Assessing the impact of emerging technologies on sustainable fruit production: A systematic review of the literature

Evaluación del impacto de las tecnologías emergentes en la producción frutícola sostenible: una revisión sistemática de literatura

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ABSTRACT

Agriculture 4.0 refers to innovations in technological tools used in agriculture to achieve different objectives, such as adapting the supply chain to avoid waste, increasing productivity and collecting mass data through ICT (Information and Communication Technologies) to meet the growing food demand of the population. The objective of this study is to conduct a systematic literature review to evaluate the impact of emerging technologies on sustainable fruit production. Initially, a bibliographic search was conducted on the technologies currently implemented in agriculture; the Bibliometrix library of the R Studio software was used, and then an analysis of relevant scientific publications published in the last ten years was carried out through the VOSviewer® software, which allowed the construction and visualization of bibliometric networks. The results show Europe and China as the leading regions in technological development, while developing countries face economic and research limitations; in Colombia, the use of Agriculture 4.0 is focused on the implementation of satellite images for monitoring agro-climatic conditions. In summary, Agriculture 4.0 aims to achieve economic, social, and environmental sustainability in the agri-food sector through data-generating technologies to improve production, reduce costs, and ensure food safety and quality. However, there is a technology gap between developed and developing countries that affects the adoption of these innovations. More support is therefore needed from governments, academia, and the private sector to drive innovation, training, and adoption of these technologies, which can contribute to the economic, social, and environmental development of the country.

Key words: productivity, machine learning, artificial intelligence, fruits, yield, bibliometrics.

RESUMEN

La Agricultura 4.0 se refiere a las innovaciones en las herramientas tecnológicas utilizadas en la agricultura para lograr diferentes objetivos, como la adaptación de la cadena de suministro para evitar el desperdicio, el aumento de la productividad y la recolección masiva de datos a través de las TIC (Tecnologías de la Información y la Comunicación), para satisfacer la creciente demanda de alimentos de la población. El objetivo de este trabajo es realizar una revisión bibliográfica sistemática para evaluar el impacto de las tecnologías emergentes en la producción frutícola sostenible. Inicialmente, se realizó una búsqueda bibliográfica sobre las tecnologías actualmente implementadas en la agricultura; se utilizó la biblioteca Bibliometrix del software R Studio, y luego se llevó a cabo un análisis de las publicaciones científicas relevantes publicadas en los últimos diez años, a través del software VOSviewer® que permitió la construcción y visualización de redes bibliométricas. Los resultados muestran a Europa y China como las regiones líderes en desarrollo tecnológico, mientras que los países en desarrollo enfrentan limitaciones económicas y de investigación; en Colombia, el uso de la Agricultura 4.0 se centra en la implementación de imágenes satelitales para el monitoreo de las condiciones agroclimáticas. En resumen, la Agricultura 4.0 pretende lograr la sostenibilidad económica, social y ambiental del sector agroalimentario a través de tecnologías generadoras de datos para mejorar la producción, reducir costes y garantizar la seguridad y calidad de los alimentos. Sin embargo, existe una brecha tecnológica entre los países desarrollados y los países en desarrollo que afecta a la adopción de estas innovaciones. Por lo tanto, se necesita más apoyo de los gobiernos, el mundo académico y el sector privado para impulsar la innovación, la formación y la adopción de estas tecnologías, que pueden contribuir al desarrollo económico, social y medioambiental del país.

Palabras clave: productividad, aprendizaje automático, inteligencia artificial, frutos, rendimiento, bibliometría.

Introduction

Emerging technologies (ET) integrate advanced technologies like Internet of Things (IoT), Artificial Intelligence (AI), and Big Data to establish smart agriculture, aiming to address global food demands, enhance crop yield, reduce water consumption, optimize pesticide use, and improve crop quality (Xu *et al.*, 2018). Drones, IoT sensors, and

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machine learning are key technologies employed in Agriculture 4.0, primarily in open-field farms (Saha *et al.*, 2018; Shafi *et al.*, 2020). The use of ET in greenhouse crop production has revolutionized agriculture in controlled environments and advanced climate control systems to optimize temperature, radiation, relative humidity, and CO_2 levels, while sensor-based fertigation increases water and nutrient use efficiency (Putra & Yuliando, 2015; Khan, 2018; Pennisi *et al.*, 2019). Vertical farming and hydroponics maximize production capacity and resource efficiency through automation, data analytics, and robotics; these technologies enhance precision in nutrient delivery, lighting, and crop maintenance (Hemming *et al.*, 2019). The integration of ET in greenhouses offers great potential for sustainable food production, with precise control of environmental conditions and increased crop yields.

