Foliar Nitrogen Estimation with Artificial Intelligence and Technological Tools: State of the Art and Future Challenges

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***Abstract*—Nitrogen plays a fundamental role in plant growth, but its high application has significant negative impacts for the farmers and the environment. This nutrient is often provided in excess to prevent plant growth limitations when it ought to be administered in the exact quantities because many farmers do not have access to technology or affordable soil and plant chemical analyses. Precision agriculture through monitoring of crop nutrition may be possible with quantitative, non-destructive methods and technological tools that allow farmers to conduct a rapid and representative verification of their fertilizer applications. In this sense, we carried out a systematic review and bibliometric analysis of recent scientific research to answer the questions: 1) Can artificial intelligence-based, non-destructive analysis of plant nutrition provide relevant information for decision-making in agricultural systems?, 2) Have recent studies reached the stage of developing technological tools to be applied in agricultural systems and field conditions?, and 3) What is the way forward to achieve popularization of the application and development of technological tools in agricultural systems? We found that non-destructive analyses of foliar nutrition need to provide more supportive information for decision-making given the challenge of interpreting and replicating results in agricultural systems operating under uncontrolled conditions, such as field conditions. To address this issue, we propose developing accessible technological tools, such as mobile applications, tailored to farmers' needs. However, most studies had not yet considered developing a technological tool as part of their objectives. Therefore, it is critical to develop accessible and affordable technologies and monitoring systems that approach precision agriculture since the conservation and sustainable management of natural resources demands translating scientific knowledge into supporting tools that reach farmers and decision-makers worldwide. The way forward is innovation through technological developments that enhance current agricultural systems.**

***Keywords*—Digital images; spectral data; estimation models; technological tools; nitrogen**

I. Introduction

Deficiencies of macro and micronutrients essential for plant growth can limit crop yields. As a result, farmers increase the use of chemical fertilizers to prevent nutrient limitations [1]. Unfortunately, the excessive use of fertilizers to ensure good production is popular today, despite the high costs involved and the fact that it is one of the most influencing factors in the degradation of soils and aquifers [2].

Ensuring effective fertilizer management is one of the main paradigms of precision agriculture. Precision agriculture is a strategy that seeks to increase productivity in agricultural fields by improving crop yields and assisting farmers in management decisions using high-tech analysis tools [3]. This type of agriculture requires the intensive collection and processing of spatio-temporal data on crops [4].

The most widespread method to obtain crop nutrient data to verify that fertilization is adequate fertilization was achieved is by carrying out destructive analyses of plant tissue and soils using laboratory chemical procedures, given that fertilization should complement soil available nutrients and the requirements of each crop. However, the periodic and systematic achievement of this type of analysis is time-consuming and costly, and the results are sometimes difficult for farmers to interpret. As a result, these activities are never performed at all or, in the best case, on a rare basis as a routine check of fertilization efficiency, and "panic" over-fertilization prevails.

There are also non-destructive methods for diagnosing the nutritional status of plants, which are fast but less accurate. These methods include the use of color charts for visual evaluation of plant leaves [5], sensors for chlorophyll measurement [6], and the use of digital information, such as images, for plant color analysis [7], all of which can support the implementing of precision agriculture. For example, on the one hand, [8] reviewed the available information for determining plant nitrogen through remote sensing. They found that there is still a need to generate more knowledge, especially in the agricultural domain, even though their research has identified guidelines to help selecting the appropriate sensor based on the specific objective of each study.. On the other hand, [9] also explored the usefulness of remote sensing. They focused on evaluating nitrogen in cereals, concluding that accurate and timely field monitoring is essential to guarantee crop performance and protect the environment by adjusting applications of fertilizers. However, while these methods can save resources, they are not always within the reach of farmers. This may be due to the cost of acquisition (in the case of sensors), the impossibility of applying them (image analysis requires computational algorithms), or the difficulty in understanding the results (chlorophyll measurements are not interpretative).

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In this sense, the scientific community has made significant efforts to develop non-destructive methods and technologies to reduce the negative impacts of over-fertilization on the environment. Artificial intelligence (AI) branches, such as Machine Learning (ML) and computer vision with Deep Learning (DL), have been used to provide consistent assessments of the nutritional level of distinct types of crops in a fast, economical, and reliable way [10], [11]. However, farmers apply AI-generated models for estimating the nutritional status of plants in uncontrolled conditions within agricultural systems in a very sparse manner. In addition, these automated systems hardly evolve to the innovation of a technological tool, such as software, web systems, or mobile applications, to support farmers in non-destructive and cost-effective field determinations.

One of the most significant nutrients studied with AI models is nitrogen (N) due to its fundamental role in plant growth through cell division, protein synthesis, and enzyme production [12]. However, there is evidence that excessive N addition has led to significant negative impacts on the environment, such as aquifer contamination [13], [14], harmful accumulation of nitrates and nitrogen dioxide (carcinogenic substances) in cultivated plants [15], and the acceleration of soil acidification and salinization through N transformation processes [16]. Therefore, N must be administered only in the precise amount needed to satisfy the nutritional goals.

The fact that N concentration is related to leaf color in many plants makes color a valuable parameter that serves as a basis for estimating foliar nitrogen levels [17]. For example, [18] presents the results of a conducted review of non-destructive techniques for determining foliar N, based primarily on color analysis parameters. They found that digital image processing attracts agricultural scientists due to its promising results and moderate cost.

Quantitative chemical or biochemical analyses and color measurements made on the same plant tissue, and critical foliar nutrient concentration values, are required as references to establish color values and build color charts that accurately reflect measured nutrient levels [19]. Several color guides have been produced and printed on paper for the main cereals, given that nutritional deficiencies are evident in grasses [20]. Mobile applications have also been developed in recent years [21], [22].

