frontiers | Frontiers in Sustainable Food Systems

TYPE Systematic Review
PUBLISHED 09 January 2023
DOI 10.3389/fsufs.2022.1053921

OPEN ACCESS

EDITED BY
Chu Zhang,
Huzhou University, China

REVIEWED BY
Abderahman Rejeb,
Széchenyi István University, Hungary
Pan Gao,
Shihezi University, China

*CORRESPONDENCE
Vahid Kayvanfar
vkayvanf@gmail.com

SPECIALTY SECTION
This article was submitted to Sustainable Food Processing, a section of the journal Frontiers in Sustainable Food Systems

RECEIVED 26 September 2022
ACCEPTED 30 November 2022
PUBLISHED 09 January 2023

CITATION
Yousaf A, Kayvanfar V, Mazzoni A and Elomri A (2023) Artificial intelligence-based decision support systems in smart agriculture: Bibliometric analysis for operational insights and future directions. *Front. Sustain. Food Syst.* 6:1053921. doi: 10.3389/fsufs.2022.1053921

Artificial intelligence-based decision support systems in smart agriculture: Bibliometric analysis for operational insights and future directions

Arslan Yousaf, Vahid Kayvanfar*, Annamaria Mazzoni and Adel Elomri

Division of Engineering Management and Decision Sciences, College of Science and Engineering, Hamad Bin Khalifa University, Qatar Foundation, Doha, Qatar

As the world population is expected to touch 9.73 billion by 2050, according to the Food and Agriculture Organization (FAO), the demand for agricultural needs is increasing proportionately. Smart Agriculture is replacing conventional farming systems, employing advanced technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), and Machine Learning (ML) to ensure higher productivity and precise agriculture management to overcome food demand. In recent years, there has been an increased interest in researchers within Smart Agriculture. Previous literature reviews have also conducted similar bibliometric analyses; however, there is a lack of research in Operations Research (OR) insights into Smart Agriculture. This paper conducts a Bibliometric Analysis of past research work in OR knowledge which has been done over the last two decades in Agriculture 4.0, to understand the trends and the gaps. Biblioshiny, an advanced data mining tool, was used in conducting bibliometric analysis on a total number of 1,305 articles collected from the Scopus database between the years 2000–2022. Researchers and decision makers will be able to visualize how newer advanced OR theories are being applied and how they can contribute toward some research gaps highlighted in this review paper. While governments and policymakers will benefit through understanding how Unmanned Aerial Vehicles (UAV) and robotic units are being used in farms to optimize resource allocation. Nations that have arid climate conditions would be informed how satellite imagery and mapping can assist them in detecting newer irrigation lands to assist their scarce agriculture resources.

KEYWORDS

smart agriculture, precision agriculture, Agriculture 4.0, Internet of Things, artificial intelligence, machine learning, bibliometric analysis, operations research

1. Introduction

The Food and Agriculture Organization of the United Nations (FOA) has estimated that the world population will touch 9.73 billion by 2050 and will continue to rise until it reaches 11.2 billion by 2,100 (FAO, 2018). There is a direct correlation between population expansion and an increase in the need for food production. Both increases in population and increase in urbanization increase the risk of food shortage due to increased consumption, and the demand for nutritious agriculture, as farmlands are replaced with infrastructure and buildings (Yuan et al., 2018). There are many obstacles to agricultural output, resulting in lower crop yield, such as soil salinity in arid climates (Mohamed et al., 2019). Further, climate and soil sensitivity have an impact on crop quantity and quality (Abdel-Fattah et al., 2021). Consequently, it is critical to concentrate on surveying land resources for use in agricultural growth in dry regions (Saleh et al., 2015). The agriculture industry is one of the key sources of national income in developing countries. Hence, using new technology to improve the agriculture sector is critical to these countries' national economies. In addition to providing the raw materials required for the industrial process, agricultural production includes the production of food for humans and cattle. Smart Agriculture aims to address these concerns through increasing productivity, better allocation of resources, adapting to climate change and overcoming food wastage.

Fundamentally, both Smart Agriculture and Precision Agriculture utilize the Internet of Things (IoT) or information technology to improve spatial management procedures to maximize crop yield while avoiding the overuse of fertilizers and pesticides (Auernhammer, 2001; Bacco et al., 2019; Chiu et al., 2022). Unlike Precision Agriculture, Smart Agriculture, also known as Agriculture 4.0, further employs advanced technologies such as Artificial Intelligence (AI) and Machine Learning (ML) to tackle a variety of crop-related difficulties by enabling the examination of changes in atmospheric conditions, soil properties, moisture, etc. The AI and IoT technology enable the connection of a variety of distant sensors, including ground sensors, robots, and Unmanned Aerial Vehicles (UAV), since it allows items to be linked and operated automatically through the internet (Almetwally et al., 2020; Chiu et al., 2022; Javaid et al., 2022). Despite Smart Agriculture technology evolving fast, academics feel that the technology is still at a nascent stage. Agricultural IoT application is currently fragmentary, and its usefulness for integration in agricultural development has not been fully investigated. This necessitates further research in combining Smart Agriculture with Operation Research (OR) theories (Hu et al., 2020).

Bibliometric analyses on Smart Agriculture have also been conducted in the past. Abdollahi et al. (2021) conducted a bibliometric analysis between the years 2002 to 2021 to investigate the application of Wireless Sensor Networks (WSN) in agriculture. Rejeb et al. (2022a) conducted a bibliometric analysis between the years 2000–2021 to understand the comprehensive application of drones in agriculture. Rejeb et al. (2022b) looked at the applications of Artificial Intelligence (AI) in agriculture between the years 1992–2021 by conducting a bibliometric analysis. Rejeb et al. (2022c) analyzed the applications of the Internet of Things (IoT) in Agriculture between the year 2012–2020 by conducting bibliometric analysis. However, past bibliometric analyses tried to understand how the technologies such as WSN, AI, and IoT were being integrated into agriculture practices over the years, but there are few, if not any, bibliometric analyses on the application of Operations Research (OR) theories in Smart Agriculture or Agriculture 4.0 at a comprehensive level to understand how such theories have been applied in farms that have already integrated technologies such as AI and IoT systems. A complete evaluation of the studies on Operation Research (OR) in IoT-based intelligent agriculture is expected, considering this context. The research questions are (1) How have OR theories are being evolved over the last two decades to a more advanced and complex level? (2) Which OR theories are being applied to Smart Agriculture, and in what context? (3) How are Decision Support Systems (DSS) being applied to optimize Smart Agriculture, and for which objectives? (4) How are OR theories being applied to aid in achieving Smart Agriculture objectives? (5) What are the trends, gaps, and future research prospects in the application of OR in Smart Agriculture?

The rest of the manuscript is outlined as follows: The methodology used to conduct bibliometric analysis is discussed in methodology section. The results and discussions, compromising of descriptive, keyword, and historical analysis, applications of DSS, as well as thematic analysis, are conducted in results and discussion section. The gaps, extracted insights, and future directions are discussed in gaps, future work, and insights section. Finally, an extensive conclusion comprising theoretical and practical implications, as well as limitations, are presented in conclusion section.

2. Methodology

In order to convey a holistic overview of the past literature on Smart Agriculture at a broad level over many the years, it would be ideal to conduct a bibliometric analysis over a traditional and systematic literature review. Traditional literature review lacks a transparent and systematic approach, and as a result, it is more likely to be biased (Kraus et al., 2020). While systematic literature review is more methodological to allow researchers to collect relevant research papers to conduct analysis in a systematic way to identify research gaps (Chakraborty et al., 2021). Whereas, bibliometric analysis can be applied to large data collection to allow us to visualize and reveal the advancement of a discipline in a statistical and mathematical method Rejeb et al. (2022b). It supports all the main areas of the classical bibliometric approach and provides various analyses using a graphical or visualization method (della Corte et al., 2019). A structured content analysis using bibliometric analysis allows researchers to identify themes and is a powerful and reliable approach for conducting a literature review (Chakraborty et al., 2021). This research is focused on gaining a rounded overview of the OR applications in Smart Agriculture, and in order to do so, it would be more feasible to conduct a bibliometric analysis for better visualization of how research has been gaining popularity and what are the research gaps. Moreover, the articles collected would require to be analyzed from different angles in an unbiased manner, which both traditional and systematic literature reviews do not provide. Hence, the bibliometric analysis would be an optimum choice.

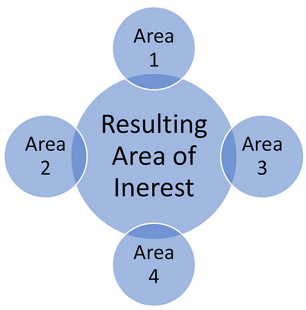

FIGURE 1
Radial venn diagram.

Bibliometric analysis has been conducted to present a state of intellectual structure and to highlight the key trends of OR in smart agriculture. The analysis is performed using R-package bibliometrix (Harzing and Alakangas, 2016), an application designed for quantitative research in Bibliometrics or Scientometrics. It supports all the main areas of the classical bibliometric approach and provides various analyses using a graphical or visualization method (della Corte et al., 2019).

As mentioned, to conduct a comprehensive overview of past literature on Smart Agriculture at a broad level, a wide variety of keywords is used to capture the maximum number of papers within a defined framework. Bibliometric analysis of the collected material in this article is conducted in six phases: (1) Descriptive analysis, (2) Keyword analysis, (3) Historical analysis, (4) Application of DSS in Smart Agriculture, (5) Thematic analysis, and (6) Research gaps and future directions, and (7) Conclusions.

During the first phase, a set of keywords was outlined in a selected database to capture the past research work in the area of smart agriculture. Figure 1 depicts a Radial Venn diagram merging four different areas with specific keywords, highlighted in Table 1, to collect material of interest to us (Resulting Area of Interest). Boolean operators "OR" and "AND" were used to achieve the desired merged area of research.

As shown in Table 2 and Figure 2, Scopus was used as an online database to search for material. Two rounds of the search were made, wherein the search term was confined to Keywords in the first and the Article Title in the other. Since publications within the field of OR in Smart Agriculture were near negligible before the year 2000, as shown in Table 4, and to highlight the interconnection between the literature paper, the search was limited to final article papers published in English, and the time range was set between 2000 and 2022. To further refine the

TABLE 1 Terms used for Scopus database search.

