UAV Remote Sensing applications and current trends in crop monitoring and diagnostics: A Systematic Literature Review

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***Abstract*— Crop monitoring and diagnosis are crucial for efficient agricultural production, and unmanned aerial vehicle (UAV) Remote Sensing can assist in achieving this goal. This article offers an automated Systematic Literature Review (SLR) of UAV Remote Sensing for crop monitoring and diagnosis. This review analyzes the primary scientific applications and trends in this area using Deep Learning techniques to automatically select relevant articles and validate them through full reading. The SLR collected over 800 papers, of which 64 met the selection process. The articles selected by Deep Learning classifiers were successfully cataloged with high accuracy in pre-selecting articles for review. F1 scores of 93% were achieved in tests with unpublished examples for the classifier model. The review of the 64 primary studies reported a peak in UAV Remote Sensing applications in 2020, attributed to the increasing diffusion of precision farming practices with technological equipment. The UAV Remote Sensing application objectives included crop monitoring, pest and disease detection, yield prediction, and plant nutrition. Artificial Intelligence, particularly Machine Learning and Deep Learning, are widely used for UAV Remote Sensing analysis. The NDVI is the most applied vegetation index for crop condition assessment and monitoring. The proposed solution for automating the literature selection process for precision agriculture-related scientific articles can be used in other areas that require extensive literature review.**

Keywords: UAV images, Crops, Remote Sensing, Vegetation index, Deep Learning.

I. INTRODUCTION

Crop monitoring and diagnosis are essential to ensure productivity and efficiency in agricultural production [1]. With the advancements in technology, there are various technologies and tools to perform these tasks more efficiently and accurately, such as the use of images captured by unmanned aerial vehicles (UAV) [2].

UAV images offer multiple advantages for crop monitoring, including obtaining high spatial resolution aerial images, broader coverage of the study area, and capturing images at different times of the day to generate maps and models that facilitate decision-making [3] [4].

In this sense, a bibliographic review is a valuable tool to understand a specific state of the art. It allows for collecting, analyzing, and synthesizing published literature on that subject at a particular point in time. However, selecting articles presents limitations since it is a manual task requiring knowledge and expertise from researchers. This can be a laborious and time-consuming process, as repositories contain a large number of articles. In addition, the manual selection process can also be subject to human errors, and it can be challenging to ensure that all relevant papers have been identified [5].

The process begins with identifying keywords, which are set to be searched in different databases and result in hundreds of articles that must be evaluated to determine their relevance. Different criteria are used to select articles, including reading the titles, abstracts, and keywords, and once a list of relevant articles has been selected, the full documents are read. The selection of the most relevant articles in the study area lets to obtain accurate and reliable results.

With this background, this document proposes a Systematic Literature Review (SLR) on using UAV Remote Sensing for crop monitoring and diagnosis to analyze the main scientific applications and trends in this area. To do this, automatic article selection was applied using Deep Learning techniques, and the selected articles were validated through full reading. With this, it is expected to provide a valuable and updated tool for research and decision-making in agriculture.

II. METHODOLOGY

To conduct the SLR, the process proposed in [6] was adapted (Fig. 1). The first step was to define the research questions, followed by defining the relevant keywords and repositories for data acquisition. Once the articles were obtained, the selection criteria were defined. In the next step, data mining was performed to discover patterns in the dataset, followed by classification to categorize or label data based on its features. Finally, data extraction was carried out to fill in the adapted form.

A. SLR Research Questions

The SLR aims to review published studies on the different applications of UAV imagery in crops. The research questions were formulated according to the purpose of the present study (Table 1) and were answered by selecting and analyzing primary studies.

