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The evolution of precision agriculture and food safety: a bibliometric study

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Introduction: Food safety issues pose a significant threat to humanity. Precision agriculture leverages advanced technologies for real-time monitoring and management, improving agricultural productivity and sustainability while safeguarding food security. Nonetheless, acquiring a thorough comprehension of this continually shifting panorama remains of vital significance.

Methods: This study conducts a comprehensive bibliometric review of precision agriculture and food safety, utilizing quantitative methods to identify past, current, and future evolution. It includes citation, co-authorship, co-citation, and co-words analyses.

Results: Publications emerged in 1994 and began to rise significantly since 2019. Citation analysis verified influencing works and journals, whereas co-authorship analysis identified how authors, institutions, and countries collaborate in this field. Co-citation analysis then classified past and current hotspots into four clusters: remote vegetation monitoring techniques, technological innovations and agricultural decision-making, precision agriculture and sustainable development, and deep learning in agriculture. After that, the co-occurrence of keywords revealed emerging trends, such as precision cultivation and yield prediction, smart agricultural technology and food management, precision information for climate change adaptation, and precision agriculture and food security.

Discussion: The findings provide insights for scholars, policymakers, researchers, practitioners, and industry stakeholders. They guide future research directions and address pressing challenges in agriculture and food safety.

KEYWORDS

precision agriculture, food safety, bibliometric analysis, Web of Science, VOSviewer

1 Introduction

Food safety has long been a global concern. The food safety landscape is marked by significant challenges and repercussions, as evidenced by the FAO and WHO. Shockingly, contaminated food causes over 200 diseases worldwide, with 1 in 10 people falling ill each year. Among them, children below the age of 5, who represent 9% of the population, bear 40% of foodborne diseases.[1] These figures starkly depict the severity of food safety issues and highlight the urgent need for solutions. Food shortages further exacerbate these concerns,

1 FAO, WHO. *Food standards save lives - A Guide to World Food Safety Day 2023*. Available from: www.fao.org/world-food-safety-day (accessed April 2, 2024).

underscoring the importance of ensuring food supplies' safety and availability (Zeng et al., 2023; Żurek and Rudy, 2024). Recognizing its intrinsic connection to agriculture is central to safeguarding food safety, from cultivation and production to processing and distribution (Davies and Garrett, 2018; Kimhi, 2024; Misra et al., 2022). Elements like soil quality, water access, pests, and diseases directly induce contaminant prevalence (Taneja et al., 2023). Addressing food safety necessitates a holistic approach encompassing the entire agricultural continuum, emphasizing sustainable and responsible practices to safeguard public health and well-being (Agrimonti et al., 2021).

Precision agriculture has emerged against this backdrop. It involves the use of advanced information technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), and cloud computing to achieve timely monitoring and analysis of various aspects, including fields, crops, and hydrology, thereby enabling precise management and addressing food safety concerns by enhancing production efficiency and resource utilization (Molin et al., 2021; Savary et al., 2019; Sishodia et al., 2020). However, employing precision agriculture to support food safety is not without challenges. It relies on accurate data and information, thus requiring substantial investment and technical support (Van Loon et al., 2020). Additionally, effective integration and transition from traditional agricultural practices to precision agriculture necessitate changes in habits and the promotion of operating skills among agricultural practitioners (Klerkx and Rose, 2020).

Recent studies have begun exploring the impact of precision agriculture on food safety. Existing bibliometric analyses have explored various technologies within the domain of precision agriculture. For instance, Mesías-Ruiz et al. (2023) introduce 39 emerging technologies to solve crop protection challenges. Kumari et al. (2023) further review the application of Machine learning (ML) and AI within the agriculture supply chain. After that, Liu et al. (2023) determine AI technologies' current state, focal points, and prospective research directions in food safety studies.

However, while studies have examined specific technologies within precision agriculture and food safety, they tend to provide fragmented insights, lacking a comprehensive analysis that integrates findings across various technologies and practices. Thus, although individual technologies may be well-studied, their collective impact on food safety remains unclear. Moreover, even when some studies focus on multiple precision agriculture technologies, they often fail to examine their direct relationship with food safety, leaving a gap in understanding how these technologies synergistically enhance food safety outcomes. The study aims to address this gap by conducting a comprehensive analysis through bibliometrics, utilizing the 1994–2024 data from the Web of Science (WoS) database and visualizing the pertinent literature with VOSviewe. Four specific objectives guide it:

1. Identifying Influential Works: To discern the most influential publications in precision agriculture and food safety through citation analysis.
2. Analyzing Collaboration: To examine the collaboration patterns among authors, institutions, and countries via co-authorship analysis.
3. Spotting Research Hotspots: To identify significant past and current research hotspots by co-citation analysis.
4. Revealing Emerging Areas: To unveil emerging research areas within precision agriculture and food safety through co-occurrence of keywords.

By realizing above objectives, the study makes several contributions to the field. Firstly, it provides a comprehensive bibliometric analysis that encapsulates the current status at the intersection of precision agriculture and food safety. By identifying influential publications and collaboration patterns, this study offers a detailed mapping of the scholarly landscape, enhancing our understanding of key players and their contributions. Secondly, this work highlights emerging research hotspots and future directions, thus helping researchers identifying historical focus and guiding them toward critical areas that require further exploration. Thirdly, the findings not only enhance the theoretical understanding of precision agriculture in relation to food safety but also offer practical insights for stakeholders across various sectors. It offers actionable insights into how precision agriculture can be effectively leveraged to enhance food safety. Policymakers can leverage the findings to inform their strategies and funding priorities, while researchers and practitioners will benefit from an overview of influential works and emerging trends. The identification of thematic clusters will guide future research directions, ultimately fostering collaborations that address pressing agricultural and food safety challenges.

2 Literature review

2.1 Challenges to food safety

The increasing complexity of food production necessitates a robust response to the myriad challenges affecting food safety. Climate change has increased weather variability, complicating agricultural planning and operations. This unpredictability can result in potential crop failures and reduced yields, which directly threaten food availability and safety (Agrimonti et al., 2021). Furthermore, the rise in pest populations and diseases, exacerbated by changing climatic conditions, poses a significant threat to food production systems, leading to increased reliance on pesticides and chemicals that can compromise food safety (He et al., 2023). Resource scarcity, particularly concerning water and arable land, further intensifies these challenges. As available agricultural land diminishes and water resources become increasingly limited, farmers face difficulties in maintaining consistent production levels (Dahane et al., 2022; Dhillon and Moncur, 2023). This scarcity not only affects the quantity of food produced but can also impact its quality, as stressed crops are more susceptible to diseases and pests, ultimately leading to food safety concerns (Wang and Frei, 2011).

Moreover, globalization has introduced market volatility, which can disrupt food supply chains. For instance, the COVID-19 pandemic has exposed critical weaknesses in food supply chains, leading to significant disruptions that have resulted in food shortages and heightened food safety concerns as consumers faced diminished access to fresh and safe food options (Sharma J. et al., 2021). These disruptions have not only increased food prices but also raised alarm over the safety of food products, as prolonged supply chain interruptions can compromise food quality and increase the risk of contamination, further exacerbating food insecurity in many regions (Rasul, 2021). This illustrates the urgent need for resilient food systems that can withstand such shocks.

Addressing these challenges is crucial to safeguarding food security and public health in an increasingly unpredictable global environment. Precision agriculture can play a vital role in this context by optimizing resource use, enhancing crop resilience, and improving monitoring and management practices. By implementing precision farming techniques, farmers can adapt more effectively to climate variability, mitigate pest and disease risks, and ultimately enhance consumer food safety. This shift toward precision agriculture is not merely beneficial but necessary to ensure a stable and secure food supply in the face of ongoing and future challenges.

2.2 The adoption of precision agriculture

Precision agriculture has gradually become vital for countries worldwide to ensure food safety and promote agricultural modernization and sustainable development (Gebbers and Adamchuk, 2010). Precision agriculture technology enhances crop yield and quality while improving ecological conditions (Pierce and Nowak, 1999). From the perspective of global practice, precision agriculture constitutes four elements: geographic positioning, data collection, data analysis, and precise processing. This framework enables functions such as data collection, decision support, and variable rate control.

2.2.1 Global positioning systems and remote sensing

The foundation for precision agriculture relies on Global Positioning System (GPS), which provides accurate positioning for data collection and implementation. Oksanen and Backman (2013) utilized GPS for tractor navigation systems, reducing labor inputs. Tijmen Bakker et al. (2011) developed a real-time Kinematic Differential Global Positioning System (RTK-DGPS) autonomous navigation system, which showed that autonomous robots in field navigation enhance farming efficiency and increase crop yields. Blok et al. (2019) employed a 2D laser radar scanner for robot navigation between rows. Llorens et al. (2011)used laser radar to scan fruit trees, estimating canopy volume with notable detection and navigation effects in orchards.

Remote sensing is also used to acquire real-time information on agriculture. It involves monitoring farmland with sensors mounted on aircraft and satellites and collecting information about crop growth and soil conditions (Khanal et al., 2017; Mulla, 2013). Compared to traditional monitoring methods, remote sensing technology offers advantages such as low cost, strong timeliness, minimal atmospheric interference, and high resolution, creating new tools for agricultural data collection. Bodrito et al. (2021) showed that satellite remote sensing and drone technology can effectively predict crop yields and implement precise fertilization strategies. Moreover, the application of sensor technologies allows farmers to collect critical data on soil moisture, temperature, and nutrient levels, enhancing the granularity of agricultural management practices (Li et al., 2024; Teixeira et al., 2023). Agricultural remote sensing has expanded from merely monitoring crop growth to include precise fertilization, irrigation, and other areas. According to the International Drone Association, the application of drones in the civil sector is expected to contribute $82.1 billion to the U.S. economy from 2015 to 2025, with over 80% coming directly from agriculture (Zhang H. et al., 2021).

2.2.2 Internet of things, geographic information systems

The IoT and Geographic Information Systems (GIS) analyze the data collected from GPS and remote sensing, enabling real-time monitoring of farmland and forming a spatial information database that supports precision management. IoT technology uses sensor networks to continuously collect data on soil moisture, temperature, light intensity, and more, providing a rich data source for farmers to make informed decisions based on environmental conditions (Finger et al., 2019; Tzounis et al., 2017; Asim et al., 2024). Big data analytics enhances this process by analyzing vast amounts of data to identify trends and patterns that can inform agricultural practices (Wolfert et al., 2017).

GIS technology excels in integrating and analyzing spatial data, allowing for detailed visualization and assessment of geographic patterns, relationships, and changes over time. Chelaru et al. (2011) used GIS technology to analyze changes in the agricultural environment, providing data for agrarian production forecasting and early warning. Ding et al. (2010) studied soil organic phosphorus based on GIS, predicting the spatial distribution of organic phosphorus in agricultural soils in southwestern Australia and evaluating phosphorus loss conditions.

2.2.3 Machine learning and artificial intelligence

Machine learning (ML) and AI technology enhance precision agriculture by applying advanced algorithms to conduct in-depth analyses of agricultural data. Machine Learning utilizes advanced algorithms to analyze vast amounts of agricultural data. ML algorithms can identify patterns and correlations within datasets that may not be immediately apparent, allowing for more accurate predictions regarding crop yields, pest infestations, and disease outbreaks (Zha et al., 2020). By continuously learning from new data, these algorithms adapt to changing conditions on the farm, providing real-time insights that help farmers make informed decisions (Dhillon et al., 2023; Kübert-Flock et al., 2023). For example, random forest regression models have been utilized to predict the yields of crops planted in rows based on multisource satellite data, demonstrating the potential for improved forecasting accuracy (Terra et al., 2021).

Artificial intelligence extends the capabilities of traditional agricultural practices by applying complex models and algorithms to support intelligent decision-making. AI systems are designed to analyze data from various sources, including IoT sensors, satellite imagery, and historical agricultural records (Misra et al., 2022). By synthesizing this information, AI assist farmers in developing scientific production plans tailored to their specific conditions and goals. For example, it can recommend optimal planting times, crop rotations, and pest management strategies based on predictive analytics (Kumari et al., 2023). Additionally, AI technologies provide insights into market trends and consumer preferences, enabling farmers to adjust their production strategies to meet demand (Liu et al., 2023).

2.2.4 Precision fertilization and pesticide application technology

Precision agriculture requires precise fertilization and irrigation based on the actual conditions of the farmland (Drusch et al., 2012; Sharma A. et al., 2021). Traditional fertilization and irrigation methods often lead to waste and pollution, while precision fertilization and pesticide application technologies effectively address these issues. It selectively applies pesticides based on target presence and characteristics, reducing pesticide deposition in non-target areas (Bongiovanni and Lowenberg-Deboer, 2004; Robert, 2002). Thus, Precision pesticide application technology helps to achieve better outcomes, lower costs, and less environmental pollution while improving crop disease resistance and product quality (Tian, 2002). Back et al. (2014) designed an image-based application rate measurement system to control granular fertilizer application rates. Reyes et al. (2015) developed a variable rate fertilizer automatic control system to enhance fertilization precision. Yu (2019) studied an online testing system for solid fertilizer application rates in a seed fertilizer drill machine, achieving precise measurement of application rates.

