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Review Article

A systematic review on precision agriculture applied to sunflowers, the role of hyperspectral imaging

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ABSTRACT

Sunflower is an annual species of the Asteraceae family, and it occupies a relevant position in the world market business as one of the most important oilseed crops. Given the current geopolitical situation and climate change, the agri-food supply chain of sunflower is in crisis. In this context, precision agriculture, especially remote sensing, can address demands for more production and greater sustainability. The aim of the present systematic review is to evaluate the available scientific literature on precision agriculture applied to sunflower crop, specifically the use of hyperspectral data to calculate vegetation indices or create crop growth models. The systematic review follows specific guidelines and a well-described review protocol. A total of 104 studies were included in the review, starting from raw search in different data sources (Scopus, Web of Science, Springer Link, and Science Direct) and following with the application of inclusion criteria. Results focused on the following main topics: crop management (i.e., management zones, yield prediction, vegetation indices correlations), sunflower crop growth monitoring (i.e., identify different growth stages and vegetation parameters), weed management, and industrial applications. The role of hyperspectral sensors has been thoroughly investigated to help choose ideal wavelengths related to vegetation indices. Future research should prioritise water stress management, time-saving evaluation of new sunflower hybrids, and crop growth models.

1. Introduction

Cultivated sunflower (*Helianthus annuus* L.) is an annual species of the Asteraceae family, representing one of the most important crops all over the world. As reported in Fig. 1, sunflower production increased globally from 6.8 million tons (Mt) cultivated on 6.7 million ha (Mha) in 1961 to 58.2 Mt cultivated on 29.5 Mha in 2021 (FAO, 2023).

The plot shows that global harvested area, production, and yield have increased over the years but with different trends, for example harvested area and production increased proportionally until the early 2000s. Then, the total production increased more than the cultivated areas. The trend is confirmed by a 70 % increase recorded in yield in the last 20 years. Successful research on resistances or tolerances to biotic or abiotic stress, the introduction of hybrids with better characteristics, plant breeding to improve agronomic performances explain sunflower growth (Giannini et al., 2022). As pointed out recently by Pilorgé, sunflower crop occupies an important position in the world market business representing the 3rd oilseed produced in the world (9 % of the global production), the 4th in vegetable oils market (9.2 % of the global production), and the 3rd oilseed meal produced (5.6 % of the global production) (Pilorgé, 2020).

Sunflower is an important oilseed crop also because of its "adaptability, suitability to mechanization, low labor needs and high protein and oil contents" (Canavar et al., 2010). Sunflower is a spring–summer crop. Its yield might be affected by environmental and technological factors (Ion et al., 2015). This is why its cultivation is concentrated in a few countries in the central and eastern parts of Eurasia, which have a continental climate. Sunflower is predominantly cultivated in Russia and Ukraine due to their favorable growing conditions, contributing over 50 % of the total global production (FAO, 2023), as shown in Fig. 2.

Agriculture faces the global context of climate crisis and population growth producing more (Giannini et al., 2022). To address this challenge it is important to improve yield potential through the agronomic and breeding progress (Chawade et al., 2019; Fischer et al., 2014), increase cropping intensity (Cassman, 1999; Sandler et al., 2015) or a combination of both while maintaining the actual cropping area

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(Monzon et al., 2018). The critical situation requires an equally strong response through good advancements such as anticipating sowing dates (Asbag et al., 2009; Barros et al., 2004), improving tolerance to drought stress (Hussain et al., 2018; Rauf, 2008), create new adaptable hybrids (Gul et al., 2021; Duca et al., 2022) to increase the yield, and explore new areas of cultivation to increase global production.

To make the scenario even more worrying is the current geopolitical situation involving the Russian-Ukrainian conflict. It has shaken the agri-food supply chain because of their global importance as exporters (Jagtap et al., 2022). According to Hassen and El Bilali, export restrictions have an impact on 78 % of sunflower oil exports with consequent implications for global food pricing and food security (Ben Hassen and El Bilali, 2022).

Sunflower production has become increasingly important as a substitute for palm oil. Anushree et al. assessed that "palm oil happens to be among the products which cause immense ecological damage" (Anushree et al., 2017). The actual crisis involving sunflower oil could reverse the positive trend of substitution of palm oil. So, knowledge about the environmental impact of palm oil should empower the search for solutions to address the economic crisis affecting the sunflower oil market and avoid palm oil returns.

Finding appropriate strategies to deal with the context of geopolitical and environmental crisis is crucial for sunflower global market. Sunflower cultivation has its own importance and must be increased in terms of cultivated area, whereas its global demand will increase (Meijaard et al., 2020). Moreover, the rise in commodity prices should encourage a rethinking of agricultural practices and boost precision farming management (Legrand, 2022). Precision agriculture can be considered one of the best strategies to address these challenges.