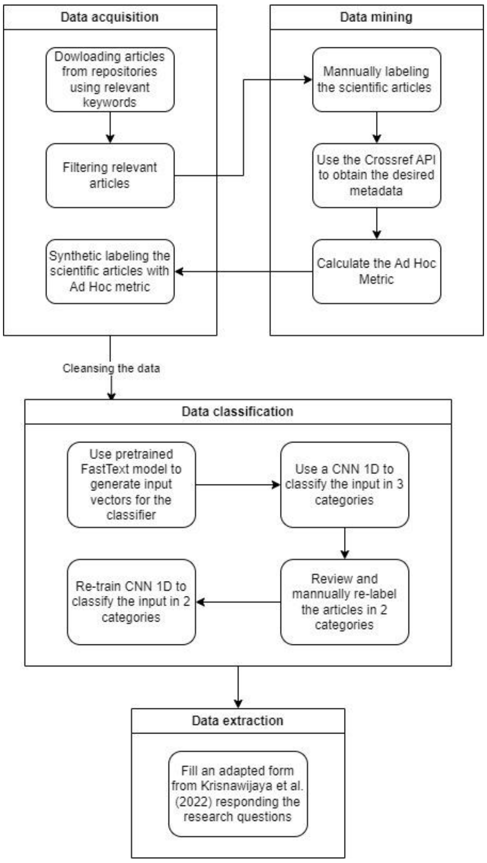

Fig. 1. SLR process used in this study.

TABLE 1. LIST OF RESEARCH QUESTIONS

No	Questions
RQ1:	What crops have been studied using UAV Remote Sensing data?
RQ2:	What are the objectives of UAV Remote Sensing applications in crops?
RQ3	What technologies are adopted for UAV Remote Sensing applications in crops?
RQ3.1	What type of UAV was adopted for capturing aerial images?
RQ3.2	In what spectral bands are aerial images typically analyzed?
RQ4	What are the techniques adopted to analyze aerial imagery data?
RQ4.1	What specific data analytics tasks have been targeted in using these images?
RQ5	What vegetation indices have been used in these studies?

The first research question aims to identify crop types that the primary studies analyzed. The second question aims to determine the purpose of UAV Remote Sensing applications in crops. To comprehend the applications of UAV Remote Sensing in crops, it is essential to understand the associated technologies, including the type of drones and spectral bands used. Understanding of the latest techniques and tasks for analyzing aerial image data is crucial; as it can significantly impact the quality of extracted information, particularly for addressing the third and fourth research questions. Lastly, the fifth research question aims to identify the vegetation indices used in primary studies as indicators of vegetation health.

B. Data Acquisition

An electronic search was conducted in high-quality articles databases such as ACM Digital, IEEE Explorer, Science Direct, Scopus, Springer, and Taylor and Francis to identify potential studies that could address the research question. The search was limited to a six-year interval, i.e., articles published since 2017, to ensure that the information is as up-to-date as possible in agriculture. The keywords used in the electronic search included agriculture, UAV images, drone, and Remote Sensing.

The automatic article search provided approximately 900 journal articles, conference articles, and book chapters. To select studies relevant to the present research, the criteria outlined in Table 2 were applied to filter the results.

TABLE 2. SELECTION CRITERIA

No	Criteria
C1	Papers full text available.
C2	Papers written in English.
C3	Non-duplicated papers across different repositories.
C4	Papers published in a scientific journal.
C5	No review articles, surveys, or abstract compilations.
C6	Applied research papers.
C7	Papers that address applications in crops.
C8	Papers that use UAV aerial imagery.

After applying the criteria C1 - C5 on a quick glance at the titles and descriptions, 734 articles were filtered. Table 3 shows the distribution of these articles in different databases, with Scopus containing the highest number of articles (182), and Taylor and Francis containing the lowest number of articles (3).

C. Data Mining

Once the criteria were applied, part of the resulting data was manually labeled by an expert into three levels of relevance (***high***, ***medium***, and ***null***) using an empirical paradigm based on his evaluation of each article. This manual labeling process took three weeks to complete. This was a time-consuming and exhaustive process that led to a dataset of 40 labeled articles. However, the limited size of the resulting labeled dataset posed a challenge for training. To address this, an objective technique for labeling scientific articles was employed to increase the training dataset's size. The technique involved creating synthetic data points using an ad hoc metric that combined three thresholds. Specifically, the metric was calculated as follows:

Ad hoc metric = (number of citations × impact factor) / (years since publication)

This ad hoc metric formula was chosen due to its simplicity and that by analizing its distribution was found to be leptokurtic and positively skewed, which aligns with the reality that most published works do not reach the pinnacle of the scientific community in terms of the number of times they are referenced, longevity, and impact on the journal where they were published.

To extract key information for the metric, including publication year, journal name, and number of citations, a metadata mining process that utilizes the Crossref API was employed. Specifically, each article's DOI was passed through the API to obtain these metrics and calculate the ad hoc metric. In the end, this technique helped to increase to 84 labeled articles, where there exists a strong correlation between the ad hoc metric and the classification labels assigned by the experts.

