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Drones in vegetable crops: A systematic literature review

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ABSTRACT

In the context of increasing global population and climate change, modern agriculture must enhance production efficiency. Vegetables production is crucial for human nutrition and has a significant environmental impact. To address this challenge, the agricultural sector needs to modernize and utilize advanced technologies such as drones to increase productivity, improve quality, and reduce resource consumption. These devices, known as Unmanned Aerial Vehicles (UAV), with their agility and versatility play a crucial role in monitoring and spraying operations. They significantly contribute to enhancing the efficacy of precision farming.

The aim of this review is to examine the critical role of drones as innovative tools to enhance management and yield of vegetable crops cultivation. This review was carried out using the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) framework and involved the analysis of a wide range of research published from 2018 to 2023. According to the phases of Identification, Screening, and Eligibility, 132 papers were selected and analysed. These papers were categorized based on the types of drone applications in vegetable crop production, providing an overview of how these tools fit into the field of Precision Farming. Technological developments of these tools and data processing methods were then explored, examining the contributions of Machine and Deep Learning and Artificial Intelligence. Final considerations were presented regarding practical implementation and future technical and scientific challenges to fully harness the potential of drones in precision agriculture and vegetable crop production. The review pointed out the significance of drone applications in vegetable crops and the immense potential of these tools in enhancing cultivation efficiency. Drone utilization enables the reduction of input quantities such as herbicides, fertilizers, pesticides, and water but also the prevention of damages through early diagnosis of various stress types. These input savings can yield environmental benefits, positioning these technologies as potential solutions for the environmental sustainability of vegetable crops.

Introduction

In the past decades, precision agriculture has emerged as a significant solution to address the increasingly pressing challenges associated with agricultural production, including the production of vegetable crops. With climate change posing threats to agricultural resources and a steadily growing global population, the need to efficiently and sustainably enhance food production becomes essential. According to the report "Future of Food and Agriculture: Alternative Pathways to 2050″ by the United Nations Food and Agriculture Organization (FAO), the global population is projected to reach nearly 10 billions by 2050, leading to a corresponding increase in demand for food crops [1]. At the same time, the surfaces and water resources available for agriculture are becoming increasingly scarce [1,2]. In this scenario, society places immense pressure on agriculture, driving towards increased crop yields without compromising quality, while simultaneously reducing operational costs and global pollution.

Within the agricultural context, vegetables play a primary role; indeed, they are considered protective foods, providing essential nutrients to the human diet due to their richness in vitamins, fibres, minerals, and nutraceuticals [3]. Furthermore, regular consumption of fruits and vegetables contributes to the risk reduction of numerous diseases, including cardiovascular diseases and cancer [4].

Overall efficient and sustainable cultivation techniques become necessary. Precision agriculture plays a paramount role among the techniques that are transforming agricultural production, and can be regarded as one of the most promising solutions [5].

In this context, there is a growing adoption of advanced and intelligent techniques and technologies, such as artificial intelligence and unmanned aerial vehicles (UAVs) [6]. These vehicles enhance the

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cultivation processes, as they can perform monitoring and spraying missions, thus optimizing the efficiency of pesticide, fertilizer, and water usage. They promptly identify stress induced by pests, diseases, nutritional and water deficiencies, while also facilitating the spraying procedure [7]. The applications of UAVs in agriculture are different and include nearly all agricultural productions. For example, applications in viticulture, olive cultivation, orchards, herbaceous crops, as well as vegetable cultivation, are well-established [8–13].

The main objective of this review is to analyse how drones can be employed in precision agriculture concerning vegetable crops. This study aims to provide a critical and comprehensive synthesis on the topic through a systematic literature review of the last six years, focusing on the key objectives that can be achieved using drones in this field.

Drones in agriculture

Drones are currently one of the most representative technologies in the evolution of precision agriculture in the scientific and productive world. However, their history began in other fields of application. The drone, in fact, originated as a tool to be employed in the military sector, aiming to safeguard the integrity of human personnel in reconnaissance and surveillance missions. Over time, their use has extended well beyond the military context, finding applications in various sectors, including entertainment, transportation, security, photography, and environmental exploration [14].

The most common designation is "Unmanned Aerial Vehicles" (UAV). They can also be defined by other acronyms, many of which are of Anglo-Saxon origin: in addition to "Remotely Piloted Aircraft System" (RPAS), they may be referred to as "Unmanned Aerial System" (UAS), "Aerial Robot" or simply "Drone" [15].

These terms refer to a complex system consisting of the aerial platform, one or more components and/or sensors making up the payload, and a ground station in communication with the flight controller of the platform. Within the flight controller, components dedicated to the orientation and movement of UAVs are present, including gyroscopes, magnetic compass, GNSS module, pressure sensor, and triaxial accelerometer [16].

UAVs are generally categorized based on various attributes, including aircraft types, wing types, takeoff/landing direction, payloads, flying altitude, etc. [17].

According to the classification by Watt et al. [18], they can be distinguished as MAV (Micro (or Miniature) or NAV (Nano Air Vehicles), VTOL (Vertical Take-Off & Landing), LASE (Low Altitude, Short-Endurance), LALE (Low Altitude, Long Endurance), MALE (Medium Altitude, Long Endurance), HALE (High Altitude, Long Endurance).

The most used platforms in precision agriculture fall into the LASE class and are fixed-wing systems or multirotors, such as helicopters, quadcopters, hexacopters, octocopters, etc. VTOL multirotor platforms, widely employed for crop monitoring, generally weigh less than 5 kg excluding the payload. They are equipped with interchangeable lithium batteries, and are easily transportable, facilitating transfers between different fields.

UAV platforms can be controlled by the operator through the ground station, remaining in the field of vision, or they can fly in automatic mode, following a trajectory defined by the user through waypoints during the flight plan design phase.

Payloads can include sensors and cameras for data collection or even specialized equipment for tasks such as crop spraying [Section 4.7]. Although the sensors that drones can be equipped with are numerous, the most commonly used on UAV platforms for agricultural purposes are:

-Visible cameras, RGB (Red, Green and Blue): these are the simplest cameras capable of producing grayscale or color images for characterizing the visible properties of plants and their growth [19,20].

-Multispectral cameras: capable of producing images in different bands of the spectrum. These cameras typically cover the visible (VIS) and Near InfraRed (NIR) portions of the spectrum and can be used to calculate most vegetation indices used in agriculture. Many of these indices have been used by different authors in the papers included in this review, and they are summarized in Table 1 [8,21].

-Hyperspectral cameras: this type of sensor provides images in a high number of bands with very high spectral resolution, detecting a vast amount of information. The application of these cameras allows for in-depth analysis of crops, providing information on the presence of various pathogens [42,43].

-Thermal cameras: they provide images with information about the temperature of each pixel. These sensors enable thermal alterations

Table 1
Vegetation Indices included in this review.

Acronym	Index name	Equation	Reference
NDVI	Normalized Difference Vegetation Index	$\frac{\rho\ 800-\rho\ 680}{\rho\ 800+\rho\ 680}$	[22]
TVDI	Temperature Vegetation Dryness Index	$\frac{(Ts-Ts\ \min)}{\left(a+b\left(\frac{\rho\ 550\ -\rho\ 680}{\rho\ 550\ +\rho\ 680}\right)-Ts\ min\right.}$	[23]
RVI	Simple Ratio Index	$\frac{\rho\ 800}{\rho\ 680}$	[24]
GNDVI	Green Normalized Difference Vegetation Index	$\frac{\rho\ 800-\rho\ 550}{\rho\ 800+\rho\ 550}$	[25]
OSAVI	Optimized Soil Adjusted Vegetation Index	$(1+0.16)*\frac{\rho\ 800-\rho\ 680}{(\rho\ 800+\rho\ 680+0.16)}$	[26]
SAVI	Soil Adjusted Vegetation Index	$\frac{\rho\ 800-\rho\ 680}{\rho\ 800+\rho\ 680+L}*(1+L)$	[27]
NGRDI	Normalized Green Red Difference Index	$\frac{\rho\ 550\ -\rho\ 680}{\rho\ 550\ +\rho\ 680}$	[28]
MSR	Modified Simple Ratio	$\frac{((\rho\ 800/\rho\ 680)-1)}{\sqrt{\left(\left(\frac{\rho\ 800}{\rho 680}\right)+1\right)}}$	[29]
MCARI	Modified Chlorophyll Adsorption Ratio Index	$((\rho\ 730-\rho\ 680)-0.2*(\rho\ 730-\rho\ 550))*(\rho\ 730\ /\rho\ 680)$	[30]
Ci_{green}	Chlorophyll Index green	$\left(\frac{\rho\ 800}{\rho\ 550}\right)-1$	[31]
$Ci_{rededge}$	Chlorophyll Index red edge	$\left(\frac{\rho\ 800}{\rho\ 730}\right)-1$	[31]
CCCI	Canopy Chlorophyll Content Index	$((\rho\ 800-\ \rho\ 730)/(\rho\ 800+\rho\ 730))/((\rho\ 800-\rho\ 550)/(\rho\ 800+\rho\ 550))$	[32]
GLI	Green Leaf Index	$\frac{2\ \rho\ 550-\rho\ 680-\ \rho\ 450}{2\ \rho\ 550+\rho\ 680+\rho\ 450}$	[33]
NDRE	Normalized Difference Red Edge	$(\rho\ 800-\ \rho\ 730)/(\rho\ 800+\rho\ 730)$	[34]
TBI $_{(530,\ 734,\ 514)}$	Three-band Spectral Index	$\frac{\rho\ 530-\rho\ 734}{\rho\ 734+\rho\ 514}$	[35]
WDVI	Weighted Difference Vegetation Index	$\rho\ 800-(a*\rho\ 680)$	[36]
PRI	Photochemical Reflectance Index	$\frac{\rho\ 531-\rho\ 570}{\rho\ 531+\rho\ 570}$	[37]
RDVI	Renormalized Difference Vegetation Index	$(\rho\ 800-\rho\ 680)/\sqrt{(\rho\ 800+\rho\ 680)}$	[38]
MTVI 1	Modified Triangular Vegetation Index1	$1.2\ [1.2\ (\rho 760-\rho 580)-2.5(\rho 650-\rho 580)]$	[39]
CWSI	Crop Water Stress Index	$\frac{(Tc-Ta)\ -\ (Tc-Ta)LL}{(Tc-Ta)UL\ -\ (Tc-Ta)LL}$	[40]
ExG	Excess Greenness Index	$\left(\frac{(2*\rho\ 550)-\rho\ 680-\ \rho\ 450}{\rho\ 680+\rho\ 550+\rho\ 450}\right)$	[41]

identification on the leaf surface induced by water stress conditions, making them particularly useful for water management [44,45].

-Laser Imaging Detection and Ranging (LiDAR): these are active sensors that leverage the physical operating principle of Radio Detection and Ranging (RADAR). In particular, these sensors emit a light pulse (laser, in the case of LiDAR) or microwaves (RADAR) and measure the return of the pulse reflected by the target using a detector, calculating the time [46,47]. These sensors provide physical measurements of the geometry and volumes of canopies [48].

Materials and methods

A systematic literature search method was employed to compose this review, following the guidelines set forth by PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) (https://doi.org/10.1136/bmj.n71, Consulted on May 3rd, 2023) [49]. The research method encompassed identification, screening and eligibility procedures. This systematic analysis of the literature was chosen due to its methodical, replicable, and comprehensive approach. This method aims to mitigate bias risks through precise and exhaustive literature searches, thereby offering a transparent and scientifically rigorous process. Moreover, it provides a detailed account of the procedures followed by the authors.

Identification

The research was conducted in May 2023. The Scopus database was used to perform the systematic review. Titles, abstracts and keywords were used as the search fields within the Scopus electronic database. The query used in the search encompassed 112 fields (as detailed in the document 'Query ricerca bibliografica Review.docx'). The chosen keywords were selected based on preliminary research and their demonstrated usefulness in finding relevant articles.

Furthermore, the results obtained from Scopus were filtered with the following criteria: (1) The paper was published between 2018 and 2023, (2) The paper was not a review or conference review, (3) The paper was not a book or book chapter, (4) The paper was not a letter, erratum, data paper, note, (5) The paper was not a conference paper. In total, 864 papers were identified, and the search results were saved in the Scopus database for subsequent analyses. The process followed is shown in Fig. 1.