2.2.5 Regenerative agriculture technology

Regenerative agriculture is a holistic approach aimed at protecting and restoring food and agricultural systems by promoting soil regeneration, increasing biodiversity, improving water cycles, and enhancing overall ecosystem services. This method addresses degradation caused by industrial and conventional agricultural practices through sustainable farming and grazing techniques that rebuild soil organic matter and foster healthy ecosystems (Muhie, 2022). The benefits extend beyond soil health; they also lead to improved water infiltration and increased microbial abundance, which are essential for effective nutrient and moisture management (Basche et al., 2016). Moreover, regenerative practices reduce production input costs while effectively increasing crop yields, achieving enhanced efficiency and cost-effectiveness (Kaye and Quemada, 2017). Additionally, this approach considers animal welfare, contributing to improved livestock yield and quality (Palm et al., 2014).

2.2.6 Climate-smart agriculture technology

In 2009, the Food and Agriculture Organization (FAO) proposed the concept of "climate-smart agriculture" (CSA), exploring a strategy that ensures the sustainability and stability of global agricultural productivity while actively promoting carbon fixation and emission reduction to effectively mitigate the adverse impacts of climate change (Food and Agriculture Organization of the United Nations, 2013). CSA enhances food safety through a multifaceted approach that improves resilience, productivity, and sustainability in food systems, such as knowledge-smart practices, water-smart techniques, soil-smart strategies, and livestock management. Knowledge-smart practices equip farmers with essential tools and information, such as crop insurance and weather-based advisory systems, enabling them to make informed decisions that safeguard their yields (Qureshi et al., 2022). Multispectral and hyperspectral imaging support climate-smart agriculture by helping to identify plant stress and nutrient deficiencies early in the growing season (Lipper et al., 2014). Water-smart techniques, including drip irrigation and rainwater harvesting, ensure efficient water use, minimizing the likelihood of waterborne diseases affecting crops and enhancing overall food quality (Qureshi et al., 2022). Bai et al. (2016) found through APSIM simulations that optimizing planting density, sowing dates, water and fertilizer management, and plant protection measures can significantly improve crop yields and stability.

By implementing soil-smart practices, such as crop rotation and bio-fertilizers, CSA fosters healthier soils that lead to robust crops, thereby reducing the risk of disease and pest infestations. In terms of livestock management, livestock-smart practices focus on improving animal health through better feed and disease management, ensuring that meat and dairy products are safe for consumption (Qureshi et al., 2022). Together, these CSA practices bolster food production and create a safer and more reliable food supply, essential for addressing the challenges posed by climate change and urbanization.

2.3 The multifaceted impact of precision agriculture on food safety

Precision agriculture promotes food safety through several interconnected pathways.

2.3.1 Enhancing crop yields and stability of food supply

Precision agriculture promotes food safety by enhancing crop yields and improving resource efficiency. By advanced technologies such as satellite imagery, GPS, and IoT sensors, farmers can optimize the application of inputs like water, fertilizers, and pesticides (Drusch et al., 2012; Pandey and Pandey, 2023; Sharma A. et al., 2021). Research shows that these technologies result in higher crop productivity while reducing resource waste (Pesonen et al., 2014). Enhanced soil organic matter and microbial activity, achieved through precision agriculture practices, lead to healthier soils that support more robust crops.

In addition, precision agriculture stabilizes food supply within urban agriculture, thereby improving food safety. Urban agriculture reduces the distance food travels from farm to table, minimizing the risks associated with contamination during transportation. By producing food closer to consumers, urban farms can maintain freshness and quality, ensuring that safety standards are upheld (Rodríguez et al., 2022). Urban farmers can monitor and manage crop growth more effectively with precision agriculture, such as climate-smart approaches and digital decision-support systems, ensuring optimal conditions for production (Ebenso et al., 2022). This localized approach allows for quicker responses to environmental change, directly contributing to more consistent yields.

Moreover, the increased productivity provided by precision agriculture is essential for addressing the food demands of a rapidly growing global population (Tilman et al., 2011). As climate change and urbanization threaten traditional farming methods, precision agriculture offers innovative solutions to increase resilience. By adapting to local conditions and understanding the specific needs of crops, farmers can ensure a stable food supply even in unpredictable environments (Cao et al., 2017; Lin et al., 2023). This stability is critical not only for food security but also for the overall economy, as agricultural productivity directly impacts income and employment in rural areas.

2.3.2 Improving food quality monitoring across the supply chain

Another significant impact of precision agriculture is its ability to enhance the monitoring of food quality throughout the supply chain. Technologies such as blockchain and big data analytics facilitate improved traceability of food products from farm to table (Kumari et al., 2023). This traceability ensures that safety standards are met at every stage of production, processing, and distribution (Davies and Garrett, 2018; Kimhi, 2024; Misra et al., 2022). For instance, blockchain technology allows for the secure recording of every transaction and movement of food items, creating an immutable record that can be accessed by all stakeholders (Peng et al., 2022).

In the event of a food safety incident, this level of traceability enables rapid identification of affected batches, making it easier to recall contaminated products and prevent them from reaching consumers (Shafi et al., 2022). Enhanced monitoring mechanisms also allow for real-time assessment of food quality, ensuring compliance with safety regulations and standards (Pesonen et al., 2014). This proactive approach both protects consumers and fosters greater transparency in the food system, thereby enhancing consumer confidence in the safety and quality of their food (Pontikakos et al., 2010).

2.3.3 Reducing chemical inputs for healthier food products

Precision agriculture contributes to food safety by minimizing reliance on chemical fertilizers and pesticides, which have been linked to various health and environmental concerns. Pande and Arora (2019) have shown that excessive chemical use not only poses risks to human health but also adversely affects soil health, sustainability of productivity, and environmental stability. By employing targeted application methods based on real-time data, farmers can significantly lower the quantities of chemicals used, thereby reducing the risk of harmful residues in food products (Bongiovanni and Lowenberg-Deboer, 2004; Robert, 2002).

Through the implementation of integrated pest management and crop rotation strategies enabled by precision agriculture, farmers can adopt more sustainable practices that prioritize natural pest control methods and reduce the need for chemical interventions (Zimmermann et al., 2021). This shift not only enhances the safety of food products but also contributes to environmental sustainability (Miao et al., 2010). Consumers are increasingly seeking products that are free from harmful chemicals, and precision agriculture helps meet this demand by producing healthier food options (Jeong and Bhattarai, 2018).

2.3.4 Early detection and management of plant diseases and pests

Precision agriculture enhances food safety by enabling the early detection and management of plant diseases and pests (Jones and Naidu, 2019). Utilizing advanced technologies such as machine learning algorithms, drones, and imaging technologies, farmers can continuously monitor crop health in real time. These systems can detect subtle changes in crop conditions that may indicate the onset of disease or pest infestations before they escalate into significant problems (Grünig et al., 2021; Khanal et al., 2017; Mesías-Ruiz et al., 2023; Mulla, 2013).

This proactive approach allows for timely interventions, which are crucial in protecting crop yields and maintaining food safety (Mohanty et al., 2016). For instance, drones equipped with multispectral cameras can assess plant health over large areas, identifying stress factors that may not be visible to the naked eye (Shahrooz et al., 2020). Early detection systems not only reduce the economic losses associated with crop failures but also mitigate the risk of foodborne illnesses linked to contaminated products (He et al., 2023). By addressing these issues swiftly, farmers can ensure the delivery of safe, high-quality food to consumers, thereby reinforcing the overall integrity of the food supply chain (Kumari et al., 2023).

2.4 Stakeholders of precision agriculture and food safety

Different stakeholders play vital roles in the implementation and impact of precision agriculture. Farmers, as the primary implementers, utilize advanced technologies to enhance productivity and economic returns (Zhang et al., 2002). However, their adoption of these technologies often hinges on their level of training and accessibility. Many farmers face challenges such as inadequate educational resources and insufficient technical support, limiting their ability to implement precision agriculture effectively (Saiz-Rubio and Rovira-Más, 2020; Weersink et al., 2018). Addressing these barriers through targeted training programs and accessible resources is essential for maximizing the benefits of precision farming and fostering sustainable agricultural practices.

The increasing awareness of food safety from consumers, who represent another critical stakeholder group, drives demand for high-quality, pesticide-free products (Bongiovanni and Lowenberg-Deboer, 2004; Robert, 2002). Pontikakos et al. (2010) indicate that consumers are more likely to choose foods produced with sustainable practices, viewing precision agriculture as a means to enhance food safety and reduce harmful residues. This shift in consumer preferences underscores the importance of transparency in food production.

In this circumstance, policymakers help to shape the landscape for precision agriculture through the development of supportive policies and funding mechanisms (Singh, 2018). They are tasked with creating a regulatory framework that not only encourages the adoption of innovative technologies but also ensures that food safety standards are upheld and that agricultural practices are sustainable (Sparrow and Howard, 2021). By facilitating collaboration among farmers, consumers, and the agricultural sector, policymakers can help create an environment conducive to the successful implementation of precision agriculture.

2.5 Cases in precision agriculture achievements

The adoption of precision agriculture technologies varies between developing and developed countries. Developing countries often rely on cost-effective methods due to limited resources, while developed countries leverage advanced technologies to enhance productivity and food safety.

2.5.1 Developing countries

In developing countries, the adoption of precision agriculture technologies is often constrained by limited resources, infrastructure, and skilled labor. These nations typically operate small-scale and fragmented agricultural systems, which challenge the realization of economies of scale. Consequently, farmers tend to adopt low-cost, accessible technologies that enhance food safety without imposing substantial financial burdens.

Countries like India, which have relatively small and dispersed arable land, have developed a precision agriculture model that focuses on high-value crops combined with selected precision agriculture technologies (Alagh, 2011). For example, Indian tea farmers employ quick soil mapping and targeted labor allocation. The structured nature of tea planting allows for quick soil mapping once the conditions of each plot are understood. Labor can be organized based on the specific characteristics of each field, allowing for tailored interventions that compensate for technological limitations (Pathak et al., 2022). This approach not only improves productivity without requiring substantial financial investment but also ensures that the crops are cultivated under optimal conditions, thereby enhancing food safety through better quality control.

Additionally, low-cost diagnostic tools, such as chlorophyll meters and leaf color charts, have become vital for smallholder farmers in countries like the Philippines and Indonesia. These tools help farmers monitor nitrogen levels in crops, which is crucial for producing safe and nutritious food (Mazloumzadeh et al., 2010). By enabling farmers to make informed decisions about fertilization, these technologies directly contribute to food safety.

In South Africa, small-scale farmers utilize mobile phone data to monitor soil moisture conditions, allowing them to make timely agricultural decisions that optimize crop health (Dlamini et al., 2023). By enabling farmers to make informed decisions about fertilization, these technologies directly contribute to food safety (Mondal and Basu, 2009).

2.5.2 Developed countries

In contrast, developed countries like the USA leverage advanced precision agriculture technologies to enhance food safety through large-scale and intensive farming practices. The prevalence of larger farms facilitates the implementation of sophisticated precision agriculture techniques, leading to improved crop yields and safer food products. Governments in these countries prioritize the development of precision agriculture through policy support, funding, and infrastructure investments (Daberkow and McBride, 2003). The focus on data-driven decision-making allows farmers to optimize inputs and maximize outputs effectively, which underpin food safety initiatives (Basso et al., 2001).

In the USA, pilot demonstrations of precision agriculture technologies are conducted to assess their benefits, particularly concerning food safety. Researchers analyzed data from comparative experiments to evaluate the economic and safety impacts of new technologies. Universities play a crucial role in showcasing the advantages of precision agriculture, helping farmers understand how these methods can reduce the use of harmful chemicals while maintaining high food safety standards (Yost et al., 2017). This direct approach to showcasing the benefits of precision agriculture has proven to be an effective method for technology dissemination. For instance, soybean farmers in the USA utilize remote sensing technologies such as satellite imagery and drones to monitor crop health. This enables them to significantly reduce chemical usage while enhancing food safety and yield quality (Arjoune et al., 2022).

In Denmark, experts from the National Agricultural Advisory Center provide guidance on precision agriculture technologies, ensuring that local agricultural advisory agencies receive the latest knowledge. This close connection between specialists and farmers fosters the adoption of best practices, thereby improving food safety standards in the region (Pedersen et al., 2004).

Japan's focus on developing portable precision agriculture devices reflects the need for accessible solutions in smaller farmland areas. Innovations like sensitive soil moisture sensors and precise fertilization machines are tailored for small-scale farms, promoting food safety by enhancing management practices and reducing the risk of over-fertilization (Shibusawa, 2001).

3 Research design and methodological approaches

3.1 Bibliometric approach

This study employed bibliometric analysis to examine keywords, sources, countries, and references from existing publications, providing an evaluation of the developmental trajectory, current status, and future directions within precision agriculture and food safety. This method was instrumental in organizing scientific literature into a structured format (Almas et al., 2022; Fauzi, 2023; Yan et al., 2022), enhancing its accessibility and comprehensibility (Fauzi et al., 2023; Yao et al., 2022), and making it popular in multiple research fields (Wider et al., 2023; Zakaria et al., 2023).