Sensors play a crucial role in the success of IoT in agriculture, facilitating map-based and sensor-based approaches to manage spatial and temporal changes in agricultural production to improve yields and sustainability (Zhang *et al.*, 2014; Ferrández-Pastor *et al.*, 2016; Tzounis *et al.*, 2017). Remote sensing, enabled by Wireless Sensor Networks (WSN), finds diverse applications in agriculture, including vegetation health evaluation and crop stress detection. Integration of AI models with remote sensing data enables crop yield prediction, while real-time monitoring of soil and atmospheric conditions through IoT sensors enhances agricultural practices, optimizing efficiency, productivity, and profitability while minimizing waste and environmental impact (Mulla, 2013; Rajak *et al.,* 2023).

Efficient and sustainable crop production requires accurate meteorological data collection and monitoring of greenhouse gas emissions. Various technologies, such as weather stations, WSN, drones, and intelligent recognition systems, are utilized for these purposes (Malaver *et al.*, 2015; Ojha *et al.*, 2015; Johnson *et al.*, 2016; Shafi *et al.*, 2019). AI-based recognition systems assist early detection and classification of crop diseases, pests, and weeds, using remote sensing and multispectral cameras (Sun *et al.*, 2018). Remote monitoring and optimization of irrigation and fertilization systems using IoT sensors, AI-based data analysis, and decision support systems are emerging soil management trends in Agriculture 4.0 (Agudelo Cano *et al.*, 2023). Intelligent water quality monitoring systems with IoT sensors are deployed to measure various parameters for effective water management.

Fruit crops can be established in both open-field and protected conditions. IoT applications in fruit agriculture facilitate enhanced monitoring and management of soil moisture, temperature, humidity, and light intensity. IoT sensors placed in orchards and fields collect real-time data, allowing farmers to make data-driven decisions regarding irrigation, fertilization, and pest control (Disraelly *et al.*, 2011). This leads to optimized resource utilization, improved crop yield, and increased quality of fruits (Ebrahimi *et al.*, 2017; Kamilaris *et al.*, 2017; Abbasi *et al.*, 2022). In Latin America, where agriculture plays an important role in the economy, the adoption of IoT in fruit crops has been accelerating (Aker, 2011; Puntel *et al.*, 2022; Strong *et al.*, 2022). Colombia has recognized the potential of IoT to improve productivity and sustainability in the agricultural sector. Initiatives have been launched to adopt IoT sensors in fruit orchards, enabling continuous monitoring of environmental conditions and facilitating precision farming practices (Pineda, Pérez *et al.*, 2022; Pineda, Tinoco *et al.*, 2022; Agudelo Cano *et al.*, 2023). These sensors provide farmers with valuable insights and enable early detection of issues such as diseases or pests for prompt and targeted interventions (Ramírez Alberto *et al.*, 2023).

The use of IoT in fruit agriculture in Colombia offers several advantages, including increased efficiency, reduced costs, and minimized environmental impact (Rodríguez *et al.*, 2021; Arrubla-Hoyos *et al.*, 2022). By leveraging IoT technologies, Colombian fruit farmers can optimize resource management, conserve water through precise irrigation techniques, and minimize the use of agrochemicals (Ziesche *et al.*, 2023). Additionally, IoT-enabled systems can improve traceability and transparency in the supply chain, ensuring the delivery of safe and high-quality fruits to consumers (De la Peña & Granados, 2023). The aim of this article was to conduct a systematic literature review to assess the impact of emerging technologies on sustainable fruit production, identifying and describing the current status of sustainable fruit production as well as the challenges and opportunities presented by the incorporation of emerging technologies.

Materials and methods

Scopus databases were used to search for open access articles published in the last decade. The search was limited to specific topics, and the 2,000 most relevant were analyzed using the terminology of title, abstract and keywords (Tab. 1). The review of the evolution over time of research conducted in the world on the use of ET in agriculture and the map of the main countries producing scientific research in the fruit sector were carried out using the Bibliometrix library from the R software. The VOSviewer® software was used to visualize bibliometric networks based on the connection and linkage between the keywords of the documents.

