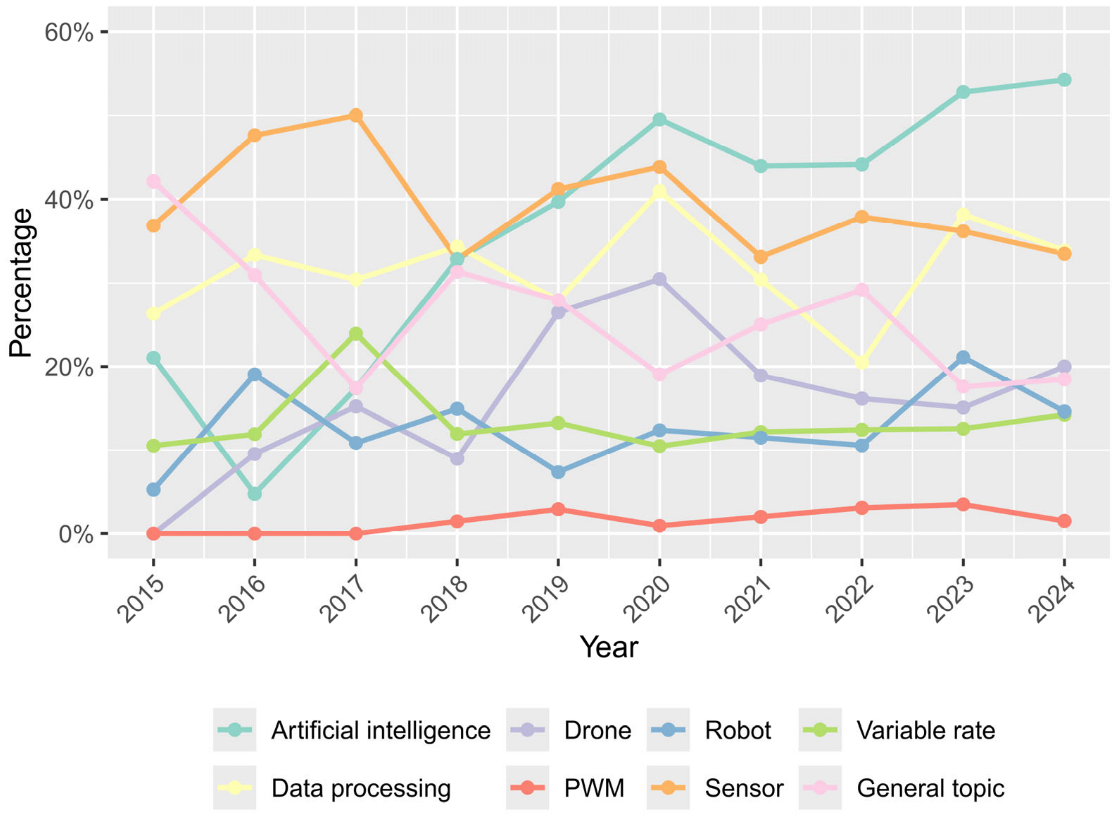

Figure 13. Percentage time trend of the topics.