Screening

The authors reviewed the titles and abstracts of all the 864 articles found. The inclusion criteria and progression to the next stage were: (1) The paper included UAV applications, (2) The paper included applications on vegetable crops. Out of the previously selected 864 papers, only 182 met the criteria. These papers were exported to the personal Zotero library.

Eligibility

The authors examined all the 182 papers by reading the entire text of each paper. Papers with the following characteristics were excluded: (1) The full text was not available, (2) The paper did not actually involve the use of drones in vegetables cultivations, (3) The paper did not pertain to precision agriculture applications. In this phase, 50 papers did not meet the criteria, while 132 articles were used as the foundation for conducting this review.

Data analysis

The 132 papers that successfully passed the Identification, Screening, and Eligibility stages were exported to Excel. Data analysis was conducted using this software to consolidate the results from various studies

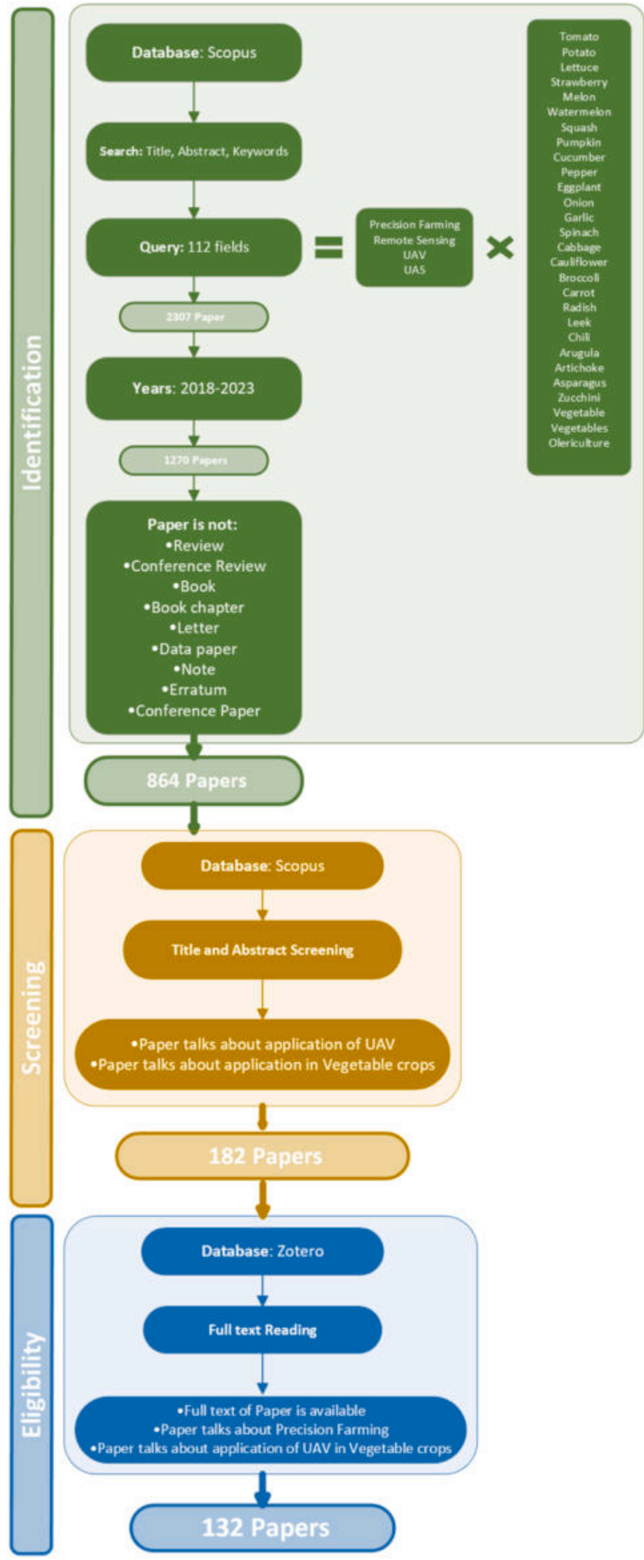

Fig. 1. Flowchart illustrating the consecutive stages and results of the identification, screening, and eligibility procedures.

on the topic of this review. The following data were extracted from each study: Title, Author, Year, analysed Species, Family, Study purpose, Sensor type(s), Sensor spectral range, Number of sensor bands, Post-processing techniques, Vegetation indices, and results obtained. The data extracted during this phase were analysed and evaluated. The data analysis revealed heterogeneity in the objectives obtained by using drones, and they were summarized into seven goals as described in section 34.

Through data analysis, significant trends in this field of study have been identified. Fig. 2 graphically represents the distribution of the papers based on the crop families studied. In particular, 52 % of the papers focused on UAV applications within the Solanaceae family, underscoring the central role of crops like potatoes, tomatoes, peppers, and eggplants in both scientific research and agricultural production. The Brassicaceae family ranks second at 13 %, encompassing crops like cabbage, cauliflower, and radish. Subsequently, there are Cucurbitaceae (9 %), Amaryllidaceae (8 %), Amaranthaceae (6 %), Rosaceae (5 %), Asteraceae (5 %), and Apiaceae (2 %).

In this phase, an analysis of the bibliographic sources was conducted, with a particular focus on evaluating the journals and conferences included. For each journal or conference within the review, the evaluation parameters on the Scopus platform were examined to assess the relevance of the utilized sources. This platform calculates scientific journals relevance using three key parameters:

- CiteScore: this index measures the average citations received per document published within the considered series.
- Source Normalized Impact per Paper (SNIP): this parameter assesses the citations received relative to the expected citations for the series' subject field, thereby normalizing the impact of citations within the context of the relevant discipline.
- Scimago Journal Rank (SJR): this index measures the weighted citations received by the series, taking into account both the subject field and the prestige of the citing series. The citation weighting is contingent on the subject field and the prestige (SJR) of the citing series.

The aforementioned indices, referred to 2022, were extracted for each journal included in the review and are summarized in Table 2.

Results

The selected papers under review have been categorized into seven distinct groups. Each of these categories represents a specific task that drones can undertake within the realm of precision agriculture applied to vegetable crops. Each task is addressed as an individual section within this review. These sections are arranged in a logical sequence. Initially, the papers pertaining to UAV applications for crop monitoring throughout their growth cycles are discussed. In particular, the first section deals with crop identification and segmentation within images captured by drones, with the same principles applied to weed detection in the "Crop and Weed Detection" (section 4.1). Subsequently, papers primarily focused on photogrammetry are described in the "Morphological and Geometrical Feature Extraction" (section 4.2). Then, papers related to "Crop Health and Stress Monitoring" (section 4.3) are addressed, followed by "Disease and Pest Scouting" (section 4.4), "Water Management" (section 4.5), and finally leading to papers concerning yield estimation in the section titled "Yield, Biomass, and Ripening Estimation" (section 4.6). Additionally, papers that explore the

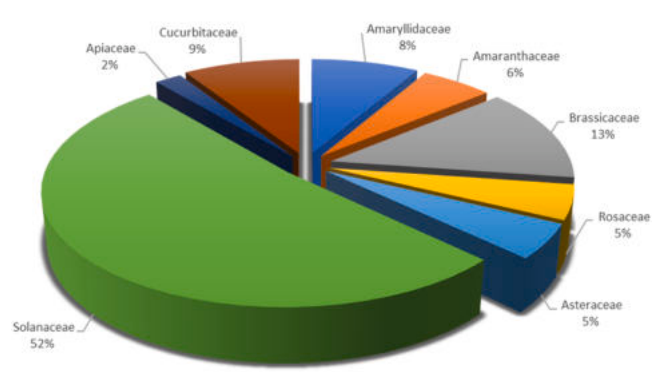

Fig. 2. Distribution of the papers based on the families of the species under study, along with their percentages.

Table 2
Relevance indices of the sources considered in the review.

Source title	Number of papers	CiteScore	SJR	SNIP
Acta Horticulturae	2	0.5	0.149	0.167
Agricultural Water Management	5	10.7	1.524	2.018
Agriculture	4	3.6	0.561	1.162
Agronomy	9	5.2	0.663	1.215
Agronomy Journal	2	4.3	0.586	0.889
American Journal of Potato Research	1	4.6	0.39	0.938
Applied Sciences	2	4.5	0.492	0.974
Autonomous Air and Ground Sensing Systems for Agricultural Optimization and Phenotyping	4	0.7	0.166	0.235
Biosystems Engineering	1	10.1	1.061	1.931
Canadian Journal of Remote Sensing	1	3.9	0.619	0.651
Computers and Electronics in Agriculture	7	13.6	1.587	2.473
Drones	2	6.1	0.845	1.884
Engineering in Agriculture, Environment and Food	1	4.9	0.325	0.568
European Journal of Remote Sensing	1	7	0.66	1.131
Field Crops Research	1	9.6	1.396	2.001
Frontiers in Plant Science	10	7.1	1.231	1.580
Horticulturae	2	2.4	0.487	0.969
International Journal of Advanced Computer Science and Applications (IJACSA)	1	2.1	0.258	0.512
International Journal of Applied Earth Observation and Geoinformation	4	10.2	1.628	1.833
International Journal of Remote Sensing	3	7	0.732	1.030
IOP Conference Series: Earth and Environmental Science	1	0.8	0.197	0.255
ISPRS Journal of Photogrammetry and Remote Sensing	1	19.2	3.308	3.280
Journal of Applied Remote Sensing	2	3.4	0.388	0.564
Journal of Biosciences	1	4.8	0.586	0.599
Journal of Experimental Botany	1	12	1.823	1.619
Journal of Sensors	1	2.6	0.366	0.774
Journal of Unmanned Vehicle Systems	1	N/A	N/A	N/A
Multidimensional Systems and Signal Processing	1	5.2	0.516	1.045
PFG – Journal of Photogrammetry, Remote Sensing and Geoinformation Science	1	6.4	0.801	1.172
Plant Disease	1	4.5	0.677	1.058
Plant Methods	2	10.6	1.121	1.904
Plant Phenomics	1	12	1.341	1.563
PLOS ONE	1	6	0.885	1.253
Precision Agriculture	9	11.1	1.209	2.183
Remote Sensing	25	7.9	1.136	1.532
Remote Sensing for Agriculture, Ecosystems, and Hydrology XXI	1	0.7	0.166	0.235
Sensors	3	6.8	0.764	1.317
Smart Agricultural Technology	9	2.6	N/A	0.666
Soft Computing	1	7.7	0.819	1.349
Spanish Journal of Agricultural Research	1	1.9	0.249	0.55
Spatial Information Research	1	4	0.448	0.851
Sustainability	1	5.8	0.664	1.198
Sustainable Computing: Informatics and Systems	1	8	0.869	1.515
The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences	2	1.8	0.274	0.427

applications of UAVs as tools for aerial spraying are discussed in a separate section titled "Aerial Spraying" (section 4.7).

Fig. 3 illustrates the goals achievable by drones in precision agriculture applied to vegetable crops, along with the respective number of dedicated papers. Specifically, the most extensively studied category was “Crop Health and Stress Monitoring”, followed by “Crop and Weed Detection” and “Morphological and Geometrical Feature Extraction”. “Aerial Spraying” was indeed the category with the fewest number of dedicated papers, despite a growing scientific interest in this topic.

Fig. 4 shows the distribution of the examined papers by year. A clear upward trend is evident from 2018 to 2022, with 36 papers published in 2022 and 26 papers published by mid-2023, as compared to 7 and 14 papers published in 2018 and 2019, respectively.

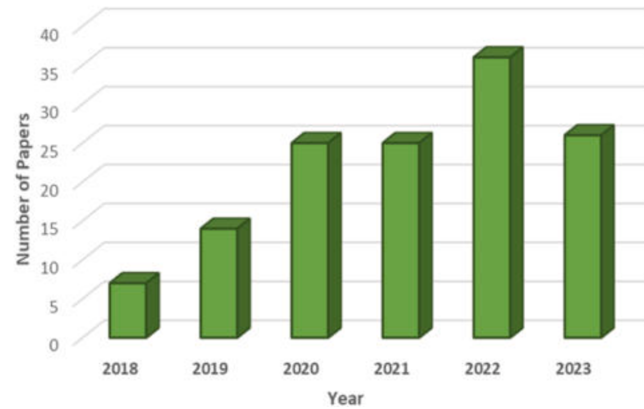

Fig. 4. Paper distribution per year in the period 2018–2023.

Crop and weed detection

Table 3 shows an overview of the different algorithms used by the examined authors with reference to Crop and Weed Detection. For each reference, the best algorithm among the ones that were tested is reported, together with its accuracy.