Results and discussion

The Scopus search yielded a total of 47,319 articles in Group A, 1,050 in Group B, 6,878 in Group C, and 172 in Group D. Figure 1 depicts the use of WSN in agriculture, enabling real-time monitoring of crops, soil, and weather conditions to improve food crop yields and alleviate the workload on farmers (Ojha *et al.*, 2015). However, energy efficiency poses a challenge for WSN, especially in remote areas with limited access to energy. Recent research focuses on developing energy-efficient WSN that can operate using renewable energy sources (Zhang & Meng, 2021).

TABLE 1. Search groups in Scopus.

GROUP	Search string
A	("Internet of Things" OR "Artificial Intelligence" OR "Machine Learning" OR "Data science" OR "Robotic") AND ("Agriculture" OR "Smart Farm" OR "Precision Farm")
B	("Internet of Things" OR "Artificial Intelligence" OR "Machine Learning" OR "Data science" OR "Robotic") AND ("Agriculture" OR "Smart Farm" OR "Precision Farm") AND ("Colombia")
C	("Internet of Things" OR "Artificial Intelligence" OR "Machine Learning" OR "Data science" OR "Robotic") AND ("Agriculture" OR "Smart Farm" OR "Precision Farm") AND ("fruit" OR "fruit growing")
D	("Internet of Things" OR "Artificial Intelligence" OR "Machine Learning" OR "Data science" OR "Robotic") AND ("Agriculture" OR "Smart Farm" OR "Precision Farm") AND ("fruit" OR "fruit growing") AND ("Colombia")

Machine learning algorithms can analyze data collected by WSN, providing information on crop growth patterns and early identification of potential problems. This information helps to make decisions in agriculture, such as determining optimal planting and harvesting times (Tan *et al.*, 2021). In Colombia, there are diverse edaphoclimatic conditions that favor the production of fruit species; differential monitoring according to species is needed to improve sustainability. Monitoring involves aspects such as physiology, pests, postharvest, costs and labor. Most crops in Colombia, including fruit trees, are located in remote areas where power grids are often not available and where the availability of communication networks is low. Therefore, the use of WSN in agriculture, specifically in crop monitoring, can be a valuable tool to improve crop sustainability (Hernández Leal, 2016).

An important increase in scientific article production was identified between 2014 and 2022, reaching 711 articles (Fig. 2). This growth is attributed possibly to increased research

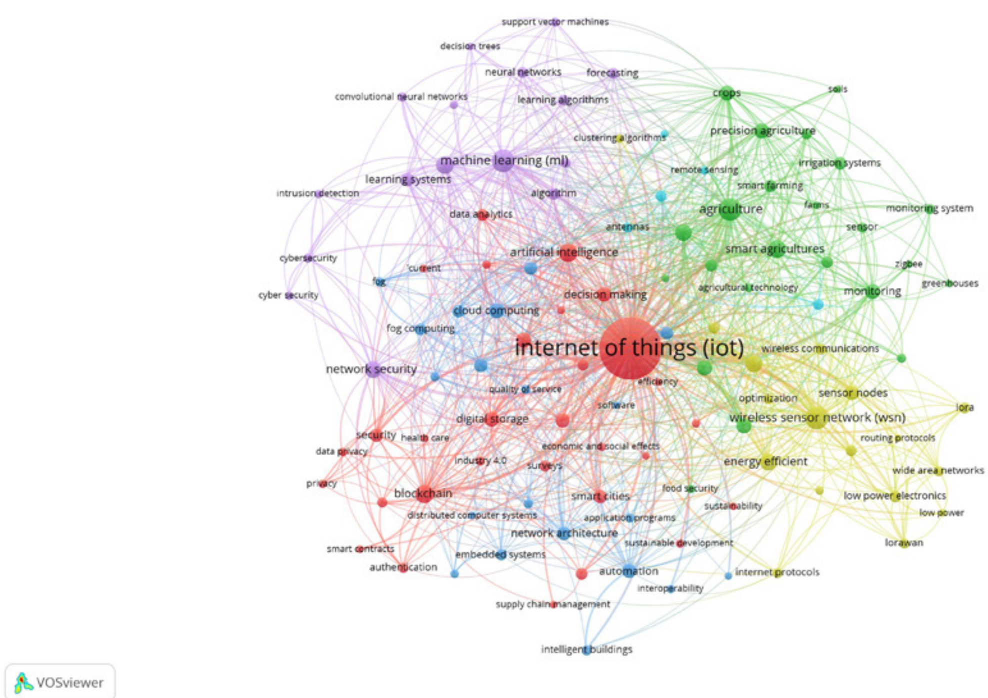

FIGURE 1. Correlation between the most used keywords ("Internet of Things" OR "Artificial Intelligence" OR "Machine Learning" OR "Data science" OR "Robotic") AND ("Agriculture" OR "Smart Farm" OR "Precision Farm") in the search for GROUP A. The map was generated by VOSviewer®.

on IoT, particularly in the areas of security, surveillance, health, architecture, construction, and precision agriculture (Kusek, 2018).