Area/Operator	Terms
Area 1	("vertical*" OR "smart*" OR "integrat*" OR "urban*" OR "greenhouse" OR "precision" OR "UAV" OR "Unmanned Aerial Vehicle" OR "Soil" OR "Irrigation")
Operator	AND
Area 2	("farm*" OR "agri*")
Operator	AND
Area 3	("Internet of things" OR "IOT" OR "Artificial Intelligence" OR "AI" OR "machine learn*" OR "pattern* recognition*" OR "classif*" OR "industry 4.0" OR "cloud computing" OR "big data" or "Web of Things" Or "Mobile of Things")
Operator	AND
Area 4	("math* model*" OR "Decision*" OR "plan*" OR "schedul*" OR "simulat*" OR "optimiz*" OR "heuristic*" OR "greedy*" OR "tabu* search*" OR "exact* method*" OR "constraint* method*" OR "constructive approach*" OR "metaheuristic*" OR "local* search*" OR "math* program*" OR "linear* program*" OR "integer* program*" OR "dynamic* program*" OR "constraint* program*" OR "approximate* dynamic* program*" OR "queu*" OR "game*" OR "markov* process*" OR "markov* decision* process*" OR "mdp*" OR "multi* objective*" OR "multi* criteria" OR "monte carlo*" OR "deterministic*" OR "stochastic*" OR "robust* slack* allocat*" OR "cluster*" OR "Fuzzy")

Asterisk (*) is used to include any variation at the end of a search term. For instance, farm* will find farms, farming, farmer, etc.

TABLE 2 Query search.

Query	Criteria
1	- From the Scopus database collection - Search terms in keywords alone - Refined by: ○ Document type: Article ○ Language: English ○ Timespan: 2000–2022 - Articles appeared: 1,787 ○ Refined further with the discarding of articles in subject areas as shown in Table 3, resulting in 1,291 articles
2	○ From the Scopus database collection ○ Search terms in the Article title - Refined by: ○ Document type: Article ○ Language: English ○ Timespan: 2000–2022 - Articles appeared: 29 ○ Refined further with the discarding of articles in subject areas as shown in Table 3, resulting in 25 articles

scope of interest to generate better graphs and results, articles of specific subject areas, as shown in Table 3, were discarded. A total of 1,305 articles were collected and exported in BibTex format to be readily used for Biblioshiny software to conduct a range of bibliometric analyses. Figure 2 shows the flowchart of the literature selection process.

3. Results and discussion

This paper uses an approach similar to that of some scholars (Aria and Cuccurullo, 2017) to draw a structure for a literature review in OR in Smart Agriculture. The approach is based on (1) data collection, (2) data analysis and visualization (3) Interpretation. The following section outlines the outcomes of the methodology phase described earlier.

3.1. Descriptive analysis

Table 4 shows statistics of publications through the past two decades. It includes the number of published articles (yearly and cumulative) from 2000 to 2022 and the total number of articles that have cited the chosen articles. The data illustrate that the number of articles in the scope of OR in Smart Agriculture gradually increased from 2000 to 2017, whereafter it dramatically increased, along with the number of citations per year. We should point out that the reason that we started with the year 2000 is because of the limited number of articles (max. 2000) that could be downloaded from the saved library in Scopus in one file to be imported into the Biblioshiny application; however, most of the studies have been done in the recent two decades, as well.

Some of the highly cited articles relating to operations research in smart agriculture focused on crop identification using machine learning (ML) techniques (van Niel and McVicar, 2004; Peña-Barragán et al., 2011; Ghosal et al., 2018), precise irrigation using remote sensing and machine learning (Thenkabail et al., 2009; Goap et al., 2018), smart farming using the IoT (Mendas and Delali, 2012; Muangprathub et al., 2019), crop prediction using simulation modeling (Ines et al., 2013; V. Rodriguez-Galiano et al., 2014), and using Unmanned Aerial Vehicles (UAV) for crop identification (Torres-Sánchez et al., 2015; de Castro et al., 2018). The wide variety of topics of high citation demonstrates the diversity of the research streams in Smart Agriculture.

Likewise, some of the major categories of operations research in smart agriculture were identified through the Scopus database, which included agricultural and biological sciences (about 40% of the articles published), Environmental Science (38%), Computer Science (28%), Engineering (16%) and decision sciences (2%). The most cited countries in the Scopus database included the USA (4,825 citations), Italy (3,826 citations), China (3,767 citations), and Spain (1,841 citations), indicating the regions around the world contributing significantly to the field of operations research in smart agriculture. Further, Figure 3 is a combination of annual scientific production and annual trending topics generated using bibliometrix. The graph indicates the increasing interest of researchers in the field of operations research in smart agriculture and, further, the increased complexity of the knowledge applied in smart agriculture.

Topics were less sophisticated in terms of smart agriculture and operations research between the years 2000 and 2017 since AI and ML methods were not well researched to be better applied in agriculture. The topics commonly discussed were decision support systems and management of information technology for the optimization of agriculture (such as crops, waste management, soil erosion, and water use). From 2017, the trending topics indicate more complexity and precise management of agriculture as research within AI and ML grows further, in turn improving agricultural production and practices. The topics trending since 2017 are focused on algorithms, climate change, precision agriculture, decision trees, remote sensing, and predictive analytics error in smart agriculture.

The crease in complexity and development of sophisticated applications of Operations Research is an indication of the increased need of the agriculturists to overcome challenges faced to optimize their farming practices. Furthermore, the sudden increase in the number of articles and total citations from the year 2017 is also an indication toward the increasing interest of researchers in the application OR in Smart Agriculture.

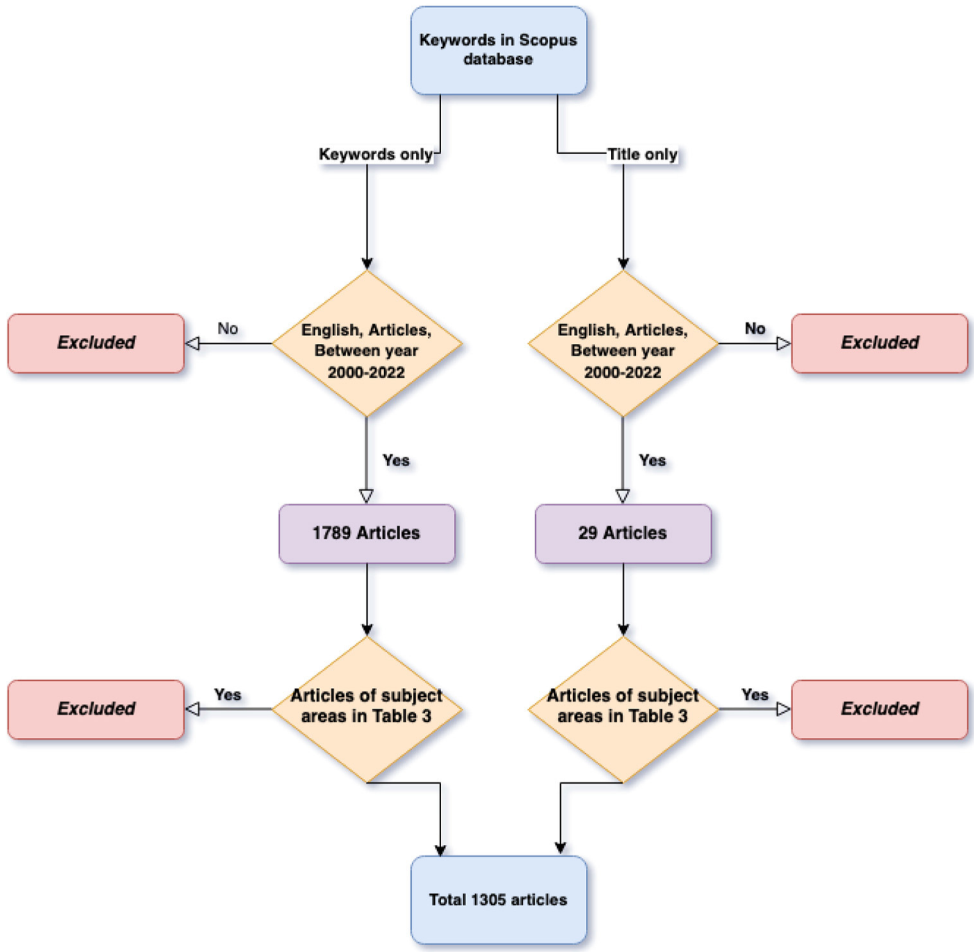

FIGURE 2
Flowchart of the literature selection process.

3.2. Keyword analysis

This section details keyword analysis, which is useful for conveying an overall summary of an article. Further clustering and multiple correspondence analyses will be conducted to better understand the research directions within the scope of operations research in smart agriculture. Biblioshiny, a data-mining and statistical application, was used to generate the information required for the analysis. The word treemap (Figure 4) was generated for high-frequency keywords with a minimum of 85 occurrences. It has the top 40 keywords frequently used by scholars in Operations research in smart agriculture.

The highest keyword occurrences are for agriculture (7%), remote sensing (4%), crops (4%), and artificial intelligence (4%), as listed in Figure 4, which indicates that major research areas in operations research in smart agriculture are focused on agricultural crops through the use of IoT and AI. In terms of agricultural sectors, the most frequently used are crops, irrigation, precision agriculture, and agricultural land. Table 5 lists the frequent keyword terms used within the collection

TABLE 3 Articles of subject area discarded.

Subject area	Query 1	Query 2
Biochemistry, genetics, and molecular biology	289	2
Immunology and microbiology	228	–
Medicine	54	–
Pharmacology, toxicology, and pharmaceutics	17	–
Arts and humanities	2	–
Nursing	6	–
Neuroscience	3	–
Physics and astronomy	112	3
Veterinary	4	–

of 1,305 articles between 2000 and 2022. With the refined key terms used to capture the relevant topics, we were able to obtain an even percentage of articles that focused on agricultural systems (such as soil, land use, irrigation, etc.) using different smart approaches, which included AI, remote sensing and machine learning. Within the agriculture group, some of the highest cited articles discussed object-based crop classification (Peña-Barragán et al., 2011), remote sensing for agricultural applications (Weiss et al., 2020), predictive modeling of agricultural pollution (V. F. Rodriguez-Galiano et al., 2018), and managing farms through the use of information systems (Espejo-Garcia et al., 2020).

TABLE 4 Statistics of publications.

Year	No. of articles	Cumulative no. of articles	Total citations	Cumulative number of citations
2000	4	4	20	20
2001	3	7	14	34
2002	2	9	18	52
2003	4	13	13	65
2004	10	23	115	180
2005	8	31	62	242
2006	13	44	132	374
2007	8	52	104	478
2008	20	72	360	838
2009	33	105	315	1,153
2010	38	143	1,573	2,726
2011	51	194	776	3,502
2012	51	245	980	4,482
2013	34	279	1,116	5,598
2014	48	327	1,635	7,233
2015	55	382	1,528	8,761
2016	77	459	2,295	11,056
2017	82	541	3,246	14,302
2018	113	654	6,540	20,842
2019	153	807	7,263	28,105
2020	260	1,067	9,603	37,708
2021	231	1,298	–	–
2022	7	1,305	–	–

Top-cited articles on remote sensing discussed various aspects, such as Thenkabail et al. (2009) using remote sensing to simulate a Global Irrigated Area Map (GIAM) to assist precision agriculture (Weiss et al., 2020) and discussing the applications of remote sensing in agriculture, (Ines et al., 2013) combining remote sensing and simulation to increase maize crop production, and (Torres-Sánchez et al., 2015) using Unmanned Aerial Vehicles (UAV) in remote sensing methods for better crop identification. It can be deduced that remote sensing techniques are commonly employed in agriculture to achieve better mapping, improve crop yields and classification to enhance productivity, and achieve automated smart agriculture.