This work aimed to carry out a systematic review and bibliometric analysis of the current state of scientific knowledge on the evaluation of the nutritional status of plants using a quantitative, AI non-destructive approach, to provide relevant information for decision-making in agricultural systems under field conditions. This review's contribution is to present recent knowledge and identify its potential for the generation of accessible technological tools that might serve as low-cost support for promoting the rational and adequate use of fertilizers within the framework of sustainable precision agriculture.

II. Materials and Methods

The traditional methodology "Preferred Reporting Items for Systematic Review and Meta-Analysis" (PRISMA) [23] was followed to conduct a systematic review of current scientific knowledge. This review mainly focuses on nitrogen content, as color characteristics can conveniently detect nitrogen deficiencies and excessive concentrations for adequate fertilization of crops.

The PRISMA methodology was complemented with the PSALSAR methodology [24]. In addition, a bibliometric analysis was carried out to evaluate the production, visibility, and impact of the scientific literature related to the topic of study (see Fig. 1).

The research questions posed for this review were: 1) Can artificial intelligence-based non-destructive analysis of plant nutrition provide relevant information for decision-making in agricultural systems?, 2) Do studies reach the stage of developing technological tools for application in agricultural systems under field conditions?, and 3) What is the way forward for the popularization of the development and application of technological tools in agricultural systems?

Relevant platforms were used to search for information. The selected databases were Scopus[1], Science Direct[2], and Web of Science[3]. Initially, the search terms were specific, including "nitrogen" and "color", however, the results were limited; so, the search was broadened to include the keywords "machine learning" and "deep learning" (see Table I). The search was restricted to publications from the last ten years, as this work aims to gather information on the most recent technologies and processing methods.

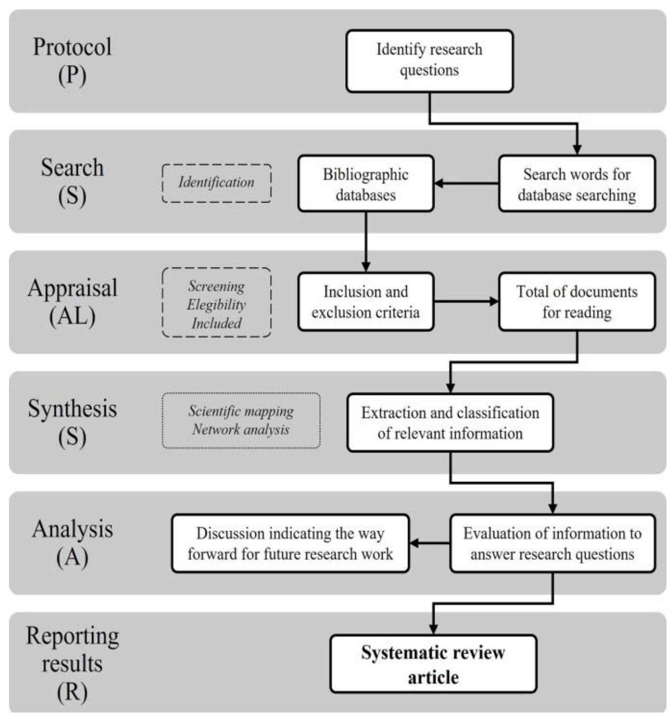

Fig. 1. Phases of the psalsar methodology applied in this systematic review. Scientific mapping and network analysis were performed as part of the bibliometric analysis.

[1] Web link: https://www.scopus.com/search/form.uri?display=advanced
[2] Web link: https://www.sciencedirect.com/
[3] Web link: http://webofscience.com/

TABLE I. SEARCH TERMS FOR COMPILING SCIENTIFIC ARTICLES ON PROCESSING DIGITAL PLANT LEAF IMAGES TO EVALUATE THEIR NUTRITION

Data bases	Searching string		No. of articles *	Consultation date
Scopus	Article title, abstract, keywords	"nitrogen" AND "color" AND "plant leaf" AND "image processing"	15	September 19, 2023
		"plant leaf" AND "deep learning" AND "nitrogen"	10	
		plant leaf AND machine learning AND nitrogen	22	
Science Direct	Advanced Search Find articles with these terms	"nitrogen" AND "color" AND "plant leaf" AND "image processing"	104	September 19, 2023
		"plant leaf" AND "deep learning" AND "nitrogen"	80	
		"plant leaf" AND "machine learning" AND "nitrogen"	152	
Web of Science	Search in: Collection Editions: All	nitrogen (All Fields) and color (All Fields) and plant leaf (All Fields) and image processing (All Fields)	74	September 19, 2023
		plant leaf (All Fields) and deep learning (All Fields) and nitrogen	48	
		plant leaf (All Fields) and machine learning (All Fields) and nitrogen	222	

[a.] The documents considered include review and research articles written in English from 2013 onwards.

The collected articles were evaluated using inclusion and exclusion criteria based on the objective of the review work. The inclusion criteria were a) search words exist in the title, keywords, or summary, b) the article must be written in English, c) the article's publication date is less than ten years, d) ML or DL models were used, e) the precision or uncertainty of the predictive models was calculated, and f) relevant gray literature documents (not conference proceedings) are acceptable. The exclusion criteria did not consider duplicate articles and documents not accessible.

After omitting inaccessible or duplicate articles and checking that the search words existed in the title or keyword section, 174 documents were left for initial review, which were downloaded from the search platforms and stored locally. Subsequently, the abstract of all articles was read and classified into two groups: 1) studies focused on the identification of nutrient levels, and 2) studies for the detection of pests and diseases in plant leaves, which were discarded. In total, 111 articles were collected using images and data from the leaves of different plants for the study of nutrient levels. A second search was carried out from the references cited in those articles to obtain 123 articles for full reading.

