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Artificial intelligence and IoT for water saving in agriculture: A systematic review

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ABSTRACT

Smart irrigation and fertigation offer three key benefits: sustainability through water conservation, increased productivity via targeted fertigation that activates only when necessary, and enhanced efficiency through remote control and high-precision sensors. This document presents a comprehensive review of the most significant innovations in this field over the past five years. The main components analyzed include sensors for monitoring and data acquisition, protocols and Internet of Things architectures for network management, and Artificial Intelligence models for decision-making and predictions. This study followed the PRISMA 2020 protocol and made use of data from Scopus and Web of Science. A total of 130 articles were identified as relevant and examined in detail. Alongside summarizing the collected articles, the review also includes an analysis of proposed future developments to inspire new research and drive innovation in this domain.

1. Introduction

In the face of global population growth and the increasing impact of climate change, the future of agriculture is at a critical stage. Water plays a crucial role in sustaining life and supporting agricultural activities. However, effectively managing water resources for irrigation, both on a private and agricultural scale, presents a significant challenge in today's world [1]. With a substantial increase in food demand projected for the coming years, sustainable solutions are imperative to enhance agricultural yield and production.

Scientists are working to envision the future, considering socio-economic challenges and environmental impacts [2]. Scenarios based on CO2, methane, and nitrous oxide concentrations have been developed. The IPCC AR6 [3] outlines various scenarios with differing levels of severity. According to the Copernicus Interactive Climate Atlas (C3S) [4], temperatures in Europe are expected to rise rapidly. In the worst-case scenario, a significant increase in temperature could drastically reduce water availability, particularly in certain regions of Europe, where the risk of water scarcity may increase more than fourfold.

Achieving these objectives calls for the integration of innovative technologies, strategic resource management, and a shift towards more sustainable farming practices. Efficient resource utilization, particularly water and fertilizers, is a pivotal factor in improving agricultural yield. The pressing issue of water scarcity in many parts of the world, combined with agriculture's status as a primary consumer of this essential resource, underscores the urgency of this matter. Approximately 70% of global groundwater withdrawals are attributed to agricultural purposes, with around 38% of irrigated land relying on this vital resource. However, excessive groundwater extraction for intensive agricultural purposes raises concerns about food security, access to clean water, climate resilience, and the ecological balance of wetlands and water bodies dependent on groundwater.

For these reasons, several technological research fields have embarked on projects to achieve efficient and sustainable use of water and fertilizers. The two fields that are significantly impacting this sector are the Internet of Things (IoT) and Artificial Intelligence (AI).

The Internet of Things (IoT) is continuously expanding, thanks to the decreasing cost of sensors and the variety of available type. Nowadays, it has become increasingly straightforward to install large quantities of sensors due to advancements in communication technologies, minimal battery usage, and easy installation processes. Sensors in agriculture have become very popular and cheap, big farms are starting to understand the big advantages of using them like saving money and remote control. Examples of sensors used in agriculture include soil moisture, temperature, salinity of the soil, and stem width.

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Table 1
Table listing the query terms used to retrieve relevant articles, grouped into categories representing smart agriculture, artificial intelligence, and irrigation or fertigation. Words within the same group are aggregated in the same column and are linked using the "or" operator. Each column is then interconnected in the query with the "and" operator.

Term 1 (Title-Abstract-Keywords)	*Term 2* (Title-Abstract-Keywords)	*Term 3* (Title-Abstract-Keywords)
"smart agriculture"	"artificial intelligence"	"irrigation"
"precision agriculture"	"machine learning"	"irrigation system"
"smart farming"	"deep learning"	"automatic irrigation system"
"digital agriculture"	"fuzzy logic"	"fertigation"
"agriculture 5.0"	"decision support system"	"fertilization"
"agriculture 4.0"		

On the other side, Artificial Intelligence (AI) is now a very common field of study and researchers are continuously implementing new algorithms and new models. Thanks to it, in agriculture it is possible to create programs based on data capable of making intelligent decisions regarding irrigation and fertilization, thus avoiding waste and inefficient choices. Moreover, many AI algorithms can predict future outcomes for various variables or perform calculations based on other collected data, thereby increasing the amount of information used to make the final decision. For this purpose, both machine learning models such as decision trees or linear regression, and more complex deep learning models such as Convolutional Neural Networks (CNN) or Long Short-Term Memory (LSTM) can be utilized.

For all these reasons, this literature review focuses on analyzing scientific articles that aim to save water and fertilizers by utilizing cutting-edge techniques in sensor technology, IoT, and AI. Using the PRISMA 2020 protocol, we explore different perspectives on irrigation. Notably, the most recent review titled "Smart Irrigation Systems in Agriculture: A Systematic Review" [5] concentrates on urban agriculture and does not encompass the most prevalent agricultural types or innovative cultivation techniques such as soilless farming. Other reviews published in recent years do not use the PRISMA protocol or do not focus on the irrigation problem [6–11].

The objectives of this research are to answer the following questions:

1. *Which data should be collected, and which sensors should be used?* There are numerous sensors implemented to collect information about soil, as well as other techniques to analyze soil. It is important to determine which is better to use and why.
2. *How should sensors send data?* This is a challenge in agriculture, as the crops are generally large, and the sensors may be far apart from each other and numerous, resulting in a substantial amount of data that needs to be collected.
3. *Which algorithm should be used to make decisions about irrigation and fertigation?* Nowadays, there is a wide variety of artificial intelligence algorithms available. It is important to choose the most suitable for making fast and reliable decisions.
4. *Which data can be easily and usefully predicted by machine learning or deep learning techniques?* While classification and regression can be applied to all kinds of data, only specific types are valuable for making decisions in smart fertigation.

The next part of the text is divided as follows. Section 2 presents the methodology used to collect and select all the articles cited in this review. An initial analysis of the chosen articles through charts is illustrated in Section 3. An exhaustive presentation of the articles is provided in Section 4, where we attempt to answer the questions posed by this review. Future development ideas are detailed in Section 5. To conclude, the last section summarizes the work carried out and provides ideas for future reviews.

2. Methodology

The adoption of PRISMA 2020 [12] is attributed to its well-defined guidelines, which facilitate the execution of rigorous systematic reviews. Consequently, this review article adheres to the recommendations of these guidelines. The review was conducted using the comprehensive collections of the Scopus and Web of Science databases on *October 24, 2024*.

A tailored query was utilized for each dataset, with syntax adjustments based on the specific rules governing each dataset's structure. The query utilized represents a conjunction of three groups of synonyms. Each term within a group is connected to other terms in that group by a disjunction. The three primary keywords from which we derived these groups are: smart agriculture, artificial intelligence, and irrigation or fertigation. To enhance the query's efficiency, ChatGPT-3.5 was employed to optimize it and incorporate synonyms for the principal terms. A detailed list of all words used in the query can be found in Table 1.