The aim of this work is to review the updated and relevant scientific literature on precision agriculture and remote sensing applications on sunflower crops. Specifically, the detection of vegetation indices to find correlation with crop growth models based on hyperspectral imaging.

1.1. Precision agriculture

The cornerstone definition of precision agriculture (PA) is "doing the right thing, in the right place, at the right time" (Pierce and Nowak, 1999). PA can be better explained as a key component of an integrated management system involving on-field observations, data management and action deeply linked to the crop needs (Roy and Food and Agriculture Organization of the United Nations, 2006).

The application of techniques of PA is crucial to improve production efficiency, productivity, and sustainability of the agri-food chain (Ilari et al., 2023; Stafford, 2000; Zhang et al., 2002) while avoiding the negative effects due to both the waste of chemical products and the poor yield caused by insufficient input application (Liaghat and Balasundram, 2010). PA strategy is based on a combination of different technologies such as Geographic Information System (GIS), Global Positioning System (GPS), and advanced data processing (Adekunle, 2013; Du et al., 2008; Liaghat and Balasundram, 2010). According to Liaghat and Balasundram, PA protocol must include at least these three steps: (i) gathering information about the case study, (ii) processing and analysing the information obtained, and (iii) implementing appropriate changes to precision management. Regarding the first point, there are several techniques to get information in agriculture, for example, through remote and proximal sensing. This review focuses on gathering information through remote sensing applied to sunflower crops.

The term "remote sensing" (RS) was first used in the 1960s by the staff of the Geography Branch, Office of Naval Research. After World War II, aerial photo interpretation underwent a strong expansion in use but "photo" was referred to the visible spectrum only, and "aerial" was also limited if considering the potential of Earth observation (Fussell and Rundquist, 1986). RS is the science of gathering and interpreting information about objects by using sensors that are not in physical contact with the observed object (Liaghat and Balasundram, 2010; Wójtowicz et al., 2010).

The principle of remote sensing is the use of the electromagnetic spectrum involving visible, infrared, and microwave regions to detect the features of different surfaces. Each object has its own characterization of wavelength, and it is important from the agricultural point of view to distinguish healthy vegetation, bare soil, and water (Bojan et al., 2014; Shanmugapriya et al., 2019). Each surface has its spectral signature, as reported in Fig. 3. Furthermore, RS is used to detect plant