D. Classification

After cleansing the data in the most conservative way, the text representation is carried out by the pre-trained FastText model, which is a powerful text representation model that can capture the semantic relationships between words by breaking them down into subwords [6], and it was used to generate feature vectors for each article's abstract.

The final module corresponds to the classification of the text using a 1D CNN. The feature vectors generated by FastText were allocated in a matrix of 84 (training data) by 13000 (maximum text sequence size) that was fed into a 1D CNN to classify the articles into one of the three levels of relevance. The 1D CNN obtained 84% accuracy and it was trained using a cross-entropy loss function, 22 epochs, batch size 21 and Adam as the optimizer.

The model was executed to classify the 734 articles, which led to the preselection of 129 articles classified as high. Later an expert read their abstracts and selected 73 of those articles as highly relevant, at this stage the expert also applied the criteria C6 - C8. Finally, three experts thoroughly read the 73 full documents, which took one month to complete, selecting 64 final articles. Further experimentation was carried out using the same classification methodology, but this time training with 30% of the 129 articles review by the expert into only two levels of relevance: high and low, and it was not necessary to use synthetic labeling as before, producing 82 articles (Table 3). This experimentation was carried out with the objective of determining if the reading process of the three experts could be reduced.

TABLE 3. OVERVIEW OF THE SEARCH QUERY AND SELECTION PROCESS

Database	Automated search	Manual selection criteria	Automatic selection criteria
ACM Digital	77	0	0
IEEE Explorer	154	0	2
Science Direct	147	18	21
Scopus	182	38	50
Springer	161	7	8
Taylor and Francis	13	1	1
Total	734	64	82

E. Data Extraction

To extract information from the primary studies, a form based on previous research [7], was used. To do this, some articles were read randomly to identify the most relevant parameters. This process was interactive since, as the reading of the articles progressed, new parameters were determined for the form. A total of 64 primary studies [1-4], [8-67] were analyzed using this form to answer the research questions.

The form included general information such as DOI, URL, title, year, citations, journal, journal ISSN, repository, authors, author affiliation, and research country. Specific information about the study was also recorded, such as the type of crop and field, objectives of the research, goals of aerial imagery applications, flight planning/mission control, image preprocessing software, sensor model, drone model, drone type, spectral bands, vegetation indices, technique, architecture/model, data analytics task.

III. RESULTS

This section presents the results of extracting information from the 64 primary studies. To provide insight into the research questions, a descriptive statistic summarizes the general information. This statistic enables a better understanding of the underlying data and conveys essential information relevant to the research.

A. General Statistics

The distribution of primary studies from 2017 to 2022 shows a remarkable increase starting from 2018, reaching a peak of 17 publications in 2020 (Fig. 2). A decrease in publications is observed from 2021. In 2022 only 10 publications were recorded, possibly due to the analysis cutoff date being in June. However, this data was included, given the relevance of understanding the trends regarding applications and techniques used for UAV image analysis.

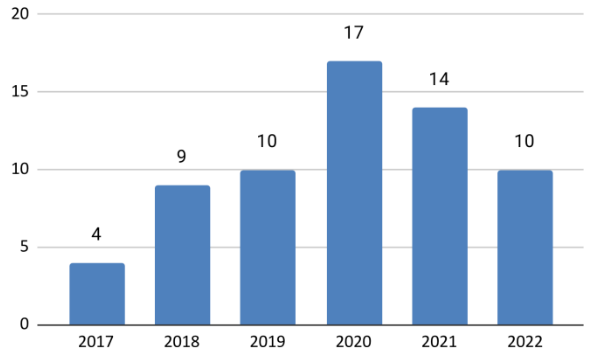

Fig. 2. Year of publication of primary articles. *Cutoff analysis date June 2022.

According to Fig. 3, China and the USA have contributed the most, with 18 and 12 papers, respectively. Brazil and Spain follow with four papers each, while Australia and France each have three papers. Additionally, two papers were contributed by Canada, Italy, Mexico, South Korea, and Switzerland.