In addition, the query implements three specific filters:

- *Publication Year:* Only papers published after 2019 are considered, ensuring that all selected works are recent and reflect innovative projects.
- *Document Type:* Only documents classified as "article" are included.
- *Publication Source:* Only articles published in journals are selected, as journal articles are intended for wide circulation and are often cited as authoritative sources.

As a result, we obtained 331 articles from Scopus and 152 from Web of Science. From Scopus, we export a CSV file, and from Web of Science, we export an XLSX file. Each file contains the following fields: "title," "abstract," "keywords," "year of publication," "names of the authors," "affiliations," and "title of source." Utilizing R code, the CSV file from Scopus is converted, and the two sets of articles are merged, with duplicates removed. After merging, the total number of unique articles is 351, indicating that only 20 articles retrieved from Web of Science were not found in Scopus.

To select the relevant studies, we utilized the open-source tool ASReview [13]. This tool offers a user-friendly interface for visualizing the titles and abstracts of retrieved articles. Additionally, it ranks articles from most to least relevant based on the prior knowledge provided by the reviewer. This ranking system is advantageous as it allows the reviewer to sequentially read articles related to the same topic or similar research areas. The initial selection process is based on the titles and abstracts, applying the following exclusion criteria:

- The article is a review, survey, or overview (n = 43).
- The article is not written in English (n = 3).
- The article is not open access (n = 8).
- The article does not address automatic irrigation (n = 2).
- The article does not use AI algorithms or not explain how these algorithms are trained (n = 32).

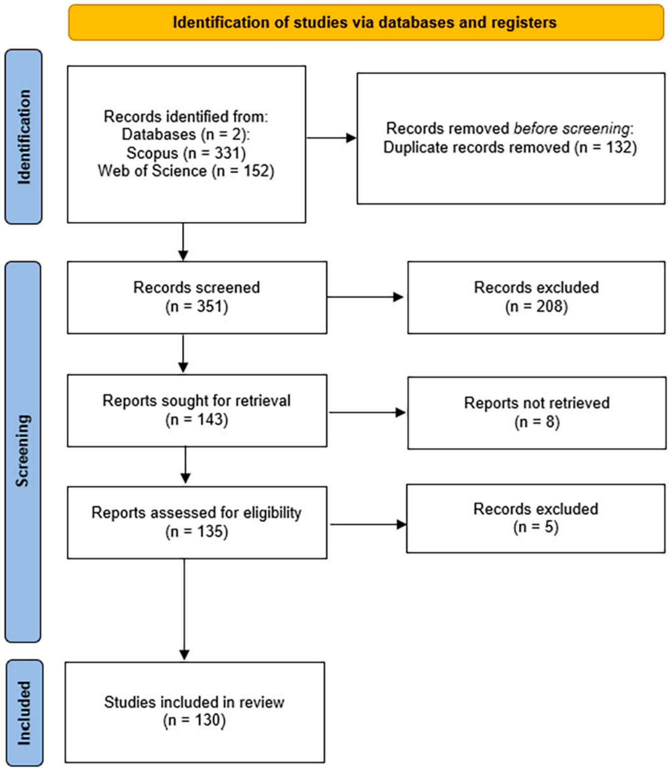

Fig. 1. The PRISMA 2020 inclusion–exclusion flowchart.

- The research topic is not directly related to irrigation. Specific excluded topics include predicting null values in datasets, data communication management, anomaly detection, intrusion detection, reducing IoT energy consumption, plant disease detection, plant or soil segmentation, crop type classification, smart cities, drones, predicting water quality, and predicting the weather (n = 128).

Following this selection process, all articles labeled as relevant are read in full. If any are found to be irrelevant, their label is adjusted accordingly. At this stage, only 5 articles were reclassified as irrelevant. The final count of relevant articles stands at 130. The summary of the steps applied in this literature review can be visualized in the flow diagram shown in Fig. 1.

To create a comprehensive and insightful list of articles, an Excel file was developed. For each article, the following details were meticulously recorded:

- Title and Summary: the title of the paper along with a brief summary of its content.
- Publication Year and Location: the year in which the article was published and the location where the experiment was conducted.
- AI Algorithm and Model: the specific AI algorithm used, including any metrics obtained from the test set.
- Cultivation Technique: the type of cultivation technique employed, whether traditional soil-based or more innovative methods.
- IoT Communication Protocol: the communication protocol utilized for the Internet of Things (IoT) integration.
- Primary Objective: the main task of the paper, categorized into five distinct classes representing specific experimentation objectives (e.g., irrigation management, soil moisture prediction, nitrogen prediction).
- Sensors and Features: the sensors used or developed, along with the features collected and utilized for experimentation.
- Dataset Availability: a link to the dataset if available, or information on how to obtain it upon request from the authors.

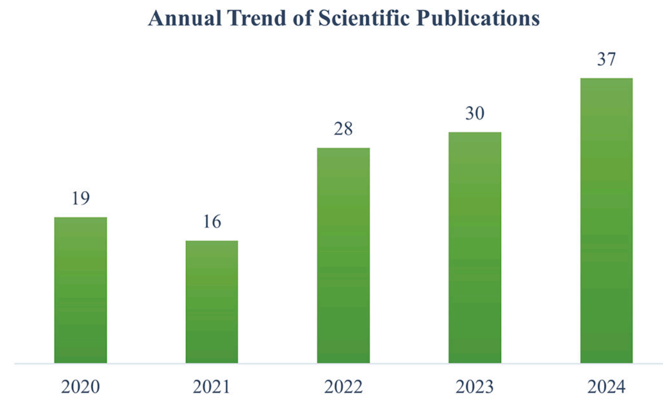

Fig. 2. Bar chart showing the number of relevant publications analyzed in the review, categorized by year of publication. Obtained using VantagePoint.

- Future Developments: a summary of potential future developments and possible improvements to the project.

This structured approach ensures a thorough understanding and easy reference for each article, facilitating further research and analysis.

3. Data visualization and preliminary analysis

In this section, we will assess the outcomes of our research by comparing various articles and emphasizing the key elements. To gain an initial understanding of the data utilized, we employed VantagePoint software. This tool enables the graphical representation of tabular data. Consequently, starting from the Excel file created during the previous phase, we generated histograms, pie charts, and other visualizations based on the collected information.

The first graph to be analyzed is the bar chart that shows the amount of publications for each year. As shown in Fig. 2, the year with the highest number of publications is 2024, with 37 articles. Additionally, the graph indicates an upward trend in the number of articles since 2020. This demonstrates how the topic of sustainability and resource conservation in agriculture is becoming increasingly important.

In the world map depicted in Fig. 3, the distribution of experimental research is clearly illustrated. Notably, China and India stand out, with 21 and 11 articles respectively, indicating these countries as the primary hubs for experimental activity. The map also reveals that experiments have been conducted across nearly all global regions, with the exception of northern Asia.