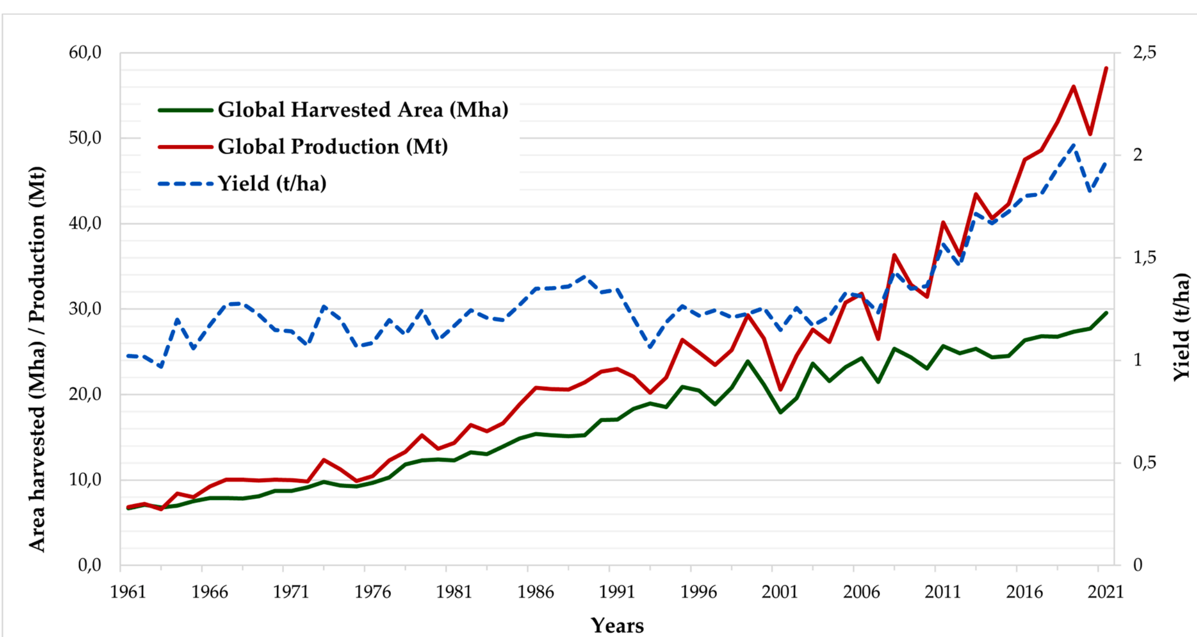

Fig. 1. The plot represents the global sunflower trend over the last 60 years, based on data extracted from the FAOSTAT database. The green line indicates the global harvested area (expressed in million hectares), the red line shows the global production (expressed in million tons), and the dashed blue line indicates the yield (expressed in tons per hectare). Note that data up to 1990s have been estimated, while below are reported official data except for 2021 production, which was also estimated.

diseases (Zhang et al., 2016; Feng et al., 2017; Choosumrong et al., 2023; Ma et al., 2023) or nutritional disorders (Li et al., 2014; Klem et al., 2018; Feng et al., 2020; Zha et al., 2020), as demonstrated by the available and extensive scientific literature.

Remote sensing has many advantages. It is a non-destructive method to gather information, data may be collected over large geographical areas, and it can provide fundamental biophysical information (Liaghat and Balasundram, 2010). In addition, there are many types of sensors that are adaptable in different fields of application according to the specific spatial, spectral, radiometric, and temporal resolution. Sensors are generally equipped on satellites, aerial platforms (such as UAVs, unmanned aerial vehicles), and ground-based platforms (Sishodia et al., 2020). In recent years, remote sensing carried out with UAVs has gradually become more widespread in agriculture thanks to their advantages and the mini-sized and low-cost sensors that have been developed (Adão et al., 2017; Deng et al., 2018; Lu et al., 2020).

Spectral imaging system means producing "a stack of images of the same object at different spectral wavelength bands" (Wu and Sun, 2013). According to Wu and Sun, there are multispectral, hyperspectral, and ultraspectral imaging. Considering only the first two sensors, because they are actually widespread and applicable, both multispectral and hyperspectral are based on the acquisition of images by measuring a spectrum of electromagnetic energy (Adão et al., 2017). The difference among them is the number of bands and their width. Hyperspectral sensors acquire hundreds of images of the object corresponding to a high number of bands and spectral resolution normally less than 10 nm. Multispectral ones acquire few images, usually with about 10 bands and a spectral resolution larger than 10 nm (Adão et al., 2017; Wu and Sun, 2013; Govender et al., 2009). Choosing a hyperspectral sensor rather than a multispectral has pros and cons, summarized in Table 1.

1.2. Hyperspectral imaging applied in agriculture

Hyperspectral imaging (HSI) is an advanced spectroscopic technique made up of a light source, a wavelength dispersion device, a camera, a translator and a computer (Ma et al., 2019; Feng et al., 2021; Rogers et al., 2023). HSI is important to acquire both spatial and spectral information. A growing interest concerns the application of HIS in monitoring e forecasting agro-food production (Khan et al., 2022).

Hyperspectral sensors equipped on UAVs are functional to predict crop yield and quality, to diagnose water and nutritional stress, to detect weeds and disease, and high-throughput phenotyping (Feng et al., 2017; Lowe et al., 2017; Lu et al., 2020; Feng et al., 2020; Chen et al., 2023b). It can be considered a rapid and non-destructive method to monitor crop yield due to the amount of information extractable (Kurihara et al., 2023; Liu et al., 2023; Ren et al., 2023). Thanks to the spectrum continuity, hyperdata are suitable for chlorophyll, carotenoid, and anthocyanin pigments quarrying (Chen et al., 2023a). Based on this information, researchers create growth models and estimate parameters for site-specific management useful to farmers.

Hyperspectral images can also be used to assess nutritional status of the crops calculating vegetation indices and chlorophyll content (Li et al., 2023b; Lleó et al., 2023). In detail, nitrogen content assessment is the major challenge for farmers for reducing fertilisers (Dai et al., 2023) and researchers focuses on how to extract nitrogen content information for cotton (Li et al., 2023c), wheat (Fan et al., 2023; Ju et al., 2023; Li et al., 2023a), corn (Han et al., 2022; Jia et al., 2023; Ranghetti et al., 2023), olive trees (Rubio-Delgado et al., 2021), and rice (Moharana and Dutta, 2016).

Lastly, hyperspectral data must be processed to extract information (Lu et al., 2020). Pre-processing is required and involves radiometric, atmospheric, and spectral calibration to achieve more accurate results. Generally, software packages are available that automate these corrections. Then, data analysis can be performed with traditional approaches, i.e. linear regression (Fei et al., 2024; Mahesh et al., 2015), or innovative ones, i.e. machine/deep learning (Centorame et al., 2024; Silva et al., 2024) and radiative transfer models (Upreti et al., 2019; Wang et al., 2021).