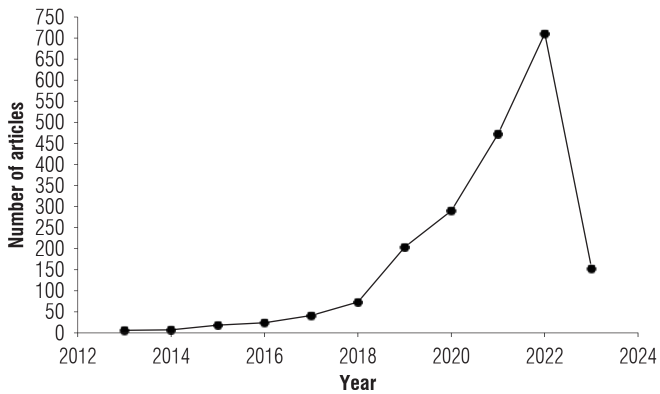

FIGURE 2. Evolution of articles produced globally in the last decade related to research on ET used in agriculture. The graph was generated by Bibliometrix R package.

According to the results of group B (Fig. 3), the use of remote sensing in biodiversity conservation predominates in Colombia. Remote sensing allows non-invasive data collection, making it possible to monitor changes in habitats and ecosystems, critical for the protection of threatened species and the identification of conservation areas. It also facilitates the study of land cover, essential for land use planning, natural resource management and climate change mitigation. Colombian agriculture faces challenges from climate change, particularly from El Niño and La Niña phenomena (CIAT, 2013; Instituto Interamericano de Cooperación para la Agricultura, 2016; Melo León *et al.*, 2017), which affects agroecosystems and the economy. To estimate risk and manage soil, water, and crops, modeling and prediction tools with remote sensing and AI can be used. These tools collect data on crops and the environment and use machine learning algorithms to predict and detect problems. Thus, farmers can make data-driven decisions that improve yields, reduce resource wastage, and increase profitability (Akhter & Ahmad, 2022).

Models incorporating data on weather patterns, soil characteristics, and crop-specific parameters are useful to forecast yields and growth rates. They provide valuable information on managing the impact of these factors on agricultural productivity, contributing to global food security (Candelaria Martínez *et al.*, 2011; Benos *et al.*, 2021). Colombia