The research employed citation analysis, along with co-authorship, co-citation, and co-word analyses, which enriches the examination of structural aspects and aids in charting future directions (Fauzi et al., 2022b). Citation analysis was used to evaluate the impact of articles by citations a publication receives. It is crucial for mapping and identifying impacting works in a specific field (Weerakoon, 2021). Co-authorship analysis investigated the collaborations and interconnections among authors, their affiliations, and the publishing locations they represent (Tamala et al., 2022). Co-citation analysis compiled instances of concurrent citations made to various documents and employs these counts to assess the degree of similarity or relatedness among those documents (Fauzi, 2023). Co-word analysis measured the co-occurrence frequency of keywords from titles, author keywords, and abstracts, thereby exploring inherent connections and directing potential topics (Su and Lee, 2010; Verma et al., 2023). Theme analysis entails organizing scholarly literature to reveal coherence and evolving patterns (Fauzi et al., 2022a; White and McCain, 1998). The significance of prominent publications is derived from frequencies and linkage strength (Bashar et al., 2021).

3.2 Study design and data processing

This paper begins with a meticulous selection of relevant literature, followed by an approach encompassing both quantitative and qualitative analyses. This dual-pronged methodology aims to uncover significant findings and subsequently formulate pertinent conclusions.

3.2.1 Literature search methodology

To minimize the risk of missed or misdirected searches, the study implemented the search strategy in Table 1. This process started with a selection of relevant literature, utilizing the Web of Science (WoS) database, which is recognized for its quality and extensive coverage of scholarly content (Yadav and Banerji, 2023). This database was widely recognized as the most esteemed and extensively used data sources on publications and citations, providing comprehensive access to worldwide prestigious research (Birkle et al., 2020; Martín-Martín et al., 2021). The choice of a single database such as WoS reduces the complexity and potential human error associated with consolidating data from multiple sources (Donthu et al., 2021).

The "Search Keywords" column employed combinations including ("precision agricultur*" or "precision farming*" AND "food safety*" or "food security*" or "food hygiene*" or "food quality assurance*"), ensuring a wide range of relevant literature was captured. This search string consists of two sets of representative terms related to the thematic field of investigation.

3.2.2 Inclusion and exclusion criteria

To ensure the quality of the selected literature, this study established specific inclusion criteria. The time frame included works published until March 24, 2024, and the search was confined to the "TOPIC" retrieval area, encompassing titles, abstracts, and keywords (Latino and Menegoli, 2022). The study adopted a broad scope, encompassing all meso-level topics linked to the keywords identified in the "Citation Topics Meso" section, aiming to capture interdisciplinary research that intersects with precision agriculture and food safety (Wider et al., 2023). As for "Document Type," all types (e.g., articles, reviews, conference proceedings) were included to ensure a broad collection of relevant research outputs. The selection process was restricted to articles published in English to enhance accessibility and comprehension among the academic community, given the predominance of English in scholarly communication (Kotobiodjo et al., 2024; Lukambagire, 2024).

The study employed the PRISMA (2020) guidelines to analyze and exclude articles from the dataset (Kotobiodjo et al., 2024; Kraus et al., 2020; Latino and Menegoli, 2022), as shown in Figure 1. Duplicate records were merged to ensure that each article was unique in the sample (Kotobiodjo et al., 2024). Then, articles were screened based on their titles and abstracts to eliminate those that were not relevant to the topic (Latino and Menegoli, 2022; Suchek et al., 2021). This procedure finally resulted in the identification of 416 articles.

TABLE 1 Search string.

WOS database	ALL
Time period	Up to March 24, 2024
Search field	TOPIC
Search keywords	"Precision agricultur*" or "precision farming*" AND "food safety*" or "food security*" or "food hygiene*" or "food quality assurance*"
Citation topics meso	ALL
Document type	ALL
Languages	English

3.2.3 Analytical techniques by VOSviewer

Bibliometric analysis can be conducted using a variety of tools, such as CiteSpace and VOSviewer, which offer user-friendly interfaces; the Bibliometrix package in R, which relies on code commands; and Pajek and Gephi, which focus on constructing complex network analyses. Among them, VOSviewer has become an increasingly popular software. It highlights essential similarities and connections across various research domains (Yao et al., 2022), including technology, geography, agriculture, economy, and education. By clustering dispersed knowledge, the software reveals similarities and relevancies across diverse themes, allowing scholars to analyze the relationships between different areas of research (Eck and Waltman, 2010).

Due to its outstanding visualization capabilities and user-friendly interface (Wang and Frei, 2011), VOSviewer 1.6.18 software was chosen as the tool in the current study. This research identified significant publications, research collaborations, hotspots, and academic trends through density, overlay, and network analysis. Density analysis created maps for both publication citation analysis and sources citation analysis, visually representing the concentration of research. Overlay analysis was used to identify authorship patterns. It visualized the temporal dynamics of collaboration among authors, highlighting shifts in research partnerships over time. Network analysis generated maps for multiple dimensions, including organizations co-authorship analysis, countries co-authorship analysis, co-citation analysis, and co-word analysis. Network diagrams illustrated the relationships between authors, institutions, and

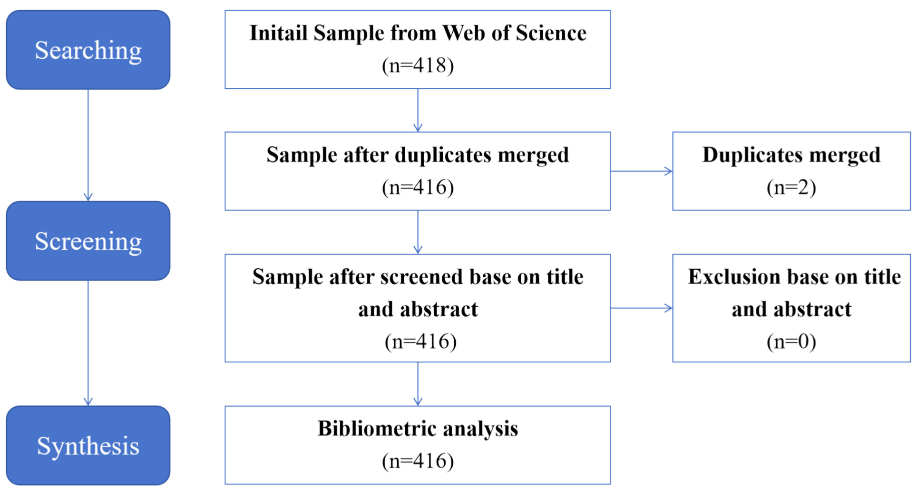

FIGURE 1
Review protocol according to PRISMA (2020) guidelines.

countries, and the connections between keywords and cited works. These graphs provided a detailed overview of the research landscape, allowing researchers to gain a deeper understanding of precision agriculture and food safety.

Additionally, this study employed a qualitative thematic approach to extract critical insights from the reviewed publications. This process began by grouping the publications into categories based on shared themes and ideas. By doing so, researchers were able to identify common patterns and trends across the different studies. Next, it organized the information from each category in tables and narrative summaries. This allowed for a clear presentation of the feature of each theme. Finally, descriptive labels were assigned to each category, providing a concise way to refer to the different groups of publications. These labels helped to clarify the distinctions between the categories and facilitated further discussion and analysis of the findings (Mashari et al., 2023).

4 Results

4.1 Publication trends

The WoS search yielded 10,098 citations for the selected publications ($N = 418$), with 9,867 citations excluding self-citations. The H-index, indicating the impact and productivity of the research, stood at 47, showcasing the significance of the contributions. Each article received 24.16 citations on average, highlighting the attention and recognition garnered by precision agriculture and food safety research. This compilation of 418 articles reflects a growing demand for studies within this domain, under-scoring research's increasing importance and relevance in precision agriculture and food safety. While the area commenced in 1994, major progress was not realized until 2019. Since then, there has been a remarkable increase in the volume of relevant publications, reaching 116 in 2023. Citations have also been documented since 1994, with a consistent upward trend observed from 2007 onwards. Since 2020, each subsequent year has seen citations increase approximately 1.5 times compared to the preceding year. By 2023, the aggregate count of citations had surged to 3,008. Figure 2 illustrates the progression of publications and citations spanning from 1994 up until March 24, 2024, further emphasizing the growing influence of precision agriculture and food safety research.

4.2 Citation analysis

This section employs density visualization techniques to unravel document and source citation analyses. Document citation analysis focuses on the flow of citations among individual publications, while source citation analysis examines the citation behavior of specific sources (Figure 3).

4.2.1 Most impactful documents

Utilizing a citation threshold of 15 or more, a refined subset of 137 documents was extracted from the original pool of 418 studies for further analysis. Among these, 81 were published in 2020 or later. The top three cited publications were Gebbers and Adamchuk (2010) (658 citations), Atzberger (2013) (597 citations), and Maimaitijiang et al. (2020b) (385 citations). Table 2 showcases the top 10 papers ranked by citation count. These highly cited publications underscore their significant influence on precision agriculture and food safety. Future research should build upon these influential works to advance knowledge and practice in precision agriculture and food safety.

Figure 3 presents a density analysis visualization that maps out the web of document links. This figure intuitively reveals the links and influence of documents through the size and color of the nodes. Notably, "Gebbers and Adamchuk (2010)" was in the red zone, indicating a high link, suggesting that it played a central role in the

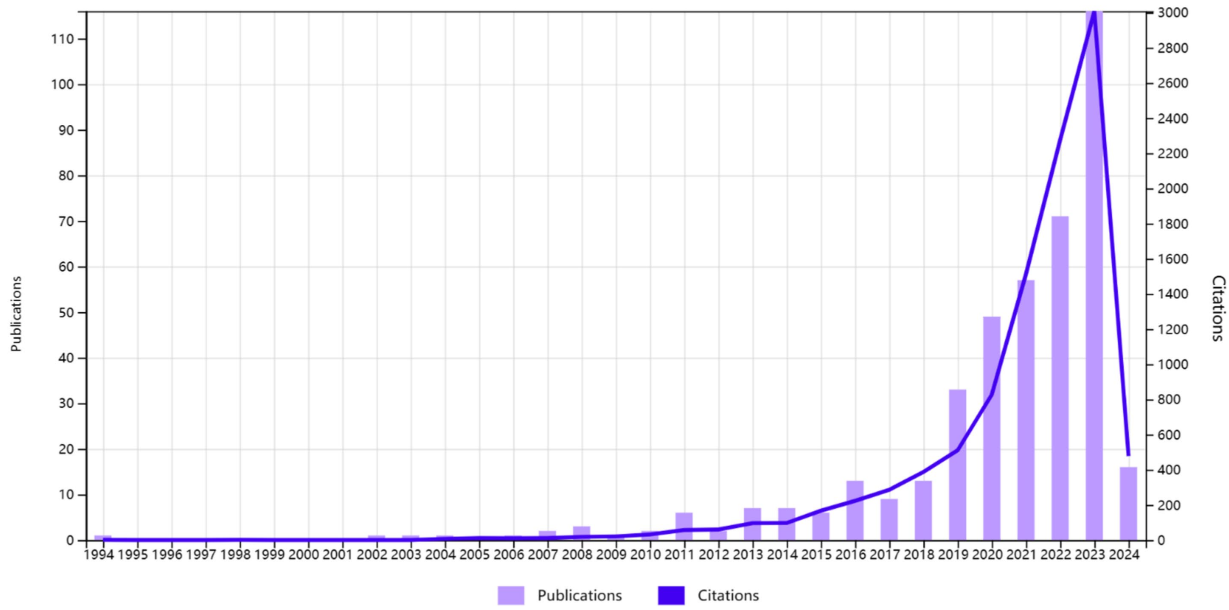

FIGURE 2
The number of publications and citations.

field. Gebbers and Adamchuk (2010) claimed the top position with 15 links when the studies were arranged based on their connectivity. Following closely were Robert (2002), Cao et al. (2017), and Kendall et al. (2022), each with five links, indicating their significant contributions as well. Furthermore, an analysis of publication years shows that earlier research continued to be highly linked, while more recent publications were gradually gaining attention. This trend suggests that while established works remain influential, newer research is beginning to carve out its place in the academic discourse, potentially driving future innovations and developments in precision agriculture and food safety.

4.2.2 Sources of publications

By applying a rigorous threshold criterion, which necessitates each source to have at least one contributing document and a minimum of 10 citations, 125 journals out of the 261 sources were identified. Table 3 underscores the top 10 sources garnered distinction through their towering averages of citation counts. Science from AAAS led the list, boasting an average of 658 citations. Agronomy for Sustainable Development from INRA and Computers & Operations Research from Elsevier followed closely, with 358 and 254 average citations, respectively. These high citation averages indicate that these sources are key platforms for advancing knowledge and fostering collaboration in the field of precision agriculture and food safety.

The graphical presentation in Figure 4 offers a visual breakdown of source density analysis, arranged based on their cumulative link strength. Prominent sources such as "science," "remote sensing," and "agronomy-basel" were located in the red zones, underscoring their important impact in the field of precision agriculture and food safety. At the forefront stands Science, published by AAAS, which leads the pack with a formidable total link strength of 24. Following closely in second and third positions are Remote Sensing and Agronomy-Basel, both from MDPI, showcasing total link strengths of 22 and 19, respectively. The analysis also reveals a diverse array of topics covered by these sources, including precision agriculture, food science, and environmental sustainability. The clustering of journals reflects the multidisciplinary character of current research trends, emphasizing the importance of cross-disciplinary collaboration. The role of these influential journals in disseminating diverse research perspectives is critical for advancing knowledge and fostering innovation in precision agriculture and food safety.