2. Research methodology

The scope of systematic review is to evaluate all available research relevant to the topic. So, it is important to formulate research questions to be answered through a systematic and replicable scientific method. Searching, selecting, and deepening articles must be a clear process (Moher et al., 2009). In order to perform rigorous reviews, it is necessary to have guidelines (Grant and Booth, 2009). The present systematic review has been carried out following the "Guidelines for performing

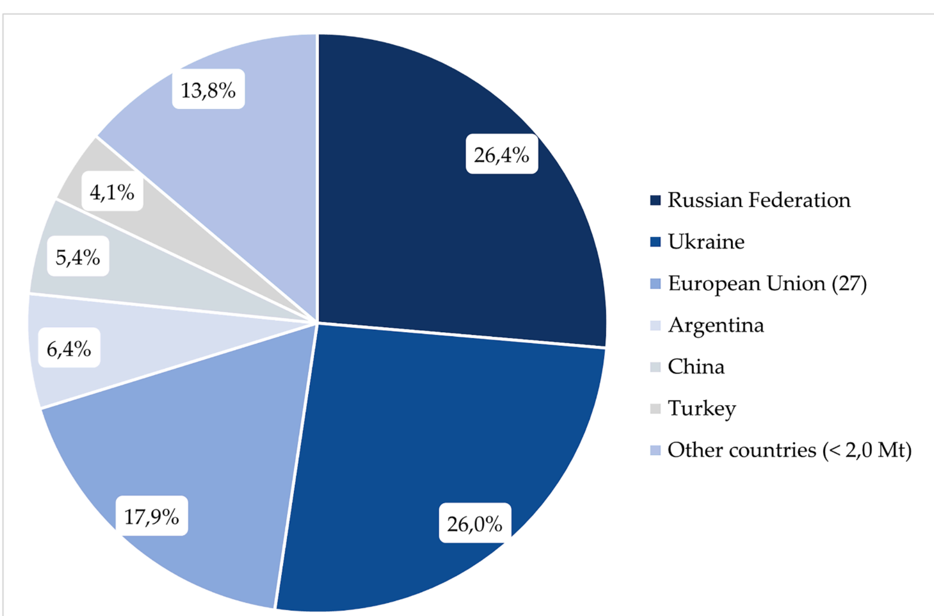

Fig. 2. The major producers of sunflower in 2020 based on data extracted from the FAOSTAT database: Russia Federation and Ukraine are the biggest producers in the world, followed by the European Union (27), Argentina, China, and Turkey.

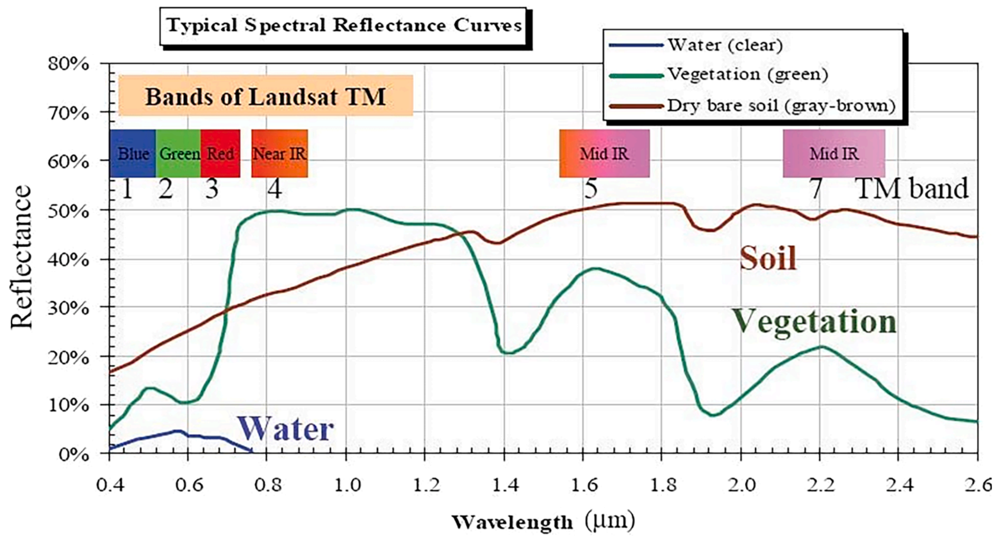

Fig. 3. The plot has been taken from Bojan et al., 2014 (Bojan et al., 2014). It represents the typical spectral reflectance curves of healthy vegetation, dry, bare soil, and clear lake water.