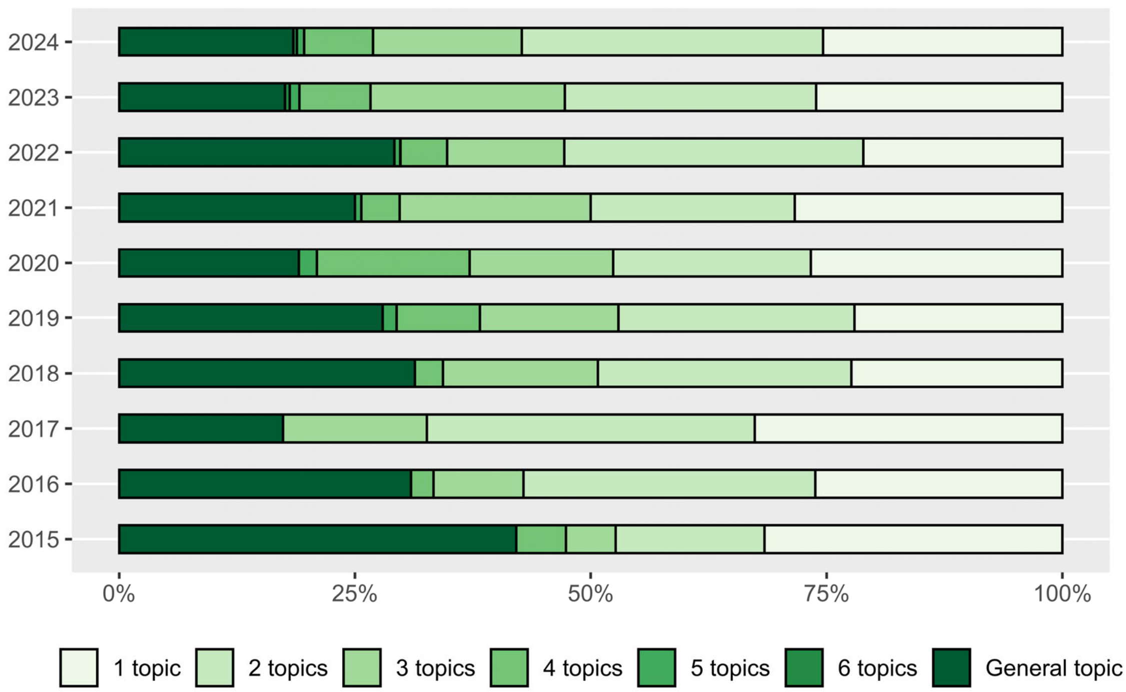

Figure 14. Percentage distribution of topics per year.

Besides evaluating how frequently and consistently specific topics appeared together during this decade, the underlying thematic structures and technological synergies emerging in the field of PAT-PPP were analyzed. To do it, a correlation analysis was performed within the entire decade, in order to verify whether they exhibited similar trends over time. For each topic pair, the correlation (Pearson) coefficient and the corresponding *p*-value were calculated using the cor.test() function in R. The correlation matrix revealed several significant relationships among key technological domains in precision agriculture (Table 4).

Table 4. Matrix of significance for inter-topic correlation coefficients over the years.

	VRT	Drone	Robot	PWM	DP	Sensor	AI
Variable-Rate Technology	***	**	**	*	***	***	***
Drone	**	***	*	NA	***	***	***
Robot	*	**	***	ns	***	***	***
Pulse-Width Modulation	***	NA	ns	***	***	***	ns
Data Processing	***	**	***	*	***	***	***
Sensor	**	**	***	**	***	***	***
Artificial Intelligence	***	***	***	ns	***	***	***

***: $p < 0.001$; **: $p < 0.01$; *: $p < 0.05$; ns: $p > 0.05$; NA: Not Available.

The “artificial intelligence” class demonstrated strong and consistent associations with nearly all other technologies, showing highly significant correlation (*p*-value < 0.001) with the “variable-rate technology”, “drone”, “robot”, “data processing”, and “sensor” categories. These results indicate that AI-based systems are increasingly integrating across the technological spectrum, as well as reinforcing their central role in modern agriculture. The “variable-rate technology” class also showed high correlations with all technologies, especially with the “data processing” and “sensor” classes, pointing out their reliance on real-time data acquisition and interpretation. On the other side, the “pulse-width modulation” system showed no significant correlation with the “artificial intelligence” and “robot” topics, despite being significantly related to the “variable-rate technology”, “data processing”, and “sensor” domains. This may reflect its more specialized role in spray control, with less dependency on advanced decision-making algorithms.

Overall, these findings supported the notion of an evolving technological landscape where artificial intelligence, tools for data processing, and sensor systems play a pivotal role in facilitating the enhancement of the performance of field machinery and decision support systems.

4. Summary and Future Directions

Nowadays, precision agriculture (PA) has emerged as a key element in the transition toward sustainable, efficient, and digital farming systems. This bibliometric analysis is an essential tool for comprehensively understanding the development of scientific knowledge, mapping research trends, and thematic evolution in the adoption of precision agriculture technologies (PATs) aimed at reducing agrochemical use. The methodological rigor of this research, including the development of targeted search strategies and accurate keyword-based classification, ensured a robust and representative dataset. This bibliometric review, spanning the period of 2015–2024 and leveraging data from Scopus and Web of Science databases, aimed at mapping the scientific landscape of modern pesticide use reduction strategies within the PA domain. The analysis, encompassing co-authorship, co-citation, and co-occurrence methodologies facilitated by VOSviewer, provided an overview of research trajectories and emerging themes. Furthermore, the cleaning and deduplication processes ensured a solid, representative, and methodologically reliable sample.

Results revealed a growing interest in integrating advanced technologies, such as artificial intelligence, drones, sensors, and data processing, as central pillars for optimizing PPP use. These interconnected topics represented key domains of development, underscoring the scientific community's efforts toward sustainable agricultural practices. Their parallel rise after 2020 highlighted a technological convergence aimed at reducing agrochemical use through data-driven interventions. Particularly, AI-based approaches support predictive models for guiding decision-making processes that replace conventional calendar-based spraying with targeted applications. Drones, when combined with AI and wireless sensor networks, serve as both fast data acquisition and variable-rate spraying tools, allowing localized treatments. The integration of advanced data processing techniques ensures that large volumes of agronomic information can be translated into actionable strategies, further improving the treatment efficiency. Overall, the increasing adoption of PATs reflects a paradigm shift toward precision crop protection, where PPP use is optimized and sustainability goals are actively pursued.