The analysis of dataset availability in the experiments is crucial for enabling the replication of results and the application of different techniques by other research groups. Fig. 4 presents a pie chart illustrating the percentage distribution of datasets based on their accessibility: available via a direct link (Yes), available upon request (On request), not available (No), and those with no information provided on dataset availability (N/A). The smallest segment represents the datasets that are readily available, underscoring the urgent need for the development of freely accessible datasets to facilitate broader research efforts.

During a comprehensive review of the articles, the AI models used were also detailed. Many articles experiment with multiple machine learning and deep learning algorithms. For clarity, the plot in Fig. 5 reports the model that achieved the highest results for each article. If an article used two models sequentially, both models are represented as separate entities in the bar chart. This explains why the number of AI algorithms in this plot exceeds the number of relevant articles. Fig. 5 shows that the most frequently utilized models are Random Forests (RF) and Neural Networks (NN), followed by Decision Support Systems (DSS), Long-Short Term Memory (LSTM), and Support Vector Machines (SVM). Models mentioned in a single article usually represent highly specialized algorithms, often developed by the researchers themselves.

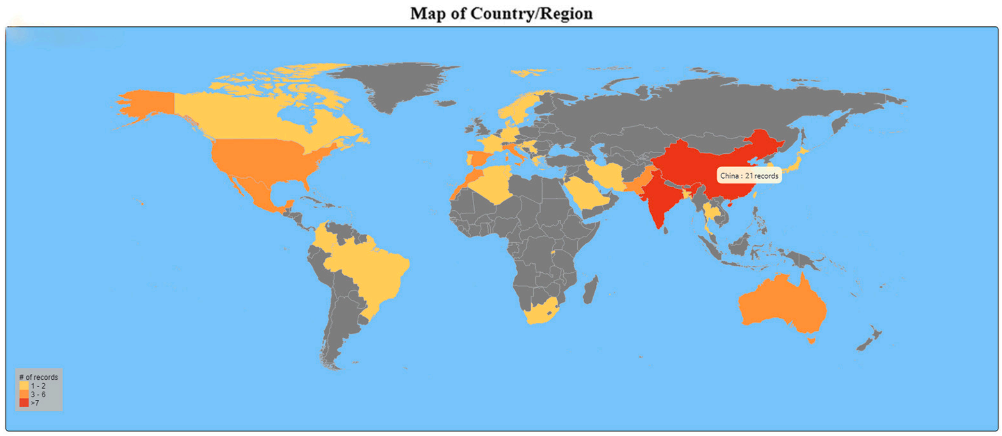

Fig. 3. Map showing the distribution of publications by country, highlighting the geographic areas most active in research on smart irrigation technologies. Obtained using VantagePoint.

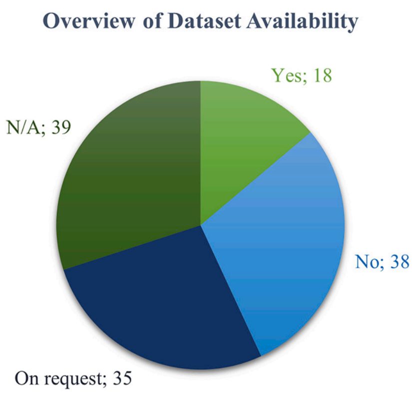

Fig. 4. Pie chart illustrating the availability of datasets in the reviewed articles, categorized as openly available (Yes), available on request (On request), not available (No), or unspecified (N/A). Obtained using VantagePoint.

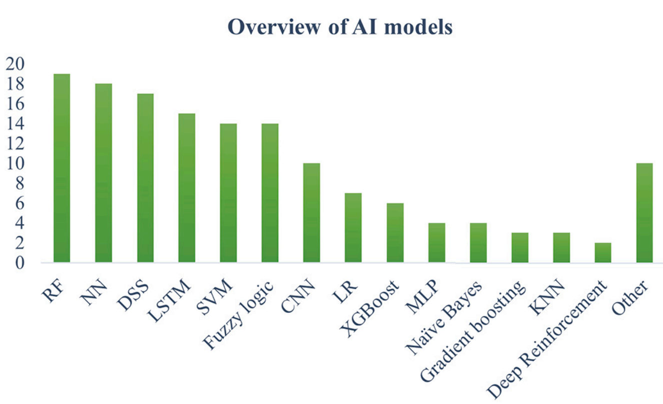

Fig. 5. Bar chart depicting the frequency of different AI models applied in the reviewed studies. Obtained using VantagePoint.

Consequently, in the graph, they have been categorized under “Others”, encompassing ten distinct entities, each representing a different algorithm. There is a notable balance between the use of deep learning algorithms and machine learning algorithms.

If we examine the bar chart in Fig. 6, it becomes evident which communication techniques are most frequently utilized in the context of IoT nodes. Notably, a significant number of papers (87 articles) do not employ IoT. These articles often depend on pre-existing datasets or public data, such as satellite or weather images, instead of utilizing their own sensors. Alternatively, they may use cameras without IoT protocols or cameras mounted on drones. Among the communication techniques,

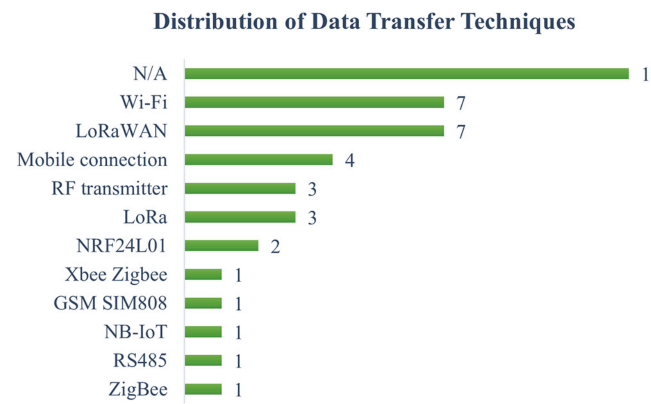

Fig. 6. Bar chart showing the frequency of different IoT communication protocols used in the reviewed studies. Obtained using VantagePoint.

Wi-Fi and LoRaWAN emerge as the most commonly used due to their straightforward implementation and suitability for agricultural applications. Wi-Fi is particularly favored for its ease of use with a limited number of sensors, while LoRaWAN is valued for its low power consumption and ability to manage numerous nodes. Additionally, seven papers employed less common communication protocols, such as RF transmitters or RS485.

Upon reviewing the articles, a significant disparity in cultivation techniques was immediately observed. Notably, 101 articles focused on soil-based cultivation, while only 6 addressed traditional greenhouse cultivation. This disparity is further accentuated in the pie chart presented in Fig. 7, which shows a mere 4 research experiments on soilless agriculture, aquaponic, and hydroponic. It is important to note that 19 articles did not specify the cultivation technique used, a critical piece of information necessary for comparing results and thoroughly evaluating the outcomes.