Crop detection

When utilizing images acquired through UAV to extract information about plant morphology or health, they must undergo a processing procedure. One of the initial crucial steps in this process is Crop Detection [50]. Crop detection refers to crop identification, classification, segmentation, and/or mapping [51]. This process allows for isolating the crop of interest, referred to as Region Of Interest (ROI), within the images, while excluding everything that is not ROI, known as the background [52]. This background could simply be the soil, but it can also be highly heterogeneous. For instance, Kim et al. [53] extracted the canopy of onions and garlic from a complex background consisting of plastic mulch, soil, and shadows under varying lighting conditions. Huang et al. [54] recognized the canopy of zucchinis intercropped with sunflowers. Regarding the methodologies employed to extract the crop from high-resolution images captured by drones, two primary categories can be distinguished: object-based methods, such as Object-Based Image Analysis (OBIA) or Geographic Object-Based Image Analysis (GEOBIA), and pixel-based methods, which primarily utilize Machine Learning and Deep Learning algorithms (Fig. 5) [55].

Modica et al. [56] compared and evaluated different object-based methods and machine learning algorithms for segmenting and classifying onion crops, achieving the best results with Support Vector Machine (SVM) and Random Forest (RF) algorithms. Valente et al. [58] proposed an automatic machine vision method to identify and count spinach plants. This method, through the combination of Otsu’s method and transfer learning Convolutional Neural Network (CNN), achieved an accuracy of 95 %. Machefer et al. [59] on the other hand, used a Mask R-CNN for plant counting and sizing in potato and lettuce, achieving a multiple object tracking accuracy (MOTA) of 0.78 for potato plants and 0.91 for lettuces. This evaluation metric has the advantage to synthesize other error sources such as false positives, missed plants and identity switches, allowing for the assessment of the performance of object detection algorithms [74].

Through these methodologies, it is possible to monitor the development of crops from the early growth stages, estimating the seedling

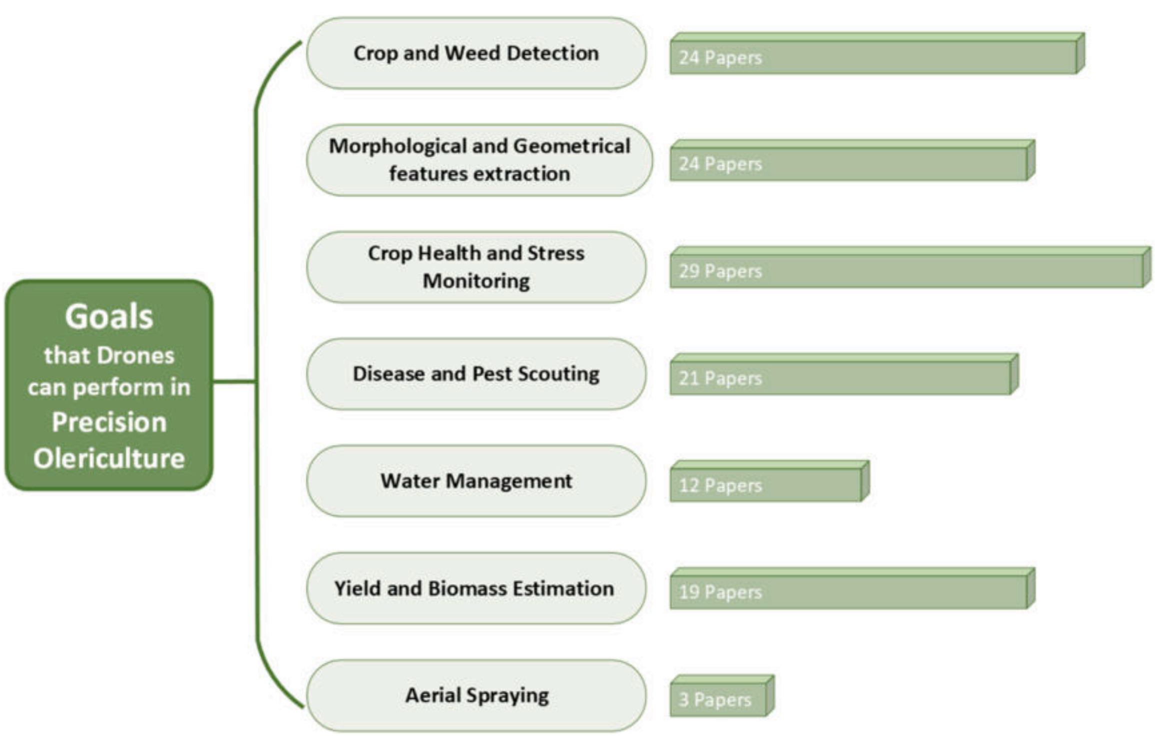

Fig. 3. Distribution of the papers based on their research goals, with the number of articles within each section.

Table 3
Overview of the different algorithms used by the authors for Crop and Weed Detection.

Specific Task	Crop	Method/ best algorithm	Accuracy	References
Detection of ROI: extracting crop from image	Carrot; Cabbage; Spinach; Potato	Attention Based Recurrent Convolutional Neural Network (ARCNN)	92.80 % (OA)	[50]
	Cabbage	DeepLab V3+	0.9 (MIoU)	[51]
	Tomato	Local maxima Extraction and Baesyan Segmentation	0.98 (OA)	[52]
	Onion e Garlic	CIE L*a*b* color space and mean shift (MS)	84.6 % (ASP)	[53]
	Zucchinis	OCRNet	mIoU 94.4 %	[54]
	Cabbage	Mask R-CNN	86.63 % (mAP)	[55]
	Onion	Random Forest (RF)	91.20 (PA)	[56]
	Chili	prototypical network	96.46% (LA)	[57]
Plant counting, density estimation	Spinach	Excess Green Index and Otsu thresholding methods + AlexNet	98.6% (OA)	[58]
	Potato	Mask R-CNN	0.781 (MOTA)	[59]
	Lettuce	Mask R-CNN	0.918 (MOTA)	[59]
	Strawberry	Fully convolutional network (FCN)	0.67 (PPMC)	[60]
	Potato	Excess Green Index and Otsu thresholding methods	0.96 (R^2)	[61]
	Potato	Faster Region-based Convolutional Neural Network (FRCNN) framework	0.80 (R^2)	[62]
Weed detection	Cabbage	Convolutional Neural Network (CNN)	92.41% (OA)	[63]
	Strawberry	Improved faster R-CNN	95.3 % (AA)	[64]
	Onion	You Only Look Once (YOLOv3)	93.81 % (AP)	[65]
	Lettuce	Regression between total cover values (25 calibration images) and total weight measured	HC	[66]
	Pepper	U-Net	71.20% (MIoU)	[67]
	Onion	Maximum Likelihood (ML) and Support Vector Machine (SVM) algorithms	< 85% (OA)	[68]
	Spinach	visual transformers (ViT)	99.63% (OA)	[69]
	Strawberry	Semi-Supervised Generative Adversarial Network (SGAN)	90% (AA)	[70]
	Spinach	CNNs, Residual Network (ResNet)	94.34% (AUCs)	[71]
	Spinach, pepper	Faster RCNN	98.3% (CA)	[72]
	Spinach, pepper	You Only Look Once (YOLO) v5s,	0.712 (AP)	[73]

Overall accuracy (OA); Mean intersection over union (MIoU); Average Segmentation Performance (ASP); Object Detection Accuracy (mAP); Segmentation Accuracy (PA); Location Accuracy (LA); Multiple Object Tracking Accuracy (MOTA); Hight Correlation (HC); Pearson Product Moment Correlation Coefficient (PPMC); Correlation Coefficient (R2); Average Accuracy (AA); Average Precision (AP); Area Under Curve (AUCs); Classification Accuracy (CA).

percentage through seedling identification. For instance, D. Zhang et al. [57] developed a detection framework based on a prototypical network for chili seedling crop detection, achieving a location accuracy of 96.46 %. Barreto et al. [60] extended a fully automatic method for counting maize seedlings to strawberries, with prediction errors lower than 4 %. For the estimation of potato crop emergence, Li et al. [61] developed a semi-automatic image analysis software, obtaining results comparable to manual field assessment ($r^2 = 0.96$). In addition to evaluating crop emergence and seedling identification, it is also possible to monitor plant density variation throughout the season, as demonstrated by Mhango et al. [62] in a study conducted on potatoes.

Once the crop is identified, it becomes feasible to proceed with various other tasks, both of photogrammetric and spectral nature, which are individually addressed in the subsequent sections.

Weed detection

The effective control of weeds is of paramount importance in agriculture, which is why the use of herbicides is widespread. However, to reduce herbicide usage, a method called "site-specific weed management" (SSWM) is increasingly gaining traction [75]. This approach capitalizes on the fact that weeds are not uniformly distributed within a field but tend to form clusters, providing a significant opportunity for herbicide savings [76]. The use of high-resolution images acquired through drones enables efficient identification and differentiation of weeds from the main crop. This aspect has garnered attention from various authors who have conducted different studies, employing different methodologies and applying them to various types of vegetables crops. For instance, Ong et al. [63] in cabbage cultivation, Khan et al. [64] in strawberry cultivation, and Parico and Ahamed [65] in onion cultivation. These systems have also been implemented in protected environments; Pallottino et al. [66], for example, estimated the exact weed amount on baby-sized red lettuce under a polyethylene multi-tunnel greenhouse using a light drone.

Another interesting application was observed in a study conducted by Gutiérrez-Lazcano et al. [67]. These authors successfully identified and segmented Cuscuta spp. plants, a worldwide-distributed weed known to pose problems for various types of crops.

The methodologies employed for weed detection rely on classification algorithms that discriminate between weeds, the main crop, and the background. These algorithms can be categorized into three main groups: supervised, semi-supervised, and unsupervised, based on how the labelling process for generating the training dataset occurs. Rozenberg et al. [68] used two supervised classification algorithms, Maximum Likelihood (ML), and Support Vector Machine (SVM), for weed identification in onion fields. A significant challenge of supervised methods is the need for a sufficiently large dataset to train the model, which is a time-consuming and tedious task. To address this issue, Reedha et al. [69] proposed a Visual Transformers (ViT) approach to reduce the size of the labelled dataset, demonstrating the potential of this method in weed classification in beet, parsley, and spinach fields. Khan et al. [70], on the other hand, introduced a new semi-supervised method, an algorithm that generates an additional training dataset for model training. This method achieved an accuracy of 90 % for classifying weeds in pea and strawberry fields with 80 % of the training data left unlabelled.

Regarding non-supervised methods, Bah et al. [71] proposed a fully automatic learning method (unsupervised) for weed detection (Fig. 6); this method yielded results comparable to supervised methods in tests conducted in spinach fields, with only 1.5 % differences in accuracy. In training a deep learning model, the number of epochs required to train accurate and robust algorithms must be considered. In a study evaluating the effect of the number of epochs in Faster Region-Based

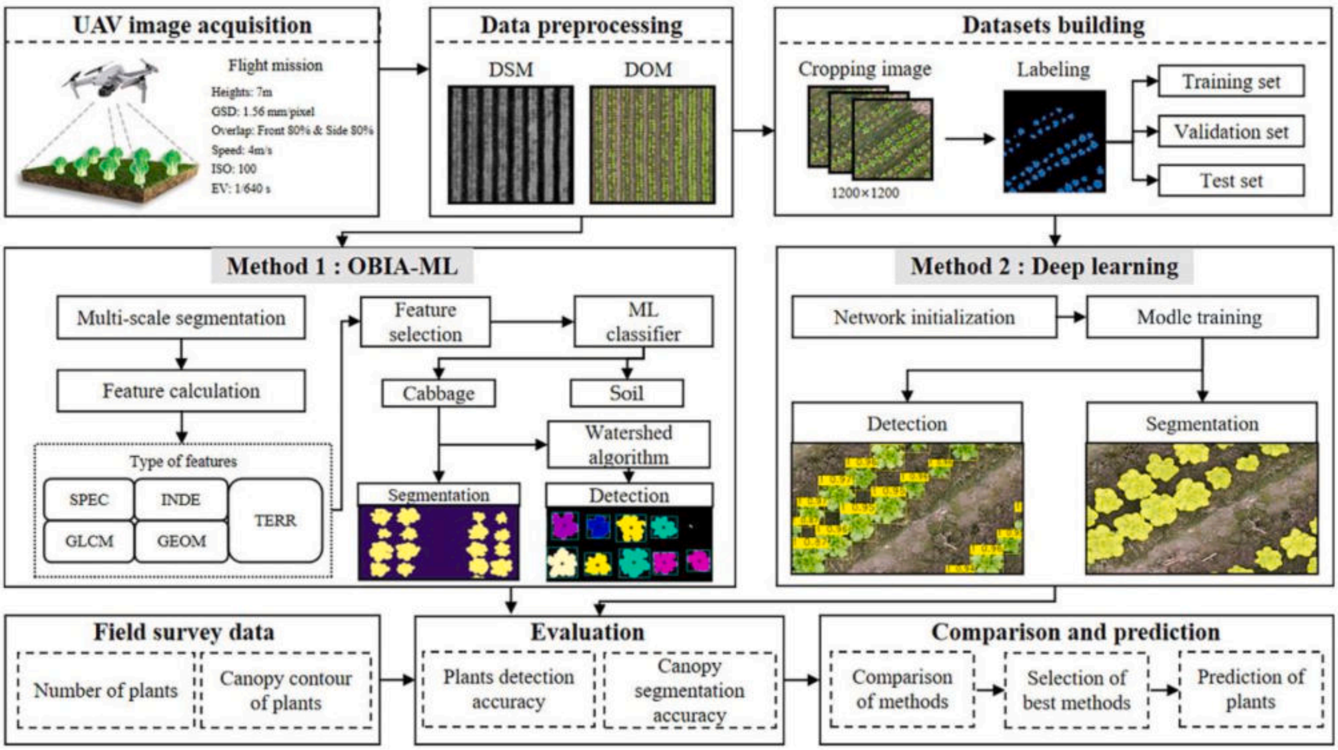

Fig. 5. Crop extraction processes framework [55].