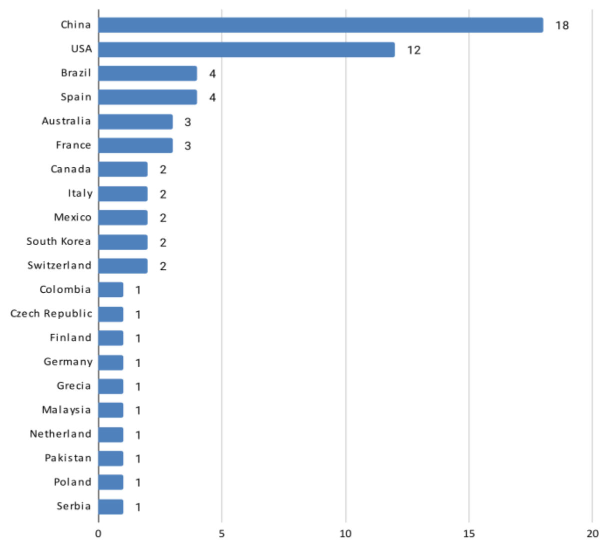

Fig. 3. Number of studies per country.

Fig. 4 illustrates that the Remote Sensing journal has published the most studies related to applications and trends in using UAV images for monitoring and diagnosing crops, with 18 papers. Precision Agriculture follows with seven papers, while Agronomy and Computers and Electronics in Agriculture have six papers, and Sensors has three papers. According to Fig. 5, the most cited papers, with more than 200 citations, are [39], [45], [61]. Moreover, [14], [29], [62] have received over 100 citations, while [24], [9], [66], and [23] have less than 100 citations.

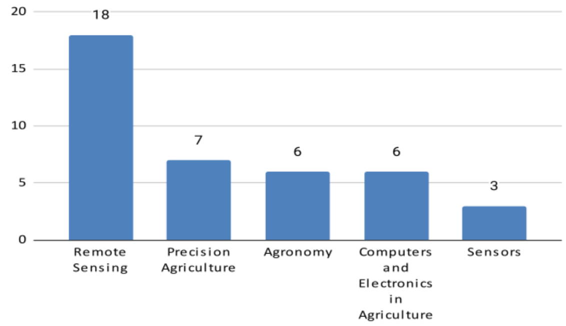

Fig. 4. Top five publication journals.

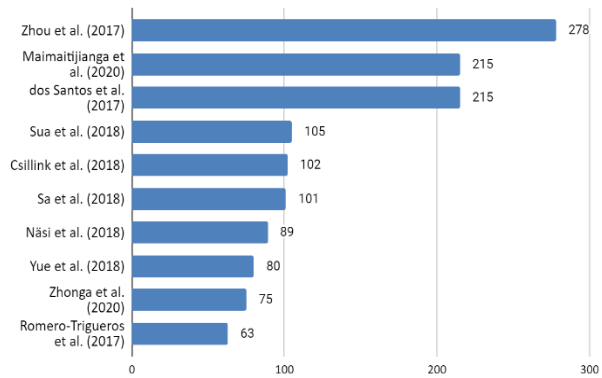

Fig. 5. Top ten cited papers.

B. *RQ1: What crops have been studied using UAV Remote Sensing data?*

For the analysis, nine types of crops were classified according to their use. Additionally, studies that analyzed more than two crops were grouped into a single category called "different crops". As shown in Fig. 6, the most studied crops were cereals, with 21 documents. This category encompasses crops, such as corn, wheat, oats, sorghum, and rice. Followed by fruit trees and studies analyzing more than two crops, with 12 documents. Notably, two studies [66] and [38] analyzed 15 and 6 crops, respectively. On the other hand, oil crops, tubers and root vegetables, fiber crops, grass, other crops, and bulb vegetables were less represented. Specifically, the "other corps" category comprised [1] and [35], which studied spinach and lemon myrtle, respectively.

Table 4 displays that China strongly emphasizes the study of cereals, with most of their analyses centered around wheat (8 out of 13 articles). In contrast, the USA primarily directs their research toward fruit trees, particularly citrus, wine grape, and apple. On the other hand, countries such as France and Spain concentrate on different types of crops, such as fruit crops and the different crops category.

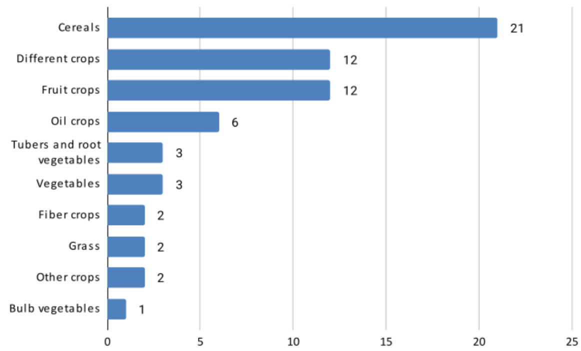

Fig. 6. The number of primary studies according to their crop type analysis.