4.3 Co-authorship analysis

4.3.1 Authors of publications

Among the pool of 2,101 authors under consideration, a selective cohort of 86 authors was identified based on having contributed at least two documents and garnered at least one citation. Table 4 highlights the foremost 10 authors who have excelled based on their exceptional average number of citations. Fritschi, Maimaitijiang, Sagan, and Sidike occupy the top spots, each demonstrating a remarkable average of 252 citations per author, underscoring their significant contributions and influence within precision agriculture and food security. These authors play pivotal roles in advancing research and innovation in this area. Their work not only contributes to the academy but also has practical implications for improving agricultural practices and food security.

Figure 5 presents a visual representation of the web of co-authorship, constructed based on the authors' names. Each node represents an author, and the connections between them indicate co-authorship on shared publications. The color gradient—from blue to yellow—represents the publication timeline, with blue indicating earlier years (2018 or before) and yellow signifying more recent years (2024). The visualization reveals distinct clusters of authors who collaborated, indicating a strong network of co-authorship. A foremost example of clusters in the map encompasses seven authors who were particularly prevalent during the year 2023. In another cluster of seven authors, the average year of publication for these seven authors was 2010.33, 2019.5, 2020.5, 2017, 2013.67, 2018, and 2023, respectively. The second-largest cluster, comprising six authors, prominently stood out in 2021. Concurrently, the third-largest cluster, boasting five authors, appeared notably in 2023.5, further underlining the dynamic nature of co-authorship networks and their evolution over time. These patterns underscore the dynamic nature of co-authorship networks and their evolution, suggesting that collaborative research is increasingly

TABLE 2 Top 10 articles ranked by citation.

No.	Year	Author	Title	Citation	Links
1	2010	Gebbers and Adamchuk (2010)	Precision Agriculture and Food Security	658	15
2	2013	Atzberger (2013)	Advances in Remote Sensing of Agriculture: Context Description, Existing Operational Monitoring Systems and Major Information Needs	597	4
3	2020	Maimaitijiang et al. (2020b)	Soybean yield prediction from UAV using multimodal data fusion and deep learning	385	2
4	2010	Miao et al. (2010)	Long-term experiments for sustainable nutrient management in China. A review	358	4
5	2020	Sharma et al. (2020)	A systematic literature review on machine learning applications for sustainable agriculture supply chain performance	254	2
6	2012	Tey and Brindal (2012)	Factors influencing the adoption of precision agricultural technologies: a review for policy implications	237	2
7	2003	Jarecki and Lal (2003)	Crop Management for Soil Carbon Sequestration	227	0
8	2014	Sabaté and Soret (2014)	Sustainability of plant-based diets: back to the future	204	0
9	2016	Brevik et al. (2016)	Soil mapping, classification, and pedologic modeling: History and future directions	194	1
10	2022	Misra et al. (2022)	IoT, Big Data, and Artificial Intelligence in Agriculture and Food Industry	192	0

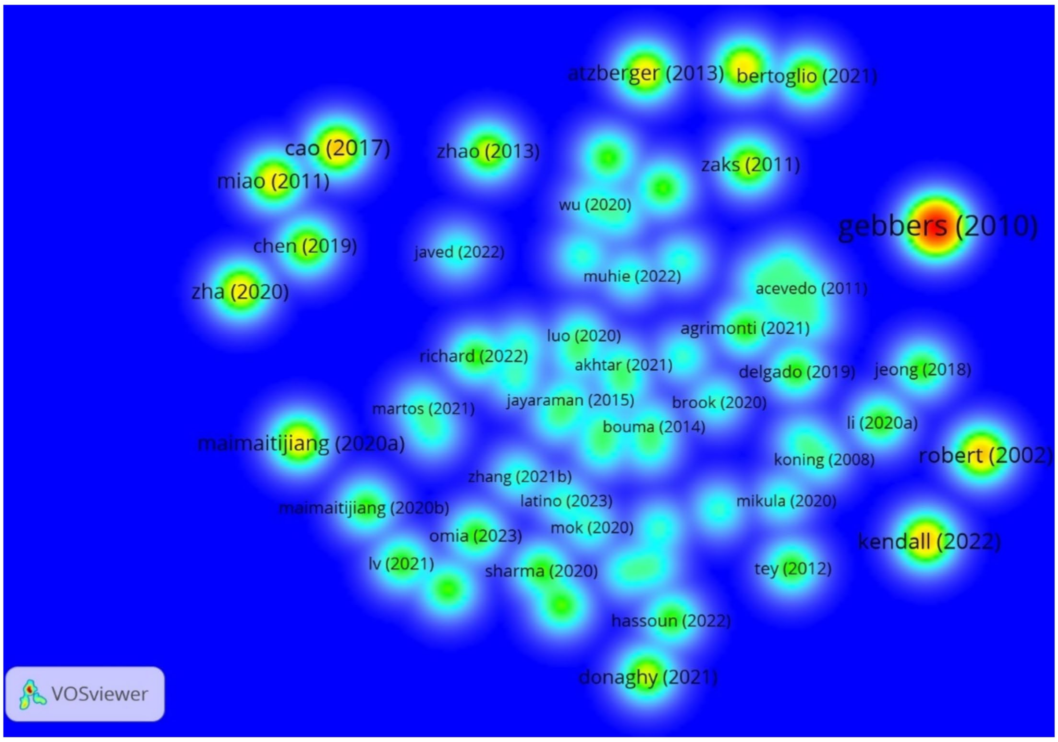

FIGURE 3
The density visualization of documents citation analysis.

TABLE 3 Top 10 sources ranked by average citation.

No.	Source	Publisher	Publication	Citation	Total link strength	Average citation
1	Science	AAAS	1	658	24	658
2	Agronomy for Sustainable Development	INRA	1	358	4	358
3	Computers & Operations Research	Elsevier	1	254	4	254
4	Critical Reviews in Plant Sciences	Taylor & Francis	1	227	0	227
5	American Journal of Clinical Nutrition	American Society for Nutrition	1	204	0	204
6	IEEE Internet of Things Journal	IEEE	1	192	3	192
7	Proceedings of the National Academy of Sciences of the United States of America	National Academy of Sciences	1	184	2	184
8	Journal of the Science of Food and Agriculture	Wiley	1	157	3	157
9	Journal of Plant Nutrition and Soil Science	Wiley	1	136	1	136
10	Ecosystem Services	Elsevier	1	126	5	126

important in addressing complex issues in precision agriculture and food security. Additionally, it highlights emerging connections among authors like "ismaili, maryem" and "hittiou, abdelaziz," suggesting new collaborative efforts in recent years. This trend emphasizes the importance of fostering collaboration as a means to enhance knowledge sharing and advance the field.

The figure illustrates how collaboration can lead to the formation of research teams that focus on certain topics. For example, the collaboration in one of the largest clusters involving Yuxin Miao focused on optimizing fertilizer use in precision farming (Cao et al., 2017; Miao et al., 2010; Zhao et al., 2013). Their research addressed the critical need for sustainable practices that enhance crop yields while minimizing environmental impact, reflecting a major trend in agricultural research. This consistency with previous study of Tian (2002) suggests a growing recognition of the need for environmentally friendly agricultural methods.

The other seven-author cluster containing Maninder Singh Dhillon facilitated the topic on precision agriculture and agricultural decision-making (Dhillon et al., 2023; Kübert-Flock et al., 2023). They focused on remote vegetation monitoring techniques and machine learning in agricultural decision-making, which helps in enhancing crop yield predictions and promoting sustainable agricultural practices. Their work

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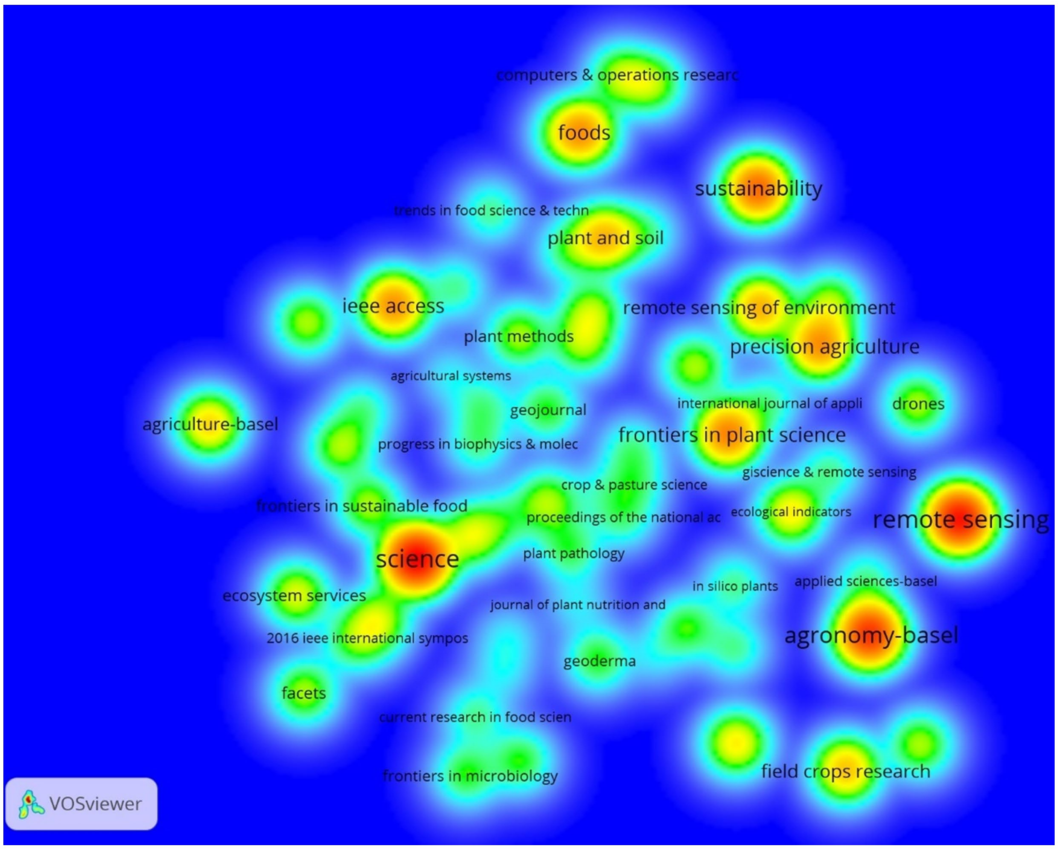

FIGURE 4
The density visualization of sources citation analysis.

TABLE 4 Top 10 authors ranked by average citation.

No.	Author	Publication	Citation	Total link strength	Average citation
1	Fritschi, Felix B.	2	504	6	252
2	Maimaitijiang, Maitiniyazi	2	504	6	252
3	Sagan, Vasit	2	504	6	252
4	Sidike, Paheding	2	504	6	252
5	Zhang, Fusuo	3	457	4	152.33
6	Wei, Qingshan	2	249	0	124.5
7	Miao, Yuxin	6	629	11	104.83
8	Brevik, Eric C.	2	201	4	100.5
9	Miller, Bradley A.	2	201	4	100.5
10	Pereira, Paulo	2	201	4	100.5

exemplifies the integration of technology in agriculture, highlighting the importance of data-driven approaches to improve outcomes.

Moreover, the joint research conducted by the four most cited authors—Maitiniyazi Maimaitijiang, Vasit Sagan, Paheding Sidike, and Felix B. Fritschi—on using Unmanned Aerial Vehicles (UAVs) and data fusion technologies for crop monitoring had also significantly advanced the understanding of remote sensing methodologies in agriculture (Maimaitijiang et al., 2020a; Maimaitijiang et al., 2020b). Their work also emphasized that technological innovations facilitate improved decision-making processes and enhance operational efficiency in farming. The emergence of these topics highlights a significant trend toward integrating advanced technologies into agricultural practices, which is corroborated by findings from Pierce and Nowak (1999) and Chelaru et al. (2011).

4.3.2 Affiliation of publications

By implementing a criterion requiring a minimum of three publications and five citations per organization, 56 institutions were identified out of the 834 organizations. Table 5 presents an overview of the leading 10 institutions, ranked according to their impressive

TABLE 5 Top 10 institutions ranked by average citation.

No.	Institution	Country	Publication	Citation	Total link strength	Average citation
1	University of Missouri	USA	3	504	0	168
2	University of Minnesota	USA	6	580	10	96.67
3	The Ohio State University	USA	4	325	5	81.25
4	The University of Adelaide	Australia	4	275	3	68.75
5	Leibniz Centre for Agricultural Landscape Research	Germany	3	202	1	67.33
6	University of Cambridge	England	3	186	5	62
7	Wageningen University & Research	Netherlands	6	367	6	61.17
8	Mississippi State University	USA	3	174	1	58
9	Norwegian Institute of Bioeconomy Research	Norway	3	172	6	57.33
10	Universiti Putra Malaysia	Malaysia	5	278	1	55.6

average citation count. All the first three institutions were originated from the USA. The University of Missouri was ranked top with an amazing average of 168 citations per publication. The University of Minnesota and the Ohio State University followed, boasting 96.67 and 81.25 average citations, respectively. The results suggest that these institutions are prolific in their research output and produce work that is highly regarded and frequently cited by peers, indicating their influence in shaping the research area.