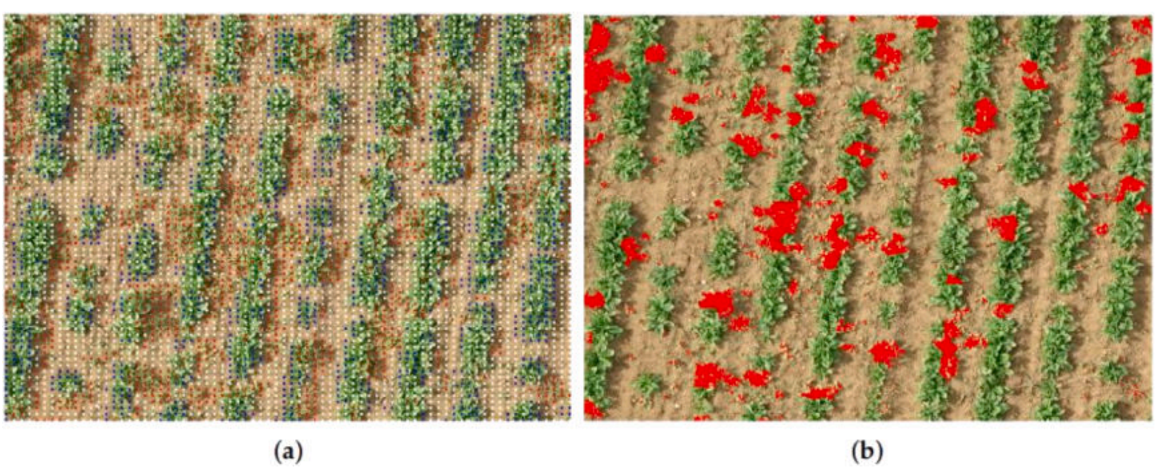

Fig. 6. UAV image classification with models by unsupervised data in a spinach field. (a) samples obtained after using a sliding window, without crop line and background information. Blue, red, and white dots mean that the plants are identified as crop, weed, and an uncertain decision, respectively. (b) in red the weeds detected after crop line and background information has been applied [71].

Convolutional Neural Network on weed classification accuracy, Ajayi and Ashi [72] observed that an increasing number of epochs significantly improved weed classification accuracy in various crops, including pepper and spinach. Additionally, Ajayi et al. [73] assessed the impact of the number of training epochs on YOLO (You Only Look Once), identifying 600 as the optimal epochs for achieving the best performance.

Following the preceding steps, it is possible to generate prescription maps for herbicide distribution, which can be used for the implementation of SSWM through the use of aerial spraying or machinery equipped with Variable Rate Technology (VRT) [77].

Morphological and geometrical features extraction

Phenotyping is the process of evaluating both the plant physical and morphological characteristics and their phenological stage. Drones can capture high-resolution images of crops and analyse them to extract information about size, shape, architecture, and even phenological stage (Table 4).

Zhang et al. [87] mapped the dimensions of cabbage, estimating length and width, using a multispectral camera-equipped drone at an altitude of 10 m with a spatial resolution of 5 cm. Din et al. [101] recognized the growth stage of onions combining deep learning techniques with multispectral data. Meanwhile, Kim et al. [95] utilized UAV-RGB based imagery with a spatial resolution of 0.64 cm at an altitude of 20 m for estimating biophysical properties of cabbage and radish.

Through image analysis techniques, photogrammetry, machine and deep learning algorithms, specific crop parameters can be calculated.

Table 4
Morphological and geometrical crop parameter extracted from remote sensing images for specific task and crop.

Specific Task	Crop	Crop Parameter	Reference
Phenotyping	Potato	Canopy Height and Crop Coefficient	[78]
		Canopy ground cover, height and volume	[79]
		Lead Area Index	[80]
		Lead Area Index	[81]
	Tomato	Canopy Height and Crop Coefficient	[78]
		Canopy Cover and Height	[82]
		Canopy Height	[83]
		Lead Area Index	[84]
	Melon	Lead Area Index	[81]
	Cauliflower	Head diameter, Height and Curvature	[85]
		Head Volume	[86]
	Cabbage	Canopy Length and Width	[87]
		Canopy Height	[83]
	Eggplant	Canopy Height	[83]
	Lettuce	N.S.	[88]
Canopy Biomass Estimation	Potato	Canopy height and textures	[89]
	Potato	Canopy height and Fractional vegetation cover	[90]
	Potato	Number of leaves	[91]
	Strawberry	Canopy Area, height and volume	[92]
	Onion	Green canopy cover, height and volume	[93]
Spraying volume Determination	Potato	Canopy coverage and height	[94]
Growth Status Monitoring	Cabbage	Canopy Height and Vegetation Fractions	[95]
	Cabbage	Canopy height	[96]
	Radish	Canopy Height and Vegetation Fractions	[95]
	Pumpkin	Canopy height	[96]
	Broccoli	Canopy Cover, spectral features	[97]
Phenological stage recognition	Potato	Canopy height	[98]
	Cucumber, muskmelon, squash, pumpkin and watermelon	Approach based on Deep Learning Classification Algorithm	[99]
	Lettuce		[100]
	Onion		[101]

Among these parameters, estimating plant height has been a sought-after goal for several authors. Jamil et al. [96] estimated the height of cabbage and pumpkin plants using UAV-based RGB imagery, achieving excellent correlations with field-measured data, with r^2 values of 0.86 and 0.94, respectively for cabbage and pumpkin. Moeckel et al. [83] obtained r^2 values ranging from 0.87 to 0.97 on eggplant, tomato, and cabbage. Encisoet al. [82] achieved r^2 values of 0.98, 0.97, and 0.99 in three different tomato varieties, confirming the reliability and accuracy of these tools for plant height estimation. Malachy et al. [78] compared four different methods for extracting single height crop values from Crop Height Model (CHM) and subsequently estimating the crop coefficient (Kc) in both potato and tomato crops. Among these four methods (Mean, Sample, Median, and Peak), the Mean and Sample ones emerged as the best crop height predictors (R^2=0.84 and 0.80, respectively).

Also Leaf Area Index (LAI) has been estimated in different studies. Roosjen et al. [80] assessed LAI in potato fields, and Zhu et al. [81] in four different crops, including potatoes and melons. The latter achieved excellent correlation with field-measured data, with an r^2 of 0.85 and a root mean square error (RMSE) of 0.41 m^2/m^2. Certain crops, such as cauliflowers, allow for precise and rapid aerial geometric characterization due to their upward-oriented and exposed plant structure and head shape. This factor facilitates the rapid and accurate monitoring of large areas, providing detailed information about plant phenology, as confirmed by studies conducted by several authors [85,86,97].

One of the direct applications that can be derived from having biometric parameters such as plant area, height, and volume resides in the capability to readily estimate crop biomass. This parameter has been estimated, for example, in strawberry cultivation by Zheng et al. [92] and in onion cultivation by Ballesteros et al. [93]. Some tubers, like potatoes, growing underground, prevent direct characterization of productive organs. As a result, estimating plant geometry and above-ground biomass is of great interest for the agronomic insights it can provide [89–91].

Indeed, by combining metrics like Canopy Coverage and Plant Height, it is possible to estimate the appropriate spraying volume [94].

Rapid phenotyping can also be an excellent tool for breeders: De Jesus Colwell et al. [79] developed a method to demonstrate how the use of point cloud data obtained from low-cost UAV images can be employed to create 3D surface models of plant canopies on potatos. From these models all the morphological and geometric characteristics can be extrapolated, paving the way for a large-scale expansion of future genotype-phenotype association studies (Fig.7). An efficient application of drone-based phenotyping has been observed in tomatoes, where it was utilized to assess the effectiveness of certain biostimulants [84]. In lettuce, image phenotyping was employed to evaluate inbred lines with varying carotenoid content [88]. Through the identification of plant morphological characteristics, it is also possible to identify specific phenological stages. In potatoes, it was possible to determine the onset of tuberization, a crucial phenological stage for adapting irrigation management, by calculating plant height detected by drone [98]. Identifying specific phenological stages like flowering can be particularly important for cucurbits, where the flower represents one of the final products. For this purpose, Mithra and Nagamalleswari [99] developed a transfer learning algorithm using the *CuCuFlower* dataset, capable of identifying the genus and gender of 9 cucurbit species, including cucumber, muskmelon, squash, pumpkin, and watermelon. Detecting flowering can also be significant for crops where the flowering process is pivotal for genetic improvement actions, as in the case of lettuce [100].

Crop health and stress monitoring

In vegetables cultivations, one of the fields where drone usage has become more established and widespread is the accurate and geospatial assessment of plant health and stress levels (Table 5).

This practice has proven to be one of the most common and rooted applications in vegetable cultivation [120] and today it can be carried out with various methodologies and using different sensors. For instance, in potato cultivation, Théau et al. [102] employed a thermal infrared sensor for stress scouting and calculated the Temperature Vegetation Dryness Index (TVDI), resulting in accurate scouting maps. Meivel and Maheswari [103] used a multispectral camera and calculated various vegetation indices, including Normalized Difference Vegetation Index (NDVI). Meanwhile, Butte et al. [104] proposed a deep learning algorithm named Retina-Unet-Ag, capable of detecting healthy and diseased plants, with an average Dice Score Coefficient (DSC) of 0.74.