Table 1
The table summarizes the pros and cons related to the application of hyperspectral sensors mounted on drones in agriculture.

Pros	Cons
Ability to capture detailed information in both spectral and spatial ranges (Adão et al., 2017)	High cost of cameras, especially lightweight versions to be equipped on UAV platform (Deery et al., 2014)
Specific wavelengths used to measure biomolecules such as chlorophyll, carotenoids, and such (Gevaert et al., 2015)	Many terabytes of storage space are needed for Big Data (Ang and Seng, 2021) and a lot of processing time is required (Lowe et al., 2017)
The non-destructive method applicable to both qualitative and quantitative analysis (Wu and Sun, 2013)	On-the-go application is not currently recommended because of the long processing time needed (Wu and Sun, 2013)

Systematic Literature Reviews in Software Engineering” (Kitchenham and Charters, 2007) and the PRISMA statement (Page et al., 2021) by adapting them to precision agriculture topic. In this paragraph, the steps that led to the review are described.

Planning the review is the first step. It is important to identify the needs to write the review and to formulate the right research questions. These questions represent the common thread of the whole work. To properly accomplish the review, a protocol must be developed and evaluated by supervisors to assess its suitability. The second step is conducting the review by searching publications, making a primary selection based on inclusion criteria, and then an in-depth analysis, followed by data extraction and analysis. In the end, the third step includes processing the results obtained and drawing up responses to each research question. Planning and conducting the review are outlined in the following subsections, while results are described in section 3.

2.1. Research questions

The present systematic review is inspired by the knowledge gap about the application of hyperspectral cameras in sunflower cultivation. In particular, the work aims to detect the relationship between hyperspectral data and vegetation indices and crop growth models already existing in the literature. To achieve these goals, three questions were asked to clarify the need for research.

1. What are the applications of precision agriculture in sunflower cultivation, especially in remote sensing?
   a. Application of precision agriculture strategies.
   b. Application of remote sensing techniques.
2. What are the actual applications of hyperspectral sensors in cultivated sunflower?
3. How do hyperspectral data correlate with vegetation indices and crop growth models?
   a. Vegetation indices are built up using hyperspectral data.
   b. Correlation between hyperspectral data and crop growth model.

2.2. Development and evaluation of the review protocol

The review protocol, required by the guidelines cited above, is important to correctly develop the research by reducing the risk of bìas and leading to the systematic literature review. The protocol is described in this subsection.

Firstly, different data sources have been selected to answer the research questions, and this step is based on the relevance to the topic. At this point, keywords have been entered in the search bar. Inclusion criteria, described in detail below, were applied to publications found. Results obtained were carefully examined based on the title and abstract. The purpose was to check only publications related to the issue. If the publication was not related to any of the research questions, then it was discarded. On the contrary, it has been downloaded. Subsequently, an in-depth analysis was conducted on the potentially useful publications by reading the full article. In this last step, the most important aspect was to evaluate the full article according to its compliance with the research questions.

The review protocol and its adequacy to scientific research have been assessed by two supervisors. To minimize the risk of bìas, the protocol must be followed step-by-step. First, research questions have been formulated to reduce the conceptual bìas. Then, inclusion criteria were strictly and equally applied to each paper. Finally, data analysis has been carried out to include only those articles that actually meet the needs for research.

2.3. Application of the review protocol

The research activities were carried out in December 2022, and the last access was made on 07 March 2023. In order to start the search, four data sources have been selected: Scopus (https://www.scopus.com/), Web of Science (https://www.webofscience.com/), Springer Link (https://link.springer.com/), and Science Direct (https://sciencedirect.com/). Inside each database, the research was conducted by combinations (C) of different keywords (K), as reported in Table 2. Keyword combinations were chosen carefully to answer the research questions.

In order to realize the systematic literature review, 20 different searches were performed (4 sources and 5 keyword combinations each). Thanks to these research criteria, a total of 15,407 publications have undergone the screening selection procedure: 256 from Scopus, 375 from Web of Science, 7,973 from Springer Link, and 6,803 from Science Direct. Pay attention to the order of publications set by the search engine because a search on Scopus is sorted by date, while a search on Web of Science, Springer Link, and Science Direct is sorted by relevance.