Out of the 56 institutions selected, some were not interconnected, leaving 38 groups clustered into six clusters within the organizational network (Figure 6). Each node represents an organization in the network analysis of these organizations, and the connections between them indicate shared authorship on publications. The color-coded nodes reflect different clusters of collaboration, highlighting interaction among institutions. Chinese institutions stand out as being particularly active in their collaborative endeavors, showcasing a commitment to advancing research in precision agriculture and food safety. Prominent nodes such as "China Agricultural University" and "Chinese Academy of Sciences" were located in central clusters. China Agricultural University and the Chinese Academy of Agricultural Sciences were at the forefront of collaboration, tied for the top spot with each having collaborated extensively, co-authoring projects alongside 11 distinct institutions. Ranked further down the list, the Chinese Academy of Sciences engaged in collaborative efforts with seven diverse organizations. The strong connections among these institutions suggest a robust network of partnerships, which is essential for advancing research initiatives. As the agricultural landscape continues to evolve, such collaborative networks will be crucial for addressing emerging issues related to food security.

Collaborative efforts among various institutions were advancing agricultural practices and forming various research areas. For instance, the partnership between China Agricultural University and University of Minnesota focused on improving nitrogen management in rice cultivation by utilizing UAV remote sensing and machine learning, thereby enhancing precision cultivation and yield predictions (Zha et al., 2020). This aligned with another collaboration between the same institutions, which seeks to optimize nitrogen use in wheat-maize cropping systems while minimizing environmental risks, thereby promoting sustainable agricultural practices that protect natural resources (Cao et al., 2017). Furthermore, the joint research of China Agricultural University and Norwegian Institute of Bioeconomy Research leveraged UAV technology to monitor nitrogen status in winter wheat fields, enhancing remote vegetation monitoring techniques and facilitating effective decision-making in smallholder farming (Chen et al., 2019). This trend toward integrating technology in agriculture reflects a broader movement within the field, as highlighted by Qureshi et al. (2022) and Bai et al. (2016), who noted the increasing reliance on precision agriculture technologies to improve efficiency and sustainability.

Real-time monitoring not only helped in managing inputs more effectively but also equipped farmers with the information needed to adapt to changing environmental conditions. Additionally, a partnership between University of Putra Malaysia and University of Adelaide reviewed the factors influencing the adoption of precision agricultural technologies, providing valuable insights for policymakers to increase technology uptake in agriculture (Tey and Brindal, 2012).

Another significant collaboration between China Agricultural University and Chinese Academy of Agricultural Sciences investigated the impacts of fertilizer intensification in China's HHH Plains, promoting resource-efficient practices while ensuring sustainable development (Kong et al., 2014). These collaborations not only fostered the development of innovative agricultural solutions but also tackled pressing issues related to food security and environmental stewardship. The increasing number of partnerships signifies a trend toward more holistic approaches to agricultural research, which underscore the importance of collaboration in tackling complex challenges in agriculture.

4.3.3 National origins of publications

All 86 countries published on precision agriculture and food safety were included in the analysis. They were ranked by average citations, shown in Table 6. Peru and Austria ranked top two (184 and 166.4 average citations), while New Zealand ranked third (109 average citations). The high citation averages suggest that these nations are leaders in addressing challenges related to agriculture and food security. As the field continues to evolve, the contributions from these nations will be essential for advancing knowledge and practices that promote precision agriculture on a global scale.

Given the disconnected nature of certain countries in precision agriculture and food safety, the resulting national co-authorship network comprises 74 nations, organized into six clusters. Each node

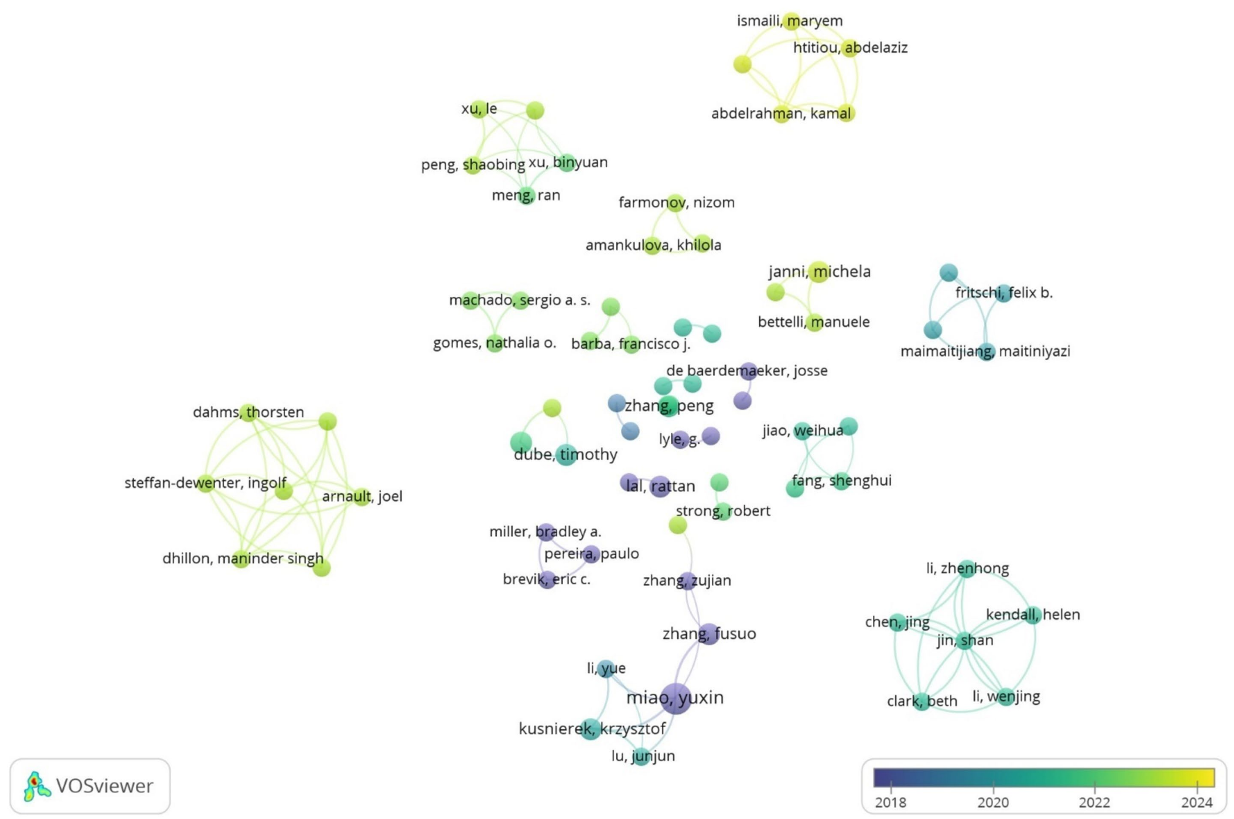

FIGURE 5
The overlay visualization of authors co-authorship analysis.

represents a country, while the connections between them indicate co-authored papers. The color coding helps identify clusters of collaboration, with different colors representing distinct groups of countries. This arrangement reflects the varying levels of collaboration and interconnectivity among these countries within these specialized fields. Figure 7 presents the network analysis visualization of countries. The USA emerged as a clear leader by a wide margin, co-authoring with 43 countries. India and Germany ranked second with 28 collaborations. Then, England followed with 27 links. This visualization underscores these countries' essential contributions and influence in the precision agriculture and food safety domain. The connections among these countries suggest robust research networks that facilitate knowledge exchange and joint initiatives, which are critical for tackling food security issues by precision agriculture practices.

The visualization reveals a diverse array of countries involved in research, including both developed and developing nations. For instance, China was prominently highlighted in red. Its connections with various countries, especially the USA, India, and several European nations, underscored China's role as a central hub for research partnerships. This suggests that China was not only advancing scientific research domestically but was also actively participating in international collaborations. Another large agricultural country, Brazil, represented in green, signified its growing involvement in international research cooperation. The connections with countries like India and Australia indicated that while Brazil's research influence might be smaller relative to larger nations, its trend of engaging in international collaboration was on the rise.

International collaborations among countries were important in advancing innovative topics and addressing agricultural challenges. For instance, a partnership between Germany emphasized how integrating advanced technologies can optimize resource use and enhance food security (Gebbers and Adamchuk, 2010). Similarly, a collaboration between China and England highlighted the significant role of AI in improving food safety and quality while reducing waste, showcasing the benefits of technological innovations across borders (Liu et al., 2023). Additionally, joint efforts among the USA, Germany, and China showcased the global effort to develop innovative tools for real-time plant health monitoring, contributing to precision agriculture (Wu et al., 2020). Furthermore, a work by researchers from the USA and Australia illustrated how big data can enhance food safety management across international food supply chains (Donaghy et al., 2021). In a review led by India and England (Sharma et al., 2020) explored how machine learning improve agricultural sustainability on a global scale. Meanwhile, a paper co-authored by researchers from Australia and the USA addressed the challenges posed by viral diseases in agriculture and emphasized the need for integrated strategies, illustrating the collaborative effort to enhance global food security (Jones and Naidu, 2019). The economic impacts of UAV technology in agriculture, studied by Germany and China, revealed how these innovations improve efficiency and profitability for farmers (Quan et al., 2023).

TABLE 6 Top 10 countries ranked by average citation.

No.	Country	Publication	Citation	Total link strength	Average citation
1	Peru	1	184	2	184
2	Austria	5	832	22	166.4
3	New Zealand	2	218	11	109
4	Lithuania	2	201	12	100.5
5	Norway	8	475	35	59.375
6	Poland	8	463	20	57.875
7	Cyprus	2	106	4	53
8	USA	90	4,744	249	52.71
9	Singapore	3	136	8	45.33
10	Germany	30	1,336	72	44.53

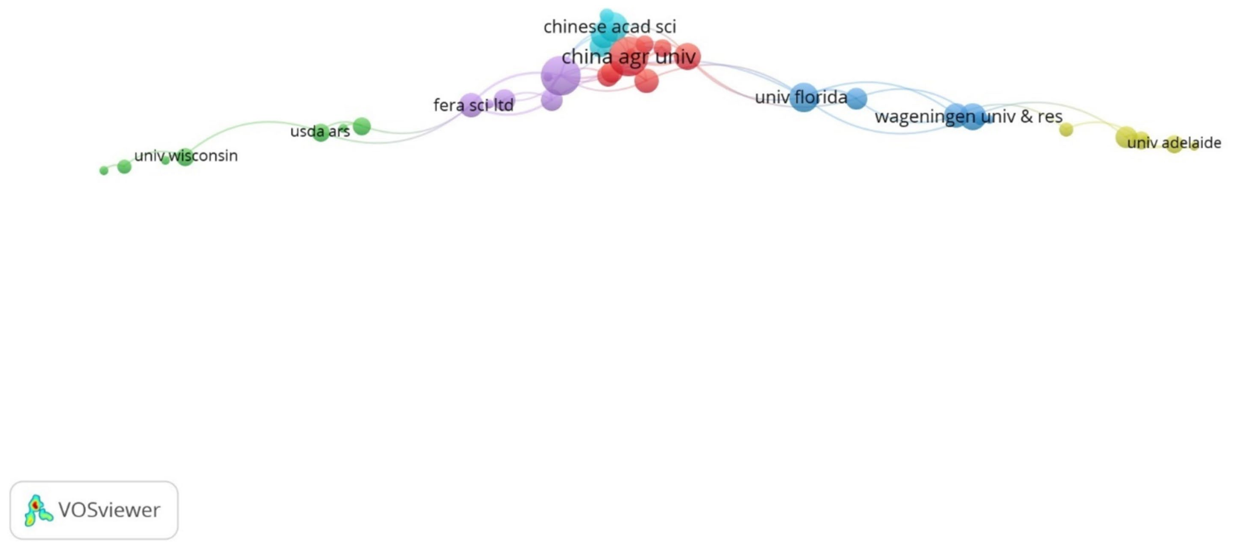

FIGURE 6
The network visualization of organizations co-authorship analysis.

These international collaborations illustrate how cross-border partnerships are essential in developing innovative solutions to enhance agricultural productivity and improve food security in an increasingly interconnected world. The rising trend of such collaborations reflects the importance of shared knowledge and resources in addressing complex agricultural challenges, supporting findings from (Lubag et al., 2023), which underscore the necessity of global cooperation in research.

4.4 Co-citation analysis

The paper opts for document co-citation to map the intellectual framework. It justified this preference over author co-citation based on concerns Hota et al. (2020) raised regarding potential misinterpretations stemming from authors' participation in other research areas. Employing a threshold of nine, the co-citation analysis yielded 65 items from 28,645 cited references. Table 7 highlights the top 10 co-cited references. Notably, the top three references were Godfray et al. (2010), Gebbers and Adamchuk (2010), and Wolfert et al. (2017), with 41, 33, and 26 citations, respectively. The prominence of these references underscores their role in shaping the discourse and guiding the development of this domain.

Figure 8 visualized the network analysis on the relationships among publications based on how frequently they were cited together. Each node represents a publication, and the connections between nodes indicate co-citation relationships, with different colors highlighting various thematic clusters.

The co-citation approach uncovered four thematic clusters, each distinguishable by identically colored nodes. Table 8 summarizes this analysis, detailing cluster labels, publication count, and critical works within each cluster.

Cluster 1 (Red), titled "Remote Vegetation Monitoring Techniques," encompasses 20 publications showcasing advancements in this field. Early methods relied on spectral indices like Normalized Difference Vegetation Index (NDVI), alongside algorithms to quantify biophysical properties such as the leaf area index (LAI), chlorophyll content, and biomass (Tucker, 1979; Yang et al., 2017; Zhou et al., 2017). Besides, Soil-Adjusted Vegetation Indices (SAVIs) were

TABLE 7 Top 10 documents ranked by co-citation.