The scientific community has increasingly recognized the solid connections between measurable parameters through these platforms and the degree of plant health. Many recent studies, in fact, use UAVs as tools for evaluating and quantifying plant responses to specific treatments. For instance, crop's response to different irrigation treatments was evaluated by Garcia-Garcia et al. [115] in tomato cultivation; they used NDVI to estimate the dynamics of Canopy Cover (CC) with varying water supply, while Fullana-Pericàs et al. [116] tested NDVI, Simple Ratio Index (SR), and Green Normalized Difference Vegetation Index

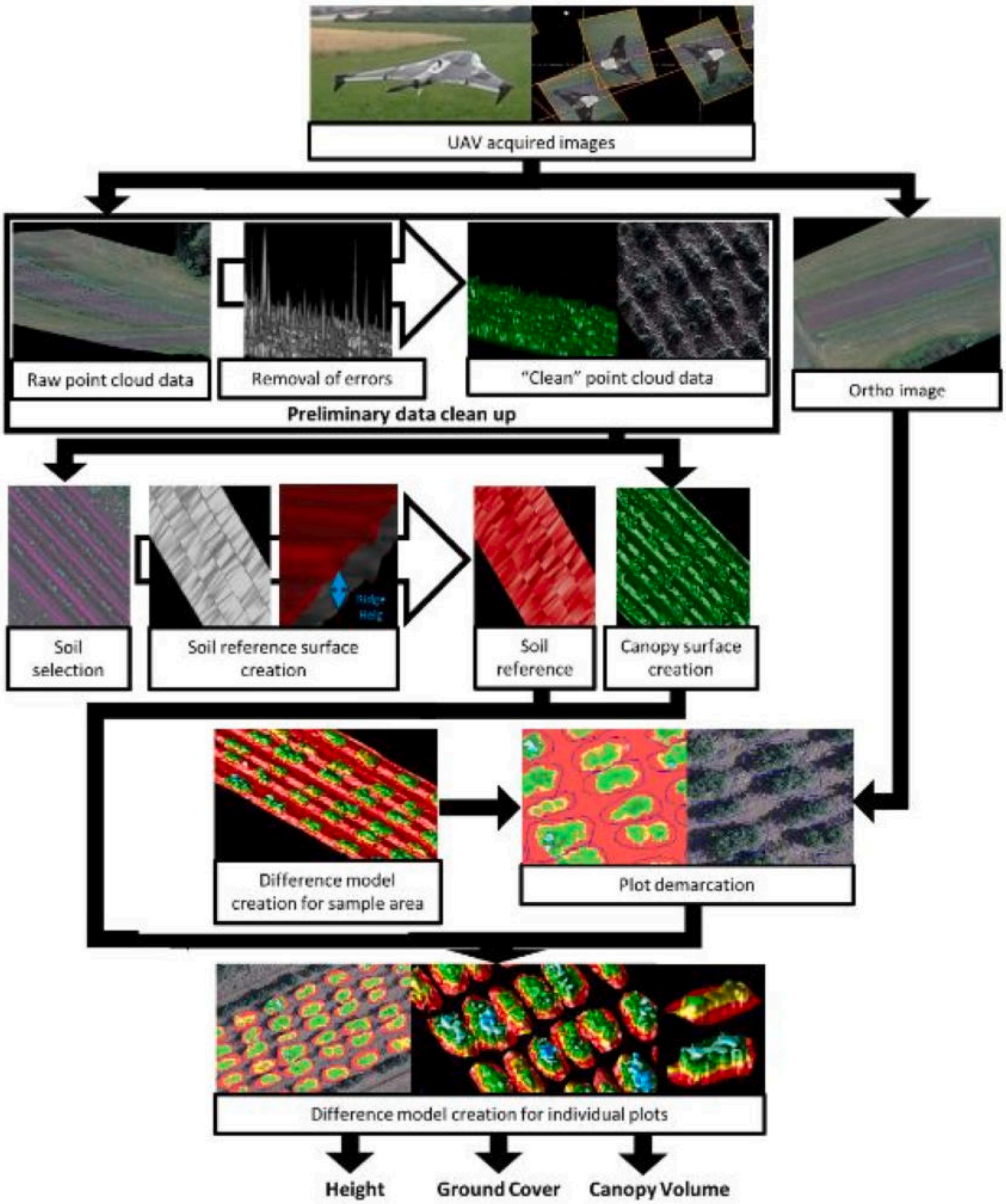

Fig. 7. Acquisition of quantitative data on potato plant canopy structure using a Structure from Motion algorithm from UAV acquired images in [79].

(GNDVI) in combination with conventional leaf-level physiological and agronomic measurements in an experiment involving 91 different genotypes. In both studies, the indices showed excellent correlations with field-measured comparison data. Kasper Johansen et al. [117], analysed biomass variation under different saline stress conditions in tomato cultivation, too (Fig. 8). Marconi et al. [118] investigated the capability of a UAV-RGB based crop monitoring system to determine the best management practices for three different tomato varieties by comparing different planting dates, plant density, use of plastic mulch, and fertilization rate, demonstrating these systems' ability to assess plant responses to treatments and select the best management practices.

Similar types of applications have been found in studies conducted on other crops: Mwinuka et al. [121] used GNDVI, NDVI, and Optimized Soil Adjusted Vegetation Index (OSAVI) to assess the interactive effect of nitrogen and water in an eggplant field. Sharaf-Eldin et al. [129] evaluated responses to water stress and potassium deficiency in squash using three-band Spectral Indices and a Machine Learning model. In potato, Coelho et al. [105] employed NDVI as an indicator of crop development under varying calcium inputs. In cabbage cultivation, the effect of nanonutrient applications was determined by analysing their relationship with various vegetation indices, including NDVI, GNDVI, Normalized Green Red Difference Index (NGRDI), and chlorophyll content, with good results [122]. A UAV with a multispectral sensor was used to monitor the crop cycle in onion cultivation by Messina et al. [11] aiming to identify the optimal nitrogen input to maximize productivity,. Specifically, the Soil-Adjusted Vegetation Index (SAVI) was employed for crop vigor monitoring, which also showed significant correlations with yield.

Table 5
Overview of the papers included in this section, divided by specific task, species, and family.

Family	Specie	Specific Task	Reference
Solanacee	Potato	Crop health and stress monitoring	[102,103,104,105,106]
		Chlorophyll content	[107,108,109]
		Nitrogen status	[110,111,112,113,114]
	Tomato	Crop health and stress monitoring	[115,116,117,118]
		Chlorophyll content	[119]
	Pepper	Crop health and stress monitoring	[120]
	Eggplant	Crop health and stress monitoring	[121]
Brassicaceae	Cabbage	Crop health and stress monitoring	[122,123]
		Nitrogen status	[124]
Amaryllidacee	Onion	Crop health and stress monitoring	[11,125,126]
Asteracee	Lettuce	Chlorophyll content	[127]
Apiacee	Carrot	Nitrogen status	[128]
Amaryllidacee	Garlic	Crop health and stress monitoring	[126]
Cucurbitacee	Squash	Crop health and stress monitoring	[129]

Studies with different approaches have been identified on the topic of crop monitoring. Messina et al. and Ryu et al. [125,126] compared NDVI maps derived from UAV and satellite platforms for monitoring onion and garlic crops. In both studies, the high resolution offered by drones provided advantages over satellite platforms, allowing for the removal of the soil effect on crop NDVI, which is not possible using images from satellite platforms. On the other hand, Farooque et al. [106] proposed a method to translate images from an RGB sensor for calculating NDVI map. Lee et al. [123] developed a calibration method for NDVI calculated from drone, using a handheld hyperspectral sensor. Specifically, the reflectance data measured in the field through a portable spectroradiometer were correlated with data measured from the drone, creating a calibration equation method for UAV spatial information. The calibration allowed the authors to create a precise normalized distribution vegetation index (p-NDVI) map.

Chlorophyll content

Chlorophyll is the essential pigment for photosynthesis and is responsible for plant's ability to capture solar energy. A high level of chlorophyll indicates efficient photosynthesis and a good state of leaf health and overall plant well-being, while low presence of this pigment may indicate stress or a problem. There are several methods to measure leaf chlorophyll levels; however, many of these are destructive and/or require human presence in the field. The Soil Plant Analysis Development (SPAD) method belongs to the latter category, which is widely used but demands the presence of a technician in the field and provides point measurements without georeferencing.

Drones equipped with multispectral and/or hyperspectral sensors, with their high resolution, provide precise and geospatialized measurements of chlorophyll content, enabling the creation of chlorophyll content maps for crops. Li et al. [107] worked on a chlorophyll estimation method using hyperspectral data, providing two machine learning models. Specifically, they found that the Partial Least Squares (PLS) model achieved the best estimates of potato chlorophyll content in the bud stage and tuber-growth stage, while the Stepwise Regression (SR) model achieved the best estimates in the tuber formation stage and starch accumulation stage (Fig. 9). Yang et al. [108], using multispectral data and indices such as SAVI, Modified Simple Ratio (MSR), Simple Ratio Vegetation Index (RVI), and NDVI, combined with Machine Learning and a Stacking Ensemble Algorithm, managed to provide highly accurate chlorophyll content estimates. Yin et al. [109] used UAV-based multispectral vegetation indices as input in models such as Random Forest (RF), Support Vector Regression (SVR), Partial Least Squares Regression (PLSR), and Ridge Regression (RR) to predict chlorophyll content in potato crops. Comparing the results with field-measured data using the SPAD chlorophyll meter, the authors achieved the best performance with RF, reaching an R^2 of 0.76 and a RMSE of 1.97.

Other researchers have conducted studies with the aim of identifying the most effective indices for this purpose. For instance, Bhandari et al. [127] found the best performance with the Modified Chlorophyll Adsorption Ratio Index (MCARI) in a study conducted on lettuce. In the case of potato cultivation, Yin et al. [109] identified Chlorophyll Index green (CI_{green}) and Chlorophyll Index red edge ($CI_{red\ edge}$) as the best predictors of chlorophyll content. In tomatoes, Angel and McCabe [119] developed a model that utilizes machine learning algorithms for the

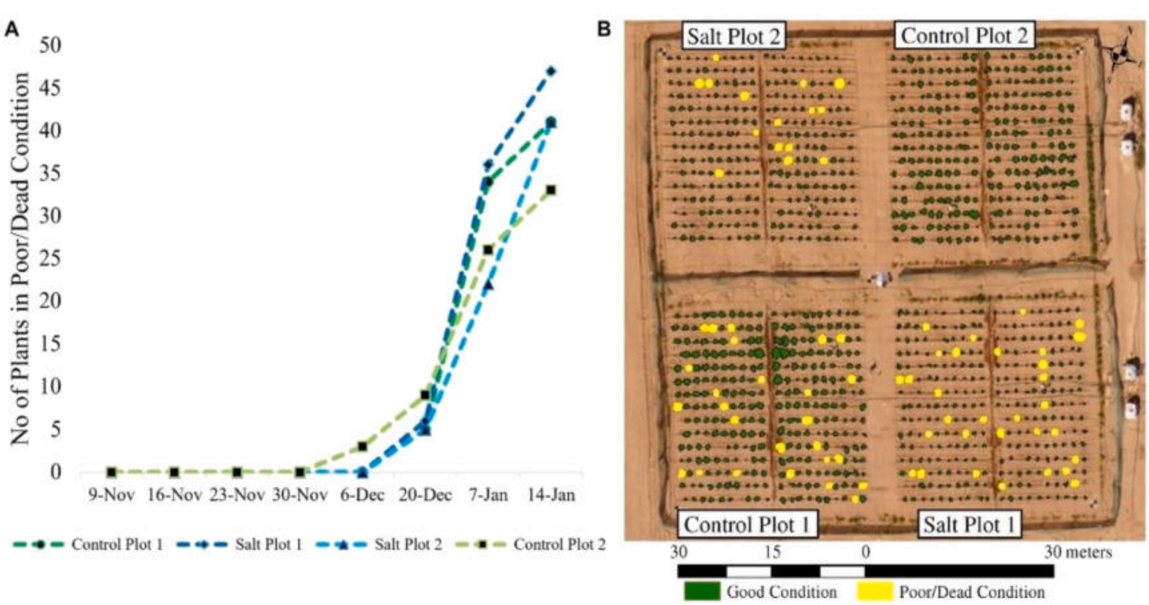

Fig. 8. Salinity stress detection in tomato field. (A) Cumulative number of plants either missing or being in a poor/dead condition throughout the growing season; and (B) mapped plants in either good or poor/dead condition [117].

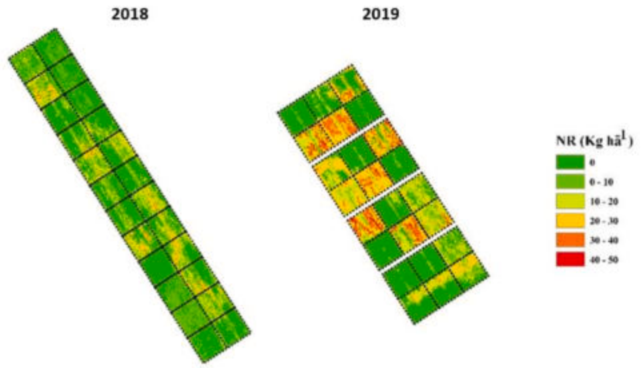

Fig. 9. Nitrogen requirement maps for mid-season potato growth in field experiments predicted from UAV data in [110].

retrieval of spatially and multi-temporal Leaf-Chlorophyll Dynamics.