In order to categorize the articles based on their objectives, five distinct categories were established. These classes can be broadly categorized into two macro groups: management and prediction. The management category includes research that focuses on the automatic management of irrigation or fertigation, whereas the prediction category encompasses studies that utilize data to forecast specific variables. Table 2 provides an overview of the chosen categories and the number of papers associated with each. Within the prediction category, most articles aim to forecast future soil moisture levels to facilitate irrigation planning. Other classes within this category address the prediction of variables such as nitrogen levels and evapotranspiration. The largest category, “Other Features Prediction” encompasses a variety of features predicted by individual articles. Assigning a separate category for each

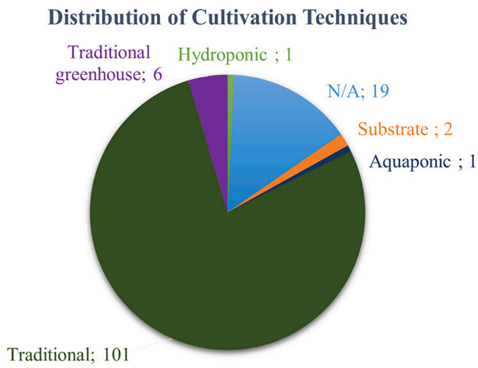

Fig. 7. Pie chart categorizing the reviewed studies by type of cultivation technique, including soil-based, greenhouse, and soilless methods. Obtained using VantagePoint.

Table 2
Table summarizing the distribution of reviewed articles across different research objectives.

Records	Categories
37	Other features Prediction
36	Management Irrigation
22	Soil moisture Prediction
14	Management Fertigation
10	Nitrogen Prediction
10	Evapotranspiration Prediction

predicted feature would have resulted in approximately 20 categories, many containing fewer than five articles. Therefore, it was deemed more efficient to consolidate these into a single, comprehensive category.

To effectively gather information from the field of interest and train artificial intelligence techniques, it is essential to employ sensors capable of monitoring the characteristics of the soil and crop canopy. Consequently, each article reviewed was cataloged based on the sensor models used in the experimentation, grouping them according to the information collected. This comparative analysis enables the identification of the most commonly used sensors and models in various experiments.

The most frequently used sensors measure environmental temperature and humidity, strategically positioned near the field of interest. As shown in the Fig. 8, the DHT22 and DHT11 sensors are predominantly used. Other models were utilized in only one of the selected relevant experiments.

The second most commonly used type of sensor measures soil humidity, a crucial parameter for effective irrigation management and a pivotal aspect of this research field. The YL-69 sensor is the most prevalent, appearing in five articles. Several other models were employed, most of them in a single article, except for the VH400, SKU:SEN0193, TDR-315N, RS-WS-N01-TR, and Sentek Drill & Drop models, which were used in two trials. Notably, only two experimental sensors were employed, with relevant articles documenting their use cited accordingly. Additional sensors used to detect soil moisture include: WaterScout SM 100, 200SS, EC-1258, MS-10, ML2x, FC-28-1, LM393, HXM-80, CRS-1000/B, TEROS-10, and LSE01.

Other types of sensors are categorized below according to the type of information they collect:

- Atmospheric pressure: MP-180
- Rain: MH-RD, YL-83, WatchDog 1120 Rain Gauge, T1592P
- Coma temperature: GY-906 (used in two articles), GM320
- Solar irradiation: LI-200S, BH1750 (used in three articles), BGT-JYZ2
- Soil temperature: SHT11, THERM200, DS18B20 (used in three articles), BetaTherm 10K3A1
- Leaf area: LI-3000C, AccuPAR LP-80
- Stem diameter: HL-T1010A
- Nitrogen, potassium, and phosphorus levels: RS485 IP68 (used in three articles), N-Sensor
- Soil conductivity: LSE01, MEC10, DualEM
- pH level: SEN-00239
- UV intensity: LDR 5 mm, VEML6070, GUVA-S12SD
- Chlorophyll level: SPAD-502 (used in four articles), SPAD-502 Plus, Dualex® Scientific, MultispecQ v2.0, MC-100

For weather information, many articles utilize data from national or regional public stations, while a smaller number have installed weather stations in the area of interest. Models used include: Davis Grow Weather with Weather Wizard III Console, Davis Vantage Pro2, Davis Vantage Pro2 GroWeather 6820c, Davis Vantage Pro2 Plus, and Metos IMT-280.

Some experiments employed cameras positioned on drones or among crops, in addition to sensors. These cameras are categorized into hyperspectral, thermal, and photographic (RGB format). The models used are:

- Hyperspectral imaging: Sentera NDVI single sensor, MicaSense RedEdge M (used in three articles), Parrot Sequoia, MultiSPEC 4C, RapidScan CS-45, Rikola HSI (used in two articles), HySpex Mjolnir V-1240 (used in two articles), ASD FieldSpec 3 (used in three articles), ASD FieldSpec 4 (used in two articles), HR-512i®, STS-VIS, Cubert S185 (used in two articles), XHR-1024i, ASD HandHeld-2, DJI P4, Specim IQ, Specim AFX-17, FLIR A655sc, Nano-Hyperspec sensor, MicaSense Altum, UOcean Optics SB4000
- Thermal imaging: FLIR SC305®, FLIR SC620, Zenmuse XT2, Apogee SI-111
- Photographic images: Canon 80D, Huawei P20 Pro, GoPro HERO5 Session (used in two articles), Canon SX170 IS, DJI M-300, HP Scanjet 3800

For research utilizing satellite images, the sources of the images were meticulously documented. Seven articles use data from Sentinel-2, two articles from Planet SuperDove, two more from Sentinel-1, one article from ALOS DSM and one Sentinel-3.

In conclusion, the analysis of the relevant papers is illustrated through the word cloud in Fig. 9 generated by the article titles. As expected, the most prominent and frequent terms are “irrigation,” “agriculture,” and “farming.” Additionally, we observe a significant presence of terminology from the field of Artificial Intelligence. This word cloud visually depicts the convergence of technology and agriculture, emphasizing essential concepts and innovations pertinent to contemporary farming practices, including precision agriculture, data analytics, and advanced irrigation methods.

4. Result and discussion

Based on an initial review of the selected articles, this section will offer a comprehensive presentation of the articles, organized according to the tasks they address. The classification will progress from management tasks to prediction tasks. Each subsection will conclude with a summary of potential future developments as suggested by the articles within that specific category.

4.1. Irrigation management

In this section, we present articles dedicated to irrigation management. These articles emphasize systems that autonomously determine the optimal irrigation schedules, activation times, and precise water quantities.