For each search, up to 200 results were selected and recorded on an Excel worksheet, although 10 gave less than 200 results. The following inclusion criteria were applied: (i) full articles or conference proceedings since 2000 to date; (ii) coherence with the main theme of the systematic review by checking for title and abstract; (iii) written in the English language; (iv) open access or available for download. Contemporary, repeated publications were removed. The potentially useful publications that resulted from the pre-selection were 146, more in detail: 78 from Scopus, 38 from Web of Science, 10 from Springer Link, and 20 from Science Direct. An in-depth analysis was conducted by reading the full article. 42 articles were not coherent with the present research, and then they were removed. Lastly, a total of 104 are useful and, consequently, included in the review.

For greater clarity, two flowcharts have been included to explain the process: the first one is shown in Fig. 4 and goes from the choice of the data source to the creation of a raw database; the second one is shown in Fig. 5 and represents the application of inclusion criteria to get to the publications included in the review. At the end, the summary of the entire framework with details is reported in Fig. 6.

2.4. Data extraction and analysis

Full references of the potentially useful publications were recorded by using Microsoft Excel. For each article, data extracted are title, author (s), source, year of publication, and country of the authors. Data analysis was carried out through thematic analysis, for example, assigning one or more categories to each article focusing on the relationship between keywords and research questions.

3. Results and discussion

This section summarizes the results of the systematic review. Firstly, a brief data analysis is provided in the first part of this chapter, while a detailed analysis of the results for each research question follows.

Fig. 7 highlights the growing interest in sunflower crop and precision agriculture applied to its cultivation. Fig. 8 remarks the importance of research groups from Spain, France and China on this topic and the collaborative approach between research institutes.

3.1. Application of precision agriculture strategies

Sunflower crop is one of the most important oilseeds in the world but is usually considered in crop rotation with wheat, corn, tomato, bean, and others. So, most scientific papers relate precision agriculture strategies to sunflowers as part of crop rotation. Five main topics have been identified that are crop management, monitoring of phenological stages, water stress management, weed management, and breeding and industrial applications. More details are reported in Table 3.

Table 2
Keywords and their combinations are used to get results.

Keywords	K1 → sunflower
	K2 → precision agriculture
	K3 → remote sensing
	K4 → hyperspectral
	K5 → vegetation indices
	K6 → crop growth model
Combinations	C1a → (K1 AND K2)
	C1b → (K1 AND K3)
	C2 → (K1) AND (K4)
	C3a → (K1 AND K4 AND K5
	C3b → (K1 AND K4 AND K6)

3.1.1. Crop management

Crop management is one of the hottest topics for farmers due to its involvement in agronomic operations. The importance of crop management belongs to the possibility of gather in-field data through proximal and remote sensing techniques. Basics of precision agriculture lie in site-specific management that is also proposed as approach for sunflower cultivation (Amankulova et al., 2023; Vidican et al., 2023). In detail, crop management starts with the definition of management zones and yield prediction. Forecasting crop yield and quality enable farmers to correct agronomic measures according to plants' needs (Sishodia et al., 2020).

Perez-Quezada et al. analysed yield data at a high-resolution level using K-mean clustering to build management zones that can be used by farmers (Perez-Quezada et al., 2003). Then, a further step was made. Ali et al. tried to combine multiple-year yield data with soil properties, thanks to soil sampling techniques and Normalized Difference Vegetation Indices (NDVI) data from satellite (Ali et al., 2022). All datasets underwent descriptive statistics and geostatistical analysis, followed by clustering technique to evaluate the feasible number of management zones. Monzon et al. described the importance of crop management zones based on ecophysiological properties and highlighted the positive impact on grain yield and profit (Monzon et al., 2018).

The following articles relate to correlations between different sunflower data. Gamon et al. described both canopy structure and photosynthetic activity of sunflowers (Gamon et al., 2001). Dai et al. developed an artificial neural network model and showed that sunflower yield can be affected by salinity but soil moisture can offset the stress (Dai et al., 2011). Turhan et al. conducted an experiment about the effect of salinity during the early growth stage of sunflowers using a spectroradiometer (Turhan et al., 2008). Measured chlorophyll content and calculated NDVI enable to detect saline stress before symptoms are revealed. Lei et al. compared physical-based and machine learning tools to predict soil salinity (Lei et al., 2023) to highlight that machine learning requires less user calibration and enable prediction in complex contest, but accuracy depends on the quality of the training.

Vega et al. worked on sunflower recognition through maximum likelihood classification (Vega et al., 2015). Then, they obtained a positive correlation between NDVI, and grain yield, aerial biomass, and nitrogen content UAV images can enable the possibility to detect crop stress early. The correlation between NDVI and grain yield was recently confirmed by another study with an high coefficient of determination (0.9135) (Lykhovyd, 2021). Paudel et al. developed a correct, reusable, and modular workflow to predict yield on different crops and scales through an extensive machine learning application (Paudel et al., 2021). Lastly, Amankulova et al. trained a Random Forest regressor from yield data collected during sunflowers harvesting (Amankulova et al., 2023).