Nitrogen status

Nitrogen is one of the most crucial elements within a crop system. A low concentration of this element in leaf tissues leads to hindered growth and stress. Optimal nitrogen management enhances yield and product quality while concurrently mitigating environmental risks associated with nitrogen leaching [128]. Swift and accurate estimation of nitrogen concentration in tissues is imperative for informed decision-making in fertilization management. UAVs, owing to their adaptable usage and high resolution, are potential tools to fulfil the role of a Decision Support System (DSS) in nitrogen management. In the context of potato cultivation, Peng et al. [110] explored diverse platforms equipped with multispectral sensors for nitrogen management. They found UAVs to be valuable instruments in assessing indicators such as Plant Nitrogen Uptake (PNU), Plant Nitrogen Concentration (PNC), and Nitrogen Nutrition Index (NNI), ranking among the most precise and accurate platforms employed (Fig. 9).

On the other hand, Fan et al. [111] employed visible light vegetation indices in combination with morphological parameters derived from an inexpensive UAV digital camera to estimate potato nitrogen content, achieving R^2 values up to 0.8. Contrary results were obtained by Hunt et al. [112], who assessed the potential of NDVI and GNDVI as predictors of potato nitrogen status, yielding nonsignificant outcomes. In the case of cabbage cultivation, Besand and Katroschan [124] identified strong correlations between indices such as Canopy Chlorophyll Content Index (CCCI), Green Leaf Index (GLI), Normalized Difference Red Edge (NDRE), and NDVI and Nitrogen Status.

On the other hand, Zhou et al. [113] focused on the evaluation and comparison of hyperspectral and multispectral images for potato nitrogen status estimation. These authors observed superior performance with hyperspectral imaging, achieving stronger correlations as the width of the utilized bands decreased. They also obtained that, within the spectrum, bands situated in the visible region exhibited higher sensitivity to changes in plant nitrogen content compared to those in the infrared region. The efficacy and precision of hyperspectral imaging were also affirmed by Fan et al. [114]. They compared hyperspectral single-band reflectance with two- and three-band spectral indices for estimating potato nitrogen content, attaining optimal performance with the three-band spectral index ($TBI_{530,\ 734,\ 514}$).

Disease and pest scouting

Disease and pest management is a highly significant topic in agricultural crops. Particularly in vegetable crops, effective management of pests and diseases can lead to substantial reduction in the use of pesticides, offering substantial benefits for the environment and human health. However, an efficient, timely, and cost-effective scouting process is needed. Traditional scouting methods are labour-intensive and expensive, and do not always allow for timely intervention. This is why contemporary olericulture often tends to overuse phytosanitary products, sometimes resorting to preventive treatments without actual necessity.

Remote Sensing stands out as one of the most advanced technologies to gather such information. Moreover, the utilization of drones equipped with high-resolution cameras represents one of the most efficient techniques for scouting. Drones enable high precision and promptness at relatively low costs, offering the capacity to assess disease or infestation progression both in space and time. Table 6 outlines all the identified applications, categorized according to the crop.

The potato cultivation has been the subject of six studies, specifically: Duarte-Carvajalino et al. [131]. evaluated the severity of late blight (*Phytophthora Infestans*) in 14 different potato genotypes using multispectral images captured by drones and machine learning methods such as support vector regression, multilayer perceptron, random forest, and deep learning CNN, achieving best accuracy with deep learning CNN, random forest and multilayer perceptron. This method involved the manual extraction of each subset used to train the model, which is time-consuming and can be subject to bias. On the other hand, Rodríguez et al. [130] proposed a method that involved image segmentation through a thresholding technique, followed by the creation of training polygons, and then compared various machine learning algorithms (Fig. 10). The best results in classifying diseased plants were obtained using Linear Support Vector Classifier and Random Forest algorithms, both in terms of accuracy metrics and run time. Siebring et al. [133] employed a different approach in the detection of symptoms caused by Erwinia bacteria and PVYNTN virus in potatoes. They used high-resolution RGB images captured by drones for detecting morphological traits of plants. Subsequently, these traits were used as input in the Random Forest model, achieving a maximum F1 score of 0.75 and an average Matthews Correlation Coefficient (MCC) score of 0.47.

Jindo et al. [135] applied drones equipped with multispectral and thermal sensors to detect and estimate the effect of varying densities of *Globodera Pallida and G. Rostochiensis* (Cyst Nematodes) on four potato cultivars. They calculated NDVI, NDRE, weighted difference vegetation index (WDVI), and Red-Edge chlorophyll index and observed regressions with nematode population density, finding good correlations except for one cultivar (avarna). Similar correlations were observed with thermal data.

Table 6
Diseases and pests analysed by the authors, divided by species.

Specie	Disease and Pest	Reference
Potato	Late blight (*Phytophthora Infestans*)	[130, 131]
	Early Die Complex (*Verticillium Wilt*)	[132]
	PVY Virus	[133]
	Soft Rot (*Erwinia carotovora*)	[133]
	Early Blight (*Alternaria Solani*)	[134]
	Cyst Nematodes (*Globodera Pallida, G. Rostochiensis*)	[135]
Tomato	Target Spot (*Corynespora Cassiicola*)	[136, 137]
	Bacterial Spot (*Xanthomonas Perforans*)	[136, 137]
	Late Blight (*Phytophthora Infestans*)	[138]
	Yellow Leaf Curl Virus (*Bemisia Tabaci*)	[137, 139]
Lettuce	Root Knot Nematodes (*Meloidogyne spp.*)	[140]
	Soft Rot (*P. Carotovorum*)	[141]
Watermelon	Gummy Stem Blight (*Didymella Bryoniae*)	[142]
	Downy Mildew (*Pseudoperonospora Cubensis*)	[143]
Onion	Anthracnose (*Colletotrichum gloeosporioides and Gibberella moniliformis*)	[144, 145]
	Stemphylium Leaf Blight (*Stemphylium vesicarium*)	
Radish	Fusarium Wilt (*Fusarium Oxysporum*)	[146]
Squash	Powdery Mildew (*Podosphaera Xanthii*)	[147, 148]
Cabbage	Flea Beetle (*Psylliodes Chrysocephala*)	[149]

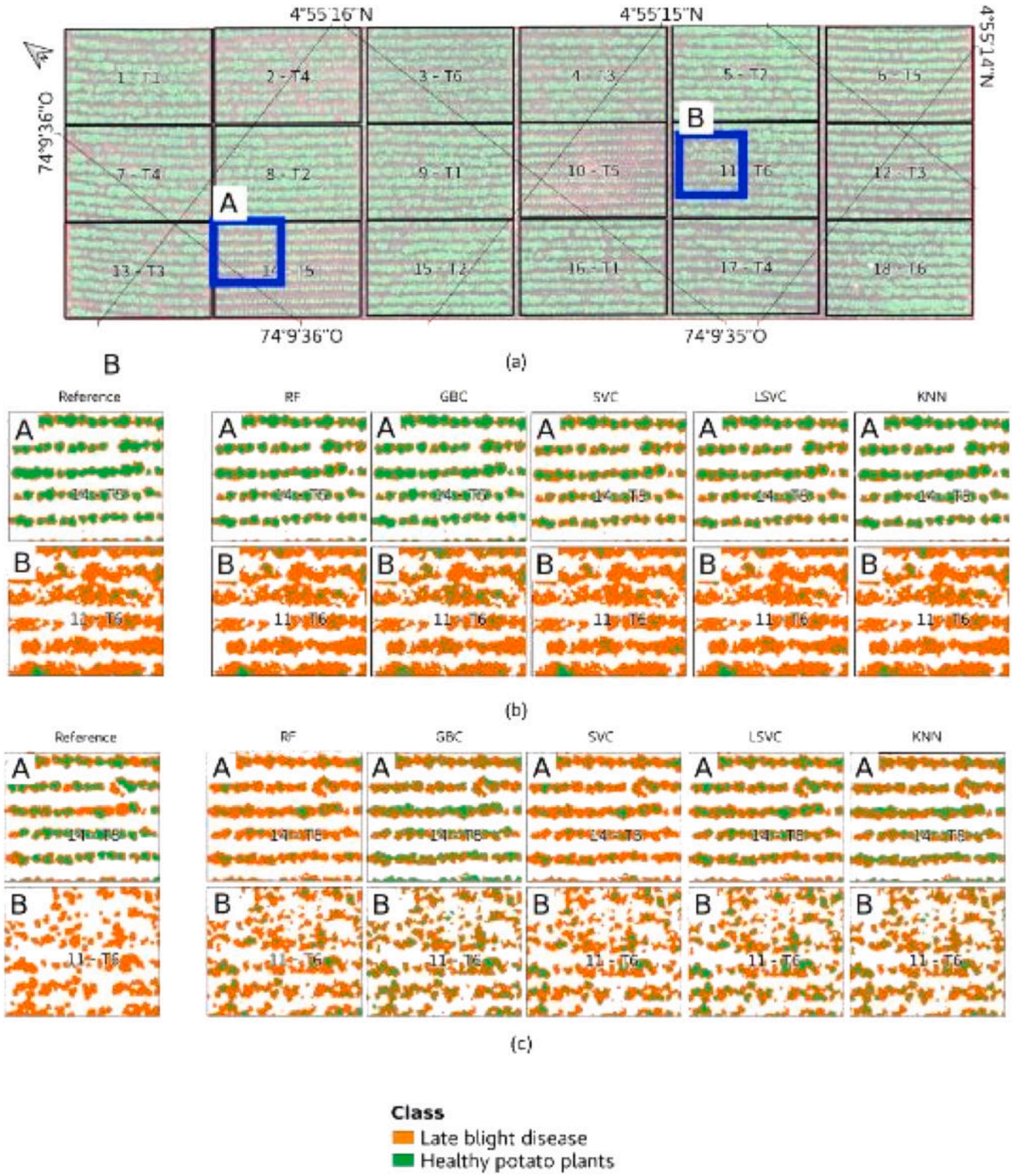

Fig. 10. Classification results for two dataset (A e B) in a study on potato field. (a) overview of the study area with regions of interest depicted in blue; (b) zoom to regions of interest for dataset A showing ground reference and the classification results; (c) zoom to regions of interest for dataset B showing ground reference and classification results [130].

Another important disease in potato cultivation is Verticillium wilt, which was the focus of the study by Lizarazo et al. [132]. These authors evaluated a machine learning algorithm that utilizes an ensemble of gradient boosting machines (GBMs) to differentiate between six levels of Verticillium wilt disease severity, achieving satisfactory results with F1 scores of 82 % for the training dataset and 84 % for the testing dataset.

Lastly, Alternaria solani infections were detected by Van De Vijver et al. [134]. They used a deep learning U-Net model to predict the density of lesions caused by this pathogen. Particularly, they employed ultra-high-resolution RGB images (0.3 mm/px) to detect the lesions and applied a deep learning algorithm to predict their density.

Regarding tomato cultivation, different authors have identified several pathogens. Abdulridha et al. [136] detected bacterial spot and target spot both in the laboratory and in the field using hyperspectral imaging mounted on a drone,. By comparing various vegetation indices, they achieved the best results with the Photochemical Reflectance Index (PRI), $NDVI_{850}$, and chlorophyll index green (Chl_{green}). Additionally, the multilayer perceptron neural network (MLP) classification method achieved a 99 % accuracy for both Bacterial Spot (BS) and Target Spot (TS).

Abdulridha et al. [137], in another study utilizing the same tools, also detected Tomato Yellow Leaf Curl Virus (TYLCV) in addition to BS and TS. In this study, the authors employed stepwise discriminant analysis (STDA) and the radial basis function to classify infected and healthy plants. This yielded classification rates of 98 % for BS and 99–100 % for TS and TYLCV diseases. The best-performing Vegetation Indices (VIs) were the renormalized difference vegetation index (RDVI) and the modified triangular vegetation index 1 (MTVI).

TYLCV was also the focus of a study by Oh et al. [139]. The authors used multi-temporal phenotypic attributes (canopy height, canopy cover, canopy volume) and VIs (NDVI, SAVI, and excess green index) extracted from UAV multispectral image data as input in an artificial neural network model. Similarly, de Oliveira Dias et al. [138] employed ultra-high-resolution RGB images for predicting late blight severity. Random forest models were constructed, yielding determination coefficients of 0.93 (four days data) and 0.81 (one day data) in the test set.

Lettuce was the subject of two studies. Cavalcanti et al. [140] estimated the effect of root-knot nematode incidence on lettuce growth by calculating vegetation indices and Vegetation Cover (VC) from RGB images. Carmo et al. [141] used multispectral images to detect lesions of Soft Rot (*Pectobacterium carotovorum*), employing Support Vector Machines (SVM) and Naive Bayes (NB) machine learning models.