No.	Year	Author	Title	Citation	Total link strength
1	2010	Godfray et al. (2010)	Food Security: The Challenge of Feeding 9 Billion People	41	112
2	2010	Gebbers and Adamchuk (2010)	Precision Agriculture and Food Security	33	80
3	2017	Wolfert et al. (2017)	Big Data in Smart Farming – A Review	26	108
4	2018	Liakos et al. (2018)	Machine Learning in Agriculture: A Review	21	115
5	2018	Chlingaryan et al. (2018)	Machine Learning Approaches for Crop Yield Prediction and Nitrogen Status Estimation in Precision Agriculture: A Review	19	84
6	2018	Kamilaris and Prenafeta-Boldú (2018)	Deep Learning in Agriculture: A Survey	19	81
7	2011	Foley et al. (2011)	Solutions for a Cultivated Planet	18	58
8	1979	Tucker (1979)	Red and Photographic Infrared Linear Combinations for Monitoring Vegetation	18	93
9	2017	Kamilaris et al. (2017)	A Review on the Practice of Big Data Analysis in Agriculture	17	79
10	2011	Tilman et al. (2011)	Global Food Demand and the Sustainable Intensification of Agriculture	17	51

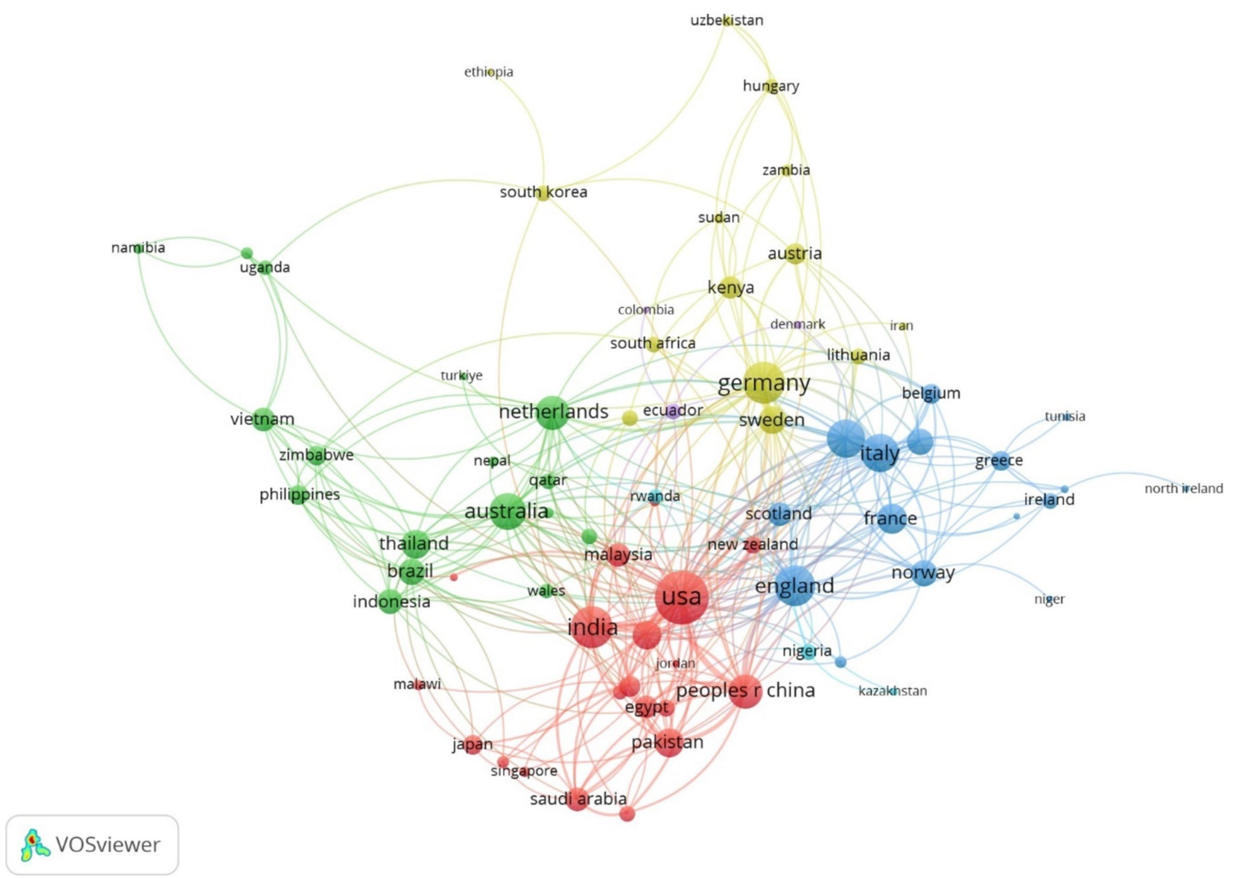

FIGURE 7
The network visualization of countries co-authorship analysis.

introduced to mitigate soil background interference in remote sensing data (Huete, 1988). Subsequently, random forest algorithms efficiently processed spectral data for vegetation monitoring (Breiman, 2001). Later, the MERIS terrestrial chlorophyll index enhanced chlorophyll estimation capabilities (Dash and Curran, 2004). Evaluation studies using satellites' NDVI and Enhanced Vegetation Index (EVI) captured seasonal changes and vegetation differences across biomes (Huete et al., 2002). Hyperspectral imaging and data fusion techniques improve the accuracy of vegetation monitoring, advancing novel algorithms for predicting green LAI and biochemical parameters

TABLE 8 Co-citation clusters.

Cluster	Label	Number	Representative publications
1 (Red)	Remote vegetation monitoring techniques	20	Huete et al. (2002), Haboudane et al. (2004), Xue and Su (2017), Maimaitijiang et al. (2017), Araus and Cairns (2014), Khanal et al. (2017), Mulla (2013), Balafoutis et al. (2017), Tzounis et al. (2017), Finger et al. (2019), Jawad et al. (2017)
2 (Green)	Technological innovations and agricultural decision-making	19	Kamilaris et al. (2017), Liakos et al. (2018), Chlingaryan et al. (2018), Weersink et al. (2018), Saiz-Rubio and Rovira-Más (2020), Zhang et al. (2002), Mahlein (2016), Bongiovanni and Lowenberg-Deboer (2004), Tilman et al. (2011), Jones et al. (2003), Dash and Curran (2004), Sharma J. et al. (2021), Mohanty et al. (2016)
3 (Blue)	Precision agriculture and sustainable development	17	van Klompenburg et al. (2020), Drusch et al. (2012), Kamilaris and Prenafeta-Boldú (2018), Hota et al. (2020), Musanase et al. (2023), Pandey and Pandey (2023), Yang et al. (2017), Zhang Y. et al. (2021), Breiman (2001)
4 (Yellow)	Deep learning in agriculture	9	Kpienbaareh et al. (2019), Cudjoe et al. (2023), Longmire et al. (2023), Masrur Ahmed et al. (2022), Ed-Daoudi et al. (2023)

(Haboudane et al., 2004). As time progresses, UAV technology advancements make remote sensing platforms more accessible, enabling rapid, non-destructive phenotyping of crops across different environments (Bendig et al., 2015; Xue and Su, 2017). Multi-sensor Unmanned Aerial Systems (UASs) data offers cost-effective high-throughput phenotyping, enabling precise plant trait and biomass estimation (Maimaitijiang et al., 2017). Field-based high-throughput phenotyping platforms revolutionized monitoring strategies with detailed insights into growth and stress tolerance (Araus and Cairns, 2014). These remote techniques facilitate a better understanding of vegetation response without physical disturbance, providing crucial information on health, growth, and environmental response.

Cluster 2 (Green), titled "Technological innovations and agricultural decision-making," contains 19 publications and discusses the significance of remote sensing, IoT, wireless sensor networks, machine learning, and big data analytics in modern agriculture. Firstly, remote sensing is vital in vegetation monitoring, as mentioned in Cluster 1, by providing high-resolution spatial and temporal data on crop health, soil conditions, and the surrounding environment (Sishodia et al., 2020). Satellites, drones, and other remote sensing platforms enable farmers to monitor their fields with unprecedented detail and make informed decisions (Khanal et al., 2017; Mulla, 2013). Furthermore, integrating IoT devices and networks further enhances agriculture by enabling real-time control of agricultural processes (Balafoutis et al., 2017). IoT sensors gather data on soil moisture content, meteorological conditions, and equipment performance, allowing farmers to make timely adjustments to resource allocation (Finger et al., 2019; Tzounis et al., 2017). Thirdly, wireless sensor networks offer detailed field data on soil properties, crop growth, and environmental conditions, enabling precise decision-making wireless sensor networks deployed across fields provide valuable data (Jawad et al., 2017; Kamilaris et al., 2017). After that, machine learning algorithms predict crop yields, diseases, and pest infestations, guiding resource-efficient and environmentally friendly practices (Liakos et al., 2018). This reduces usage and environmental impact and ensures crop health and quality (Chlingaryan et al., 2018). Big data analytics processes this information, extracting actionable insights for optimal efficiency and sustainability (Wolfert et al., 2017). However, addressing cost, complexity, and education challenges is crucial to harnessing these innovations' full potential (Saiz-Rubio and Rovira-Más, 2020; Weersink et al., 2018). This cluster reflects a trend toward the digitalization of agriculture. As these technologies continue to evolve, their integration into farming practices will be crucial for addressing the increasing demands on agricultural systems in a rapidly changing world.

Cluster 3 (Blue), titled "Precision agriculture and sustainable development," contains 17 publications and focuses on integrating advanced technologies to enhance agricultural productivity while minimizing environmental degradation. Multi-dimensional global strategies must be formulated to achieve sustainable development, including improving agrarian production efficiency, reducing environmental impact and ensuring fair food distribution (Godfray et al., 2010). Under such a background, precision agriculture emerges as a transformative approach bridging agrarian productivity while minimizing environmental degradation (Zhang et al., 2002). It revolutionizes traditional farming practices by leveraging advanced technologies such as sensors, information systems, and enhanced machinery (Gebbers and Adamchuk, 2010; Mahlein, 2016). Precision agriculture optimizes resource utilization while minimizing environmental impacts by managing inputs like fertilizers, seeds, and pesticides based on site-specific data (Bongiovanni and Lowenberg-Deboer, 2004; Robert, 2002). This targeted approach mitigates issues like pesticide resistance and nutrient imbalances, fostering long-term sustainability in agriculture and presenting a viable solution to global food security challenges (Bongiovanni and Lowenberg-Deboer, 2004; Gebbers and Adamchuk, 2010; Tilman et al., 2011). Furthermore, precision agriculture enhances the quality of agricultural produce (Gebbers and Adamchuk, 2010; Robert, 2002). Implementing decision support systems empowers farmers to monitor and manage the entire crop production chain, contributing to a more sustainable supply chain (Gebbers and Adamchuk, 2010; Jones et al., 2003). The publications in this cluster indicate that technological advancements in agriculture are essential for achieving sustainability goals while meeting the demands of a growing population.

Cluster 4 (Yellow), titled "Deep learning in agriculture," contains nine publications. Deep learning is a subfield of machine learning mentioned in Cluster 2, and its significance in agriculture has made it a distinct cluster. It revolutionizes traditional farming practices (Sharma A. et al., 2021). Deep-learning models like convolutional neural networks (CNNs) analyze vast datasets of plant images to identify subtle patterns indicative of diseases, empowering farmers with timely insights into crop health (Mohanty et al., 2016). Deep learning algorithms are also pivotal in predicting crop yields, optimizing planting strategies, and maximizing productivity while mitigating environmental risks by leveraging diverse data sources like meteorology, records, and soil characteristics (van Klompenburg et al., 2020). Moreover, integrating deep learning with IoT technologies and satellite imagery enhances precision agriculture practices. Satellite imagery and IoT sensors offer real-time data on environmental conditions, crop health, and growth patterns, which deep learning algorithms analyze to tailor irrigation and fertilization schedules for optimal crop growth (Drusch et al., 2012; Sharma A. et al., 2021). By leveraging advanced deep learning techniques, farmers can optimize production processes, minimize environmental impact, and ensure a more resilient food supply chain for future generations (Kamilaris and Prenafeta-Boldú, 2018). As research in this area continues to expand, the implications for agricultural practices and policy will be profound, emphasizing the need for ongoing investment in technology and training to harness the full potential of machine learning.

TABLE 9 Top 10 keywords ranked by co-occurrence.

No.	Keyword	Occurrences	Total link strength
1	Precision agriculture	194	591
2	Food security	90	268
3	Agriculture	55	178
4	Deep learning	34	114
5	Management	33	118
6	Machine learning	31	141
7	Climate-change	30	104
8	Big data	28	124
9	Precision farming	28	69
10	Remote sensing	28	128

4.5 Co-word analysis

Each identified keyword appeared at least nine times, with a final selection of 68 keywords from the total of 2,524 for co-word analysis. "Precision agriculture" emerged as the most prevalent keyword, appearing 194 times in the analyzed corpus. Following closely, "Food security" and "Agriculture" ranked second and third (90 and 55 occurrences, respectively). Table 9 showcases the top 10 keywords with the highest co-occurrence. The high frequency of these keywords indicates their relevance and the collaborative discourse surrounding them, suggesting that research in precision agriculture is increasingly integrated with broader discussions on food safety.