TABLE 4. CORRELATION BETWEEN THE CROP TYPE AND THE TOP FOUR COUNTRIES

Crop type	Country			
	China	USA	Brazil	Spain
Bulb vegetables	-	-	-	1
Cereals	13	1	1	0
Different crops	3	2	1	1
Fiber crops	-	2	-	-
Fruit crops	-	5	1	2
Grass	-	-	-	-
Oil crops	1	1	1	-
Other crops	-	-	-	-
Tubers and root vegetables	1	-	-	-
Vegetables	-	1	-	-

C. *RQ2: What are the objectives of UAV Remote Sensing applications in crops?*

In the analysis of the primary studies, seven objectives were identified according to their applications in an agricultural context. Table 5 presents the number of documents associated with each year and the objective, while Table 6 illustrates the relationship between the crop type and the identified objectives. The most found objective is O1: Crop monitoring, followed by O6: Pest and disease detection, O5: Irrigation management, and O7: Controlling environmental field. It is also possible to observe that the study of cereals predominates in objectives O1 and O6, followed by the category of different crops analyzed in O1 and O5 and fruit crops that dominate in applications of O1 and O2.

TABLE 5. CORRELATION BETWEEN THE YEAR AND THE OBJECTIVES FOR UAV REMOTE SENSING APPLICATIONS.

Year	Objectives						
	O1	O2	O3	O4	O5	O6	O7*
2017	1	-	-	1	1	1	1
2018	5	1	-	-	-	1	2
2019	5	4	-	-	1	-	-
2020	6	4	1	2	3	2	3
2021	7	1	-	1	1	4	1
2022	2	-	-	1	3	3	2

*O1: Crop monitoring, O2: Pest and disease detection, O3: Mapping of crops, O4: Estimation of crop production, O5: Irrigation management, O6: Fertilizer management, O7: Controlling environmental field.

TABLE 6. CORRELATION BETWEEN THE CROP TYPE AND THE OBJECTIVE FOR UAV REMOTE SENSING APPLICATIONS.

Crop type	Objectives						
	O1	O2	O3	O4	O5	O6	O7
Bulb vegetables	1	-	-	-	-	-	-
Cereals	8	3	-	4	2	7	2
Different crops	5	-	1	-	3	1	2
Fiber crops	2	-	-	-	-	-	-
Fruit crops	5	3	-	-	2	1	2
Grass	1	-	-	-	-	1	
Oil crops	3	-	-	1	1	-	2
Other crops	1	1	-	-	-	-	-
Tubers and root vegetables	-	1	-	-	-	1	1
Vegetables	-	2	-	-	1	-	-

D. *RQ3: What technologies are adopted for UAV Remote Sensing applications in crops?*

The analysis of technologies used in the primary studies included identifying UAV types and spectrum regions. Based on the analysis, multirotor drones and sensors based on the Visible light and Multispectral bands were preferred, with 20 and 15 papers, respectively. Four papers utilized Hyperspectral sensors, while other studies used a combination of two types of sensors, with three papers each for capturing both Visible light + Color-infrared and Visible light + Multispectral data. On the other hand, fixed-wing drones were primarily equipped with the combination of Visible light + Color-infrared sensors. Table 7 provides a detailed summary of the technology preferences observed in the primary studies.

TABLE 7. TOP FIVE CORRELATION BETWEEN THE SPECTRAL BANDS AND THE UAV TYPE.

Spectral bands	Multirotor	Fixed-wing
Visible light	20	0
Multispectral	15	0
Hyperspectral	4	0
Visible light + Color-infrared	3	6
Visible light + Multispectral	3	0

1) RQ3.1: What type of UAV was adopted for capturing aerial images?

A preference for Multirotor drones is observed, as they were in 52 studies out of the 64 studies, while fixed-wing drones were only mentioned in eight papers. The reason for this preference is not explicitly stated in the studies. Still, it could be attributed to factors such as higher payload capacity as in [11] and [12], who used multisensory systems for image capture (Visible light + Multispectral + Thermal infrared), as shown in Fig. 7.

2) RQ3.2: In what spectral bands are aerial images typically analyzed?