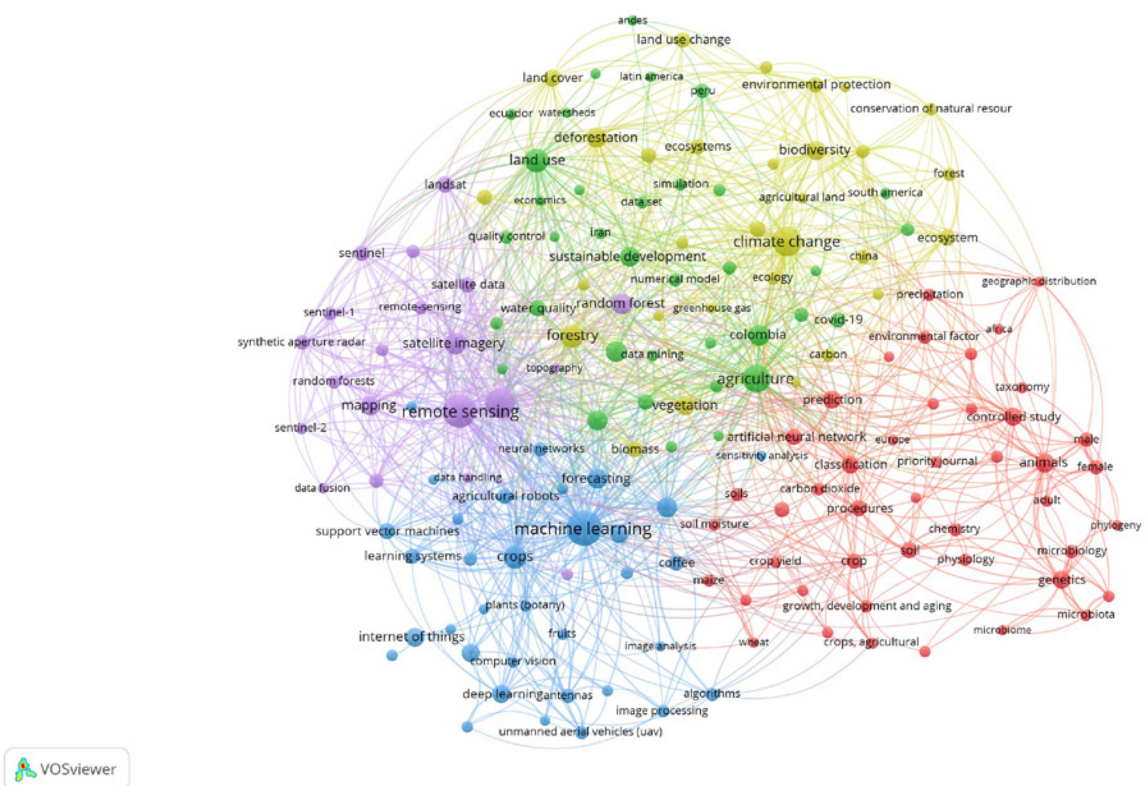

FIGURE 3. Correlation between the most used keywords ("Internet of Things" OR "Artificial Intelligence" OR "Machine Learning" OR "Data science" OR "Robotic") AND ("Agriculture" OR "Smart Farm" OR "Precision Farm") AND ("Colombia") in the search for GROUP B. The map was generated by VOSviewer®.

uses predictive models to anticipate the effects of biotic and abiotic factors on agriculture, including crop growth and ecological models. Some examples of these models are the DSSAT model (Decision Support System for Agrotechnology Transfer), which simulates the development of different crops under different climatic, management and fertilization conditions, and which has been applied in Colombia to assess the impact of climate change and climate variability on crops such as maize, rice, beans and potatoes (Sarkar, 2012); another example is the AquaCrop model, which estimates the water consumption and biomass production of crops as a function of water availability in the soil and atmosphere (Dercas *et al*., 2022). Finally, the CROPGRO (Crop Growth) model, which simulates the growth and development of leguminous crops such as beans, peanuts and soybeans, considering the effects of biotic factors such as insects, diseases and weeds, has been used in Colombia to optimize integrated pest and disease management practices (Van Loon *et al*., 2018). However, there is little implementation of phenological models in crops that allow scheduling of cultivation and harvesting activities. Machine learning, remote sensing and satellite imagery are increasingly important tools in the study of the Colombian environment and natural resources (Murad & Pearse, 2018). These applications can provide valuable information to support sustainable land use planning and management, including classifying land cover types, monitoring vegetation health, and detecting changes in land use over time. For example, researchers have studied the feasibility of early prediction of yield per coffee tree based on multispectral aerial imagery in Colombia (Sousa *et al*., 2020; Giang *et al*., 2022; Jato-Espino & Mayor-Vitoria, 2023). This type of classification can be useful for determining areas with an agricultural vocation to expand crop areas according to the specific soil and climate needs of the crops.

Furthermore, machine learning algorithms can be used to analyze data from remote sensing platforms to predict and monitor natural disasters, such as floods and landslides, which are common occurrences in Colombia (Arinta & Andi, 2019; Martínez-Álvarez & Morales-Esteban, 2019; Xie *et al*., 2020).

The results of groups A, B, and C (Fig. 4) demonstrate the prevalence of "machine learning" and "deep learning" techniques in the global fruit industry. "Deep learning" is particularly effective for image analysis and has been successfully applied in tomato crop monitoring using