Articles on AI looked at the integration of multicriteria decision analysis with GIS for agricultural land suitability detection (Mendas and Delali, 2012), GIS-based photovoltaic farm site detection (Sánchez-Lozano et al., 2014), selecting patterns and features for crop weed row mapping using UAV (Pérez-Ortiz et al., 2016), and predicting crop yield using fuzzy cognitive mapping (Papageorgiou et al., 2009). Articles in ML keyword criteria focused on designing a deep machine vision model for plant detection (Ghosal et al., 2018), managing irrigation systems in agriculture using decision support systems

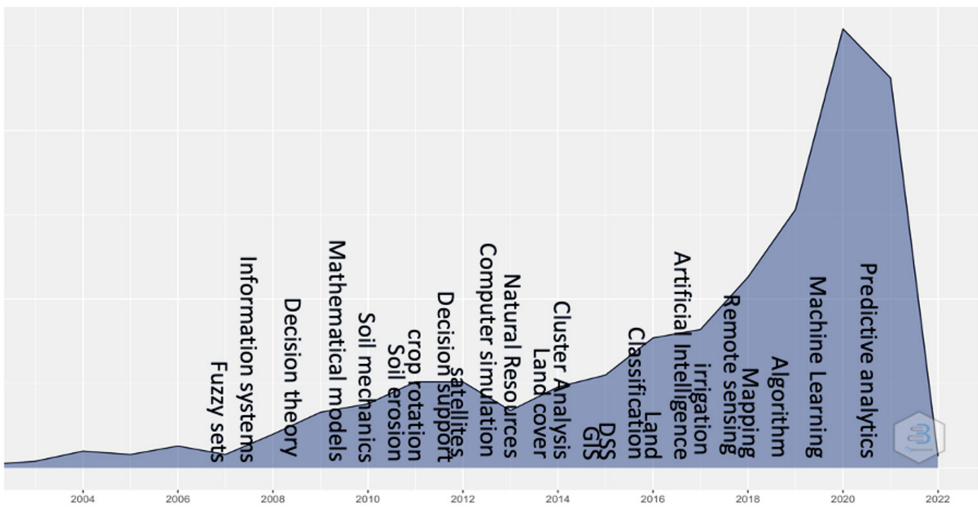

FIGURE 3
Annual scientific production graph.

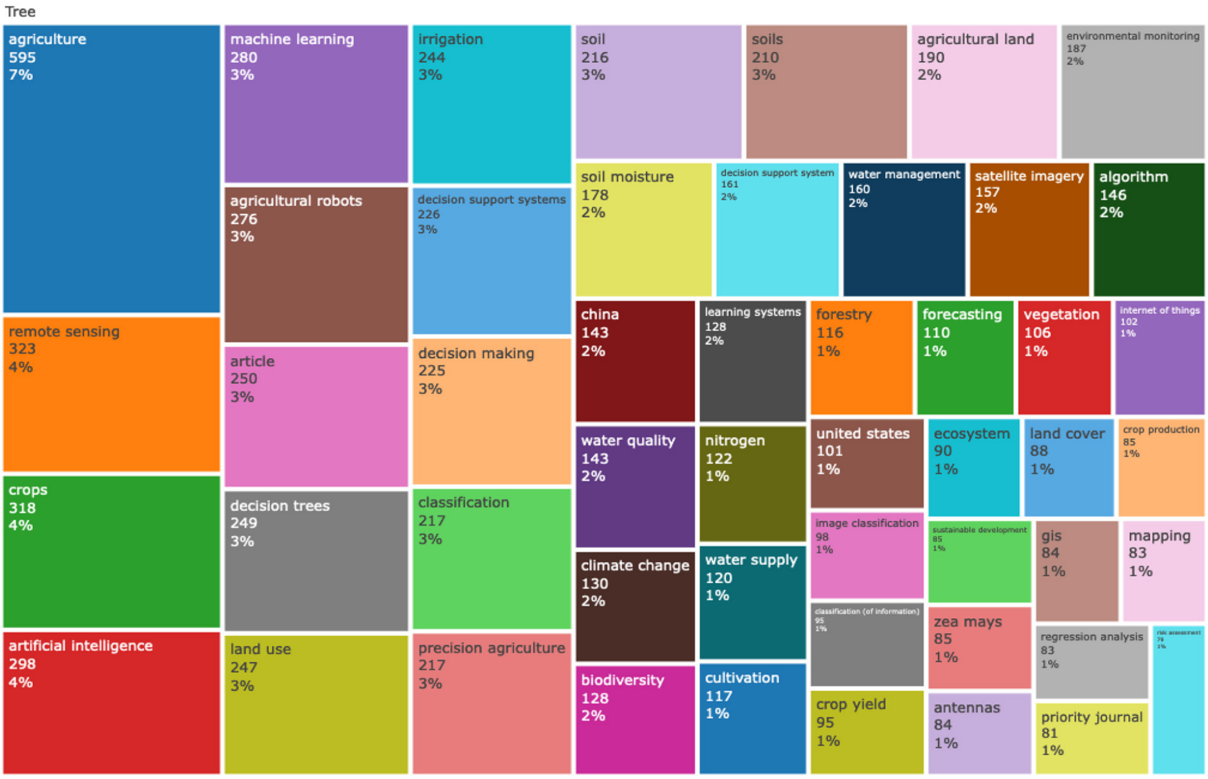

FIGURE 4
Word tree map.

(Navarro-Hellín et al., 2016), value creation through big data analytics (Saggi and Jain, 2018), etc., Other articles considered deep learning convolutional neural networks (CNN) to detect water pollution in agricultural irrigation (Chen et al., 2020), precise automated leaf detection using image feature analysis (Pantazi et al., 2019), and predicting soil moisture content using hybrid machine learning (Prasad et al., 2018).

The wide variety of highly cited articles in AI and ML, the heart of smart agriculture, indicates a great potential for future research in different agricultural segments and using big data analytics, farms are adopting more precise management.

3.3. Historical analysis

Historical network analysis allows us to cluster a number of research streams that have evolved over the years. It uses the collection of bibliography from the articles collected and generates a map of the most relevant citations (Borgman and Furner, 2002; Garfield, 2016). The direct historical network is discussed in this section, which was generated through Biblioshiny.

The number of nodes was set to 40 to show a complete overview of the different research paths. The following section will discuss the six areas of research relating to Operations research in smart agriculture; (1) Remote sensing and statistics, (2) ML approach for precise agricultural mapping, (3) Precise agricultural management using the IoT, (4) Cloud-based satellite for precise irrigation mapping (5) Decision Support Systems (DSS) to mitigate fertilizer-based loss and (6) Sustainable agriculture using ML techniques.

3.3.1. Remote sensing and statistics

Locating and extending irrigation land is important for better water management. Using remote sensing techniques to gather large amounts of data enables decision-makers to make better and more sustainable agricultural decisions. Two authors- (Zhu et al., 2014) and (Meier et al., 2018), as named in Table 6, both discussed using statistical approaches involving different vegetation indexes (NDVI) for precise irrigation to assist croplands. Both authors considered using remote sensing and IoT to generate large statistical data to achieve accurate measurements of irrigated areas for improving agricultural practices.

TABLE 5 Table of most frequently used terms.

Terms	Frequency	Terms	Frequency
Agriculture	595	Satellite imagery	157
Remote sensing	323	Algorithm	146
Crops	318	China	143
Artificial intelligence	298	Water quality	143
Machine learning	280	Climate change	130
Agricultural robots	276	Biodiversity	128
Article	250	Learning systems	128
Decision trees	249	Nitrogen	122
Land use	247	Water supply	120
Irrigation	244	Cultivation	117
Decision support systems	226	Forestry	116
Decision making	225	Forecasting	110
Classification	217	Vegetation	106
Precision agriculture	217	Internet of things	102
Soil	216	United States	101
Soils	210	Image classification	98
Agricultural land	190	Classification (of information)	95
Environmental monitoring	187	Crop yield	95
Soil moisture	178	Ecosystem	90
Decision support system	161	Land cover	88
Water management	160	Crop production	85

Zhu et al. (2014) employed remote sensing and time-series NDVI for mapping irrigated lands in China. Large statistical data were collected on different precipitation patterns, which were downscaled using a spatial allocation model to locate new irrigation areas. Meier et al. (2018) looked at using remote sensing and multi-temporary NDVI to test existing maps and used decision trees to extend irrigated areas. Such methods of detecting newer irrigation land or extending the current irrigation land support Smart Agriculture requirements by increasing productivity since water is an essential source needed by agriculture and farms to produce crops.

3.3.2. Machine learning for precise agricultural mapping

Sustainable agricultural management of water resources demands a better understanding of spatial irrigation patterns. Both articles focused on the handling of large data to achieve better and more precise irrigation in the context of a single country using the ML approach. Deines et al. (2017) looked at Northern U.S. and analyzed the high-resolution irrigation maps produced by Landsat satellite imagery over the past 2 decades using Google Earth Engine to understand the irrigation patterns to better manage the agricultural water resources. Statistical modeling involving a random forest classifier was used to understand how precipitation influenced irrigation over time.

Ketchum et al. (2020) used an ML approach to achieve better mapping of irrigated agricultural lands in the Western U.S. Similar to the first group, Google Earth Engine was used to collect past data of four different classes: irrigated agriculture, wetlands, uncultivated land, and dryland agriculture over 3 decades to cover a variety of spectra to better map the irrigated agricultural lands to improve precise agricultural practices.

The higher resolution of irrigated lands and better classification assists in enhancing precise irrigation management for farms, and such methods support Smart Agriculture goals by improving resource allocation. Table 7 shows research stream: ML for precise agriculture mapping.

3.3.3. Precise agricultural management using the Internet of Things (IoT)

The research stream illustrated that IoT practices could be more sustainable and profitable in terms of precise agriculture through better water management and fertilizer allocation than conventional models. Krishnan et al. (2020) employed smart irrigation systems based on fuzzy logic using IoT to reduce the amount of power for the watering of fields. A fuzzy logic controller was used to determine the input parameters, such as soil humidity, temperature, and moisture, to compute the output of the motor status. Farmers were assisted with smart irrigation systems through Global Systems for Mobile Communication (GSMC) to better manage the watering of agricultural fields by knowing the job status, including the soil moisture, humidity, and temperature, along with the status of motor power.

Kocian et al. (2020) used IoT-based agricultural decision support methods for crop growth prediction. A dynamic Bayesian network (DBN) was used to correlate the parameters of crop growth with the environmental control parameters through the unknown Markov Chain. The crop growth parameters included lead-area index, dry weight, and evapotranspiration on a daily basis, while the environmental control parameters included solar exposure, vapor pressure, and temperature of the controlled environment. Large expectation-maximization (EM) algorithms were used to track states and better understand the parameters of DBN.

Lin et al. (2020) focused on fertigation management based on IoT for sustainable precision agriculture. The paper addressed the irrigation and fertilizer allocation problems through a framework using IoT to manage not only at the short-term level but also in the long term. The integer linear programming model was developed to allocate limited resources among different crops to maximize the total profit (both economic and environmental).