Geographically, the United States, European countries, and China were the main contributors, with China leading in terms of volume and high-impact publications. Other countries, including India, Saudi Arabia, and Pakistan, also showed growing participation, reflecting an increase internationalization and global diffusion of research. Beyond the overall geographic distribution, region-specific differences emerged in technological focus and application scenarios. In areas such as Western Europe, North America, and China, where strong co-authorship networks were evident (Figure 5), research frequently addressed integrated solutions like AI-driven robotics and fully automated variable rate sprayers for high-value crops. This pattern corresponds to the higher representation of "artificial intelligence", "sensor", and "data processing" categories in interdisciplinary combinations (Table 3), suggesting a research environment capable of integrating multiple PAT-PPP domains. This context benefits from region-specific digital infrastructures and available investment capacities, supporting the development and integration of multiple PAT-PPP domains.

In other regions, including India and Brazil, scientific output has been rapidly growing, with application scenarios frequently oriented toward scalable and cost-effective solutions, such as low-cost UAVs for aerial spraying and low-cost sensors. This trend is consistent with the increasing representation of the "drone" category (Figure 12) and its integration with "sensor" and "data processing" classes (Table 3).

The analysis of editorial sources confirmed that a few large publishers, although with different strategies, concentrate most of the scientific output and act as amplifiers of content in a system that is increasingly interconnected. Scientific visibility is now driven by speed and high citation rates.

From the co-occurrence analysis, new sustainability-related topics clearly emerged, indicating a paradigm shift and a growing integration between technological innovation and environmental responsibility. Regarding the co-citation analysis by authors, three main lines of thought emerged within the scientific community working on PAT-PPT. This network visualization yielded a red cluster focusing on computer vision and AI, a green cluster centered on robotics and mapping for weed management, and a blue cluster addressing precision spraying and drone applications. Although they shared some methodological directions, they maintained clear differences in their approaches, key topics, and strategic visions of research.

The classification of the analyzed papers allowed us to group the literature according to well-established and emerging technologies, showing the evolution and convergence of solutions in the field of PA. The word analysis of the dataset confirmed a high level of interdisciplinarity in the research, revealing how different areas are increasingly integrated into a more complex technological landscape.

Some technologies considered "new", such as artificial intelligence, were already in use during the first five-year period of the study, while other older solutions, like PWM, are now being rediscovered and reused, showing a renewed interest linked to today's challenges.

The results highlight the importance of an integrated and multidisciplinary approach in the development of PATs and the need for strategies that promote system interoperability and sustainability in the agricultural sector. In particular, this study allowed us to

- Identify conceptual synergies between different sub-categories through a broad mapping of the literature;
- Define "bridge topics" that connect decision support systems and in-field implementation, helping the integration of technologies into complex operations;
- Analyze overlaps between research areas, showing future directions for more integrated solutions.

After structuring the corpus into seven main topics, "artificial intelligence", "sensor", and "data processing" appeared as the most transversal and connected themes, forming the backbone of advanced spraying technologies. The "variable-rate technology" class showed a strong correlation with "pulse-width modulation" ($p < 0.001$) and "sensor", confirming the importance of active modulation and localized input. On the other hand, UAVs and UGVs were strongly linked to AI but only weakly related to PWM, suggesting that active dose control is not yet fully developed in autonomous systems. PWM technology seemed to remain a very technical niche, significantly related only to some topics (VRT, data processing, sensors), and is still not well integrated into autonomous contexts. In general, the "sensor" category was a central node with strong and significant correlations to all other topics ($p < 0.01$).

Several documents, although not containing specific keywords from individual topics, were still relevant to the initial search. These were included in a transversal category called "general topic", which gathered significant contributions not easily placed within a single discipline.

To further advance in the field, future research directions should focus on enhancing the interoperability among PATs through open-source platforms and standardized communication protocols. There is also a need to investigate the socio-economic impacts of these technologies, particularly in smallholder and resource-limited farming contexts. Moreover, future studies should explore the long-term environmental effects of PATs, especially relating biodiversity, soil health, and water quality.

Overall, this bibliometric review goes beyond descriptive statistics by providing an integrated understanding of technological, methodological, and thematic trends in precision agriculture for pesticide reduction. The identification of transversal technologies, inter-topic correlations, and influential author clusters offers actionable insights for researchers, practitioners, and policymakers. These findings can guide the design of integrated, data-driven strategies to optimize pesticide use while promoting environmental sustainability, and help prioritize future research on interoperability, socio-economic impacts, and long-term ecological outcomes.

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