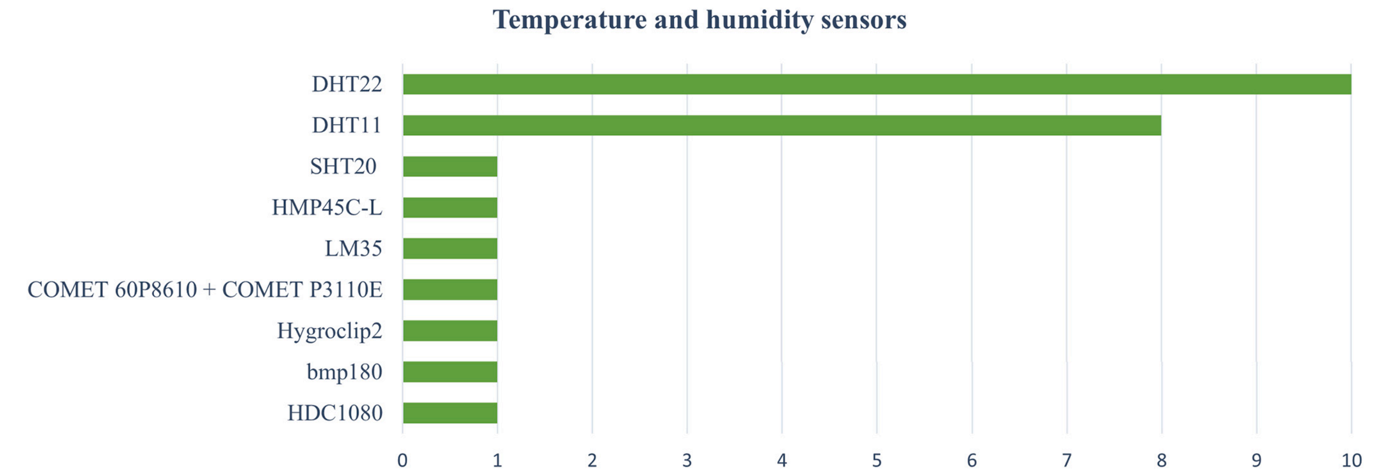

Fig. 8. Bar chart illustrating the distribution of articles utilizing different models of temperature and humidity sensors, with each bar representing the count of articles per sensor model.

Fig. 9. Word cloud generated from the keywords in the titles of pertinent articles. Obtained using VantagePoint.

Most of these articles [14–22] utilize Decision Support Systems (DSS), which leverage logic-based reasoning and sensor datasets collected from the field to provide recommendations, initiate self-irrigation, and issue necessary alerts for optimal performance at each location. Notably, certain articles, such as [17] and [18], also incorporate data visualization tools, visual analytical components, and interactive frameworks. These features enable real-time updates for farmers, making the system transparent and allowing farmers to understand the rationale behind the DSS's decisions.

Fuzzy logic is another widely employed technique in this domain [23–30]. Effective knowledge-based IF-THEN rules are designed for intelligent irrigation systems to control irrigation using real-time data. For instance, article [24] describes a system that evolves in real time and employs a weather-soil monitoring approach to determine the optimal irrigation schedule and the operation of the pulse solenoid valve. This system not only determines the need for irrigation but also specifies the duration and quantity required. These systems, alongside those based on DSS, evaluate their performance by comparing water consumption between manual and automatic irrigation methods. Research such as in article [23], demonstrates significant resource savings, reducing water consumption by 59.61%, electricity consumption by 67.35%, and increasing yield by 22.58%.

A model proposed in [31] evolves over time, self-learning by acquiring new data and continuously updating itself through training a linear regression algorithm.

Several other articles [32–42] approach the irrigation management problem as a classification task, where each class represents different levels of water demand (e.g., on/off). The most common method involves two classes (on/off), while less common are classifications with 3 or 5 classes, such as: highly unnecessary, highly necessary, necessary, non-necessary, and medium. These articles typically utilize machine learning models that work with tabular data or a hybrid approach combining machine learning models with fuzzy logic rules. Performance is evaluated using accuracy metrics, with article [41] achieving a notable 99.8% accuracy.

The accurate determination of water requirements is crucial for effective irrigation management, particularly in deciding the appropriate quantities of water to apply. To facilitate this, papers [43–48] utilize climate data and sensor information to forecast the water needs of crops and activate irrigation systems accordingly. Specifically, [43] achieves an 88% accuracy rate in predicting the weekly irrigation needs of a plantation based on climatic variables and soil measurements.

Castañeda-Miranda and Castaño-Meneses [49] oversees irrigation with a specialized focus on protecting greenhouse crops from frost. The anti-freeze system leverages weather data to forecast internal temperatures. By integrating this with soil temperature readings, it determines the frost severity and activates water spraying accordingly. Utilizing a combination of fuzzy logic and a neural network, the system achieves an impressive R^2 value of 95%.

Only one paper in this category, [50], focuses on hyperspectral images. This paper extracts features from the image, such as statistical parameters like auto-correlograms and HSV histograms. Machine learning models are then employed to classify the soil, and fuzzy rules determine the appropriate amount of irrigation.

By leveraging these advanced techniques, the articles in this section contribute significantly to the field of irrigation management, offering innovative solutions for efficient and effective water use in agriculture.

Future developments in this field exhibit several common trends: a recommendation to increase both the number and variety of sensors, the utilization of images to derive additional information, and the evaluation of algorithms in diverse contexts. Enhancements in IoT for security, speed, and energy efficiency are also emphasized. Where absent, the creation of web or mobile platforms is advised to ensure remote control for farmers. Finally, the application of Big Data techniques for managing tabular data across vast cultivation areas is suggested.

4.2. Fertigation management

Unlike irrigation-focused models, research on fertilizers is considerably less prevalent in the literature. From an extensive review, only 13 articles were identified that delve into fertigation management, which involves the combined management of water and fertilizers to nourish the soil. This is a critical task for achieving a prosperous harvest while minimizing fertilizer use and associated costs. The papers in this category are relatively heterogeneous, employing various techniques to address this issue.

The paper [51] stands out as the only study utilizing soil clustering with a k-means algorithm. This method facilitates the automatic identification of site-specific management zones for crops and, through clustering analysis, determines the appropriate quantities of fertilizers and irrigation.

Three articles, [52], [53] and [54], employ fuzzy logic but in distinct ways. Article [54] and [52] employs fuzzy rules to regulate both irrigation and fertigation. In contrast, paper [53] integrates fuzzy logic with a vision-based lettuce phenotype model to control the activation of a fertigation system. Notably, [53] is the sole study utilizing an aquaponic technique. This innovative adaptive fertigation [53] system has demonstrated higher nutrient use efficiency (99.678%) and significantly lower chemical waste emissions (14,108 mg $L^{-}1$) compared to manual fertigation methods (92.468%, 178.88 mg $L^{-}1$).