The use of IoT in smart agriculture supports the agriculture 4.0 requirements by adapting to climate change as water resources are further decreasing due to increased demand, and

TABLE 6 Research stream: remote sensing and statistics.

Author	Technology	Agricultural solution	OR characteristic	Agriculture 4.0 pillar
Zhu et al. (2014)	Remote sensing (IoT) using multi-temporary NDVI	Locating irrigation land	Statistics (spatial allocation model)	Increasing productivity
Meier et al. (2018)	Remote sensing (IoT) using time-series NDVI	Extending irrigation land	Statistics (decision trees)	Increasing productivity

TABLE 7 Research stream: ML for precise agriculture mapping.

Author	Technology	Agriculture solution	OR characteristic	Agriculture 4.0
Deines et al. (2017)	Satellite imagery using Google Earth, and Machine Learning	High resolution of irrigated land	Statistics (random forest classifier)	Better resource allocation
Ketchum et al. (2020)	Satellite imagery using Google Earth, and Machine Learning	High resolution of irrigated land	Statistics (random forest classifier)	Better resource allocation

this requires the use of smart irrigation. IoT is also being applied in Smart Agriculture, using probability to predict crop growth to increase productivity; such methods support Agriculture 4.0. Table 8 shows research stream: precise agriculture management using IoT.

3.3.4. Cloud-based satellite for precise irrigation mapping

All the articles in this stream utilized satellite imaging at a cloud-based level for better mapping of different sectors of agriculture, such as irrigation and soil moisture, to improve precise agricultural practices. Such precise and accurate agricultural practices assist farmers in adapting to climate change and increase the productivity of their crops.

Bazzi et al. (2021) focused on precise irrigation through mapping at plot scale using S1 and S2 data over 4 years (2017–2020). Two irrigation metrics were adopted for selection criteria, the first one based on Synthetic Aperture Radar (SAR) using S1 and the other optical-based using S2; both were time series. Random forest (RF) was used to build an irrigation classification model to validate the results. The proposed method demonstrated a higher accuracy of irrigation maps compared to empirical methods. Higher accuracy of irrigation mapping assists Smart Agriculture goals by better resource allocation.

Likewise, Wellington and Renzullo (2021) considered enhancing irrigated crop mapping using S2 images. Accurate mapping for irrigated areas can be challenging to generate at a small level, requiring complex models attached to image stacks. Supervised random forest was applied to the collected data for smallholder irrigation schemes, enhancing the mapping of irrigation land. Pageot et al. (2020) also looked at better detection of irrigated lands jointly using S1 and S2 along with meteorological time series to improve crop irrigation management. The study was conducted over 2 years in a temperate area to detect rainfed plots. Monthly data was cumulated, provided by satellite imaging to be readily used in Random Forest Classifier. Through the combined use of S1 (radar), S2 (optical), and meteorological (weather) time-series data, the study showed significant improvement in both classifications of irrigated crops and mapping of irrigated areas. Detecting newer irrigated lands, in turn, leads to agricultural production increasing, since there is a protentional for more availability of water.

Gao et al. (2018) formulated a synergetic technique using S1 and S2 for mapping soil moisture and irrigated areas. The paper developed an algorithm using the Water Cloud Model (WCM) to spatialize the soil water content between 2015 and 2017. Along with WCM, a decision tree approach using statistical indices of soil humidity and Normalized Difference Vegetation Index (NDVI) was used to classify irrigation maps at individual fields. By analyzing the moisture content of the soil to classify irrigation lands, the resources are better allocated for farms.

The research of Bousbih et al. (2018) was based on high-dimensional automated algorithm satellite imaging for better mapping to achieve precise management of different agricultural sectors. Support Vector Machine (SVM) was used to identify irrigated areas based on parameters of soil moisture such as mean and variance. The model was tested in Tunisia, and the research concluded that classification based on soil moisture

TABLE 8 Research stream: precise agriculture management using IoT.

Author	Technology	Agricultural solution	OR characteristic	Agriculture 4.0
Krishnan et al. (2020)	Global Systems for Mobile Communication (GSMC) or IoT	Smart irrigation	Optimization (Fuzzy logic)	Better resource allocation
Kocian et al. (2020)	IoT	Crop growth prediction	Probability (Markov Chain)	Increase productivity
Lin et al. (2020)	IoT	Fertigation management	Optimization (Integer programming)	Better resource allocation

TABLE 9 Research stream: cloud-based satellite for precise irrigation mapping.

Author	Technology	Agricultural solution	OR characteristic	Agriculture 4.0
Bazzi et al. (2021)	Satellite imaging	Precise irrigation mapping	Statistics (random forest)	Better resource allocation
Wellington and Renzullo (2021)	Satellite imaging	Enhanced irrigated crop mapping	Statistics (supervised random forest)	Better resource allocation
Pageot et al. (2020)	Satellite imaging	Detecting irrigated land in temperate areas	Statistics (random forest)	Increase productivity
Gao et al. (2018)	Satellite imaging	Soil moisture and irrigation mapping	Statistics (WCM)	Better resource allocation
Bousbih et al. (2018)	Satellite imaging	Soil moisture and irrigation mapping	Statistics (support vector machine)	Increase productivity

properties proved useful in the improved mapping of soil moisture and irrigated lands. Such precise management of irrigated lands, in turn, increases the productivity of crops. Table 9 shows Research stream: cloud-based satellite for precise irrigation mapping.

3.3.5. Decision support systems (DSS) to mitigate fertilizer-based loss

The nodes Meza-Palacios et al. (2020) and Zhang et al. (2021), as named in Table 10, have LCS and GCS of (0, 3) and (1, 2), respectively, both having a low score due to the publications being recent. Zhang et al. (2021) utilized a new structure consisting of analytical hierarchy (AHP) and modified analytical hierarchy methods (MAHP) along with metaheuristic optimization techniques to ascertain the optimum rate of nitrogen while considering the capacity and requirement constraints. Such DSS was designated to satisfy both farmers by generating high profits and the environmental experts by keeping pollution low.

Meza-Palacios et al. (2020) focused on increasing the yield of sugarcane by increasing the efficiency of fertilizer rates. The research proposed a (DSS) based on two fuzzy models, the edaphic condition model and NPK fertilization model, for a better NPK (nitrogen, phosphorous, and potassium) fertilization rate. Such DSS models enable farmers to ensure that they meet the safety standards of minimizing the impact on climate and human health.

3.3.6. Sustainable agriculture using machine learning (ML) techniques

The nodes Hamrani et al. (2020) and Abbasi et al. (2021), as named in Table 11, have LCS and GCS of (0,0) and (1,10), respectively. All three papers looked at the application of the ML approach to overcome environmental problems, to achieve sustainable agriculture. Abbasi et al. (2021) used ML algorithms to model carbon dioxide emissions from inorganic fertilizers. The paper looked at six different models, viz., random forest (RF), Feed Forward Neural Network (FNN), Radial Basis Function Neural Network (RBFNN), Extreme Learning Machine (ELM), Least Absolute Shrinkage and Selection Operator (LASSO), and Support Vector Machine (SVM). The paper retained the same input parameters, compared the output of the different models, and found that RF was the best model for predicting carbon dioxide emission from IF. Likewise, Hamrani et al. (2020) also compared three additional ML models, Deep Belief Net (DBN, Long Short-Term Memory (LSTM),

TABLE 10 Research stream: DSS to optimize fertilizer use.

Author	Technology	Agriculture solution	OR characteristic	Agriculture 4.0
Zhang et al. (2021)	Sensors	Crop yield	Optimization (MAHP)	Adapting to climate change
Meza-Palacios et al. (2020)	Sensors	Optimum fertilizer rate	Optimization (fuzzy models)	Adapting to climate change

and Convolutional Neural Network (CNN). The models were implemented using MATLAB software for comparison, and they concluded that Deep Learning methods were better at predicting greenhouse gas emissions from the soil, particularly the LSTM method.

The research papers in this research stream looked at different ML models to analyze which are useful in predicting greenhouse gas emissions from the soil. The outcome of the research stream supports the agriculture 4.0 goals of adapting to climate change.

3.4. Application of DSS in smart agriculture

The four areas that agriculture 4.0 looks to address are directly related to accurate decision-making, and researchers are designing and implementing Decision Support Systems (DSS) to optimize crop productivity while addressing them. Articles with the following keywords were filtered: Decision Support System (DSS), optimization, and simulation. From the resultant 238 articles, those which addressed the four areas of Agriculture 4.0 were filtered to highlight the models they applied in smart agriculture. Table 12 discusses the application of DSS in smart agriculture.

Researchers have used a wide variety of methods to design DSS to support farmers for better decision-making. Recio et al. (2003) utilized the application of the advanced decision-making tool AgriSupport II system to enhance the agriculture production processes. The AgriSupport II system provided farmers with decision-making solutions to improve operations like operating cost, profitability analysis, scheduling, and resource allocation. CPLEX optimizer was used to design a model algorithm that would ensure optimum decision-making suggestions by computing all feasible modes and then performing a comparative analysis of all modes to suggest the mode that is the least costly for agricultural task allocations. By adopting the AgriSupport II system, farmers are assisted in achieving higher efficiency at the least investment cost, consequently enhancing agricultural production, which is one of the requirements of Agriculture 4.0.

Conesa-Muñoz et al. (2016) and Nabaei et al. (2018) both looked at using multi-robot sensing systems to allocate agricultural work to appropriate robotic units. The multi-sensing system was tested multiple times on a Spanish farm, using both aerial and ground units, to assist farmers in the optimal distribution of tasks. Both used the metaheuristic optimization method for ground planning through Harmony Search Algorithm. The multi-robot system collected agricultural data using aerial vehicles controlled by a Mission Manager, which was connected to a Base Station Computer. The system assigned agricultural tasks to the most appropriate robotic unit, allowing farmers to supervise and manage the entire process through a multi-robot sensing system, a decision-making tool for task allocation. Accurate imaging data collected can also inform farmers about how much herbicides or pesticides are needed for the crops. Such systems can act as essential supports for Agriculture 4.0.

With the increase in the deployment of Aerial Unmanned Vehicle (UAV) in various applications, including agriculture, Alsalam et al. (2017) designed an onboard DSS system to detect the precise location of crops with disease and then delegate appropriate action to UAV, such as precise herbicide spray. Through the assistance of the Object-Based Image Analysis (OBIA) algorithm, the use of UAV can increase efficiency in work with precise crop detection and management of toxic damage on farms.

Within the scope of route planning, Keller et al. (2007) and Bochtis et al. (2012) constructed Agriculture Decision Support System (DSS) to optimize the deployment and utilization of agricultural vehicles in fields with sensitive soil. The B-pattern optimization algorithm was used as a tool to provide an optimal route. Route planning and optimization enable vehicles to consume less energy and cause less damage to sensitive soil. This will enhance crop productivity, which supports the agriculture 4.0 requirement. Most current research for the application of Agriculture Decision Support Systems (ADDS) for water resource management is related more to irrigation management. For example, Navarro-Hellín et al. (2016) designed a smart irrigation decision support system (SIDSS) for better irrigation planning through better, efficient, and accurate use of water resources. The research looked at predicting the water needs of the crops for better irrigation planning. Partial Least Squares (PLSR) and Adaptive Neuro Fuzzy Interference Systems (ANFIS) were used to provide reasoning results to generate the decision support system requirement.