Figure 9 illustrates the result of the co-word analysis, providing insights into the relationships among key concepts in research, illustrating how frequently certain terms were associated with one another. Each node represents a keyword or concept, and the connections between them indicate co-occurrence. The largest node centered around "Precision Agriculture," which was prominently displayed in the middle, indicating its significance in contemporary research. Other key nodes included "Food Security" and various terms related to remote sensing and machine learning, highlighting the interdisciplinary nature of current agricultural research. The figure depicted four distinct yet seemingly interconnected clusters of keywords. By examining these clusters, researchers can discern emerging themes, identify potential gaps in the literature, and explore the relationships between various concepts and subfields within their study area. Afterward, Table 10 summarizes the co-word analysis for precision agriculture and food safety literature. The table includes labels, numbers, and typical words.

Cluster 1 (Red), titled "Precision cultivation and yield prediction," contains 25 keywords. The integration of cutting-edge technologies

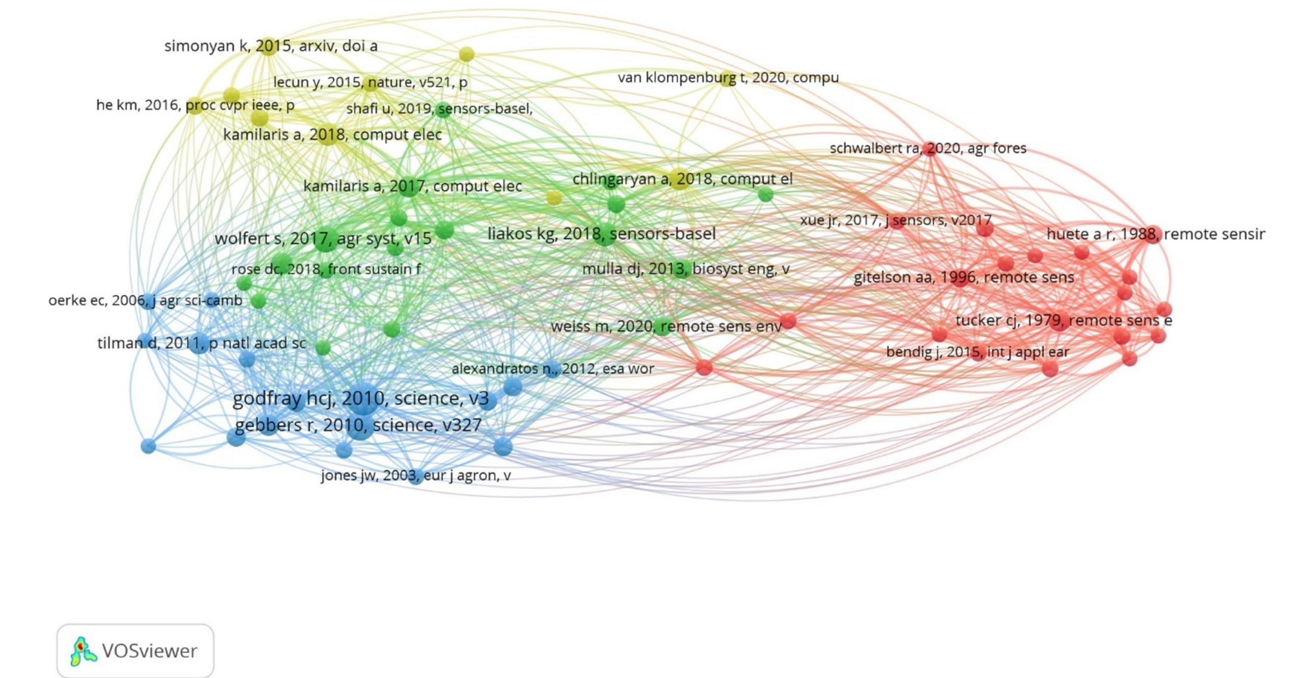

FIGURE 8
The network visualization of co-citation analysis and hotspot themes.

TABLE 10 Co-word clusters.

Cluster	Label	Number	Representative keywords	Top three keywords in occurrence
1 (Red)	Precision cultivation and yield prediction	25	Biomass, Iomass, Chlorophyll content, Corn, Grain-yield, Leaf-area index, Machine learning, Maize, Neural-networks, Nitrogen, Prediction, Productivity, Reflectance, Remote sensing, Rice, Soil, UAV, Vegetation indexes, Water, Wheat, Yield, Yield prediction.	Machine learning (31 Times), Remote sensing (28 Times), Yield (28 Times).
2 (Green)	Smart agricultural technology and food management	24	Adoption, Agriculture, Artificial intelligence, Big data, Challenges, Computer vision, Crop, Food safety, Internet of things, Precision farming, Quality, Wecurity, Smart agriculture, Sustainable agriculture, technology.	Agriculture (55 Times), Management (33 Times), Big data (28 Times), Precision farming (28 Times).
3 (Blue)	Precision information for climate change adaptation	13	Classification, Climate-change, Crops, Deep learning, Information, Random Forest, Satellite, Sensors, Stress, Time-series, Vegetation.	Deep learning (34 Times), Climate-change (30 Times), Classification (26 Times).
4 (Yellow)	Precision agriculture and food security	6	Climate change, Ecosystem services, Food security, Precision agriculture, Sustainable intensification, Use efficiency.	Precision agriculture (194 Times), Food security (90 Times), Use efficiency (10 Times).

has paved the way for yield prediction in agricultural cultivation (Musanase et al., 2023). The fusion of AI with remote sensing and UAV technology has revolutionized the monitoring and prediction of vital parameters such as soil conditions and nitrogen levels. This synergy enables farmers to assess crop health and environmental conditions promptly, predict future trends, and perform appropriate cultivation behaviors (Kpienbaareh et al., 2019; Pandey and Pandey, 2023; Zhang Y. et al., 2021). Furthermore, large-scale data analysis has empowered agricultural stakeholders to analyze diverse plant characteristics. From aboveground biomass to leaf-area index and chlorophyll content, these datasets profoundly understand the growth dynamics of major crops like corn and wheat. Leveraging the predictive capabilities inherent in these datasets, farmers can refine their cultivation to optimize both yield and quality (Cudjoe et al., 2023; Longmire et al., 2023; Maimaitijiang et al., 2020a; Maimaitijiang et al., 2020b). Furthermore, precision cultivation and prediction are significantly bolstered by the strategic deployment of machine learning models and neural networks, which have proven instrumental in enhancing productivity levels across agricultural landscapes (Masrur Ahmed et al., 2022; Taneja et al., 2023). Optimizing yield prediction by cutting-edge technologies contributes to precision cultivation and the security of food supplies (Ed-Daoudi et al., 2023; Zeng et al., 2023). The findings in this cluster highlight the importance of technological integration in modern agriculture. As these technologies continue to evolve, they offer promising solutions for enhancing agricultural productivity and sustainability, ultimately contributing to more resilient food systems.

Cluster 2 (Green), titled “Smart agricultural technology and food management,” has 22 keywords and focuses on using smart agricultural technologies to optimize food production and management processes. Implementing AI and big data analytics allows real-time tracking of crop conditions and environmental parameters, enabling growers to optimize resources, promptly address potential risks and ensure effective food management (Ahmed et al., 2023; Ayalew et al., 2013; Bojtor et al., 2021). Besides, IoT allows real-time monitoring of environmental conditions, crop health, and supply chain logistics, enhancing traceability and transparency throughout the food production and management cycle (Shafi et al., 2022). Sophisticated algorithms and sensor technology also allow for precise input of water, fertilizers, and pesticides, thereby minimizing environmental impact and maximizing yield and quality (Mabele and Mutegi, 2019; Srinivasu, 2018). Quality assurance measures, supported by these smart agriculture solutions, ensure compliance with food management standards and regulations. These smart technologies enhance transparency and accountability throughout the food supply chain by automating processes like food traceability and quality control, thus further bolstering consumer trust in the food system’s efficiency and reliability (Pontikakos et al., 2010). By embracing sustainable practices and leveraging smart technologies, the agriculture industry can meet the growing demand for safe, nutritious, and sustainable food, ensuring a more resilient and efficiently managed food supply (Davies and Garrett, 2018). Ongoing research and investment will be vital in refining smart agricultural technologies and addressing the challenges they present.

Cluster 3 (Blue), named “Precision information for climate change adaptation,” contains 12 keywords and focuses on analyzing information related to climate change, aiming to enhance agricultural resource efficiency and crop resilience to environmental stresses. Facing escalating climate change challenges, precise agricultural information becomes increasingly vital for informed decision-making and effective adaptation strategies (Cao et al., 2017; Lin et al., 2023). For example, deep learning algorithms enable the accurate classification and analysis of complex datasets, providing information about the intricate relationships between climate variables, pests, and crop responses (Grünig et al., 2021; Mesías-Ruiz et al., 2023). Satellite remote sensing offers a wide-scale and non-invasive means of monitoring environmental conditions, allowing for real-time information acquisition and assessment of climate-induced stressors such as drought and temperature extremes (Gobin et al., 2023; Vidican et al., 2023). Such precision information enables real-time monitoring and adaptation to climate change in agriculture. Furthermore, by integrating precision agriculture information, farmers can help food systems to adapt to climate change. This is achieved through improved resource efficiency, reduced waste, and enhanced traceability and quality of agricultural products (Pesonen et al., 2014). Ultimately, by investing in precision agriculture information and adopting proactive

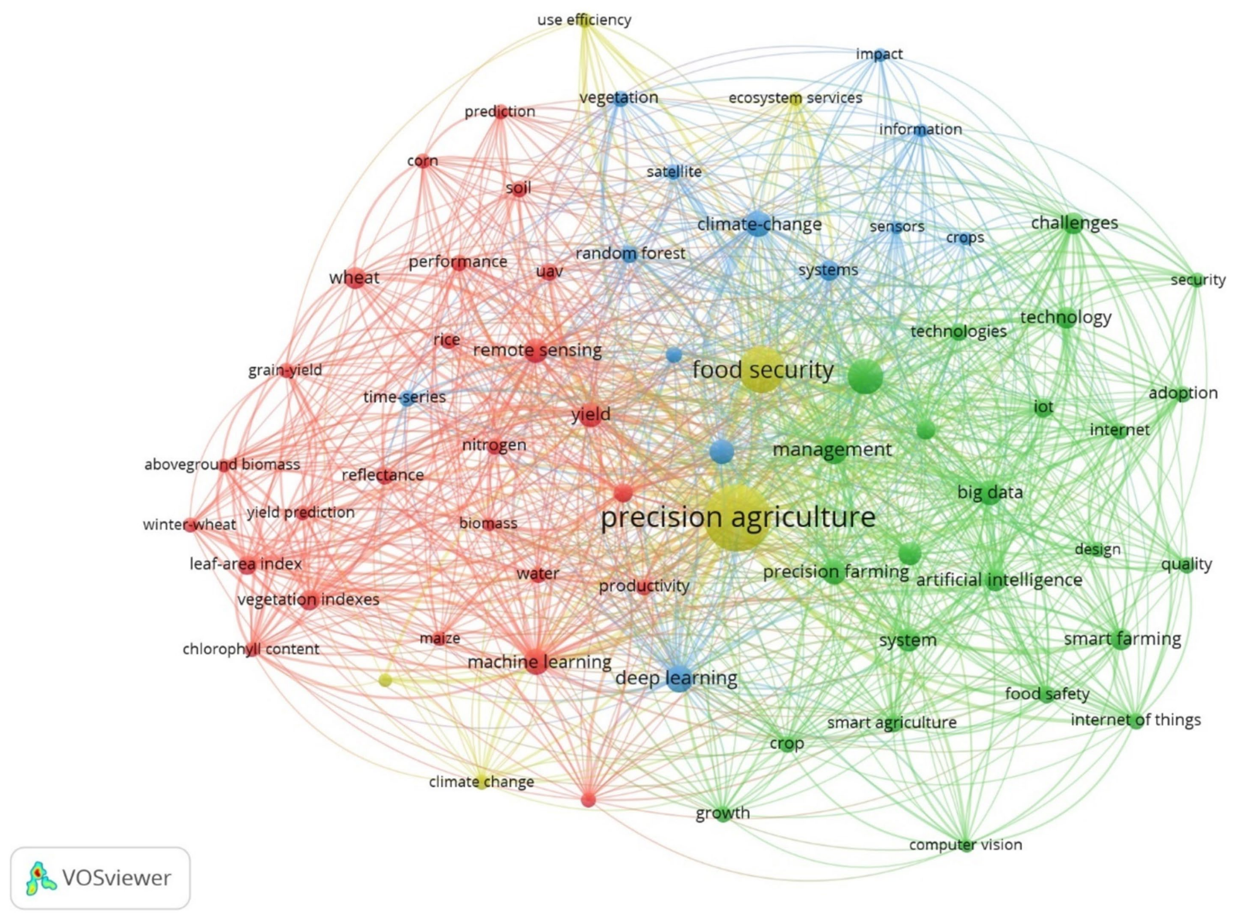

FIGURE 9
The network visualization of co-word analysis and emerging trends.

adaptation strategies, societies can build more resilient and adaptive agricultural systems better equipped to cope with the uncertainties and challenges of a changing climate (Cao et al., 2017; Kamyab et al., 2024). Therefore, as the agricultural sector confronts climate-related pressures, a commitment to leveraging advanced technologies and data-driven approaches will be essential in ensuring food security for future generations.