In watermelon cultivation, Kalischuk et al. [142] proposed a drone-assisted scouting method with multispectral cameras for Gummy Stem Blight disease, achieving early disease detection in 20 % of cases. Abdulridha et al. [143] utilized hyperspectral images to identify and classify Downy Mildew Severity Stages, achieving 62.3 % accuracy for low disease severity increasing to 91 % for higher severity.

In onion cultivation, Alberto et al. [144] created geopathological maps to detect anthracnose-twister disease-infected plants using multispectral images and SVM classification, yielding 85 % accuracy. McDonald et al. [145] explored the possibility of scouting Stemphylium Leaf Blight in onions using multispectral cameras, observing differences among disease severity levels without finding correlations with various indices.

In radish cultivation, Dang et al. [146] efficiently investigated Fusarium wilt. They segmented multispectral images captured by drones and employed a deep learning CNN algorithm for classifying diseased plants, achieving 96 % accuracy.

In squash cultivation, powdery mildew was detected in two studies using hyperspectral sensors both in laboratory and field conditions. Abdulridha et al. [147] achieved an accuracy of 89 % for asymptomatic and 96 % for symptomatic phases using the Radial Basis Function (RBF). Ganesh Babu and Chellaswamy [148] obtained 96 % accuracy for the early stage and 94.2 % for the final stage of disease using the Locality Preserving Discriminative Broad Learning (LPDBL).

Finally, Zhao and Shi [149] proposed a method for detecting Flea Beetle (*Psylliodes Chrysocephala*) in cabbage cultivation using UAV RGB images. This approach, rooted in deep learning, employs an image tiling module for initial aerial image preprocessing, followed by image restoration to remove blurriness. A novel disease detection method is then introduced, enhancing CenterNet with attention and DIoU loss, resulting in superior detection performance compared to existing methods. This method achieved an overall accuracy of 87.2 % AP50 (Average Precision at 50) and 94.7 % R^2 for pest disease detection, meeting real-world application needs.

Water management

Water resource management plays an essential role in ensuring the quantity and quality of agricultural production, as well as adapting it to climate change and making it more sustainable [162]. In fact, especially in Mediterranean environments, there is a decreasing trend in the amount of water resources and a deterioration in their quality. In Mediterranean regions, therefore, it is crucial to adopt techniques that optimize irrigation efficiency.

In this context, the use of drones is particularly advantageous. Thanks to these tools, it is possible to adopt different strategies that can improve water use efficiency. For example, optical, multispectral, and thermal sensors mounted on drones can be used to detect the crop water status (Table 7).

Multispectral and thermal sensors have been used by Coulombe et al. [151] to estimate crop water status in chili crops. Stutsel et al. [150] determined it using RGB and thermal sensors in tomato (Fig. 11), while Mwinuka et al. [154] used UAV-based multispectral sensors combined with handheld thermal sensors in eggplant.

Among these types of sensors, thermal sensors allow the calculation of Crop Water Stress Index (CWSI), the most well-known and widely used index for estimating water stress. Ekinzog et al. [152] compared three CWSI models on potato cultivation (CWSIe – empirical, CWSIt – theoretical, CWSIh hybrid) for crop water stress monitoring. These indices were good predictors of soil volumetric water content (θ) (R^2 = 0.57–0.63), obtaining the best results with CWSIh.

Other studies have used multispectral sensors to determine crop water status. For example, in tomato, photochemical reflectance (PRI) and NDVI have allowed the estimation of stem water potential [153]. While Casamitjana et al. [161] found the best correlations between surface soil moisture and Normalized Difference Water Index (NDWI) on potato.

Other approaches have involved the use of energy flux models that can be used to estimate irrigation water requirements by creating maps of crop evapotranspiration. Chandel et al. [156] adopted this approach on several crops, including potato, replacing UAV-based optical and thermal data with Landsat data in an existing model. The results showed that the UAV-based data were compatible with the model, also offering greater accuracy. Tunca et al. [155] used a two-source energy balance model (TSEB) in a bell pepper field. In this case as well, the UAV platform demonstrated great potential in mapping evapotranspiration, especially in small plots, allowing measurements at the plant level. This approach also made it possible to overcome the limitations imposed using satellites, which offer a temporal resolution of about 15 days [160]. Peng et al. [157], proposed a new energy flux modelling framework based on TSEB for high spatial resolution thermal and multispectral UAV data. The results showed excellent performance of this model for retrieving evapotranspiration (ET) dynamics, confirming the reliability and precision of these tools.

Regarding the best flight modes for estimating evapotranspiration, Ebert et al. [158] compared different flight altitudes, 30, 60, and 90 m

Table 7
Overview of the different types of sensors mounted on UAVs used in water management.

Specific Task	Type of sensor	Crop	Reference
Crop water status	Thermal and RGB	Tomato	[150]
	Thermal and multispectral	Chili	[151]
		Potato	[152]
	Multispectral	Tomato	[153]
		Eggplant	[154]
Evapotraspiration Map	Thermal and RGB	Pepper	[155]
	Thermal and multispectral	Potato	[156,157]
	Multispectral	Potato	[158]
		Tomato	[159,162]
Soil mosture estimation	Multispectral	Potato	[161]

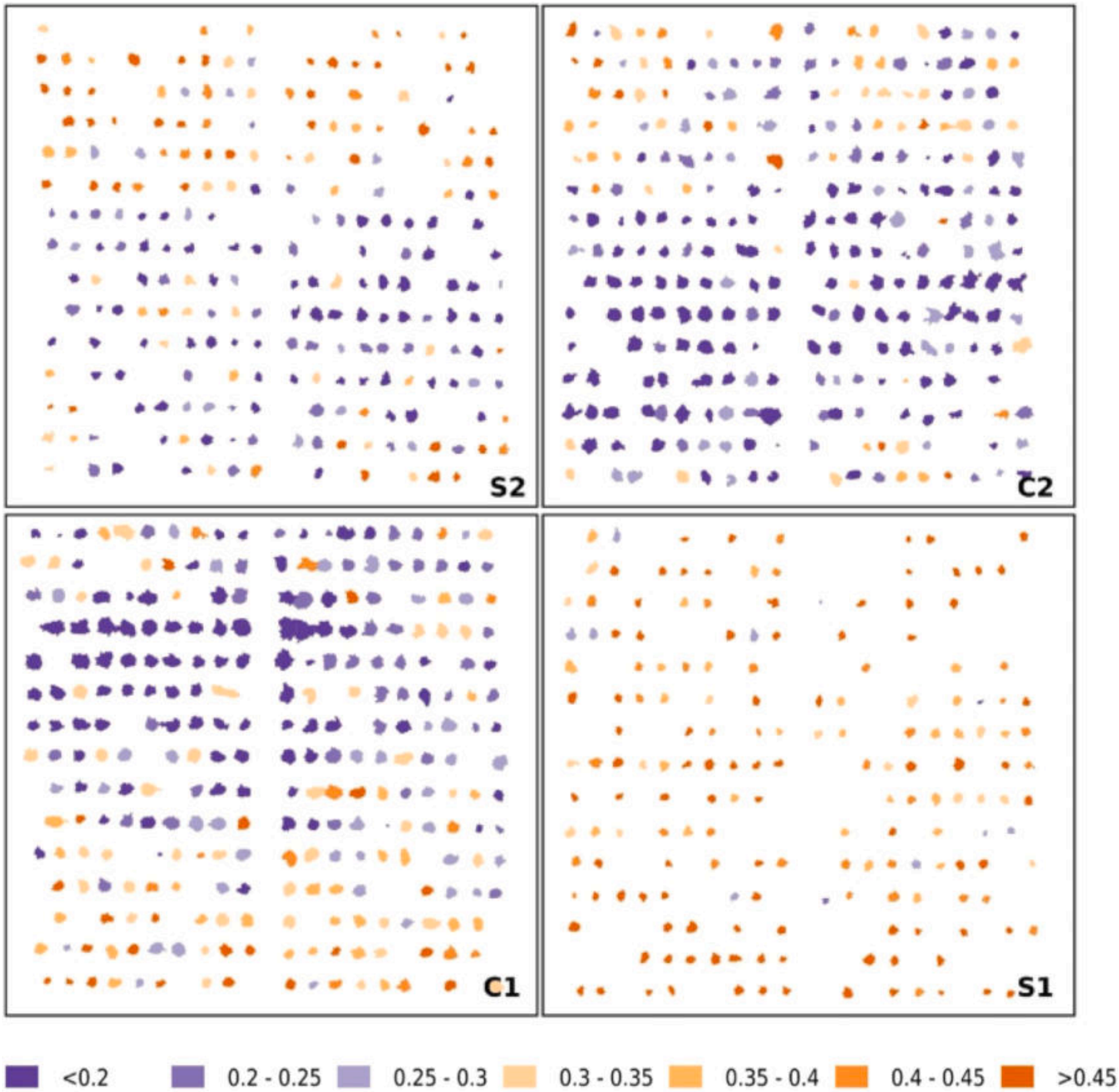

Fig. 11. Maps of CWSIs values in a tomato experimental field, in salt-treated (S1 and S2) and control (C1 and C2) plots [150].

above ground, obtaining that there are no advantages to flying at low altitudes, confirming the validity of surveys conducted even at 90 m.

Finally, another strategy for UAV-based water management is the one adopted by Rozenstein et al. [159] in a study conducted on tomato. UAV-captured multispectral images were used to estimate evapotranspiration by calculating the FAO-56 crop coefficient (Kc). Results show that this method estimated evapotranspiration to derive the irrigation dose in near-perfect agreement with best-practice irrigation, both in terms of total amount and irrigation rate.

Yield and biomass estimation

In the case of vegetable crops, the early prediction of crop productivity and quality is an important factor that allows for the best possible planning of harvesting, storage, shipping, and sales operations. This estimate is currently carried out manually, which is time-consuming and often approximate and inaccurate. The use of drones for this purpose can be a good solution, as it is one of the most established and widespread applications in agricultural crops in the scientific community [165]. In fact, drones can be used to predict yield in terms of both fruit production and biomass of multiple vegetables species. Researchers have adopted various techniques and used different types of sensors to arrive at a precise and geospatialized estimation of the yield. As shown in Table 8, one of the determining factors in the choice of materials and methods the approach to be used for this purpose is the crop habitat.

In studies conducted on crops where the productive organs were exposed and visible from aerial images, one of the strategies found was fruit detection. Using RGB sensors and object detection and counting techniques, several authors have identified and quantified the production of strawberry [165], yellow melon (Fig.12) [166] and pumpkin [163,164].

Other strategies involved the use of machine learning algorithms based on UAV multispectral data. Oliveira et al. [175] used the support vector machine (SVM) and linear regression (LR) models on strawberries, with the latter obtaining better yield estimates. In particular, the LR model obtained 99.91 % accuracy for the average fruit weight, 99.55 % for the number of fruits, and 99.94 % for the number of leaves. UAV-RGB data were instead used by Johansen et al. [172] to estimate tomato yield. For this purpose, the authors used shape features such as plant area, border length, width, and length as input to random forest models, obtaining R^2 values against fresh shoot mass, yield mass, and fruit numbers as high as 0.67, 0.44, and 0.41, respectively.

Furthermore, several authors have employed multi-source models. These models consider both geometric characteristics such as canopy

Table 8
Summary of the different yield estimation approaches in various crops.

Approach	Predicted parameter	Specie	Reference
Object Detection	Fruit yield	Pumpkin	[163,164]
		Strawberry	[165]
		Yellow melon	[166]
	Maturity level of fruit	Strawberry	[167]
		Cauliflower	[168]
	Stem density variation	Potato	[169]
Predicted model based on shape features	Fresh matter	Eggplant, Tomato and Cabbage	[170]
	Seed Yield	Spinach	[171]
	Biomass and Yield	Tomato	[172]
Predicted model based on Vegetation Indices	Dry-Biomass	Leek	[173]
	Tubers Yield	Potato	[174]
	Fruit yield	Strawberry	[175]
Multi-Source Prediction model	Fruit yield	Pepper	[176]
		Tomato	[177–179]
	Fresh and dry biomass	Spinach	[180]
	Biomass and Yield	Tomato	[181]

cover, canopy height, and canopy volume, as well as spectral characteristics, through the calculation of vegetation indices. This approach has been adopted by several authors [177–179,181] in tomato cultivation and by Tunca and Köksal [176] in pepper cultivation. This method has proven to be an effective strategy in providing the authors with more accurate and reliable predictions.