The relevant information of the selected articles was extracted and classified. This phase was complemented by scientific mapping and network analysis with the bibliometric method to identify the relationships between different research areas in the context of producing scientific papers [25]. Conducting a meta-analysis was not possible due to the wide heterogeneity of the studies reviewed.

Through scientific mapping it is possible to recognize the most influential works based on the classification and visualization of studies without the subjective bias of non-systematic literature reviews [26]. Network analysis uses graph theory to calculate the number of times that a) a document has been referenced by others (indegree), b) a particular node cites others (outdegree) [27], and c) the degree of intermediation of each element within the network (betweenness) [28].

Analysis of citations, co-citations, bibliographic coupling, co-authorship, and co-occurrence of words was applied in 117 studies of this review. In addition, 105 documents were synthesized in the supplementary material, 11 studies were not included because their methodology was unclear, and seven were review documents.

The tools used for scientific mapping and network analysis were VOSviewer[4] and biblioshiny by bibliometrix [29]. The analysis and graphical representation of the science tree were performed with Tree of Science (Core of Science, 2020), and word clouds with text mining were generated using Voyant[5]. An evaluation of the synthesized information was carried out to answer the research questions. The analysis includes narrating the results, discussing the way forward for future research work, and the conclusion [24].

III. RESULTS AND DISCUSSION

A. Bibliometric Analysis

An increasing publication trend was found, with an annual growth rate of 20.89%. China has the most publications, followed by Brazil, USA, India, and Australia. This is probably associated with the current existence of accessible devices, with better hardware and software features for data collection and the availability of free software tools that allow the processing of large amounts of information with a quantitative approach and known precision. Research from China is the most cited, followed by research from Brazil, Germany, Korea, and Iran.

Scientific mapping and network analysis with tree of science allowed identification of the most influential research on the topic of study, some of which was not considered during the information search phase. The metaphor of the tree of science to perform network analysis facilitated the recognition of connections and hierarchies based on the frequency of appearance of specific terms or concepts together in the scientific literature addressed in this review.

Given their theoretical dominance in derivative studies, the tree of science roots showed the classic documents of fundamental relevance in the subject. Twenty articles were considered the pillars of subsequent knowledge, they focused mainly on proposing and comparing the performance of different vegetation indices. Some of the early indices, which at the time were considered novel, are still in use today, such as the Soil-Adjusted Vegetation Index (SAVI), Transformed Soil-

[4] Web link: https://www.vosviewer.com/
[5] https://voyant-tools.org/, 2023

Adjusted Vegetation Index (SAVIT), Modified Soil-Adjusted Vegetation Index (MSAVI), among others [30].

The trunk of the tree of science includes 20 articles from authors that first discovered the applicability of this type of research. These documents are the central pillar of collective knowledge on the subject, and the proposal of new indices is a topic of interest. The most relevant studies explored the potential of the RGB color system through the relationship of its channels, mainly green and red, to the nitrogen content of different types of crops [31]. Other studies explored the use of spectral data [32], [33].

Three branches were identified based on underlying citations, each integrating 15 trending studies. The tree leaves represented the most recent and innovative papers citing each other, showcasing current trends framing emerging research.

The analysis of citations through scientific mapping showed that 103 of the studies considered in this review were connected, forming 12 clusters, which can be considered subfields of the central theme of the review. With the cocitations analysis, a thematic affinity was found among the documents reviewed; these studies are closely related to the extent that they have a greater number of bibliographic references in common. With the co-occurrence analysis, the most frequent keywords detected were: "vegetation indexes", "reflectance", "chlorophyll content", "regression" and "spectral reflectance".

Other reviews have been written on estimating plant nutrition with non-destructive methods. Reference [12] describes the techniques available to estimate nitrogen content, finding that several factors influence their suitability and applicability; for example, the accuracy of leaf color tables is not guaranteed since they are based on visual color inspection.

The work in [7] reviewed the use of RGB digital images for foliar nutrition estimation, finding that existing processing technology can support the development of agricultural automation by achieving low price, high efficiency, and high precision. Reference [10] studied proximal image capture with different types of sensors, concluding that studies of this type are becoming less and more dispersed, making it difficult to draw a complete picture of the state of the art of this type of research. On the other hand, [8], [34], [35] focus their reviews on obtaining and analyzing spectral information. Although these reviews give a comprehensive view of the advances in scientific literature, they do not focus on the progress of technological tools, which is the contribution of this review.

B. *Can Artificial Intelligence-based Analysis of Plant Nutrition Provide Relevant Information for Decision-Making in Agricultural Systems?*

The methodology for obtaining and analyzing information in non-destructive plant nutrition studies varies according to the types of data available and the estimation models selected. However, the overall process could be standardized into four phases commonly used for analyzing digital information with artificial intelligence (see Fig. 2). The most used measuring devices for data acquisition are conventional [36], spectral [37], [38], or modified digital cameras [39], and sensors that enable the collection of continuous and discrete numerical values [40], [41]. Some of these sensors and digital cameras can be installed on unmanned aerial vehicles (drones) to conduct canopy-level surveys [42], [43].

The data types obtained are RGB digital images [44], spectral data and images [35], and measurements with SPAD sensors [45] or color sensors [46]. In addition, it is common to calculate vegetation indices from distinct color models and spectral channels [47]. For example, the green channel is the one that has been most frequently used on its own or as part of indices for diagnosing plant nutrition levels [48], [49], [50].