Contribution [55] demonstrates an 11% reduction in fertilizer consumption through the use of a DSS. This article, along with [56], [57], [58] and [59], suggests fertilizer dosages based on rules that vary according to crop type, growth phase, and data from various sources.

Study [60] distinguishes itself by employing a Deep Reinforcement Learning model on an agricultural machine. Leveraging sensor-collected data, this model ensures the sustainable use of water resources and fertilizers. Agrorobotix's design prioritizes water sustainability while significantly enhancing land management and fertilizer efficiency.

Article [61] provides fertilizer and irrigation recommendations by leveraging crop identification and field data, as well as satellite imagery. The study evaluates various models, with the multi-layer perceptron (MLP) achieving the highest accuracy at 93%.

In [62] the fertilizer selection is converted into a classification task aimed at predefining the quantity for each fertilizer. Using tabular data and machine learning algorithms, this study achieves 99% accuracy with a multi-layer perceptron model. This article is potentially related to research [63], which employs a Non-dominated Sorting Genetic Algorithm (NSGA-II) to quickly identify optimal irrigation and fertilization strategies from thousands of solutions. The experiment results in a strategy that reduce water use by 44%, nitrogen application by 37%, and increases economic benefits by 7-8%.

Article [64] presents a neural network-based model that offers farmers crucial insights and recommendations, such as pesticide application and water motor control. By utilizing pH levels, soil moisture, and rainfall data, the neural network is trained to achieve an accuracy of 89.5%.

In this field, various applications and research approaches can be implemented. As future developments, the articles suggest, similar to the previous category of articles, the use of additional sensors to collect data and enhance the performance of IoT systems.

4.3. Soil moisture prediction

The third most frequently addressed task among the relevant articles is the prediction of Soil moisture levels. This task is crucial for irrigation management, as understanding soil moisture content enables optimal planning of water use.

In studies [65–73], a Long Short-Term Memory (LSTM) model was employed to predict the next day's volumetric soil moisture content based on historical climate and soil data. Notably, study [66] aims to predict humidity for up to three subsequent days, while study [70] focuses on predicting future humidity at three different soil depths. These projects primarily utilize meteorological and soil-related data, such as soil conductivity. All research in this category has yielded promising results. For instance, study [67] achieved a Mean Absolute Error (MAE) of 0.04, and study [65] managed to reduce water consumption by 43%. Similar research, including studies [74], [75], and [76], employs simple neural networks for the same type of prediction. Specifically, study [76] extends the prediction period to one week, achieving an R^2 value of 98%.

Soil moisture can also be predicted using simpler machine learning models like Random Forest (RF), K-Nearest Neighbors (KNN), or Support Vector Machine (SVM). Studies [77–80] utilize typical regression models with tabular data to predict soil moisture. These models report metrics similar to those of the deep learning models mentioned earlier. For example, study [77] highlights an R^2 value of 98%.

Unlike other articles, the study [81] utilizes a 24 GHz radar (K-LC1a) to measure soil moisture. The deep learning model DarkNet 53 is employed to correlate the radar signal with soil moisture, achieving an accuracy close to 90%.

Another contribution method involves using satellite or hyperspectral imagery, as seen in studies [82–86]. [85] uses satellite images generated by Sentinel-1, Sentinel-2, and ALOS DSM, while paper [82] employs images from Planet SuperDove. Both studies use machine learning models and achieve R^2 values between 80% and 90%. Hyperspectral or thermal images, captured using devices such as the Zenmuse XT2 dual camera and Nano-Hyperspec sensor, are utilized in studies [84] and [83]. These studies also employ machine learning models, achieving R^2 values of 97% for study [83] and 72% for study [84].

The articles in this category suggest future developments should focus on increasing the amount and variety of data, incorporating more calculated metrics, and conducting tests on different types of fields, plants, and locations.

4.4. Nitrogen prediction

Predicting nitrogen levels is crucial for determining the optimal timing for fertilizer application and plant management. Various sensors available on the market primarily measure nitrogen levels in the soil, but not within the plant itself. Hence, this task can significantly influence the types of data utilized for decision-making and enhance the precision of these decisions.

Current research efforts focus on predicting nitrogen levels in plants through image analysis. The images employed can be RGB, satellite, hyperspectral, or thermal. [87] provides a dataset with RGB images correlated to three nitrogen levels (N0, N75, and Nfull), made available for other researchers to train predictive models.

In study [88], satellite imagery from Sentinel-2 is used to develop nitrogen uptake scaling models by correlating the data from portable proximal sensors. This data is then utilized by a Decision Support System (DSS) to make fertilization decisions, achieving an R^2 of 81%.

Sentinel-2 images are also employed in [89] alongside hyperspectral images from three different cameras to identify the most effective method and equipment.

Studies [90–96] use hyperspectral images to predict nitrogen levels. This technique is especially effective when the camera is mounted on a drone, allowing for image capture from various areas and angles. The predictive models employed are mainly machine learning algorithms, such as the RF used in [93] studies, achieving an R^2 of 85%, and the SVM in [95] studies, with an R^2 of 96%. Notably, only the [90] study employs a deep learning model, reaching an R^2 of 96.8%.

However, a common limitation across these studies is the small size of the datasets, attributed to the labor-intensive process of measuring nitrogen levels in plants. Consequently, future advancements should focus on expanding the dataset size and incorporating images captured by drone at different heights or from different plant types.

4.5. Evapotranspiration prediction

Evapotranspiration measures the amount of water that moves from the soil to the atmosphere as vapor, due to the combined effects of plant transpiration and direct soil evaporation. Calculating evapotranspiration is crucial as it indicates how much water plants are absorbing, thereby informing irrigation requirements. Typically, this value is derived using weather stations and mathematical formulas such as the Blaney-Criddle method. However, these methods are not tailored to specific crop types or growth stages. Consequently, some research is exploring the use of AI to estimate these variables with high accuracy, thereby optimizing irrigation decisions.

In [97–104] meteorological data from local or private weather stations within the camp area are utilized. The models vary, from RF used in [103] to Deep Neural Networks in [102]. All these models achieve an R^2 greater than 90%, with [98] reaching 96%. Notably, [101] diverges by incorporating the ERA5-Land dataset in addition to weather data, resulting in more accurate predictions.

Distinct from the others, the [105] research [105] also employs satellite imagery from Sentinel-1 alongside meteorological data. Here, machine learning algorithms based on decision trees, such as XGBoost, achieving an R^2 of 95%.

Chen et al. [106] uniquely quantifies vegetation transpiration without relying on meteorological data from weather stations. Instead, it utilizes sensor data, including temperature, humidity, soil moisture, soil temperature, rainfall, solar radiation, plant height, and leaf area. Employing a random forest model, the study achieves an R^2 of 95%.