In crops where production is below the soil surface, productivity estimation is indirect, leading to various strategies. For example, in potato cultivation, Jasim et al. [174] found good correlations between yield and vegetation indices derived from multispectral images. Mhango et al. [169] used a deep convolutional neural network (CNN) for the identification and estimation of stem density, a parameter that strongly characterizes potato yield.

Additionally, in leafy vegetables, the parameter that represents productivity is biomass. This has been successfully estimated in cabbage by Astor et al. [170] through information on crop height derived from point clouds based on UAV RGB data. Haumont et al. [173] used UAV multispectral imaging for the estimation of dry biomass in leek, obtaining correlations up to R^2=0.90. Awika et al. [180] estimated spinach biomass through a predictive model that takes as input geometric information (plant height, canopy coverage, and volume) and spectral characteristics (excess greenness index (ExG), chlorophyll red-edge (Chl_{RE}), normalized difference vegetation index (NDVI) and normalized difference red-edge (NDRE)). Even in spinach cultivation, Ariza-Sentís et al. [171] adopted an approach for spinach seed yield estimation for seed production purposes, which consists in correlating the number of plants and two phenotyping variables (plant area and canopy cover percentage) with the number of harvested seeds and the thousand seed weight. The results showed a high linear correlation R^2_{adj} of 0.80.

Beyond quantitative yield estimation, some authors have conducted studies on maturity level classification. This was performed on broccoli, where Psiroukis et al. [168] employed object-based image analysis (OBIA) techniques to classify different maturity levels based on geometric characteristics of the head. For strawberries, Zhou et al. [167] identified and classified various maturity levels using YOLO v3, a Deep Learning algorithm (Fig. 13). The results showed that three strawberry maturity stages were classified with a mean average precision (mAP) of 0.88, and 0.93 for fully mature fruit.

Aerial spraying

The use of drones on vegetable crops for spraying operations has been investigated in recent studies by several authors. Drones equipped with a spraying system capable of performing targeted aerial treatments, leading to significant input savings, are used. The main components of aerial spraying drones include Brushless Direct Current Motors (BLDC), Electronic Speed Control (ESC), flight controller, GNSS system, accelerometer, gyroscope camera, transmitter, and receiver. For spraying, the two primary components are the pump and its controlling system (Fig. 14) [182].

The use of drones for spraying is becoming increasingly widespread, being a highly valuable equipment for farmers and attracting attention in the scientific community as well. In the field of vegetable crops, three notable studies have explored the applications of pesticides, fertilizers, and defoliants using UAV-sprayers. In particular, Xiao et al. conducted a study in 2020 [183] aiming to compare droplet deposition and control efficiency between UAV and electric air-pressure knapsack (EAP) sprayers on a pepper field. Despite UAV gave lower droplet coverage, density, and uniformity in deposition, it achieved greater deposition at 1.01 $\mu g/cm^2$, which was 98 % higher compared to that obtained with the EAP sprayer. This allowed for effective control of aphids and Phytophthora capsici.

Another study was carried out by Jingxin et al. [184] on fertilizer applications in pumpkins aiming to evaluate the effect of working parameters on droplet deposition. Operating the drone at a flight height of 2.5 m and a speed of 3 m/s resulted in maximal droplet deposition and a high level of attachment on the backside of the leaves. Lastly, in the case of defoliant spraying, Yapeng Liu et al. [185] assessed the effect of aerial adjuvants on droplet deposition on pepper plants. The most favourable outcomes were achieved employing the adjuvant "Puliwang" underscoring that specific adjuncts within such applications can substantially amplify droplet deposition and defoliation rate, thus augmenting treatment efficiency significantly.

These first results indicate the potential of UAVs in safeguarding and managing vegetable crops. Drones offer an innovative and valuable tool for optimizing agricultural treatments.

Discussion

The use of drones on vegetable crops has emerged as a growing research area in recent years. This review focuses on analysing the different applications of drones and the opportunities these devices offer to farmers and researchers for optimizing vegetable crops management.

Crop detection through drones represents the fundamental initial

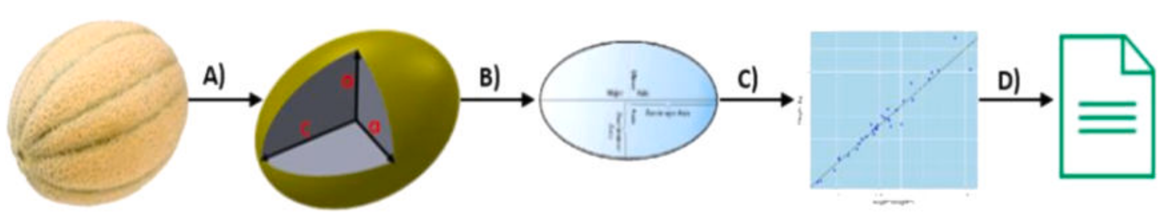

Fig. 12. Yield estimation process. Stage (A) melon by spheroid shape using pre-knowledge of melon shape, (B) conversion from 3D to 2D, (C) linear regression for yield prediction, (D) report for each melon location and yield estimation for the field [166].

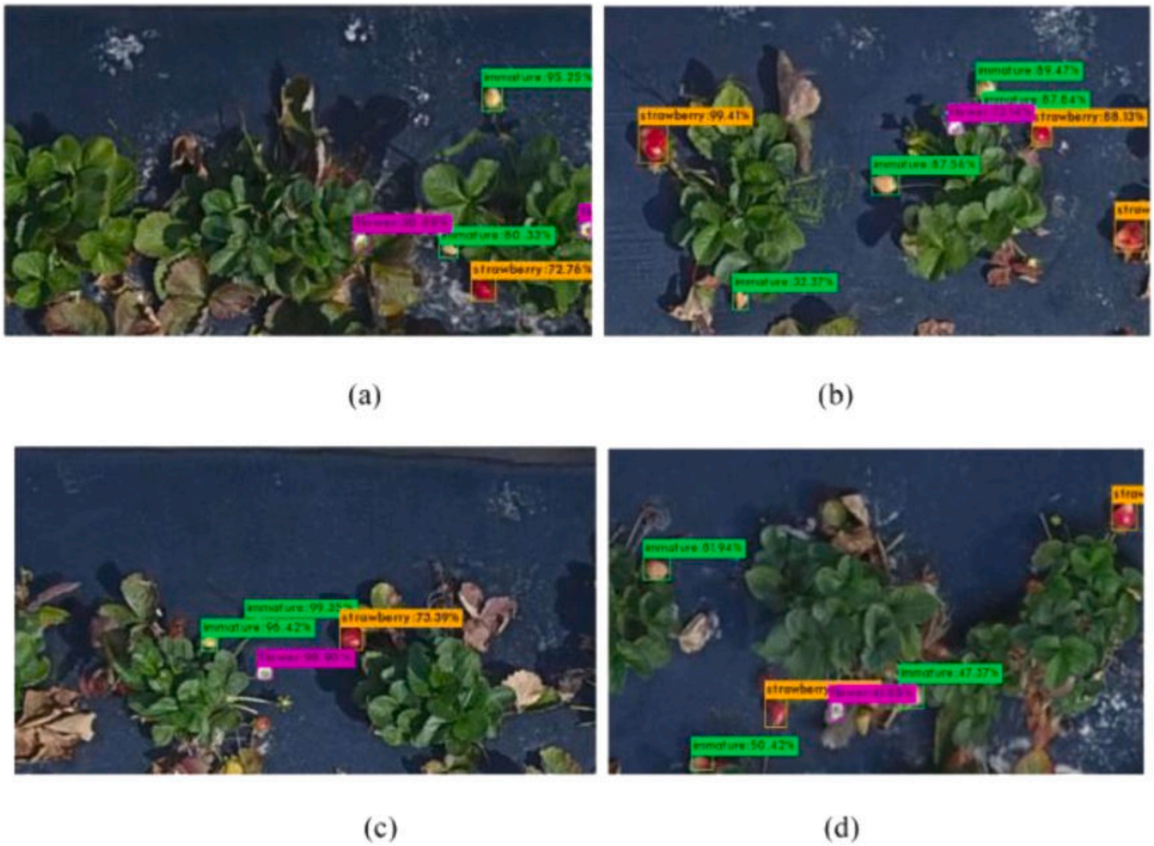

Fig. 13. Strawberry maturity detection and classification results using YOLOv3 from UAV images [167].

Fig. 14. UAV based spraying system used in different crops [182].

step to conduct further analyses of agricultural plots. By employing various types of UAV-based sensors, it is possible to identify the target crop, referred to as the Region of Interest (ROI), and isolate it [55]. This approach provides a detailed view of the crop and excludes its surroundings, facilitating rapid and efficient mapping of the different crops present in the field. The same types of sensors and methods used for crop detection, both pixel-based and object-based, also allow for the identification and mapping of weeds, where the ROI is the weeds. This process lays the foundation for site-specific weed management (SSWM) [73].

Moreover, crop detection enables further operations such as extracting morphological and geometrical plant characteristics from images captured by drones. Photogrammetry techniques enable the extraction of key parameters such as Leaf Area Index (LAI), plant height, volume, and biomass [97]. This information supports an efficient phenotyping process, benefiting not only farmers but also breeders [84].

Monitoring plant health and stress has been the most prevalent application observed in this review. Many authors have employed parameters calculated from high-resolution aerial images to assess treatment efficacy [115], confirming that these tools are now firmly established and reliable for evaluating variations in plant vigor, overall well-being, and stress in space and time. Additionally, researchers have developed specific indices and methods to generate maps of nitrogen and chlorophyll content [114,119].

Another application domain of drones is the detection of diseases and pests through remote sensing. Although still evolving, the analysed papers demonstrate that drones equipped with hyperspectral, multispectral, and in some cases, RGB sensors are efficient and reliable tools for scouting symptoms induced by pests and diseases [146]. Conversely, identifying diseases during asymptomatic stages and accurately classifying various levels of symptom severity is a continually growing field [147].

Water management is crucial for proper crop management and holds significant environmental and economic relevance. Drones equipped with both thermal and RGB/multispectral sensors can make substantial contributions to water resource management. They can calculate water stress indices, estimate evapotranspiration, and determine crop coefficients (kc), enabling precise irrigation planning and optimal water resource utilization [152,153,159].

All types of crops, including vegetables, experience an annual cycle that reaches its culmination with the harvesting phase. Drones can be useful decision support tool at this stage, as they can provide early, detailed, and geospatialized yield estimates through their utilization. This application has garnered considerable scientific interest in recent years and has found practical implementation in the agricultural sector, affording farmers the ability to plan harvesting, transportation, storage, and sales operations [163,179]. However, accurately estimating ripeness levels and classifying various levels of maturity present in the field could be a future research opportunity. Two authors have examined this aspect, respectively in strawberries and broccoli, reaching excellent results and inspiring potential applications in other crops [167,168].

The previously mentioned applications have demonstrated how drones, equipped with cameras and sensors, can efficiently monitor crops from their initial emergence to harvest. Moreover, these vehicles offer the capability to conduct various operations. One of the most innovative uses in this regard is aerial spraying. Drones deployed for this purpose are appropriately sized and equipped with various types of spraying systems. These technologies have been tested on vegetable crops in three studies involving applications of pesticides, fungicides, defoliants, and fertilizers [183–185]. The results of these applications are the basis for further research.

Conclusion

The review points out the significance of drone applications in vegetable crops and the immense potential of these tools in enhancing cultivation efficiency. Drone applications in vegetable crops in the literature are increasing more and more, with the number of dedicated papers on this subject growing year by year.

The scientific knowledge in this field, combined with the array of information that drones can provide, will be employed by agronomists, agrotechnicians, and specialized consultants in precision agriculture. These professionals will be capable of offering farmers increasingly informed and precise operational guidance, thereby contributing to the optimization of agricultural management practices and yielding economic and environmental benefits.

From an economic standpoint, drones can provide a dual advantage. Their utilization enables the reduction of input quantities such as herbicides, fertilizers, pesticides, and water but also the prevention of damages through early diagnosis of various stress types. Additionally, input savings can yield environmental benefits, positioning these technologies as potential solutions for the environmental sustainability of vegetable crops [64,104].

However, it is imperative to continue research and development to face technological challenges and make these tools increasingly accessible and effective for the agricultural sector where tradition is strong, and innovations are gradually accepted and adopted.

CRediT authorship contribution statement

Marco Canicattì: Data curation, Formal analysis, Methodology, Resources, Visualization, Writing – original draft, Writing – review & editing. **Mariangela Vallone:** Conceptualization, Funding acquisition, Investigation, Supervision, Validation, 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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