It is important to highlight that NDVI and other indices, as well as the resulting data analysis, derived from specific skills and so farmers often cannot easily access them. To address farmers' needs, Karakus and Karabork developed the Green Crop Tracker that is a reliable, fast, and low-cost software for vegetation cover estimation starting from RGB images (Karakus and Karabork, 2017). Moreover, another research team tested the fractional green canopy cover (FGCC) extracted from the Canopeo mobile app to show a strong correlation with NDVI (Lykhovyd et al., 2022). These outcomes are useful for farmers because provide tools that can help in decision making process.

3.1.2. Monitoring of phenological stages

Sunflower growth monitoring is one of the most important matters.

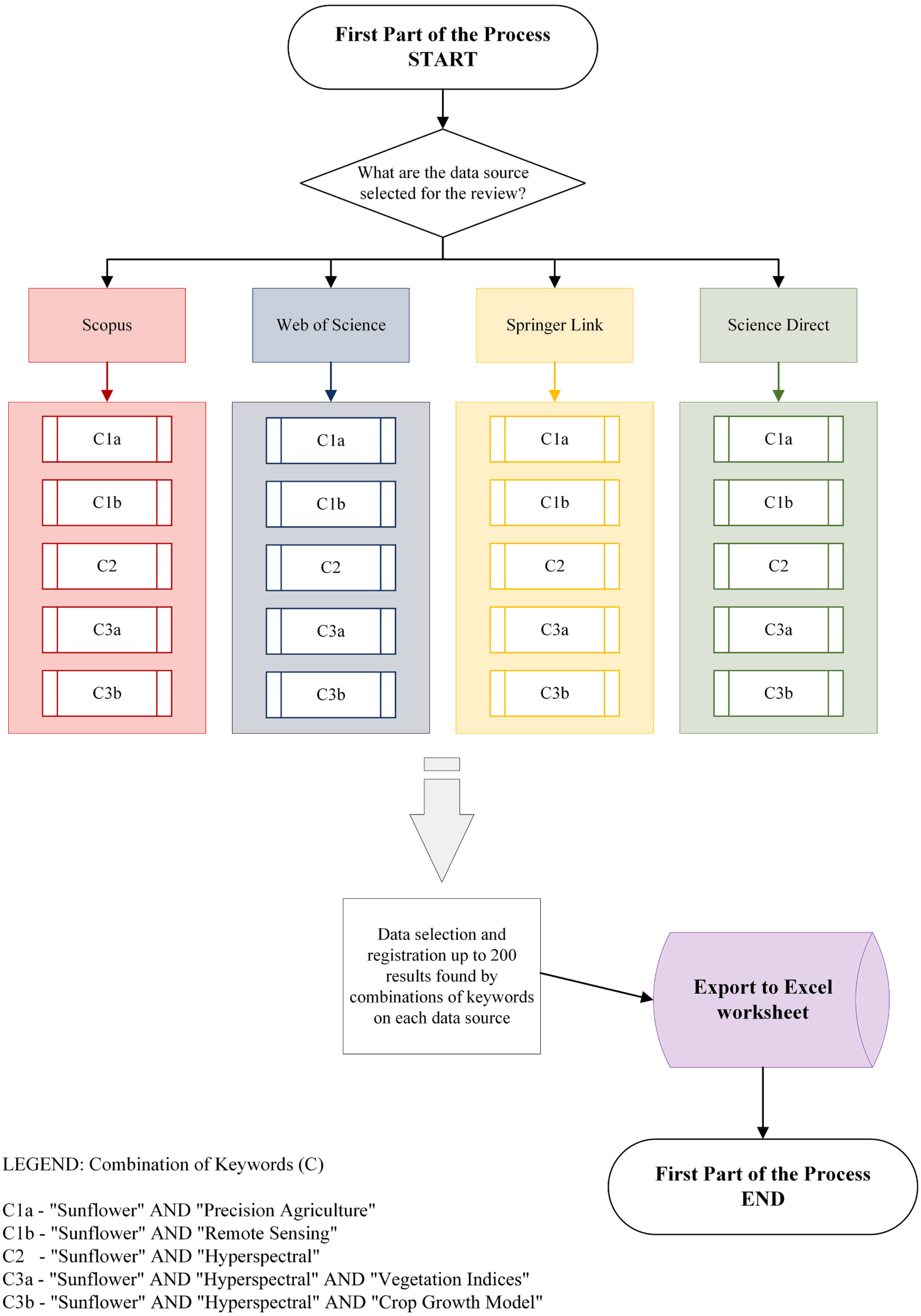

Fig. 4. The flowchart represents the first part of the process to realize the systematic literature review. Starts with the choice of search engines, coherent with the themes of the review. So, each data source is used to search for the same specific set of keyword combinations (C). Up to 200 results from each keyword combination searched on each data source were recorded on an Excel worksheet. The database of results found represents the end of the flow.