10.3389/fsufs.2022.1053921

TABLE 11 Research stream: sustainable agriculture using ML techniques.

Author	Technology	Agricultural solution	OR characteristic	Agriculture 4.0
Abbasi et al. (2021)	Sensors	Greenhouse gas emission	Probability (random forest)	Adapting to climate change
Hamrani et al. (2020)	Sensors	Greenhouse gas emission	Probability (LSTM)	Adapting to climate change

TABLE 12 Research stream: applications of DSS in smart agriculture.

Article	Model	Decision support	Programming type	Tool	Area of agriculture 4.0
Recio et al. (2003)	AgriSupport II system	Farm planning and operation	Integer Programming	CPLEX optimizer	Better resource allocation
Conesa-Muñoz et al. (2016)	Multi-robot sensing system	Task allocation	Metaheuristic algorithm	Mission manager	Better resource allocation
Nabaei et al. (2018)	Multi-robot sensing system	Task allocation	Metaheuristic algorithm	Mission manager	Better resource allocation
Alsalam et al. (2017)	On-board DSS	Optimal task allocation	OBIA algorithm	OODA loop	Better resource allocation
Bochtis et al. (2012)	ADDS for route planning	Vehicle route planning	B-pattern algorithm	iTech Pro	Better resource allocation
Keller et al. (2007)	SoilFlex	Vehicle route planning	B-pattern algorithm	Spreadsheet	Better resource allocation
Navarro-Hellín et al. (2016)	SIDSS	Optimal irrigation planning	ANFIS and PLSR	Machine learning system	Increase productivity
Giusti and Marsili-Libelli (2015)	IRRINET	Optimal irrigation planning and scheduling	Fuzzy C-Mean algorithm	Machine learning system	Better resource allocation
Schütze and Schmitz (2010)	OCCASION	Optimal irrigation planning to reduce environmental risks	SCWFP	GET-OPTIS	Adapting to climate change
Wenkel et al. (2013)	LandCaRe	Farm planning and operation to reduce environmental risks	Simulation modeling using C++	SQLite database	Adapting to climate change

Other authors, such as Giusti and Marsili-Libelli (2015), used fuzzy DSS (FDSS) using the IRRINET model to improve irrigation practices on farms. Similar to the finding of Navarro-Hellin, such fuzzy DSS assist farmers by using a predictive model and inference system of soil properties for better allocation through daily water scheduling. Fuzzy C-Mean algorithms were used to generate a decision support system for farmers by suggesting the amount of water the crops require to remain irrigated. Through better and smart management of irrigation of crops, the research supported Agriculture 4.0.

Current researchers are also addressing climate change through better farming adaptability using ADSS (El-Sharkawy, 2014; Weller et al., 2016). Schütze and Schmitz (2010) proposed a methodology, Stochastic Crop-Water Production Function (SCWPF), to quantify the effect of climate change on irrigation in agriculture. The proposed DSS was tested on farms in France, and it was concluded that the OCCASION model formulated enabled farmers with adequate data on weather and soil properties to evaluate the potential effect of climate change on farms, and OCCASION can be used to adjust decisions for irrigation scheduling and planning. Wenkel et al. (2013) presented an interactive DSS named LandCaRe, which was tested in Germany, and experimental findings showed that this system could be used to predict weather conditions and the extent of periods of vegetation. LandCaRe DSS can provide farmers with optimal decisions for improved farming practices under climate change.

3.5. Thematic map

The structure of the thematic map is generated by bibliometrix based on the clustering of the frequency of the repeated occurrences of keywords, and these clusters are known to be themes. Bibliometrix utilizes a thematic map to outline the conceptual framework of the research topics. A thematic map enables four different typologies of topics to be identified based on which quadrant they are in. The motor themes are the motifs in the upper-right quadrant. They are distinguished by a high degree of centralization and density, indicating that they have been developed and are important in the field of research.

The highly developed and isolated motifs, also known as *niche* themes, are found in the upper-left quadrant. They have matured internal links with high density but insignificant outward links and hence are of little significance in the field (low centrality). Emerging or declining motifs appear in the lower-left quadrant. They have a low density and centrality, indicating that they are underdeveloped and peripheral. Basic and transversal themes are found in the lower-right quadrant and have a high degree of centralization and low density.

These themes are significant for a study field and cover general topics relevant to all research areas of the field (della Corte et al., 2019). As shown in Figure 5, thematic mapping allows the mapping of four different themes of research. Keyword Plus was used as it allows the capture of an article's features with greater depth. The thematic map is based on two axes, one indicating the centrality or relevance of the keyword, and the other, the density or the degree of development.

Cluster #1 (C1) and Cluster #2 (C2) are both within the motor themes, where C2 is more central and less dense compared to C2. The higher central aspect of C1 indicates that the articles published within the scope of agriculture, article, and classification are concerned more with crop classification.

Some of the recent publications within C1 focus on digital soil mapping (Lagacherie et al., 2022), an intelligence-based approach for agricultural soil prediction (Nguyen et al., 2022), AI-based apple leaf disease classification (Al-Wesabi et al., 2022), and simulating various water-deficit regimes for irrigation scheduling optimization (Martínez-Valderrama et al., 2020). Recent publications indicate that C1 is more inclined toward procedures and classification of multiple aspects of agriculture segments. C2, which is also within the motor theme quadrant, is of higher density, indicating more research development in the field of crops, AI, and decision support systems compared to C1. About 37% of the total articles collected are within the scope of C2, and the recent publications merge closely with C1.

Cluster #3 (C3) and Cluster #4 (C4) are within the emerging or declining themes. Some of the recent articles in C3 discuss mapping land suitability (Carlier et al., 2021), soil prediction using AI (Nguyen et al., 2022), and modeling spatial dynamics (Sodango et al., 2021). While some articles in C4 are of emerging nature, including the combined use of machine learning algorithms and UAV (Ndlovu et al., 2021; Onishi and Ise, 2021; Qiu et al., 2021), machine vision yield monitoring (Dolata et al., 2021), artificial neural networks for crop evapotranspiration estimation (Gao et al., 2021), and usage of machine learning for crop prediction (Almeida et al., 2021).

While there was no cluster within the *niche* or isolated theme, all four clusters are shown to be interlinked through the cross-collaboration of work between different subject areas. The overall thematic map demonstrates that newer areas of study within agriculture are turning toward precision agriculture through precise modeling and estimating of maps, soil, evapotranspiration, etc., using newer and advanced technologies.

4. Gaps, future work, and insights

The comprehensive bibliometric analysis of OR in smart agriculture revealed some gaps and future directions, which are listed below:

1. Precision Agriculture focuses on the application of IoT to achieve precise farming practices. IoT has mainly been used to achieve optimization of conventional farming systems, and such optimization models are included within the DSS to assist farmers in making better decisions. The Decision Sciences database covers 2% of the total material collected from the Scopus database. Research within this scope was inclined toward better task allocation or vehicle route planning to assist farmers in better utilizing robotic units in agriculture. Most such research used complex algorithms such as metaheuristic algorithm, B-pattern algorithm, and OBIA algorithm. The DSS was initially focused toward applying OR theories to achieve better resource allocations through route planning (Keller et al., 2007; Bochtis et al., 2012), and recent papers have also focused on resource allocation but through the application of robotic units for better task allocations (Conesa-Muñoz et al., 2016; Nabaei et al., 2018) and water management for irrigation planning (Giusti and Marsili-Libelli, 2015; Navarro-Hellín et al., 2016). The application of DSS allows farmers to make better decisions for better farming; however, these methods are mostly limited to resource allocation, and there is a lack of research to address climate change, increase the productivity of the farms, or reduce agriculture waste. Moreover, there was a lack of research that utilized mathematical optimization programming, such as linear programming (LP), mixed integer programming (MIP), dynamic programming (DP), and Stochastic Programming (SP). Future research needs to incorporate such techniques to allow farmers to not only practice smart agriculture but also make decisions from the business perspective of enhancing profitability by reducing food waste.
2. Machine Learning (ML) and Artificial Intelligence (AI) application in agriculture were heavily inclined toward probability and statistics. As the world is facing water issues, an essential component of farming, much of satellite imaging methods were applied toward mapping and detecting irrigation lands (Deines et al., 2017; Ketchum et al., 2020;

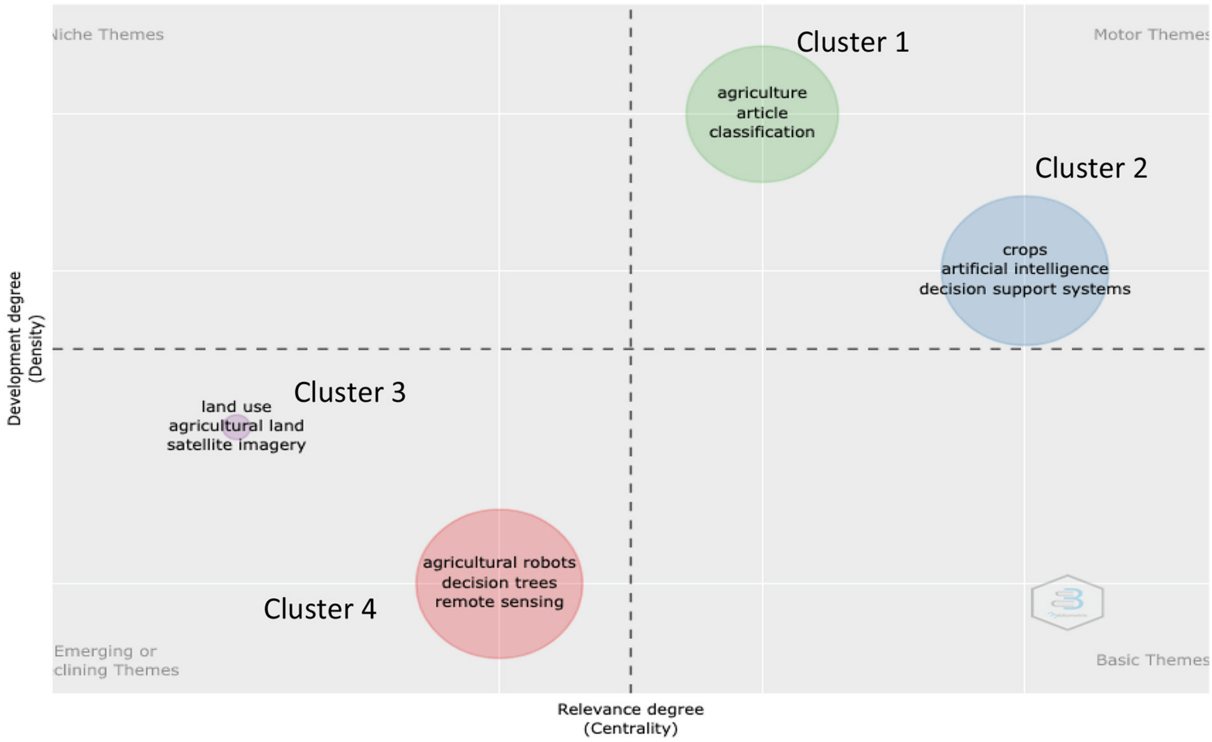

FIGURE 5
Thematic map.