The knowledge of the spectral bands most used in the primary studies provides insights into the most relevant information for crop analysis. As shown in Fig. 8, the analysis reveals that Visible light and Multispectral are the most used spectral regions, with 22 and 15 documents, respectively. Sensors capturing green, red, and near-infrared bands are also prevalent, with nine papers. In contrast, Hyperspectral sensors and the combination of Visible light + Multispectral sensors are identified in four and three documents, respectively. The limited use of hyperspectral sensors could be attributed to their high cost, as most studies mainly propose using low-cost sensors.

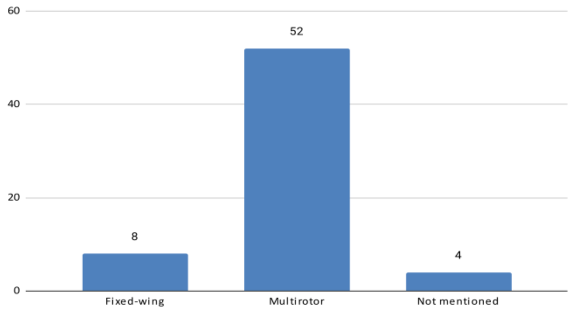

Fig. 7. Types of UAVs used in the primary articles.

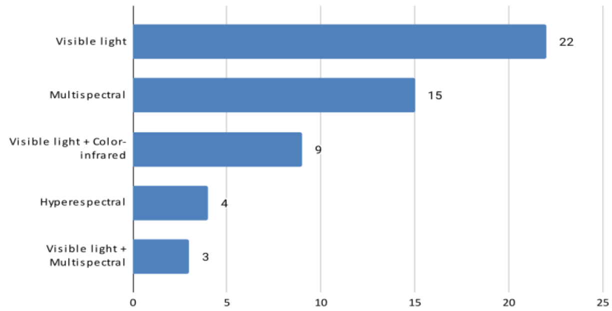

Fig. 8. Top five spectral bands applied for the analysis.

E. *RQ4: What techniques are adopted to analyze aerial imagery data?*

The analysis shows that the most used techniques for UAV image analysis are Artificial Intelligence (AI), Machine Learning, and Deep Learning, with 20 and 16 papers, respectively. Statistical analysis is also used in ten documents. In addition, some studies propose combinations of techniques such as Machine Learning + Deep Learning and Computer Vision + Machine Learning (Fig. 9).

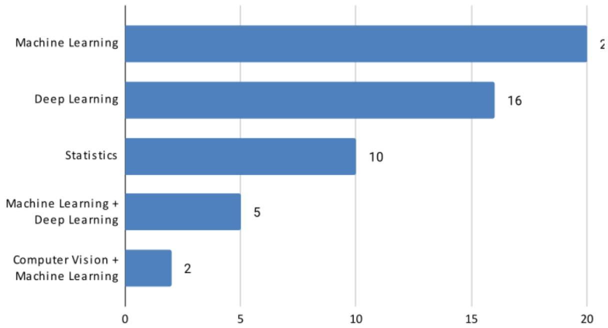

Fig. 9. Top five techniques applied for UAV image analysis in an agricultural context.

1) RQ4.1: What specific data analytics tasks have been targeted in using these images?

Applying techniques and tools to analyze large data sets and extracting information helps make informed decisions. Based on the primary studies analyzed, the most used analysis tasks are Classification and Regression, with 21 and 20 documents, respectively. These are followed by Prediction, Descriptive analytics, and Semantic segmentation task with 5, 3, and 2 papers, respectively (Fig. 10).

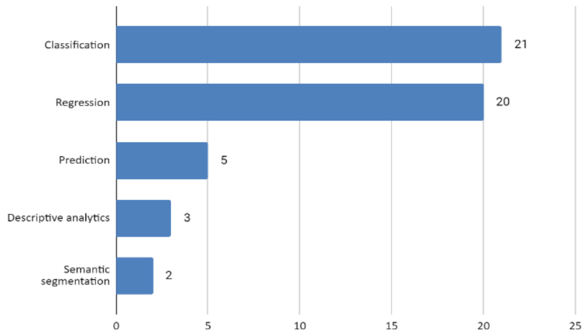

Fig. 10. Top five of the most used data analytics task.