Studies published after 2018 mainly use multi and/or hyperspectral data, probably because researchers have ventured into developing reliable and inexpensive sensors [49] and because of the increase in available computational capacity. Spectral information requires greater computational processing since it presents several bands of information across the entire electromagnetic spectrum [50]. This large amount of information can be used to produce maps of precise biophysical indicators throughout the different crop development cycles, which would allow better decision-making and the implementation of precise agriculture [3].

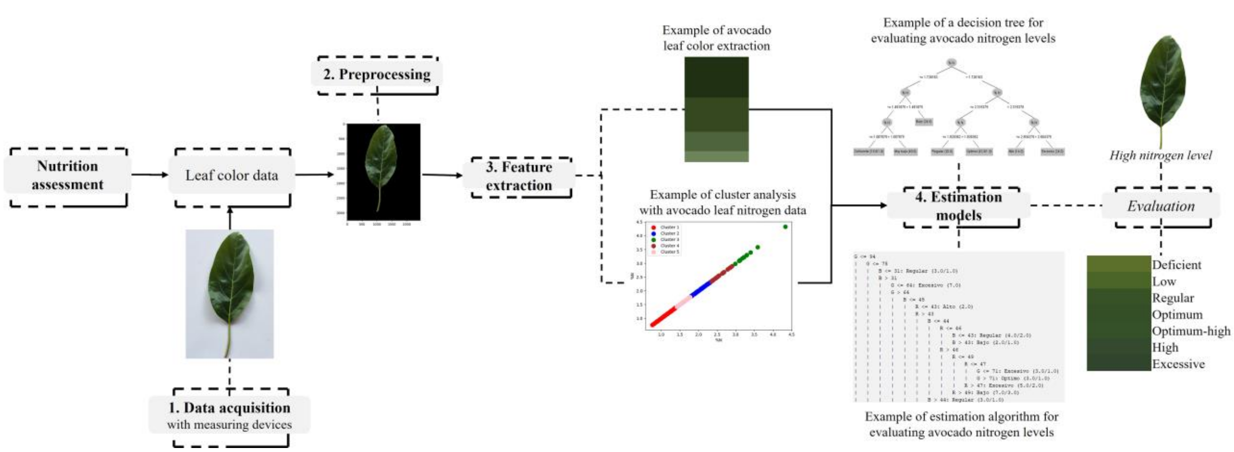

Fig. 2. Phases of data processing for the evaluation of the nutritional level of plants. Example of an assessment of the nitrogen level of an avocado leaf from the color in RGB.

Obtaining spectral information through sensors can be proximal in the field, or aerial. Satellite is the best option for the measurement of the entire field or plot quickly and free of charge. Unmanned aerial vehicles are the most advantageous option to measure quickly with high resolution and high level of detail. Leaf-based sensors are very accurate to measure at a specific point [8].

On the other hand, each data type has its limitations, for example, one of the main challenges associated with digital imaging for plant nutrition diagnostics is the illumination of the environment, as it can have a significant impact on the performance of estimation model algorithms [31]. Light variations in field conditions can severely hinder the ability of models to provide reliable estimates as, for most imaging devices, the same part of a plant may have different color attributes depending on whether the capture conditions are under sunny or cloudy conditions, also changing depending on the time of day, and even if some correction or calibration is applied [51]. In some studies, light conditions have been resolved through controlled environments, such as laboratory conditions, the creation of structures that block the passage of natural light or contact techniques [52].

The massive amounts of information are the most important limitations of using spectral data and images. Redundancy, collinearity, and noise do not favor data processing, therefore, extracting characteristic wavelengths (reducing dimensionality) is necessary for training of estimation models [53]. It should be noted that wavelengths vary, so they must be calibrated and selected according to the type and variety of plant being studied.

Another limitation for the use of spectral data is associated with the type of measurement that is performed, as this can be at the canopy level, which means that reflectance is scanned from the top layer of the leaf and the vertical distribution of nutrients in the crop is difficult to infer. Unlike leaf-level measurements, that are performed only on young leaves that better reflect the current nutritional status of the plants [54], spectral data at the canopy level create uncertainty in crop monitoring and limit the practical value of estimates at the plot and plant levels, given such heterogeneity.

Sensor differences between devices should also be considered, as they can have significant variations [55]. Technical characteristics, such as optical quality and pixel sensor type (CMOS or CCD), change between models and manufacturers [10]; therefore, proper calibration is necessary to compensate for these effects. In addition, the interpretation of measurement results may require expert knowledge and may not be accessible, given the excessive cost of some of these devices.

On the other side, preprocessing is necessary to improve and select information that will be used for training estimation models of crop nutrition levels. In the case of RGB images, the preprocessing can include reducing intensity variations between neighboring pixels (smoothing), modifying pixels whose intensity level is quite different from their neighbors (noise removal), increasing intensity variations between pixels (detail enhancement), detecting pixels with abrupt changes in intensity (edge detection), and adjusting brightness [56]. Different filters can also be applied to enhance RGB images, such as mean, median, and Gaussian [57].

Segmentation is used in RGB images for background extraction, the main challenge is capturing information under field conditions since image backgrounds can be diverse [58]. It is common to use unsupervised analysis to perform feature extraction and find patterns in the data without any prior knowledge of classes or groups, as it allows having an overview of the main sources of variation in the data. Cluster analysis and principal component analysis are among the most used algorithms.