While these models do not directly manage irrigation, they offer significant benefits. Future developments may include integrating these models into Decision Support Systems (DSS). Future studies will increase efficiency by incorporating datasets from weather stations that detect microclimates in various areas, utilizing drones, and integrating geographical data into the dataset.

4.6. Other features prediction

This section consolidates articles focused on predicting various irrigation-related values other than soil moisture, nitrogen and evapotranspiration. This category aims to highlight research that, while sharing the broader objective of optimizing irrigation and fertigation, targets different specific characteristics. Here, we present the articles not based on the variables they aim to predict, but rather on the initial data used as input for their predictive models.

Three notable papers [107–110] utilize satellite data as their primary input. Specifically, one paper employs PlanetScope data, while the other three use data from Sentinel-2. Despite targeting three distinct characteristics related to either the canopy or the soil, three studies employ random forest models for prediction and one an LSTM. Paper [107] focuses on predict net assimilation and stomatal conductance in carob trees using satellite band reflectance data. Net assimilation measures the organic matter produced by the plant after accounting for respiration, while stomatal conductance indicates the ability of stomata to regulate gas exchange between the leaf and the atmosphere. Both variables are crucial for assessing plant growth and informing irrigation practices. In contrast, paper [108] aims to evaluate and compare the predictive performance of models in estimating the Leaf Area Index (LAI), Leaf Chlorophyll Content, and Canopy Chlorophyll Content. This research also seeks to identify influential spectral bands with high predictive power for estimating the biophysical parameters of crops. [109] takes a different approach by attempting to estimate the salt content in the soil profile through periodic observations of changes in topsoil salinity using time-series remote sensing imagery. The performance of these models is noteworthy. Papers [107] and [108] achieve an R^2 value slightly over 80%, indicating high predictive accuracy. Paper [109], while slightly lower, achieves an R^2 value of 65%, still demonstrating a significant level of predictive capability. [110] combines satellite imagery with precipitation and ambient temperature data to predict NDVI and NDWI values. This research stands out as the only study focusing on predicting these values, which are crucial for assessing plant health. The study achieves high performance, with an RMSE of 0.28. By leveraging satellite data and advanced machine learning techniques, these studies offer valuable insights into various factors influencing irrigation, thereby contributing to more informed and efficient agricultural practices.

Hyperspectral imaging is prominently utilized in numerous articles within this category [111–128]. These studies employ various types of multispectral cameras, with machine learning models or simple neural networks being the primary analytical tools. Notably, [115] stands out by using a complex Convolutional Neural Network (CNN). The majority of these images are captured by drones at different growth stages to facilitate optimal comparative analysis. Studies [111–113,121,122, 124,126,127] focus on predicting chlorophyll levels through captured images. Specifically, [111] extends its analysis to predict nitrogen and carotenoid levels, which are critical for fertigation, but reports suboptimal results with an R^2 of 35%. In contrast, [113] and [127], which concentrate solely on chlorophyll prediction, achieve more robust R^2 values of 82% and 86%, respectively. Research related to fertilizers is highlighted in studies [115], [128] and [116]. Study [115] employs a CNN to predict nitrogen concentration and aboveground biomass detection capacity across diverse growing conditions in ryegrass and barley, achieving an impressive R^2 of 83%. Contribution [116] estimates the abundance of soil and urea fertilizer combinations using a neural network, yielding excellent results with an R^2 of 95%. In contrast, the purpose of the study [128] is entirely different. It focuses on data augmentation of hyperspectral images using advanced techniques to increase the size of the dataset. Predictions related to water content are addressed in studies [114,117–119,125,123]. Study [114] aims to estimate the water content in sorghum crops, while [117] evaluates models for estimating water potential (WP) in corn plants. Study [118] investigates the feasibility of various machine learning algorithms to predict water thickness equivalent in the wheat canopy. Studies [125,123,119] attempt to predict water stress levels in different types of plants. Specifically, [119] uses RGB, HS, and TIR indices to evaluate water stress in VGS outdoors. Study [125] employs a CNN for potato fields, achieving an accuracy of 89%, while [123] uses drone-captured images for grape fields. These studies predominantly utilize machine learning models such as RF and SVM, with study [118] achieving the highest performance with an R^2 of 92%. Lastly, study [120] employs hyperspectral data with a distinct objective: predicting leaf temperature and stomatal conductance in corn. The goal of this research is to quantify potential water stress throughout the growing season. In summary, hyperspectral imaging combined with advanced machine learning models provides significant insights into various aspects of agricultural research, from nutrient estimation to water content prediction.

Fine-tuning and image datasets are employed in studies [129–133]. The primary contribution of [129] is the evaluation of new architectures, such as EfficientNet and MobileNetV3, for identifying nutritional deficiencies in two distinct datasets. Study [130] presents and discusses comparative evaluations of three deep learning models—AlexNet, GoogLeNet, and Inception V3—aimed at identifying water stress conditions in three crops: corn, okra, and soybean. In contrast, [132] utilizes a VGG-based architecture to classify water stress in tomato plants using a large aerial image dataset. Study [131] distinguishes itself by employing a multimodal neural network with drop-based clustering (C-Drop) to predict the level of water stress by extracting withering characteristics. [133] evaluated and compared the performance of ResNet-50 in classifying leaf nitrogen content in strawberry plants using RGB images obtained from an HP Scanjet 3800. Notably, [131] is the only study that utilizes rock wool substrate cultivations. Performance metrics indicate that [129] and [130] achieve an R^2 of 98%, while [131] achieves an R^2 of only 43%.

The following articles delve into the analysis of tabular data captured by sensors, such as soil temperature, meteorological data, and star size. Two of these focus specifically on water stress classification. Notably, paper [134] stands out as the only project examining above-ground plants on limestone bedrock. In their experiment, data was collected from multiple vines, each subjected to different water stress regimes, resulting in a field sensor time-series dataset. Utilizing this dataset, a Gradient Boosting model was developed, achieving an R^2 of 90%. Conversely, [135] employed data from the biorestorer—a sensor they designed—to construct a ML model that classifies four possible states of water stress in tomato plants. They further incorporated novel bio-electrical characteristics from the biorestorer to predict the state of a tomato plant 24 hours in advance using LSTM-based neural networks, effectively automating the irrigation process. This study achieved an accuracy of 94%.

The analysis of electrical conductivity was addressed in works [136–138]. [136], situated more in the chemical field, utilized laboratory-calculated organic matter of the soil and an MLP model to predict future electrical conductivity levels. Paper [138] combined the use of the Extreme Learning Machine (ELM) to predict soil electrical conductivity based on parameters such as soil temperature, moisture content, and pH value. Meanwhile, [137] focused on estimating the leaching requirement across five classes (Not required, Minimum required, Average required, Maximum required, and Extreme) to optimize irrigation and reduce salinity levels in the root zone. While [136] showed moderate performance with an R^2 of 69%, [137] demonstrated more promising results with an R^2 of 94%. Additionally, the latest article in this series correlates these findings with a 38% increase in yield.