Pageot et al., 2020; Bazzi et al., 2021), mostly using the Random Forest (RF) classifiers and at times Water Cloud Model (WCM) and Support Vector Machine (SVM). While one of the recent papers (Abbasi et al., 2021) compared multiple AI and ML methods, such as FNN, RBFNN, and SVM, to draw the conclusion that the RF modeling method was optimum to be the application of prediction of carbon dioxide emission. Such development within the field of ML and AI in agriculture demonstrates that future research is more focused on statistics and probability aspects of OR theories. One primary reason could be that climate change is causing unforeseen disruptions in agriculture productivity, and in order to bring resilience to farming practices, such theories are needed to predict the unforeseen circumstances to better overcome the risks. However, such methods can be capital intensive as the application of ML and AI on large data sets require a powerful machine to conduct computation, and also the computation times are lengthy. Researchers are employing advanced knowledge of AI and ML to enable farmers to mostly for better resource allocation and sometimes for adapting to climate change or increasing productivity. There is less focus on overcoming agriculture wastage, which is one of the main pillars of Smart Agriculture. This hints at the need for further research in terms of optimization of agriculture wastages in order to overcome this large research gap. Moreover, according to thematic analysis, the articles within C4 highlighted that future streams are expected to involve more complex OR theories, AI and ML streams, with the combination of ML algorithms and UAV (Ndlovu et al., 2021; Onishi and Ise, 2021; Qiu et al., 2021) to optimize the productivity, and continue to apply ML for prediction and estimation in crop management (Almeida et al., 2021; Q. Gao et al., 2018). Such complex application of OR is hinting toward future involving the analysis of large data sets to meet Agriculture 4.0 goals.

3. The major research gap lies in most of the OR theories being applied to conventional farming systems to make them smarter and more automated. For example, some research papers looked at providing optimal decision parameters for farmers for better resource allocation using robots (Conesa-Muñoz et al., 2016; Nabaei et al., 2018), while others looked at the use of sensors with fuzzy models (Krishnan et al., 2020; Meza-Palacios et al., 2020), RF (Abbasi et al., 2021), and LSTM (Hamrani et al., 2020) to optimize crop yields and reduce greenhouse gas emissions. Moreover, some papers designed DSS for improved irrigation management (papers), while others used satellite imagery to detect or extend irrigation lands (papers). While such papers utilize

the application of IoT and ML, however, they are mainly being addressed toward optimizing traditional farming systems. About 1.5 and 1% of the total material collected addressed the application of OR in vertical farming and plant factories, respectively. With the introduction of newer farming methods such as vertical farms and plant factories to accommodate countries that do not have conditions suitable for agriculture, there is the prospect for future research in the application of newer OR theories in these newer farming methods to achieve agriculture 4.0 goals.

5. Conclusion

5.1. Discussions of findings

Research on Operations Research (OR) application in smart agriculture is increasing. The literature review aids in understanding the links and advancement of a research field and provides insights into the activities of scholars. However, the inherent subjectivity of narrative and systematic reviews is reduced by bibliometric analyses.

Our study explored the operations research knowledge applied to smart agriculture. In this context, we conducted a descriptive analysis to describe how research is increasing. It has been clear that since 2017, research has dramatically increased, as newer knowledge in the Internet of Things (IoT), artificial intelligence (AI), and machine learning (ML) approaches is being enhanced for better application in smart agriculture. This has been further validated by conducting a keyword analysis.

Then, historical analysis was also conducted by generating historiography to check how some of the research streams had evolved and what the current research publications are focused on. It was noted that the major focus was on statistics and prediction to achieve precise agriculture. This was further supported through thematic mapping, where it was noticed that emerging research was focusing on agricultural land use mapping through satellite imaging, along with agricultural robotics and remote sensing.

Further, articles within the scope of decision support system (DSS) in smart agriculture were perused within the scope of Agriculture 4.0 requirements. It was apparent that DSS models were more inclined toward better allocation of resources using smart technology; however, recent articles seem to be adopting the climate change agenda (Hamrani et al., 2020; Abbasi et al., 2021; Zhang et al., 2021).

Future research, according to thematic mapping, has shown that ML and AI applications are moving toward more complexity as complex OR theories are being combined. While most current research and the future streams within ML and AI scope are inclined toward probability and statistics to predict and estimate for reasons such as prediction of crops or evapotranspiration, and other reasons include adapting to climate change. However, there was lesser focus toward optimizing agriculture farms through reducing or reusing wastage. Moreover, RF applications of OR were more readily adopted for agriculture or irrigation mapping using satellite imaging. With the increase in the sophisticated nature of ML and AI, the future of OR is moving toward data sciences.

It was noted that most applications of ML and AI, with OR theories, were being applied to conventional farming systems. As food security and climate change are starting to become more important, and countries that have arid climate conditions, there is a prospect and need to apply OR theories within newer farming methods. And since such newer farming methods, such as vertical farms or plant factories, usually involve sensors to control the environment, there is a scope to apply the current and past OR theories within conventional farming systems that involve sensors, robotic units and UAV.

Finally, as the population is expected to increase drastically over the coming years, the agri-food demand is correspondingly expected to increase, and in order to achieve greater food security and a resilient agri-food supply chain, future research needs to utilize optimization and simulation techniques to reduce food waste, ensure better food security, and optimize agricultural resources to increase productivity within both precision and smart agriculture, and to meet agriculture 4.0 goals more holistically.

5.2. Theoretical implications

Our comprehensive bibliometric analysis within the scope of OR applications in Smart Agriculture offers valuable information to multiple stakeholders, including researchers, decision makers, and consultants, who can understand and visualize how OR theories are being applied in different areas of Smart Agriculture to optimize and design DSS. Moreover, as sustainability and climate change are taking center stage in research, researchers will be able to understand how AI, IoT and ML methods within Smart Agriculture are being applied to overcome and mitigate climate change concerns. Moreover, our research has demonstrated improving productivity and reducing agricultural waste to meet Smart Agriculture goals are areas of less focus, and this will motivate researchers to increase their area of study to overcome this gap. While researchers have been highly concentric toward irrigation planning between the years 2014 and 2015, newer research is focusing toward agriculture mapping and classification, and such future direction will also allow the researcher to apply their current knowledge in this field. Last but not least, the holistic overview of literature between the years 2000–2022 will certainly give researchers and multiple stakeholders the visual map of how research within the scope of OR in Smart Agriculture is evolving and what are the trending topics and the research gaps.

5.3. Practical implications

Nations that do not have suitable conditions for agricultural farming would have their governments trying to understand how they can make their current farming practices efficient and responsive in order to meet the increasing agri-food demand. Our bibliometric analysis, specifically the application of DSS in Smart Agriculture, would give some examples of how governments can optimize and regulate their limited resources, such as water, through irrigation mapping. Furthermore, as our bibliometric analysis is demonstrating a drastic increase in the publication within the field of OR in Smart Agriculture and the application of UAV and robotic units, governments will see the need to introduce policies to regulate the farms to ensure the safety of people and the environment is being maintained. Stakeholders who are not aware of the application of UAV and robotic units through the use of IoT and AI for better resource allocation will feel inclined toward adopting these methods to their farms. One of the major practical implications lies in understanding that most literature papers focus on OR theories in traditional farming methods. To the best of our knowledge, there are few or negligible literature papers that apply OR theories toward newer agricultural methods such as hydroponics, a part of vertical farming, plant factories or urban agriculture. Such lack of literature focus would indicate that governments and researchers would feel the need to adopt AI and IoT to make newer agricultural methods to Smart Agriculture and then apply OR theories to optimize them in order to meet Smart Agriculture or Agriculture 4.0 goals.

5.4. Limitations of bibliometric analysis

Even though our attempt to understand a holistic overview of OR theories in Smart Agriculture through bibliometric analysis has given significant contributions, this review has some limitations that needs to be addressed when reading the results. One of the major shortcomings is that we only considered the Scopus database, and our articles of selection were limited to keywords and titles only. Future research should consider other databases, such as the Web of Science and integrate the findings with our results to provide a further overview of the OR theories being applied in Smart Agriculture. Moreover, if possible, future research should try to include Abstracts within the Scopus database search to capture more literature for a deeper bibliometric analysis. Our research mainly attempted to understand what are the current OR applications in Smart Agriculture during historical analysis, and future research should increase the span of historical analysis through increasing the node above 40 on Bibliometrix to generate more research streams and trends. While Smart Agriculture is a wide field, future research may also incorporate how OR theories are being applied specifically in livestock, soil and water management through changing the keyword algorithms to incline the literature search to be more subject matter. Finally, as newer farming methods will be coming to light, future researchers should conduct a bibliometric analysis on how OR theories are being used within hydroponic, urban agriculture, or plant factories.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

AY is a graduated from Master of Science program. VK is a Post-doctoral Research Fellow, contributing in this project. AM is a Research Associate, contributing in this project. AE is Assistant Prof. and supervised this project. All authors contributed to the article and approved the submitted version.

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.