Preprocessing of spectral information is carried out to select important bands to reduce data dimensionality and improve the robustness and interpretability of the estimation models [40]. These preprocessing methods include a) first derivation to overcome band shifting and overlap problems, b) light scattering reduction, and c) reflectance to absorbance conversion to linearize the spectrometer response [59]. First-order derivatives have been the most used, with better results [60], [61]. On the other hand, feature extraction refers to calculating new information from the data. In the case of digital images, it is possible to obtain numerical values of color, texture, shape, and geometry. The final phase of the process consists of estimating and classifying plant nutrient levels through the application of trained mathematical models. Studies published before 2018 mainly used linear regression models, given their simplicity and the possibility of generating approximation functions. More recently, ML and DL models have been used, such as convolutional neural networks, which refer to a class of feedback networks applied to the analysis of digital images [62].

The regression models for estimating plant nutritional levels represent suitable solutions to complex problems thanks to the evolution of ML and DL techniques. Many of these algorithms are freely available on various platforms so that they can be easily applied by anyone with a basic understanding of their concepts [63]. However, one of the main limitations of this models is that, in many cases, users do not have enough knowledge about the algorithms they are applying. Hence, the experimental design is not always appropriate. In addition, it may not be possible to validate the congruence of models with expert knowledge, as some models are so complex that they can function as black boxes, making unfeasible to fully understand the decision process. A summary of the regression and validation models applied in the research with technological tool development considered in this review can be found in the Table II.

In conclusion, artificial intelligence-based analyses of plant nutrition are a good source of information for decision-making in agricultural systems, since its allows monitoring the state of crops by measuring and analyzing different variables. However, using this information implies expert knowledge, high computational processing capabilities, memory spaces, and, in some cases, the acquisition of expensive sensors. Therefore, at this point, its implementation in agricultural fields is not viable; so, the development of technological tools that are easy to use and accessible to decision-makers is necessary.

TABLE II. SYNTHESIS OF THE STUDIES THAT LED TO THE DEVELOPMENT OF A TECHNOLOGICAL TOOL

Reference	Tool or technology development	Branch of artificial intelligence	Input data types	Regression models	Crops	Database size	Validation methods	Models accuracy (best model)
2013 [36]	Software	Machine learning	RGB images	Stepwise multiple linear regression (shoot dry weight showed better performance)	Rice	166 observations for model calibration and 161 observations for model validation	Determination coefficient Root mean square error in prediction	0.87 0.52
2013 [64]	Four-wheel mobile structure	Machine learning	RGB images	Linear regression	Rice	140 samples to develop the prediction model and 80 samples to validate the model	Determination coefficient	0.95
2015 [44]	Smartphone application (PocketN)	Machine learning	RGB images	Linear regression (Dualex was the best method)	Rice	864 determinations for prediction, 54 for determining trueness	Determination coefficient	0.96 in leaves nitrogen content
2015 [52]	Smartphone application	Machine learning and deep learning	RGB images	Linear regression and Neural Network model (NN). The best model was NN	Maize	480 contact images	Determination coefficient Root mean square error	0.82 5.10
2020 [65]	Multispectral sensor	Machine learning	Numerical data	Rational quadratic gaussian process regression. Best model was for Soybean	Canola, maize, soybean, and wheat	Spectral data were collected from 307 leaves (121 for N)	Determination coefficient Root mean squared error	82.29 0.21
2020 [66]	Smartphone application	Computer vision	RGB images	Color difference calculated by the CIEDE2000 formula	Rice	180 leaves	Manual inspections	0.95
2021 [21]	Smartphone application	Machine learning	RGB images	Simple linear regression (carotenoid concentration was the best model)	Spinach	A total of fifty upright leaves were visually selected	Determination coefficient	0.95
2021 [67]	SPAD type portable device (SPAD-Cap) and a web GUI for data control and visualization	Machine learning and deep learning	RGB images	Partial least square regression and convolutional neural network for regression	Rape leaves and some other plant leaves of cotton, sugarcane, citrus, brassica, and bamboo	Totally 120 rape leaves and 50 others were collected and tested	Determination Coefficient Root mean square error	0.97 for rape leaf 2.5 for rape leaf
2022 [68]	Structure for taking photographs	Machine learning and deep learning	Hyperspectral images	Random forest, Support Vector Regression (SVR), partial least square regression, and artificial neuron network. Best model was SVR.	Oil palm	A training set with 50 samples was used to be modeled for each target, and a test set with 15 samples was employed to evaluate model performance	Determination coefficient for prediction Root mean square error of calibration Standard error of prediction	0.655 0.17 0.18
2022 [33]	Hardware device with a spectral camera	Machine learning	Multispectral images	Partial least squares regression	Wheat	144 samples in the calibration set and 72 samples in the validation	Determination coefficient Root mean squared error	0.79 3.94
2022 [69]	Sensor to acquire and analyze a color image	Machine learning	RGB images	Simple linear model	Winter rapeseed	In total 100 rapeseed leaves were examined	Determination coefficient	0.81
2022 [39]	Image acquisition device	Machine learning	RGB images	Random forest sequential backward selection and support vector regression were combined	Aquilaria sinensis	The original dataset contains 48 samples with 108-dimensional image features.	Determination coefficient	0.87

C. Do Studies Reach the Stage of Developing Technological Tools for Application in Agricultural Systems under Field Conditions?

Most of the studies reviewed (86%) did not consider developing a technological tool as part of their objectives. They were limited to applying regression and classification estimation models with different levels of complexity and evaluating their accuracy. Therefore, this knowledge is mainly aimed at specialists, who are usually not the decision-makers in agricultural fields. The few technological developments in the studies reviewed include software [36], mobile applications [21], [52], [66], and hardware devices, such as sensors [33], [65], [69], structures [64], and intelligent robots [70].

The development of mobile applications dates to studies published in 2015 and is resumed in works from 2017, 2020, and 2021. Only one software tool was presented in a study from 2013 [36], and the hardware appeared in documents published in different time intervals (2013-2015, 2017 and 2018, and 2020-2022) (see Fig. 3).