F. *RQ5: What vegetation indices have been used in these studies?*

Regarding the analysis of the vegetation indices (VI) used in the primary studies (Fig. 11), it can be observed that the NDVI (Normalized Difference Vegetation Index) is the most used index, appearing in 19 documents. Following closely behind are the GNVI (Green Normalized Vegetation Index) and NDRE (Normalized Difference Red Edge), with 13 and 10 papers, respectively. The ExG (Excess Green) and SAVI (Soil-Adjusted Vegetation Index), are the least utilized VIs, found in only 9 documents.

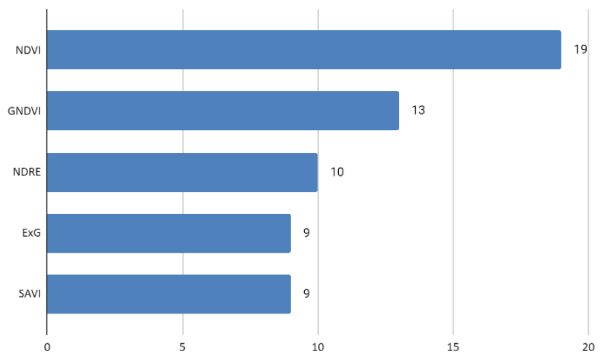

Fig. 11. Top five of the most used vegetation indices in the selected studies.

The analysis of the number of VIs used (Fig. 12) reveals that some studies have analyzed more than 30 VIs. For instance, study [50], analyzed 35 VIs, while [19] and [52] analyzed 33 VIs. On other hand, [9] and [22], analyzed with 24 and 20 VIs, respectively.

IV. General Discussion

SLR consists of three main steps: data acquisition, extraction, and information synthesis. However, it is a highly manual, time-consuming, and error-prone process that requires at least two experts [68]. The data acquisition phase, which entails selecting primary articles from a large pool of potentially relevant ones, is one of the most challenging and time-consuming aspects of the process [69]. To select primary articles, experts must read through the titles and abstracts of many potential articles, which demand a significant investment of time. In this regard, the proposed automated methodology for conducting an SLR on precision agriculture using UAV images and deep learning classifiers has been successful. The classifier model for three levels and the model with two categories achieved F1 scores of 87% and 93%, respectively, in tests with 15 unpublished examples. This finding highlights the proposal's effectiveness in selecting primary articles for SLR, resulting in a high level of accuracy while reducing the time required. Nonetheless, even with a low error rate, it is still imperative to have expert validation to ensure a precise analysis of the primary articles.

This SLR focused on UAV Remote Sensing applications for crop monitoring and diagnostics. More than 900 papers were collected, but only 64 met the selection criteria through a semiautomatic classification and a manual process. It is important to remark that the classification process not just filtered the top documents based on the ad hoc metrics, but it learnt patterns in the text and helped to discover papers with a low ad hoc metric but a high relevancy, which later were validated by experts. For example, out of 239 papers with an ad hoc metric of 0, 26 were classified as high. Similarly, among 321 papers with a metric ranging from 1 to 25, 58 were classified as high. On the other hand, 13 papers of the 35 with the highest metrics were classified as high (Fig. 12).

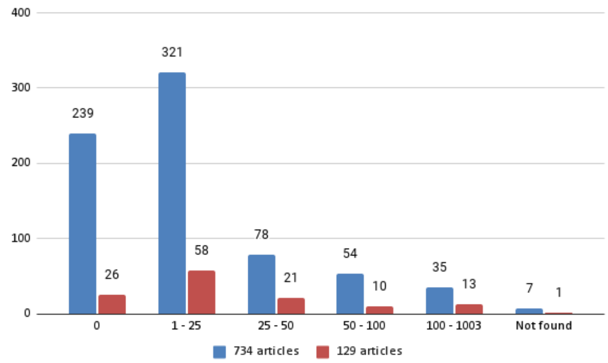

Fig. 12. Frequency distribution of articles based on ad hoc metric values across intervals for the 734 potential articles (blue) vs 129 classified as high by the CNN (red).

The number of studies reporting on agricultural applications has increased since 2018, peaking in 2020. This can be attributed to the growing popularity of precision farming practices using technological equipment [70].

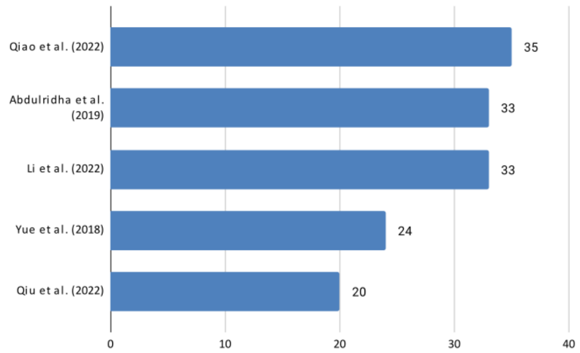

Fig. 13. Top five regarding the number of vegetation indices in the selected studies.