Wu et al. [139] utilized an RF to predict equivalent water thickness in rice, based on multi-temperature indices derived from thermal images, achieving an R^2 of 87%.

Water stress is predicted in an alternative manner by [140]. They implemented a Transformer model that utilizes relative stem diameter, environmental sensors, and an RGB camera (GoPro HERO5 Session), achieving an R^2 of 75%. Additionally, this is the only study that conducts experiments on hydroponic cultivations and employs a Transformer architecture.

Two articles [141,142] predict the levels of various fertilizers using ground sensors such as pH, soil moisture, and electrical conductivity. [142] employs an SVM on data obtained from laboratory samples, achieving an R^2 value of 98%.

Finally, [143] focused on antifreeze measures and introduced an LSTM model to predict air temperature using various input variables. The goal was to enable farmers to activate antifreeze techniques based on water usage only when necessary, thus conserving this valuable resource. This study reported outstanding results with an R^2 of 97%.

The articles within this section exhibit considerable variability, employing diverse techniques to achieve distinct objectives. To ascertain the most effective methods for each specific goal and input data, further experimental studies are required. Future research will focus on utilizing various data sources, exploring different cultural contexts, and conducting long-term experiments. This approach aims to gain a comprehensive understanding of the sustained effects of these techniques over extended periods.

5. Research open challenges and future research directions

In this section, we've gathered and emphasized the key points that will shape and guide future progress. These crucial elements serve as a roadmap for upcoming innovations, ensuring that all significant aspects are taken into account and addressed.

- *Exploring Advanced Learning Techniques*: the majority of models utilized in the experiments are based on machine learning, with only a few employing deep learning techniques. This reliance on machine learning is primarily due to its relatively lower computational requirements and ease of implementation compared to deep learning. However, future research could explore advanced methods such as Transformer models and fine-tuning, which, despite being more complex and resource-intensive, have the potential to achieve superior performance in image analysis. Moreover, the review highlights that only one study incorporates a reinforcement learning system. Reinforcement learning is a promising approach for agriculture, particularly because plant performance can change rapidly due to various environmental factors. This necessitates the continuous updating of techniques based on new data to ensure optimal decision-making. By leveraging reinforcement learning, agricultural systems can adapt in real-time to changing conditions, leading to more efficient and effective farming practices.
- *Enhancing Sensor Performance*: most reviewed articles concentrate on soil humidity and temperature sensors, while research on sensors for fertilizer levels, soil salinity, pH, or chlorophyll remains limited. This gap is primarily due to the high costs and difficulties associated with obtaining these specialized sensors. Therefore, it is crucial to develop sensors that offer longer battery life, enhanced data quality, reduced costs, and a broader range of data types. Such advancements would provide more precise information on crops and soil, enabling more informed decision-making. Additionally, lower costs would allow even small-scale farmers to integrate these advanced sensors into their operations. This democratization of technology would ensure that farmers of all sizes can benefit from precision agriculture techniques, leading to more equitable and widespread adoption of smart farming practices.
- *Improving Communication Protocols*: communicating effectively between sensors in open fields presents a notable challenge. Existing protocols frequently encounter problems like signal interference and limited range. Research should concentrate on creating robust communication protocols that guarantee reliable data transmission over long distances and in diverse environmental conditions. Key areas of focus include developing adaptive algorithms that can adjust dynamically to changing environmental factors, utilizing low-power wide-area networks (LPWAN) to extend communication range, and implementing advanced error correction techniques to reduce data loss.
- *Evaluating the Generalizability*: in many experiments, the performance of the applied methods across different fields and seasons is often not demonstrated. This lack of comprehensive testing limits our understanding of how these methods perform under varying conditions, which is crucial for gauging the generalizability of the proposed methods. To assess the applicability of smart agriculture techniques across various contexts, it is essential to conduct experiments on diverse plants and fields using consistent methodologies. This means that researchers should design their studies to include a wide range of crops and environmental conditions, ensuring that the methods are tested in different soil types, climates, and seasons. By doing so, we can gather valuable data on how these techniques perform under different circumstances, providing a more comprehensive understanding of their strengths and limitations.
- *Creating Open-Source Datasets*: One significant issue highlighted by this review is the lack of availability of datasets created and used in trials. Open-source datasets are crucial for fostering research and collaboration, as they allow researchers from different institutions and regions to access and utilize the same data. This shared access can lead to more robust and diverse research outcomes. Additionally, combining datasets from various sources can provide more comprehensive data for training complex models, enhancing their accuracy and reliability. Without accessible datasets, researchers face significant challenges in comparing performance metrics or replicating previously conducted experiments. This lack of reproducibility can hinder scientific progress and the validation of new methods. Therefore, it is essential to prioritize the creation and sharing of open-source datasets to advance the field of smart agriculture and ensure that research findings are both credible and applicable across different contexts.

6. Conclusion

Using the PRISMA 2020 protocol, this paper presents a comprehensive literature review on the subjects of smart irrigation and smart fertigation. The systematic review discussed in this context underscores a significant increase in research literature related to smart technologies for controlling and modeling irrigation systems. This field is gaining prominence as a notable research area, providing opportunities for ongoing contributions. We gathered and analyzed 130 relevant scientific articles, which exhibited significant variability in terms of datasets, AI models, and the tasks performed.

A notable disparity was observed in the cultivation techniques employed in the reviewed research. Only four studies utilized advanced cultivation methods such as soilless farming or aquaponics. Future research should aim to incorporate these innovative techniques to enhance the robustness of experimental outcomes.

The AI models employed in the reviewed studies ranged from Decision Support Systems (DSS) and fuzzy logic to machine learning and deep learning models. Notably, few articles leveraged the latest deep learning techniques, such as Transformers.

Predictable features, such as soil moisture and nitrogen levels, were commonly illustrated. Additionally, it was noted that many other soil and plant characteristics could be predicted using AI models; however, the number of experiments for these predictions remains limited, necessitating further investigation.

We have compiled an exhaustive report that consolidates the most critical information from the relevant papers. This report includes summary graphs and citations for each article, highlighting their key points. Future reviews could benefit from a more focused study on the sensors and their technical specifications used in the current state of the art.

CRediT authorship contribution statement

Lucio Colizzi: Conceptualization, Methodology, Project administration, Supervision, Writing – review & editing. **Giovanni Dimauro:** Conceptualization, Methodology, Project administration, Supervision, Writing – review & editing. **Emanuela Guerriero:** Conceptualization, Project administration, Supervision, Writing – review & editing. **Nunzia Lomonte:** Conceptualization, Methodology, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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