Most of the studies, in which the development and testing of these tools have been published, report satisfactory results in their application. Mobile apps and software were searched on the web for installation and testing but are unavailable. This is probably because they are not open access, their download is blocked in some countries, or the devices used do not meet the requirements for their installation. On the other hand, mobile and robot structures have not been commercialized to the public, their construction and use are limited to experts, so it would be difficult for decision-makers to replicate these structures.

Some tools have not been developed with a scientific approach and have not been published as research but are commercialized and available to farmers. If their accuracy is proven adequate through rigorous testing, they could be valuable options for decision-making in agricultural systems. Examples of such tools are FieldScout GreenIndex+ Nitrogen App, which is a paid application developed to manage the nitrogen needs of maize crops, and Yara ImageIT, created to calculate nitrogen uptake from foliage cover, leaf color, and the estimated brown-leaf fraction.

The limitations that hinder the transfer of knowledge and technology to farmers should also be considered. One limitation is the lack of environmental regulation, which can be lax, especially in poor and developing countries, with no restrictions on fertilizer use and no accompaniment during the production process or incentives to reduce over-fertilization, that makes the optimization of fertilization practices irrelevant. Another limitation is that technology implementation for smart agriculture can involve high costs, making it inaccessible to small and medium-sized farmers.

The rocketing price of chemical fertilizers in recent years may nonetheless change this perception and increase the interest of farmers worldwide in such fertilizer optimization tools, if not for environmental reasons, for economic concerns. Given that such scenario is unlikely to change soon, it is worth to continue developing tools that are economically accessible, with easy-to-interpret and scientific-evidence-based results. Mobile and robot technology is becoming affordable and ubiquitous and should become available to farmers at no or minimum cost to promote sustainable and precision agricultural practices.

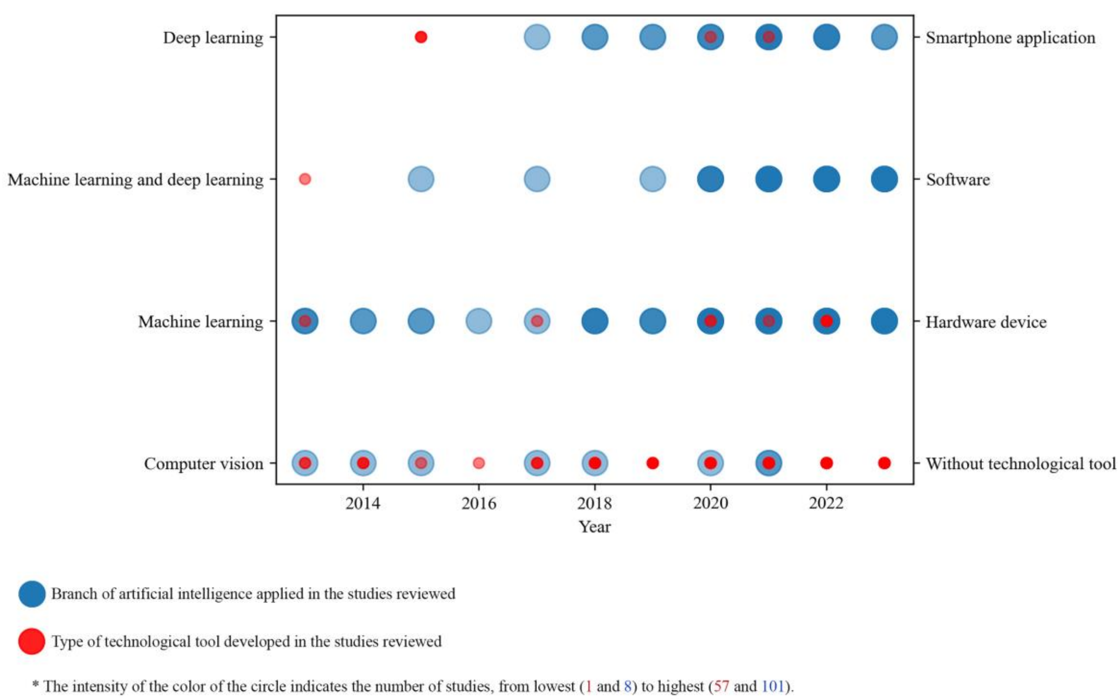

Fig. 3. Types of technological tools created, and branches of artificial intelligence applied in the studies over time.

D. *What is the Way Forward for the Popularization of the Development and Application of Technological Tools in Agricultural Systems?*

There is still much to be done in intelligence-based nutritional diagnostics for different crops, as most studies have focused on cereals, especially rice, maize, and wheat. In addition, varieties of the same crop may possess specific canopy architectures [36], different rates of coloration and leaf development, and different responses to nutritional deficiency [71]. Nutrient estimation models generated for a given crop may become less effective when applied to other varieties of the same crop, which means that it is necessary to develop a specific estimation model for each type of crop [31], [72], [73].

Similarly, the plant developmental stage must be considered, as it may affect the behavior of the variables used by the estimation models given that as plants and leaves mature, leaf color changes [74] and, as a consequence, also their spectral responses [75]. The same plant often contains leaves at different stages of development, so studies should consider conducting experiments with other varieties of the same crop at various critical stages of their growth [72], [73]. It may be more efficient to develop nutritional diagnostic tools for perennial crops, whose varieties do not change as rapidly as annual crops and whose nutritional requirements are more difficult to estimate because plantation areas are usually very heterogeneous and tree responses to fertilization are slow and less evident.