Publisher's note

References

Abbasi, N. A., Hamrani, A., Madramootoo, C. A., Zhang, T., Tan, C. S., and Goyal, M. K. (2021). Modelling carbon dioxide emissions under a maize-soy rotation using machine learning. *Biosyst. Eng.* 212, 1–18. doi: 10.1016/j.biosystemseng.2021.09.013

Abdel-Fattah, M. K., Mohamed, E. S., Wagdi, E. M., Shahin, S. A., Aldosari, A. A., Lasaponara, R., et al. (2021). Quantitative evaluation of soil quality using principal component analysis: The case study of El-Fayoum depression Egypt. *Sustainability* 13, 1–19. doi: 10.3390/su13041824

Abdollahi, A., Rejeb, K., Rejeb, A., Mostafa, M. M., and Zailani, S. (2021). Wireless sensor networks in agriculture: insights from bibliometric analysis. *Sustainability* 13, 12011. doi: 10.3390/su132112011

Almeida, G. M. D., Pereira, G. T., Bahia, A. S. R. D. S., Fernandes, K., and Marques Júnior, J. (2021). Machine learning in the prediction of sugarcane production environments. *Comput. Electron. Agric.* 190, 106452. doi: 10.1016/j.compag.2021.106452

Almetwally, S. A. H., Hassan, M. K., and Mourad, M. H. (2020). Real time internet of things (IoT) based water quality management system. *Procedia CIRP* 91, 478–485. doi: 10.1016/j.procir.2020.03.107

Alsalam, B. H. Y., Morton, K., Campbell, D., and Gonzalez, F. (2017). "Autonomous UAV with vision based on-board decision making for remote sensing and precision agriculture," in *IEEE Aerospace Conference Proceedings*. doi: 10.1109/AERO.2017.7943593

Al-Wesabi, F. N., Albraikan, A. A., Hilal, A. M., Eltahir, M. M., Hamza, M. A., and Zamani, A. S. (2022). Artificial intelligence enabled apple leaf disease classification for precision agriculture. *Comput. Mater. Continua* 70, 6223–6238. doi: 10.32604/cmc.2022.021299

Aria, M., and Cuccurullo, C. (2017). bibliometrix: an R-tool for comprehensive science mapping analysis. *J. Inform.* 11, 959–975. doi: 10.1016/j.joi.2017.08.007

Auernhammer, H. (2001). Precision farming—the environmental challenge. *Comput. Electron. Agric.* 30, 31–43. doi: 10.1016/S0168-1699(00)00153-8

Bacco, M., Barsocchi, P., Ferro, E., Gotta, A., and Ruggeri, M. (2019). The digitisation of agriculture: a survey of research activities on smart farming. *Array* 3–4, 100009. doi: 10.1016/j.array.2019.100009

Bazzi, H., Baghdadi, N., Amin, G., Fayad, I., Zribi, M., Demarez, V., et al. (2021). An operational framework for mapping irrigated areas at plot scale using sentinel-1 and sentinel-2 data. *Remote Sens.* 13, 2584. doi: 10.3390/rs13132584

Bochtis, D. D., Sørensen, C. G., and Green, O. (2012). A DSS for planning of soil-sensitive field operations. *Decision Support Syst.* 53, 66–75. doi: 10.1016/j.dss.2011.12.005

Borgman, C. L., and Furner, J. (2002). Scholarly communication and bibliometrics. *Ann. Rev. Inform. Sci. Technol.* 36, 2–72. doi: 10.1002/aris.1440360102

Bousbih, S., Zribi, M., Hajj, M. E., Baghdadi, N., Lili-Chabaane, Z., Gao, Q., et al. (2018). Soil moisture and irrigation mapping in a semi-arid region, based on the synergetic use of Sentinel-1 and Sentinel-2 data. *Remote Sens.* 10, 12. doi: 10.3390/rs10121953

Carlier, J., Doyle, M., Finn, J. A., Ó hUallacháin, D., and Moran, J. (2021). A landscape classification map of Ireland and its potential use in national land use monitoring. *J. Environ. Manage.* 289, 112498. doi: 10.1016/j.jenvman.2021.112498

Chakraborty, K., Mukherjee, K., Mondal, S., and Mitra, S. (2021). A systematic literature review and bibliometric analysis based on pricing related decisions in remanufacturing. *J. Cleaner Prod.* 310, 127265. doi: 10.1016/j.jclepro.2021.127265

Chen, H., Chen, A., Xu, L., Xie, H., Qiao, H., Lin, Q., et al. (2020). A deep learning CNN architecture applied in smart near-infrared analysis of water pollution for agricultural irrigation resources. *Agric. Water Manage.* 240, 106303. doi: 10.1016/j.agwat.2020.106303

Chiu, M. C., Yan, W. M., Bhat, S. A., and Huang, N. F. (2022). Development of smart aquaculture farm management system using IoT and AI-based surrogate models. *J. Agric. Food Res.* 9, 100357. doi: 10.1016/j.jafr.2022.100357

Conesa-Muñoz, J., Valente, J., del Cerro, J., Barrientos, A., and Ribeiro, A. (2016). A multi-robot sense-act approach to lead to a proper acting in environmental incidents. *Sensors* 16, 1269. doi: 10.3390/s16081269

de Castro, A. I., Torres-Sánchez, J., Peña, J. M., Jiménez-Brenes, F. M., Csillik, O., and López-Granados, F. (2018). An automatic random forest-OBIA algorithm for early weed mapping between and within crop rows using UAV imagery. *Remote Sens.* 10, 285. doi: 10.3390/rs10020285

Deines, J. M., Kendall, A. D., and Hyndman, D. W. (2017). Annual irrigation dynamics in the U.S. Northern high plains derived from landsat satellite data. *Geophys. Res. Lett.* 44, 9350–9360. doi: 10.1002/2017GL074071

della Corte, V., del Gaudio, G., Sepe, F., and Sciarelli, F. (2019). Sustainable tourism in the open innovation realm: a bibliometric analysis. *Sustainability* 11, 6114. doi: 10.3390/su11216114

Dolata, P., Wróblewski, P., Mrzygłód, M., and Reiner, J. (2021). Instance segmentation of root crops and simulation-based learning to estimate their physical dimensions for on-line machine vision yield monitoring. *Comput. Electron. Agric.* 190, 106451. doi: 10.1016/j.compag.2021.106451

El-Sharkawy, M. A. (2014). Global warming: causes and impacts on agroecosystems productivity and food security with emphasis on cassava comparative advantage in the tropics/subtropics. *Comput. Electron. Agric.* 52, 161–178. doi: 10.1007/s11099-014-0028-7

Espejo-Garcia, B., Mylonas, N., Athanasakos, L., Fountas, S., and Vasilakoglou, I. (2020). Towards weeds identification assistance through transfer learning. *Comput. Electron. Agric.* 171, 105306. doi: 10.1016/j.compag.2020.105306

FAO (2018). *The Future of Food and Agriculture—Alternative Pathways* to *2050*. Rome, p. 224.

Gao, L., Gong, D., Cui, N., Lv, M., and Feng, Y. (2021). Evaluation of bio-inspired optimization algorithms hybrid with artificial neural network for reference crop evapotranspiration estimation. *Comput. Electron. Agric.* 190, 106466. doi: 10.1016/j.compag.2021.106466

Gao, Q., Zribi, M., Escorihuela, M. J., Baghdadi, N., and Segui, P. Q. (2018). Irrigation mapping using Sentinel-1 time series at field scale. *Remote Sens.* 10, 1495. doi: 10.3390/rs10091495

Garfield, E. (2016). Historiographic mapping of knowledge domains literature. *J. Inform. Sci.* 30, 119–145. doi: 10.1177/0165551504042802

Ghosal, S., Blystone, D., Singh, A. K., Ganapathysubramanian, B., Singh, A., and Sarkar, S. (2018). An explainable deep machine vision framework for plant stress phenotyping. *Pro. Natl. Acad. Sci.USA* 115, 4613–4618. doi: 10.1073/pnas.1716999115

Giusti, E., and Marsili-Libelli, S. (2015). A Fuzzy Decision Support System for irrigation and water conservation in agriculture. *Environ. Model. Software* 63, 73–86. doi: 10.1016/j.envsoft.2014.09.020

Goap, A., Sharma, D., Shukla, A. K., and Rama Krishna, C. (2018). An IoT based smart irrigation management system using Machine learning and open source technologies. *Comput. Electron. Agric.* 155, 41–49. doi: 10.1016/j.compag.2018.09.040

Hamrani, A., Akbarzadeh, A., and Madramootoo, C. A. (2020). Machine learning for predicting greenhouse gas emissions from agricultural soils. *Sci. Total Environ.* 741, 140338. doi: 10.1016/j.scitotenv.2020.140338

Harzing, A. W., and Alakangas, S. (2016). Google Scholar, Scopus and the Web of Science: a longitudinal and cross-disciplinary comparison. *Scientometrics* 106, 787–804. doi: 10.1007/s11192-015-1798-9

Hu, X., Sun, L., Zhou, Y., and Ruan, J. (2020). Review of operational management in intelligent agriculture based on the Internet of Things. *Front. Eng. Manage.* 7, 309–322. doi: 10.1007/s42524-020-0107-3

Ines, A. V. M., Das, N. N., Hansen, J. W., and Njoku, E. G. (2013). Assimilation of remotely sensed soil moisture and vegetation with a crop simulation model for maize yield prediction. *Remote Sens. Environ.* 138, 149–164. doi: 10.1016/j.rse.2013.07.018

Javaid, M., Haleem, A., Singh, R. P., and Suman, R. (2022). Enhancing smart farming through the applications of Agriculture 4.0 technologies. *Int. J. Intell. Networks* 3, 150–164. doi: 10.1016/j.ijin.2022.09.004

Keller, T., Défossez, P., Weisskopf, P., Arvidsson, J., and Richard, G. (2007). SoilFlex: a model for prediction of soil stresses and soil compaction due to agricultural field traffic including a synthesis of analytical approaches. *Soil Tillage Res.* 93, 391–411. doi: 10.1016/j.still.2006.05.012

Ketchum, D., Jencso, K., Maneta, M. P., Melton, F., Jones, M. O., and Huntington, J. (2020). IrrMapper: a machine learning approach for high resolution mapping of irrigated agriculture across the Western U.S. *Remote Sens.* 12, 2328. doi: 10.3390/rs12142328

Kocian, A., Massa, D., Cannazzaro, S., Incrocci, L., di Lonardo, S., Milazzo, P., et al. (2020). Dynamic Bayesian network for crop growth prediction in greenhouses. *Comput. Electron. Agric.* 169, 105167. doi: 10.1016/j.compag.2019.105167

Kraus, S., Breier, M., and Dasí-Rodríguez, S. (2020). The art of crafting a systematic literature review in entrepreneurship research. *Int. Entrepreneurship Manage. J.* 16, 1023–1042. doi: 10.1007/s11365-020-00635-4

Krishnan, R. S., Julie, E. G., Robinson, Y. H., Raja, S., Kumar, R., Thong, P. H., et al. (2020). Fuzzy logic based smart irrigation system using internet of things. *J. Cleaner Prod.* 252, 119902. doi: 10.1016/j.jclepro.2019.119902

Lagacherie, P., Bui, S., Constantin, J., Dharumarajan, S., Ruiz, L., and Sekhar, M. (2022). Evaluating the impact of using digital soil mapping products as input for spatializing a crop model: the case of drainage and maize yield simulated by STICS in the Berambadi catchment (India). *Geoderma* 406, 115503. doi: 10.1016/j.geoderma.2021.115503

Lin, N., Wang, X., Zhang, Y., Hu, X., and Ruan, J. (2020). Fertigation management for sustainable precision agriculture based on Internet of Things. *J. Cleaner Prod.* 277, 124119. doi: 10.1016/j.jclepro.2020.124119

Martínez-Valderrama, J., Ibáñez, J., and Alcalá, F. J. (2020). AQUACOAST: a simulation tool to explore coastal groundwater and irrigation farming interactions. *Sci. Program*. 2020:9092829. doi: 10.1155/2020/9092829

Meier, J., Zabel, F., and Mauser, W. (2018). A global approach to estimate irrigated areas—a comparison between different data and statistics. *Hydrol. Earth Syst. Sci.* 22, 1119–1133. doi: 10.5194/hess-22-1119-2018

Mendas, A., and Delali, A. (2012). Integration of MultiCriteria Decision Analysis in GIS to develop land suitability for agriculture: application to durum wheat cultivation in the region of Mleta in Algeria. *Comput. Electron. Agric.* 83, 117–126. doi: 10.1016/j.compag.2012.02.003