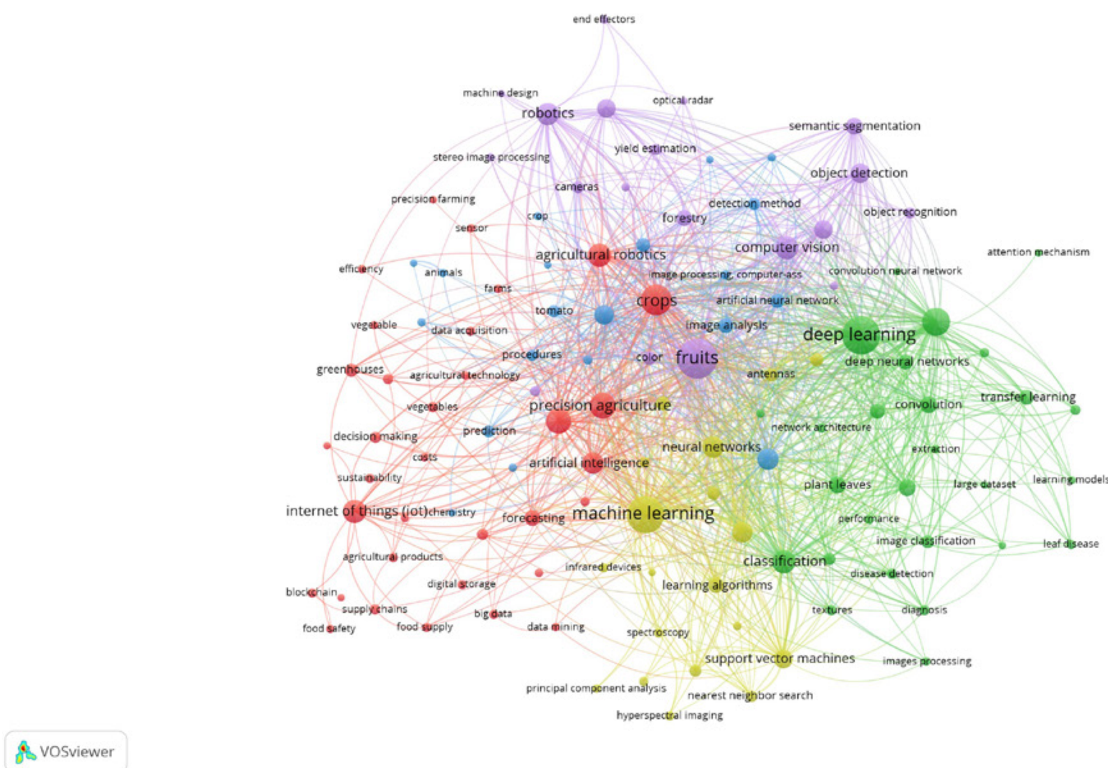

FIGURE 4. Correlation between the most used keywords ("Internet of Things" OR "Artificial Intelligence" OR "Machine Learning" OR "Data science" OR "Robotic") AND ("Agriculture" OR "Smart Farm" OR "Precision Farm") AND ("fruit" OR "fruit growing") in the search for GROUP C. The map was generated by VOSviewer®.

drones. Tomato is one of the highest volume production vegetables worldwide, with approximately 182 million t (Caruso *et al*., 2022). Deep learning-based algorithms are valuable for pest and disease monitoring in fruits as well as post-harvest sorting, by analyzing image datasets and identifying patterns that are difficult to detect (Dokic *et al*., 2020; Bouguettaya *et al*., 2022). Deep learning algorithms detect specific patterns and facilitate fast and accurate responses to problems. They also improve the efficiency and accuracy of agricultural processes. Machine learning is linked with remote sensing and IoT to promote sustainable practices. Remote sensing technologies, such as unmanned aerial vehicles (UAV), provide valuable data for precision agriculture, while IoT devices, such as WSN, collect crucial data on temperature, humidity, and soil moisture to make informed crop management decisions (Ding & Xie, 2023; Yousaf *et al*., 2023). Thus, the fusion of machine learning, remote sensing and IoT has the potential to revolutionize sustainable agriculture (Cadenas *et al*., 2023).

Figure 5 highlights China and the United States as leading producers of scientific research in the fruit sector. These countries, along with East Asia, South Asia, South America, Southeast Asia, and Southern Europe, are significant regions for fruit and vegetable production (FAO, 2021). Globally, over 50% of fruits are cultivated on agricultural land of less than 20 ha, mainly owned by families. In developing nations, these small farms produce most horticultural products, with over 80% in Asia, sub-Saharan Africa, and China (Frelat *et al*., 2016).

In Colombia, group D findings (Fig. 6) indicate the utilization of machine learning for decision-making in coffee cultivation, along with precision agriculture tools and remote sensing technologies. Machine learning algorithms accurately estimate coffee production and classify crops (Suarez-Peña *et al*., 2020). Implementing these technologies in coffee cultivation enhances efficiency, productivity, and profitability, important because the agricultural global gross domestic product of the country heavily relies on coffee, flowers, bananas, sugar, rice, and potatoes (Delgado-Delgado *et al*., 2021).