The general statistics reveal that China and the USA have the highest number of publications, which aligns with Japan's National Institute of Science and Technology Policy (NISTP) due to both countries' investments in the business sector and academia. On the other hand, the analysis of crop types reveals that cereals are the most studied, followed by the categories of different crops and fruit trees. The same analysis shows that China focuses its scientific activity on studying cereals, mainly wheat; this can be attributed to

China being the world's largest producer and consumer of wheat, producing approximately 17.5% of global production with over 128 million metric tons [71]. Meanwhile, the USA studies fruit trees such as apples, citrus, and grapes. These products are marketed nationally and internationally, significantly contributing to the country's economy. Furthermore, fruit production is a significant part of the food industry in the United States [72].

Some studies provide information on agricultural practices, such as [73] focused on Machine Learning applications in agriculture and [74] focused on the role of IoT in agriculture. However, their approach does not consider the different applications of UAV Remote Sensing in an agricultural context. The use of UAV Remote Sensing for crop monitoring, pest and disease detection, yield prediction, and plant nutrition, to name a few, is of significant interest due its contribution to sustainable [75], and environmentally friendly production.

Since technologies applied to crops are constantly evolving and advancing, it is important to keep up with trends and the latest advanced technologies can improve productivity and efficiency [76]. The type of drone and the spectral bands used in the primary studies were analyzed for a more detailed review. Multirotor drones and sensors based on visible light bands were found to be highly preferred due to their low cost and wide availability in the market, it is understandable that there is a preference for this type of sensor [7]. However, it should be noted that results of advanced experimentation based on expensive equipment are difficult to apply in real crops.

Artificial Intelligence techniques such Machine Learning and Deep Learning are widely used due to their great potential in agriculture, and they must work with large volumes of data easily accessible through UAVs [77].

Among the techniques applied for UAV remote sensing analysis, vegetation indices are considered an important method for crop condition assessment and monitoring. NDVI is the most widely applied and used index [78], due to the generation of low-cost images it generates. However, researchers often supplement their studies with additional VIs to ensure a comprehensive analysis, as a single index may not always be sufficient [79].

V. Conclusions

This article proposes a methodology towards automating the literature review process for precision agriculture-related scientific articles using a deep learning-based classifier, which in its first iteration, categorizes articles into three levels of relevance, then it only classifies the articles in two levels. The predictions demonstrate a promising approach for automating the time-consuming literature review process in precision agriculture, enabling researchers to efficiently identify and prioritize relevant articles for further analysis. Furthermore, the proposed solution can also be applied to other areas that require extensive literature review, offering a valuable contribution to the scientific community.

In future works an Exploratory Data Analisys and a simple classifier based on Machine Learning is proposed to be implemented in order to find the best parameters for determining the ad hoc metric.

Manually selecting papers based on the ad hoc metric would result in the discarding of some documents of high relevance. On the contrary, Fig. 12 shows that the implemented classifier included these documents as part of the 129 papers with high value. Additionally, these papers provided an important input for choosing the final 64 manually selected papers. The results of the second classification (automatic selection criteria trained with 30% of the 129 articles) suggest that the reading process of the three experts could be reduced. This is because this second classification produced 82 papers, which included the 64 manually selected papers.

The study involved SLR from 64 primary studies from high-impact journals, analyzing and discussing the different crop applications. Twenty-five parameters were identified in the form used to extract information from primary studies. The study highlights the usefulness of UAV imagery for crop monitoring and diagnostics. Its adoption has increased since 2018 due to precision agriculture practices and advanced technologies. UAV Remote Sensing has several objectives, including crop monitoring, pest and disease detection, yield prediction, and plant nutrition. Artificial intelligence, specifically Machine Learning and Deep Learning, is widely used to analyze the large volumes of data generated by UAV imagery.

Moreover, the primary studies emphasized the importance of vegetation indices, particularly NDVI, in assessing and monitoring crop conditions. Other indices complement the studies to provide a comprehensive insight into plants. The proposed approach can be extended to other areas requiring extensive literature review, thereby offering valuable contributions to the scientific community.

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