Cluster 4 (Yellow), titled "Precision agriculture and food security," contains six keywords. This cluster focuses on leveraging precision agriculture techniques to enhance food security by optimizing resource utilization efficiency and promoting sustainable agricultural development. By exploring precision agriculture, stakeholders aim to optimize resource allocation and minimize environmental impact while maximizing agricultural productivity, thereby ensuring a reliable food supply (Garbach et al., 2017). Precision agriculture techniques enable farmers to manage fertilizer inputs precisely, improving resource use efficiencies and yield (Zhao et al., 2013). These techniques, coupled with sustainable intensification practices like crop rotation and integrated pest management, not only boost agricultural productivity but also mitigate adverse environmental effects such as soil erosion and water pollution (Zimmermann et al., 2021). Furthermore, the adoption of precision agriculture involves integrating agroecological principles and utilizing technologies that foster resource conservation and resilience within agricultural systems. By implementing these strategies, stakeholders can improve food security and facilitate natural resource conservation and agrarian system resilience (Çakmakçı et al., 2023; Zaks et al., 2011). By investing in infrastructures, training, and governance that support precision agriculture, stakeholders can foster a culture of continuous improvement and innovation within the agricultural sector, ensuring its long-term viability and adaptability in the face of evolving environmental and socio-economic challenges while safeguarding food security (Aliloo et al., 2024). The insights from this cluster emphasize that precision agriculture is not merely a set of tools but an approach that, when effectively implemented, has the potential to transform food systems.

5 Discussion

5.1 The evolution of hotspot topics

The evolution of hotspot topics has benefited from the collaboration among authors, institutions, and countries. Author collaborations from diverse fields, including environmental science, computer science, geography, and agriculture, enhanced remote vegetation monitoring techniques (Abrahams et al., 2023). This collaborative approach also improved technological innovations and agricultural decision-making. The collaborative work by Peguero et al. (2023), applied UAV remote sensing and data analytics to create predictive models for crop performance, improving agricultural decision-making and sustainability. Similarly, collaborative efforts by Cao et al. (2017) in precision agriculture focused on optimizing fertilizer use to boost crop yields while minimizing environmental impacts. Author collaborations by Shafi et al. (2022) also advanced deep learning models that analyze large datasets to identify patterns in plant health and disease.

Institutional collaborations have further strengthened these developments. Partnerships among institutions like the Ministry of Agriculture & Rural Affairs, the Chinese Academy of Agricultural Sciences, and the University of Tokyo have created frameworks for integrating satellite, aerial, and ground-based data for remote sensing (Shi et al., 2014). This resource-sharing enhanced the accuracy and effectiveness of monitoring technologies. Additionally, these collaborations fostered the development of real-time monitoring systems that empower farmers to make informed crop management decisions (Chen et al., 2019). Research between China Agricultural University and the Chinese Academy of Agricultural Sciences promoted resource-efficient practices through fertilizer intensification (Kong et al., 2014). In deep learning, institutional partnerships advanced research on computer vision techniques that improve pest and disease detection, thereby enhancing food safety and productivity (Akbar et al., 2024).

International collaborations are also crucial. They facilitated the testing and validation of remote sensing technologies across diverse ecosystems, ensuring adaptability (Kilwenge et al., 2021). Cross-border collaborations, such as those between Ecuador and Peru, promoted the sharing of best practices that benefit farmers (Rodríguez et al., 2022). Global partnerships contributed to establishing international best practices, as demonstrated by a review led by researchers from India and England on how machine learning can enhance agricultural sustainability (Sharma et al., 2020). Lastly, international collaborations enabled the cross-validation of algorithms for pest and disease forecasting, as seen in studies involving researchers from Scotland, England, and China (Grünig et al., 2021).

Collaborations are important for enhancing food security through precision agriculture. By leveraging diverse expertise, these collaborations fostered innovation and enhanced the effectiveness of agricultural practices. Moreover, the integration of knowledge across borders not only accelerated technological advancements but also promoted resilience in agricultural systems. The evolution of hotspot topics through collaboration highlighted the need for a global approach to tackle the challenges of food security, ensuring that the sector could thrive amid ongoing global pressures.

5.2 The development of emerging trends

Author collaborations drive emerging trends in precision agriculture and food safety. In precision cultivation and yield prediction, researchers like Dhillon et al. (2023) refined algorithms that analyze historical yield data alongside current environmental conditions, essential for developing informed cultivation strategies. This groundwork supported advancements in smart agricultural technology and food management, where Kpienbaareh et al. (2019) optimized algorithms for precise resource allocation, maximizing yield while minimizing environmental impact. Furthermore, collaborations in precision information for climate change adaptation, including Agrimonti et al. (2021) and Jamil et al. (2022), have clarified the relationships between climate variables and crop responses, informing adaptive practices. Additionally, partnerships have led to models that optimize fertilizer application rates, improving nutrient use efficiency and crop yields (Cao et al., 2017; Miao et al., 2010; Zhao et al., 2013).

Institutional collaborations enhance these trends by facilitating practical applications. For example, partnerships between the University Putra Malaysia and University Sains Malaysia developed advanced yield prediction models using multi-source data and machine learning, promoting data-driven decision-making in precision agriculture (Ang et al., 2022). These efforts also improve food safety by integrating advanced technologies into risk management systems (Taneja et al., 2023). Moreover, institutional collaborations are crucial for establishing frameworks that promote precision information for climate change adaptation, as seen in the development of smart irrigation tools designed by the University of Castilla-La Mancha and the University of Córdoba to address water scarcity, which showcases a proactive approach to future agricultural challenges (Perea et al., 2019). In precision agriculture and food security, institutions are fostering a culture of knowledge sharing through training programs for farmers, indicating a trend toward community engagement in sustainable agricultural practices (Lee et al., 2017).

International collaborations further stimulate these trends by facilitating knowledge exchange. Projects between Iran and Germany develop models to predict crop yields across diverse environments, reflecting a trend in cross-border research initiatives (Fathi et al., 2023). Such global cooperation enables the implementation of innovative solutions across various contexts, such as in India, South America, Malaysia, China, and Europe (Lubag et al., 2023). In precision information for climate change adaptation, partnerships from Ethiopia and South Korea share best practices to help agricultural systems adapt to climate challenges (Sishodia et al., 2020). For food security, collaborations between Australia and the USA address agricultural diseases and enhance food safety through shared strategies (Jones and Naidu, 2019).

These collaborative efforts highlight the role of interdisciplinary cooperation in developing research trends. By integrating expertise from various fields, researchers can create effective, adaptable solutions that respond to local needs. Furthermore, institutional and international partnerships foster knowledge sharing and capacity building, essential for empowering farmers and enhancing food security.

5.3 Future research agenda

Despite advancements in precision agriculture and food safety, several gaps remain in the literature. First, while individual technologies have shown promise in improving agricultural practices, their combined effects remain underexplored. Investigating how these technologies work together in real-world agricultural settings could yield valuable insights into optimizing crop management, resource allocation, and environmental monitoring (Qazi et al., 2022). Second, insufficient longitudinal research exists on the long-term impacts of precision agriculture. As climate change continues to pose significant challenges to agricultural productivity, it is crucial to understand how adaptive strategies evolve (Adamides, 2020). Third, the socio-economic barriers to adopting precision agricultural technologies need further investigation. Farmers face various barriers, such as cost, access to technology, access to the market, and educational resources, which hinder the implementation of precision agriculture practices (Latino et al., 2022). Furthermore, the relationship between sustainability metrics and food safety requires further examination. Finally, research on policy frameworks and governance structures that facilitate the adoption of precision agriculture is needed. Understanding how policies support innovation while ensuring environmental protection and food security is essential for creating conducive environments for technology adoption (Sparrow and Howard, 2021).

This study proposes a research agenda based on the identified gaps. First, future research should explore the synergistic integration of advanced technologies such as GPS, remote sensing, IoT, GIS, machine learning, and AI. Second, there is a need for longitudinal studies that assess the long-term effects of precision agriculture. Multi-year studies should monitor the effectiveness of precision practices, tracking their impacts on crop health, soil quality, and water usage. Additionally, research should examine the socio-economic implications of technology adoption, facilitating technology adoption and assessing broader impacts on rural economies, labor dynamics, and food equity. Moreover, future research should create indicators that quantify agricultural productivity, environmental sustainability, and socio-economic benefits, enabling stakeholders to make informed decisions aligned with sustainability goals. Finally, future studies should evaluate existing policies for their effectiveness in fostering innovation while ensuring environmental protection and food security.

5.4 Implications

The findings offer theoretical perspectives on precision agriculture and food safety. Firstly, the identification of influential publications provides an overview of the scholarly landscape, facilitating a deeper understanding of key concepts and developments in precision agriculture and food safety. By citation analysis, researchers can trace the evolution of ideas and identify seminal works that have shaped the theoretical foundations of the field. Secondly, by elucidating clusters from co-citation analysis, the study contributes to past and current theoretical discussions surrounding integrating advanced technologies into agricultural practices to enhance productivity, sustainability, and food safety. Thirdly, the co-word analysis reveals emerging trends and common keyword searches for future research directions, thus laying a foundation for subsequent studies.

The practical implications of this research offer guidance for policymakers, researchers, practitioners, consumers, and industry stakeholders involved in precision agriculture and food safety. Policymakers benefit from these insights to inform their policy-making endeavors, such as prioritizing funding for research initiatives that address pressing challenges like climate change adaptation and food safety regulations. Moreover, researchers stay updated on the latest developments by referencing influential scholarly works and journals, ensuring their efforts align with current advancements. The identification of thematic clusters and common keywords provides valuable insights for shaping future research directions. Additionally, agricultural practitioners leverage these insights to adopt precision agriculture techniques, enhancing operational efficiency and promoting environmental stewardship. Implementing decision support systems based on research findings optimizes resource use and improves yield. Moreover, the findings support consumer education initiatives, highlighting the benefits of precision agriculture in ensuring food security and sustainable practices. Heightened consumer awareness drives demand for sustainably produced food. Industry stakeholders could also utilize the findings inform investment decisions and strategic planning, fostering collaborations and partnerships that advance research efforts. Identifying emerging trends guides innovation and solution development, aiding industry stakeholders in addressing challenges related to agriculture and food safety.

6 Conclusion

The research conducts a bibliometric analysis of precision agriculture and food safety to cluster past, present, and future trends. The literature emerged in 1994 and has notably increased since 2019. The analysis of document citations pinpointed the top-cited documents. In addition, Science was the most influential journal, while Fritschi, Maimaitijiang, Sagan, and Sidike were the top authors by average citations. China Agricultural University and the Chinese Academy of Agricultural Sciences had the most co-authorships. Still, based on collaboration, the USA was the most influential country on precision agriculture and food safety.

Co-citation analysis classified four past and present areas of intense focus: remote vegetation monitoring techniques, technological innovations and agricultural decision-making, precision agriculture and sustainable development, and deep learning in agriculture. Past research has primarily focused on technologies in vegetation monitoring and precision agriculture, including remote sensing, IoT, wireless sensor networks, machine learning and big data analytics. However, there has been relatively limited research on the connection between precision agriculture and food safety in the past, focusing only on how precision agriculture bridges agricultural productivity with environmental sustainability.

Clusters from the co-word analysis showed emerging trends covering precision cultivation and yield prediction, smart agricultural technology and food management, precision information for climate change adaptation, and precision agriculture and food security. As suggested by the results, future research could utilize advanced technologies to predict crop yield. It also needs to investigate the application of smart agricultural technologies further to make informed cultivation decisions. Another two future trends in the agriculture sector are utilizing precision techniques to gather data for adapting to climate change and promoting food security.

This study acknowledges several limitations that warrant consideration. Firstly, citation metrics may not fully reflect the relevance of newer studies, as recent publications have not garnered a considerable amount of citations yet, which may lead to an underestimation of their current influence in comparison with previous works (Xu et al., 2024). Secondly, the citation impact analysis predominantly centers around the first authors, potentially leading to neglecting the significant contributions made by co-authors (Zhao, 2006). This narrow focus may not provide a comprehensive view of the collaborative nature of research in precision agriculture and food safety. Thirdly, the process of identifying and interpreting clusters may be subject to personal biases, as it depends heavily on the discretion of authors (Wider et al., 2023). Fourthly, this study focuses on English-language publications, which may exclude important research published in non-English journals.

To address these limitations, future research endeavors could implement several strategies. Future research could employ meta-analyses to synthesize findings from multiple studies, thereby providing a more robust understanding of the field and capturing the impact of newer studies. Furthermore, future studies should consider a more inclusive approach that evaluates the contributions of all authors. This could involve employing qualitative analyses, such as interviews or surveys with researchers, to gain insights into the roles of co-authors and their contributions, thus providing a more nuanced understanding of collaboration in research. In addition, regarding the process of cluster identification and interpretation, future research should continue to have multiple researchers independently analyze the same dataset and reach a consensus, ensuring that the identification and interpretation of clusters are more objective and credible. Reference checks and a training phase for coders could also be used to reduce subjectivity and enhance the objectivity of the results. Lastly, analyses could include non-English literature by collaborating with multilingual researchers to provide a more comprehensive view of the field.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

JX: Conceptualization, Formal analysis, Funding acquisition, Investigation, Methodology, Software, Visualization, Writing – original draft. YC: Methodology, Software, Visualization, Writing – original draft. SZ: Funding acquisition, Writing – review & editing. MZ: Conceptualization, Supervision, Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

The Supplementary material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fsufs.2024.1475602/full#supplementary-material

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