During postharvest, there could be considerable losses of fruits due to poor handling, grading and distribution practices (Bantayehu *et al*., 2017; Singh *et al*., 2022; Knott *et al*., 2023). Machine learning and deep learning algorithms are currently being used for fruit transport and storage as well as fruit sorting and distribution after harvest by analyzing images and sensor and historical data (Knott *et al*., 2023). For example, machine learning algorithms can be used to detect defects, diseases and damage to fruit, as well as to estimate fruit quality, maturity and shelf life. In this way, fruits can be assigned to different categories or destinations according to their commercial value (Meshram *et al*., 2021). Deep learning algorithms can also be used to recognize complex patterns in fruit images, such as shape, color or texture. These algorithms can learn automatically from the data without prior programming. This can improve the accuracy and speed of fruit sorting as well as reduce costs and human error (Piedad *et al*., 2018).

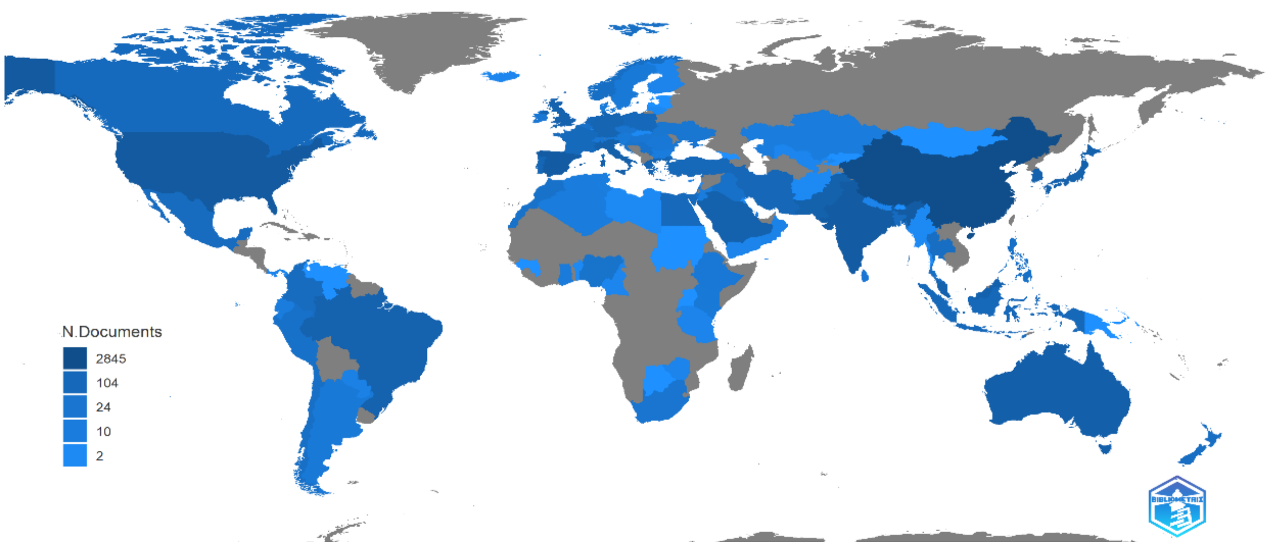

FIGURE 5. Map of scientific output generated by searching for ("Internet of Things" OR "Artificial Intelligence" OR "Machine Learning" OR "Data Science" OR "Robotics") AND ("Agriculture" OR "Smart Farm" OR "Farm precision) AND ("fruit" OR "fruit growing") GROUP C.