In general, the main weaknesses of current knowledge about intelligence-based nutritional diagnostics are: 1) given that the research has been developed mainly by and for experts, the estimation models and the few technological tools developed are complex, so decision-makers do not use them; b) training estimation models with deep learning requires a large amount of information and computational resources, which can imply a high economic investment if there are no free repositories with the necessary information or adequate computing equipment; and c) its application in agricultural systems is a challenge since most of the knowledge generated has been tested under controlled conditions, without demonstrating promising results in field conditions.

The threats lie in the limitations of the data, estimation models, and tools, which may turn them not robust enough to be applied with acceptable reliability in agricultural fields, producing deficiencies in crop performance. Estimation models require data that can be used as predictor variables of foliar nutrition. Although color has proven to be a good predictor variable for some crops [66], finding the correct variables is a challenge in other cases. Other aspects of the crop, such as leaf shape, size, age, etc., may need to be considered.

The strengths focus on the valuable theoretical knowledge generated to date, which has made possible to establish methodologies for continuing studies of new crops or varieties and different growth stages of crops that have already been studied. Given the high cost of destructive nutrition analyses, farmers use them on a limited number of samples (of leaves or soils, for example), therefore their view of nutrition status at the plot level is limited. However, using estimation models or technological tools would allow multiple estimates to be made quickly and economically to monitor crops at the plot level. So far, most studies have only estimated macronutrient deficiencies [7], [76], so there is an opportunity to generate knowledge from micronutrients.

Furthermore, in 49% of the review studies, ML has been used to generate predictive models, 16% use DL, and 28% compare the performance of algorithms from both subfields. Therefore, there is an opportunity for developing new research in which predictive models are generated using DL to estimate the foliar nutrition of different crops.

The way forward for the popularization of the development and application of technological tools in agricultural systems is the innovation. Innovation can be defined as “invention plus exploitation” [77], and the innovation process considers 1) the production of knowledge and, according to this review, there are currently sufficient advances in the scientific literature; 2) the transformation of knowledge into artifacts, which has had little progress with a scientific basis; and 3) the continuous adaptation of these artifacts, according to the needs and demands of the market. Based on the documents reviewed, we can infer that it has only been achieved by commercial tools, whose developments have yet to be published in the scientific field. Although the innovation process can follow different paths, depending on the type of product, in Fig. 4, we propose a path forward focused on generating technological tools with a scientific basis.

In the future, we glimpse a precision agriculture achieved through technological innovation, using monitoring systems and the Internet of Things for the acquisition of crop information [78]. Also, soil and climate information could be included in the estimating models, representing an improvement in their capacity and the possibility of including fertilization recommendations besides nutritional diagnosis. A monitoring system would not only identify plant nutritional deficiencies, but could calculate and provide optimal solutions, informing the user of the required nutrient supply and focusing not only on one type of nutrient but several. Also, Mobile smartphones and similar devices will soon be accessible (sensu lato, in terms of costs, operation, language, connectivity, etc.) even in the most remote areas, and developing free/low-cost applications to support farmers is becoming easier and cheaper (see Fig. 5).

Therefore, the popularization of the development and application of technological tools in agricultural systems represents a valuable opportunity to translate the scientific knowledge generated into accessible tools that bring together the recent boom of technological advances and put them in the hands of people to facilitate and promote a sustainable management of natural resources. In this regard, it is crucial to form multidisciplinary working groups that bring together experts in agronomy, sustainability, programming, robotics, electrical systems, data analysis, among others. Finally, research information should be shared in free repositories to increase the amount and variety of data available to improve the training and validation of estimation models and technologies.