Meza-Palacios, R., Aguilar-Lasserre, A. A., Morales-Mendoza, L. F., Rico-Contreras, J. O., Sánchez-Medel, L. H., and Fernández-Lambert, G. (2020). Decision support system for NPK fertilization: a solution method for minimizing the impact on human health, climate change, ecosystem quality and resources. *J. Environ. Sci. Health Part A Toxic/Hazardous Substances Environ. Eng.* 55, 1267–1282. doi: 10.1080/10934529.2020.1787012

Mohamed, E. S., Abu-hashim, M., AbdelRahman, M. A. E., Schütt, B., and Lasaponara, R. (2019). Evaluating the effects of human activity over the last decades on the soil organic carbon pool using satellite imagery and GIS techniques in the Nile Delta area, Egypt. *Sustainability* 11, 2644. doi: 10.3390/su11092644

Muangprathub, J., Boonnam, N., Kajornkasirat, S., Lekbangpong, N., Wanichsombat, A., and Nillaor, P. (2019). IoT and agriculture data analysis for smart farm. *Comput. Electron. Agric.* 156, 467–474. doi: 10.1016/j.compag.2018.12.011

Nabaei, A., Hamian, M., Parsaei, M. R., Safdari, R., Samad-Soltani, T., Zarrabi, H., et al. (2018). Topologies and performance of intelligent algorithms: a comprehensive review. *Artificial Intell. Rev.* 49, 79–103. doi: 10.1007/s10462-016-9517-3

Navarro-Hellín, H., Martínez-del-Rincon, J., Domingo-Miguel, R., Soto-Valles, F., and Torres-Sánchez, R. (2016). A decision support system for managing irrigation in agriculture. *Comput. Electron. Agric.* 124, 121–131. doi: 10.1016/j.compag.2016.04.003

Ndlovu, H. S., Odindi, J., Sibanda, M., Mutanga, O., Clulow, A., Chimonyo, V. G. P., et al. (2021). A comparative estimation of maize leaf water content using machine learning techniques and unmanned aerial vehicle (Uav)-based proximal and remotely sensed data. *Remote Sens.* 13, 4091. doi: 10.3390/rs13204091

Nguyen, T. T., Pham, T. D., Nguyen, C. T., Delfos, J., Archibald, R., Dang, K. B., et al. (2022). A novel intelligence approach based active and ensemble learning for agricultural soil organic carbon prediction using multispectral and SAR data fusion. *Sci. Total Environm.* 804, 150187. doi: 10.1016/j.scitotenv.2021.150187

Onishi, M., and Ise, T. (2021). Explainable identification and mapping of trees using UAV RGB image and deep learning. *Scientific Rep.* 11. doi: 10.1038/s41598-020-79653-9

Pageot, Y., Baup, F., Inglada, J., Baghdadi, N., and Demarez, V. (2020). Detection of irrigated and rainfed crops in temperate areas using sentinel-1 and sentinel-2 time series. *Remote Sens.* 12, 3044. doi: 10.3390/rs12183044

Pantazi, X. E., Moshou, D., and Tamouridou, A. A. (2019). Automated leaf disease detection in different crop species through image features analysis and one class classifiers. *Comput. Electron. Agric.* 156, 96–104. doi: 10.1016/j.compag.2018.11.005

Papageorgiou, E. I., Markinos, A., and Gemptos, T. (2009). Application of fuzzy cognitive maps for cotton yield management in precision farming. *Exp. Syst. Appl.* 36, 12399–12413. doi: 10.1016/j.eswa.2009.04.046

Peña-Barragán, J. M., Ngugi, M. K., Plant, R. E., and Six, J. (2011). Object-based crop identification using multiple vegetation indices, textural features and crop phenology. *Remote Sens. Environ.* 115, 1301–1316. doi: 10.1016/j.rse.2011.01.009

Pérez-Ortiz, M., Peña, J. M., Gutiérrez, P. A., Torres-Sánchez, J., Hervás-Martínez, C., and López-Granados, F. (2016). Selecting patterns and features for between- and within- crop-row weed mapping using UAV-imagery. *Expert Syst. Appl.* 47, 85–94. doi: 10.1016/j.eswa.2015.10.043

Prasad, R., Deo, R. C., Li, Y., and Maraseni, T. (2018). Soil moisture forecasting by a hybrid machine learning technique: ELM integrated with ensemble empirical mode decomposition. *Geoderma* 330, 136–161. doi: 10.1016/j.geoderma.2018.05.035

Qiu, Z., Ma, F., Li, Z., Xu, X., Ge, H., and Du, C. (2021). Estimation of nitrogen nutrition index in rice from UAV RGB images coupled with machine learning algorithms. *Comput. Electron. Agric.* 189, 106421. doi: 10.1016/j.compag.2021.106421

Recio, B., Rubio, F., and Criado, J. A. (2003). A decision support system for farm planning using AgriSupport II. *Decis. Support Syst.* 36, 189–203. doi: 10.1016/S0167-9236(02)00134-3

Rejeb, A., Abdollahi, A., Rejeb, K., and Treiblmaier, H. (2022a). Drones in agriculture: a review and bibliometric analysis. *Comput. Electron. Agric.* 198, 107017. doi: 10.1016/j.compag.2022.107017

Rejeb, A., Rejeb, K., Abdollahi, A., Al-Turjman, F., and Treiblmaier, H. (2022b). The Interplay between the Internet of Things and agriculture: a bibliometric analysis and research agenda. *Internet Things* 19, 100580. doi: 10.1016/j.iot.2022.100580

Rejeb, A., Rejeb, K., Zailani, S., Keogh, J. G., and Appolloni, A. (2022c). Examining the interplay between artificial intelligence and the agri-food industry. *Artificial Intell. Agric.* 6, 111–128. doi: 10.1016/j.aiia.2022.08.002

Rodriguez-Galiano, V., Mendes, M. P., Garcia-Soldado, M. J., Chica-Olmo, M., and Ribeiro, L. (2014). Predictive modeling of groundwater nitrate pollution using Random Forest and multisource variables related to intrinsic and specific vulnerability: a case study in an agricultural setting (Southern Spain). *Sci. Total Environ.* 476–477, 189–206. doi: 10.1016/j.scitotenv.2014.01.001

Rodriguez-Galiano, V. F., Luque-Espinar, J. A., Chica-Olmo, M., and Mendes, M. P. (2018). Feature selection approaches for predictive modelling of groundwater nitrate pollution: An evaluation of filters, embedded and wrapper methods. *Sci. Total Environ.* 624, 661–672. doi: 10.1016/j.scitotenv.2017.12.152

Saggi, M. K., and Jain, S. (2018). A survey toward an integration of big data analytics to big insights for value-creation. *Inf. Process. Manage.* 54, 758–790. doi: 10.1016/j.ipm.2018.01.010

Saleh, A. M., Belal, A. B., and Mohamed, E. S. (2015). Land resources assessment of El-Galaba basin, South Egypt for the potentiality of agriculture expansion using remote sensing and GIS techniques. *Egyptian J. Remote Sens. Space Sci.* 18, S19–S30. doi: 10.1016/j.ejrs.2015.06.006

Sánchez-Lozano, J. M., Henggeler Antunes, C., García-Cascales, M. S., and Dias, L. C. (2014). GIS-based photovoltaic solar farms site selection using ELECTRE-TRI: evaluating the case for Torre Pacheco, Murcia, Southeast of Spain. *Renew. Energy*, 66, 478–494. doi: 10.1016/j.renene.2013.12.038

Schütze, N., and Schmitz, G. H. (2010). OCCASION: New Planning Tool for Optimal Climate Change Adaption Strategies in Irrigation. *J. Irrigat. Drainage Eng.* 136, 836–846. doi: 10.1061/(ASCE)IR.1943-4774.0000266

Sodango, T. H., Sha, J., Li, X., Noszczyk, T., Shang, J., Aneseyee, A. B., et al. (2021). Modeling the spatial dynamics of soil organic carbon using remotely-sensed predictors in Fuzhou City, China. *Remote Sens.* 13, 1682. doi: 10.3390/rs13091682

Thenkabail, P. S., Biradar, C. M., Noojipady, P., Dheeravath, V., Li, Y., Velpuri, M., et al. (2009). Global irrigated area map (GIAM), derived from remote sensing, for the end of the last millennium. *Int. J. Remote Sens.* 30, 3679–3733. doi: 10.1080/01431160802698919

Torres-Sánchez, J., López-Granados, F., and Peña, J. M. (2015). An automatic object-based method for optimal thresholding in UAV images: application for vegetation detection in herbaceous crops. *Comput. Electron. Agric.* 114, 43–52. doi: 10.1016/j.compag.2015.03.019

van Niel, T. G., and McVicar, T. R. (2004). Determining temporal windows for crop discrimination with remote sensing: a case study in south-eastern Australia. *Comput. Electron. Agric.* 45, 91–108. doi: 10.1016/j.compag.2004.06.003

Weiss, M., Jacob, F., and Duveiller, G. (2020). Remote sensing for agricultural applications: a meta-review. *Remote Sens. Environ.* 236, 111402. doi: 10.1016/j.rse.2019.111402

Weller, S., Janz, B., Jörg, L., Kraus, D., Racela, H. S. U., Wassmann, R., et al. (2016). Greenhouse gas emissions and global warming potential of traditional and diversified tropical rice rotation systems. *Global Change Biol.* 22, 432–448. doi: 10.1111/gcb.13099

Wellington, M. J., and Renzullo, L. J. (2021). High-dimensional satellite image compositing and statistics for enhanced irrigated crop mapping. *Remote Sens.* 13, 1300. doi: 10.3390/rs13071300

Wenkel, K. O., Berg, M., Mirschel, W., Wieland, R., Nendel, C., and Köstner, B. (2013). LandCaRe DSS – An interactive decision support system for climate change impact assessment and the analysis of potential agricultural land use adaptation strategies. *J. Environ. Manage.* 127, S168–S183. doi: 10.1016/j.jenvman.2013.02.051

Yuan, J., Lu, Y., Ferrier, R. C., Liu, Z., Su, H., Meng, J., et al. (2018). "Urbanization, rural development and environmental health in China," in *Environmental Development, Vol. 28* (Elsevier B.V.). p. 101–110. doi: 10.1016/j.envdev.2018.10.002

Zhang, F., Sun, Q., Mehrabadi, M., Khoshnevisan, B., Zhang, Y., Fan, X., et al. (2021). Joint analytical hierarchy and metaheuristic optimization as a framework to mitigate fertilizer-based pollution. *J. Environ. Manage.* 278, 111493. doi: 10.1016/j.jenvman.2020.111493

Zhu, X., Zhu, W., Zhang, J., and Pan, Y. (2014). Mapping irrigated areas in China from remote sensing and statistical data. *IEEE J. Selected Topics Appl. Earth Observ. Remote Sens.* 7, 4490–4504. doi: 10.1109/JSTARS.2013.2296899