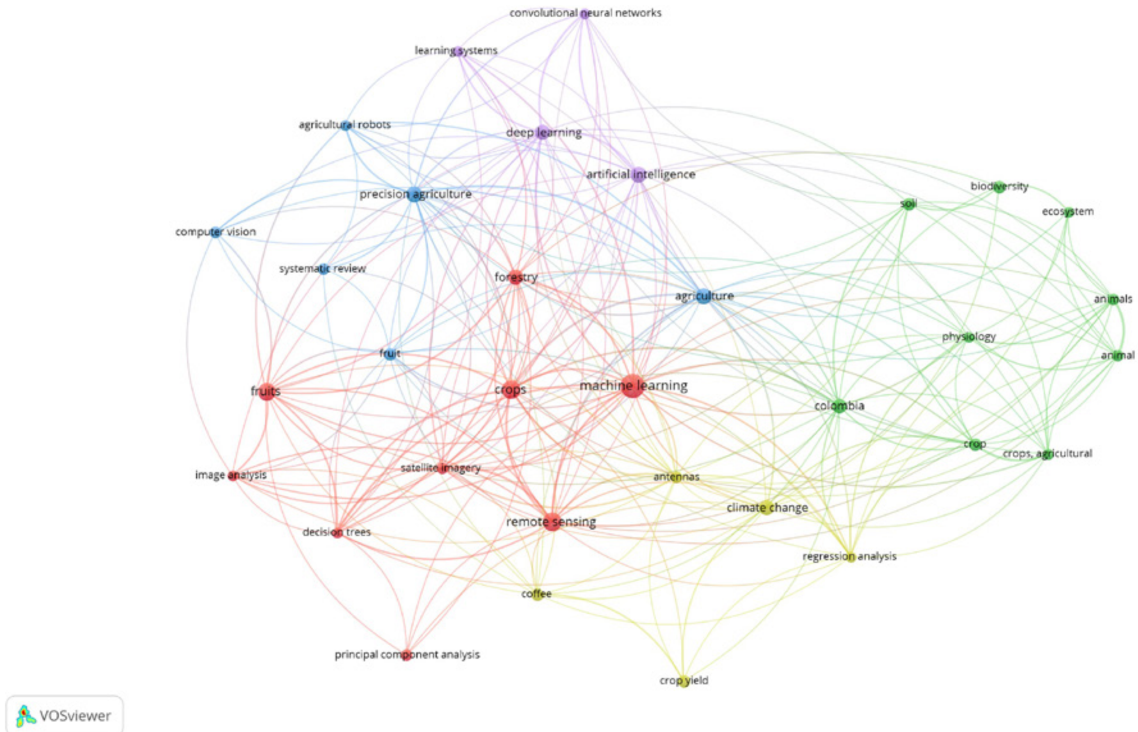

FIGURE 6. Correlation between the most used keywords ("Internet of Things" OR "Artificial Intelligence" OR "Machine Learning" OR "Data science" OR "Robotic") AND ("Agriculture" OR "Smart Farm" OR "Precision Farm") AND ("fruit" OR "fruit growing") AND ("Colombia") in the search for GROUP D. The map was generated by VOSviewer®.

Conclusions

The use of Wireless Sensor Networks (WSN) in agriculture, as evidenced in the scientific literature, has proven to be a valuable tool for real-time monitoring of crops, soil and weather conditions, contributing to improved food crop yields and easing the workload of farmers. However, the challenge of energy efficiency in remote areas with limited access to energy represents a significant obstacle to WSN implementation in agriculture. Recent research has focused on the development of energy-efficient WSNs that can operate using renewable energy sources. In addition, machine learning algorithms can analyze the data collected by WSNs, providing information on crop growth patterns and early identification of potential problems, which helps to make decisions in agriculture, such as determining optimal planting and harvesting times. In the Colombian context, where diverse soil and climatic conditions favor the production of fruit species, differential crop monitoring is crucial to improve crop sustainability, especially in remote areas with limited availability of electricity and communication networks. Therefore, the use of WSN in agriculture, specifically in crop monitoring, can be a valuable tool to improve crop sustainability. Colombian agriculture faces challenges from climate change, particularly from the "El Niño" and "La Niña" phenomena, which affect agro-ecosystems and the economy. Remote sensing and artificial intelligence modeling and prediction tools can be used to estimate risk and manage soil, water and crops. These tools collect data on crops and the environment and use machine learning algorithms to predict and detect problems. As a result, farmers can make data-driven decisions that improve yields, reduce resource waste and increase profitability.

Finally, the use of "machine learning" and "deep learning" techniques in the global fruit industry has proven to be prevalent and effective. Specifically, "deep learning" has been successfully applied in the monitoring of tomato crops using drones, tomatoes being one of the most widely produced vegetables worldwide. "Deep learning" based algorithms are valuable for fruit pest and disease monitoring and post-harvest sorting by analyzing image datasets and identifying patterns that are difficult for humans to detect. These algorithms enable fast and accurate responses to problems, improving the efficiency and accuracy of agricultural processes. In addition, 'machine learning' is linked with remote sensing and IoT to promote sustainable practices, where remote sensing technologies, such as unmanned aerial vehicles (UAVs), provide valuable data for precision agriculture, and IoT devices, such as WSNs, collect crucial data on temperature, humidity and soil moisture to make informed crop management decisions. The fusion of machine learning, remote sensing and IoT has the potential to revolutionize sustainable agriculture.

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Conflict of interest statement

The authors declare that there is no conflict of interests regarding the publication of this article.

Author's contributions

AMPP performed the bibliometric search, article writing, and bibliometric analysis and conducted the research process by leading the article review. WJCB contributed to the bibliometric analysis and performed the critical revision of the manuscript and its translation. All authors reviewed the final version of the manuscript.

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