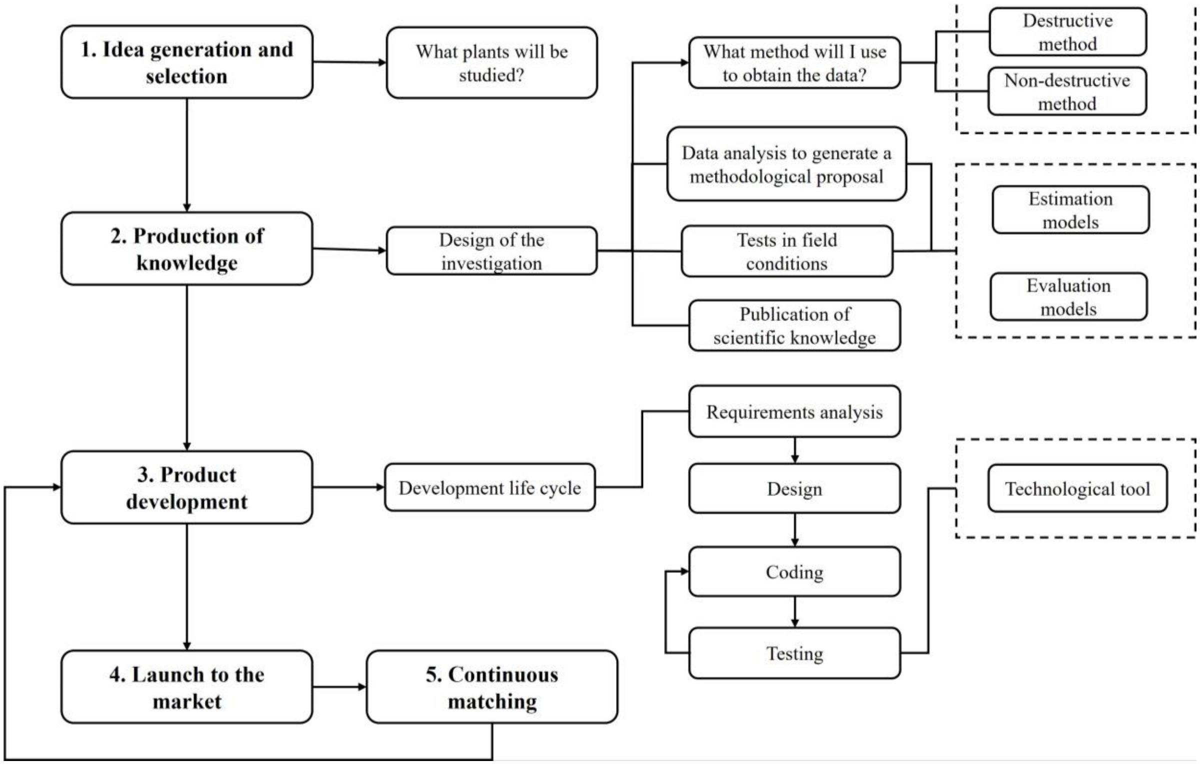

Fig. 4. Process proposal for the generation of technological tools from scientific information considering the phases of innovation and the development cycle of software or mobile applications.

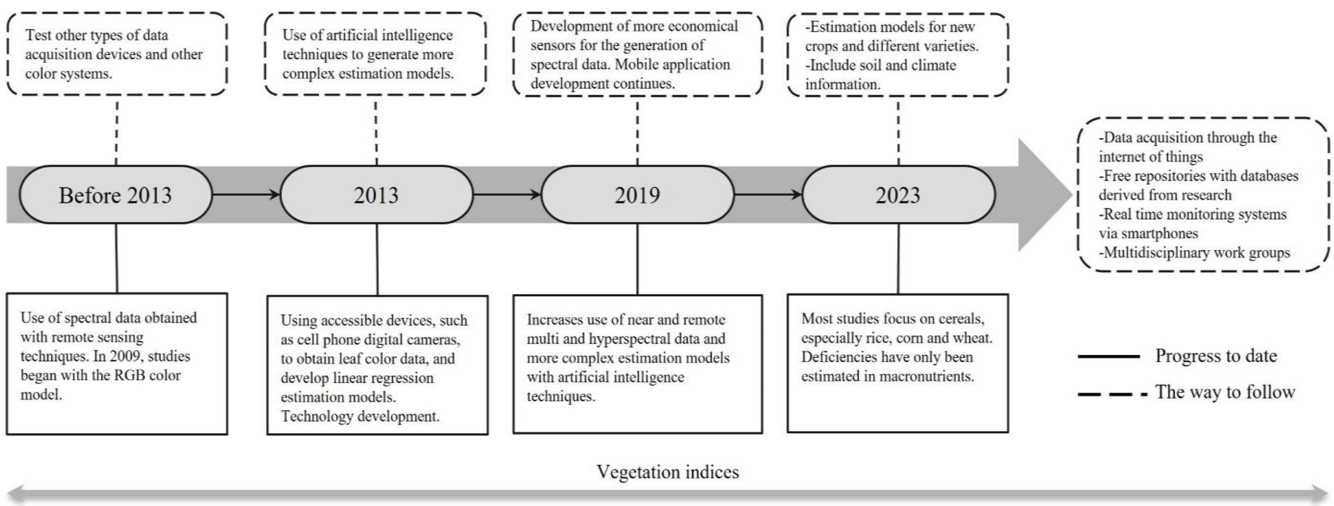

Fig. 5. Advances in assessing the nutritional status of plants with non-destructive methods and the gaps in their study, which become future opportunities, and the way forward.

IV. Conclusions

In a promising future, theoretical scientific knowledge will evolve towards technological innovation to achieve precision and sustainable agricultural systems. The estimation of foliar nutrients with AI non-destructive methods will be carried out also using more technological tools, with information acquisition achieved through the Internet of Things and with all this information stored in free repositories for use in training robust estimation models. As a direct result, real-time monitoring systems will be developed based on these models, which will integrate hardware and special software built for the particular characteristics of each crop type by interdisciplinary and scientifically based work groups, approaching alternative agriculture and seeking environmental conservation.

Nowadays, it is possible to estimate the nutritional status of crops through quick, economical, and non-destructive measurements thanks to current technological advances. These characteristics are of the utmost relevance to support farmers and advance environmental conservation. This paper presented an overview of the current state of scientific research to identify its scope to generate accessible technological diagnostic and planning tools that support farmers.

It is possible to conclude that digital image processing has evolved to allow the detection of slight visual alterations in plant color and morphology using appropriate technology. At the same time, through predictive models, it is possible to solve problems of approximation and classification of values with acceptable precisions, with sufficient, representative available data. However, the main limitation lies in the limited development of technological tools accessible to all types of farmers and other non-expert users. These tools should include robotic systems, specialized software, and mobile applications for decision-makers that can be used and tested in practical field environments.

The scientific community must prioritize advancing science and technology that improves the quality of life, especially those that help produce healthy and safe crops in a healthy environment. The skills required to achieve these goals are within our reach, as can be inferred from the research presented in this review. Although there are still challenges and constraints to overcome, progress is being made in the right direction to achieve a brighter future in agriculture that focuses on preserving natural resources and biodiversity while enabling the production of high-quality food.

Acknowledgments

This work was financed by Dirección General de Asuntos del Personal Académico (DGAPA) from the National Autonomous University of Mexico (UNAM) through projects PAPIIT-IN223824 granted to M.E.G., PAPIME PE106021 granted to H.F.M., and a postdoctoral fellowship granted to Á.G. Thanks to the National Laboratory of Ecotechnological Innovation for Sustainability (LANIES-UNAM) for hosting and supporting this work and to Sergio. R. Tinoco M. for his comments on this work.

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