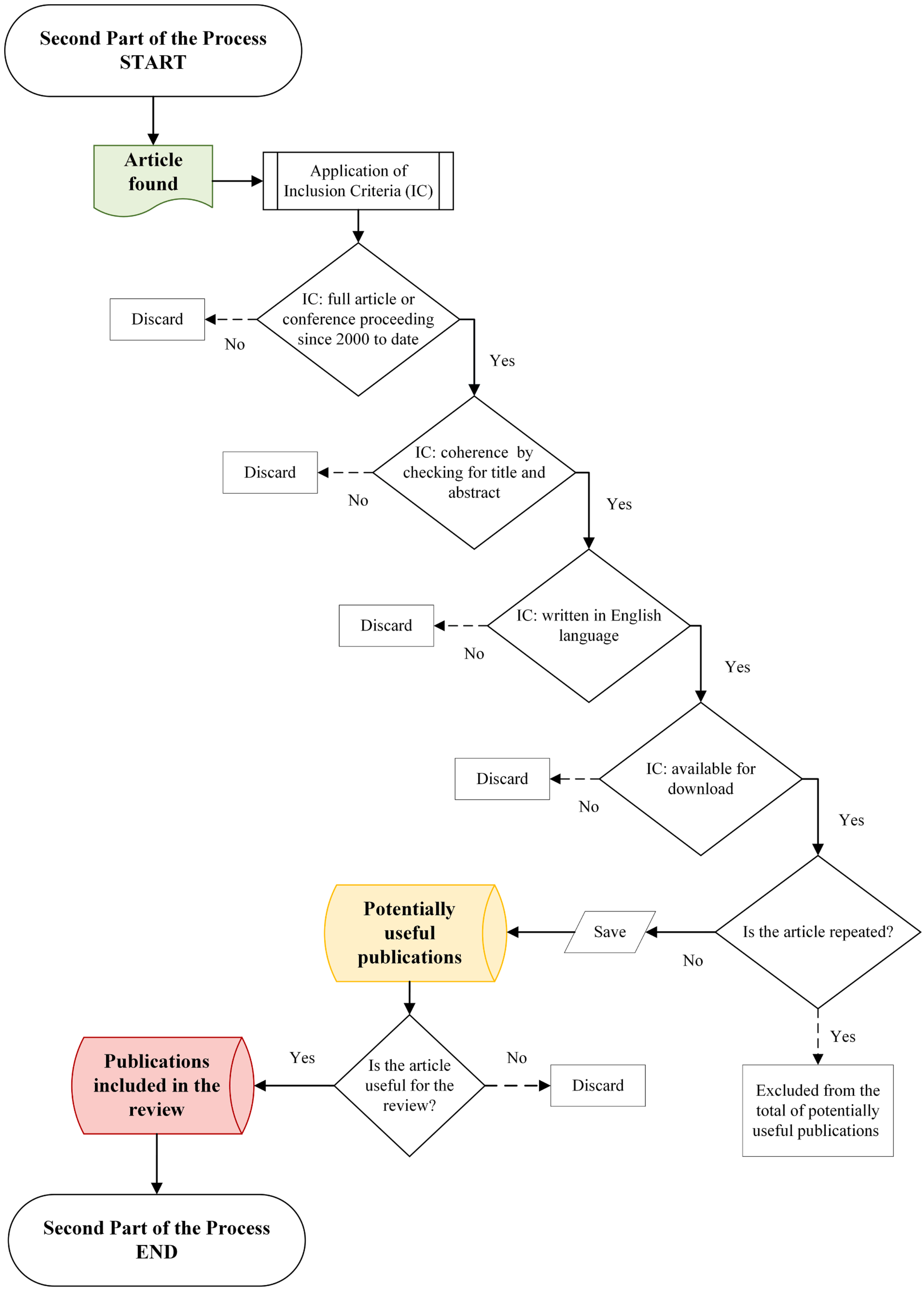

Fig. 5. The flowchart represents the second part of the process to realize the systematic literature review. The steps described in the flowchart refer to a single article found, so this means that the same process has been repeated 2,600 times (1 time for each article in the database). The flowchart describes the application of the inclusion criteria to get the potentially useful publications first and then the publications included in the review.

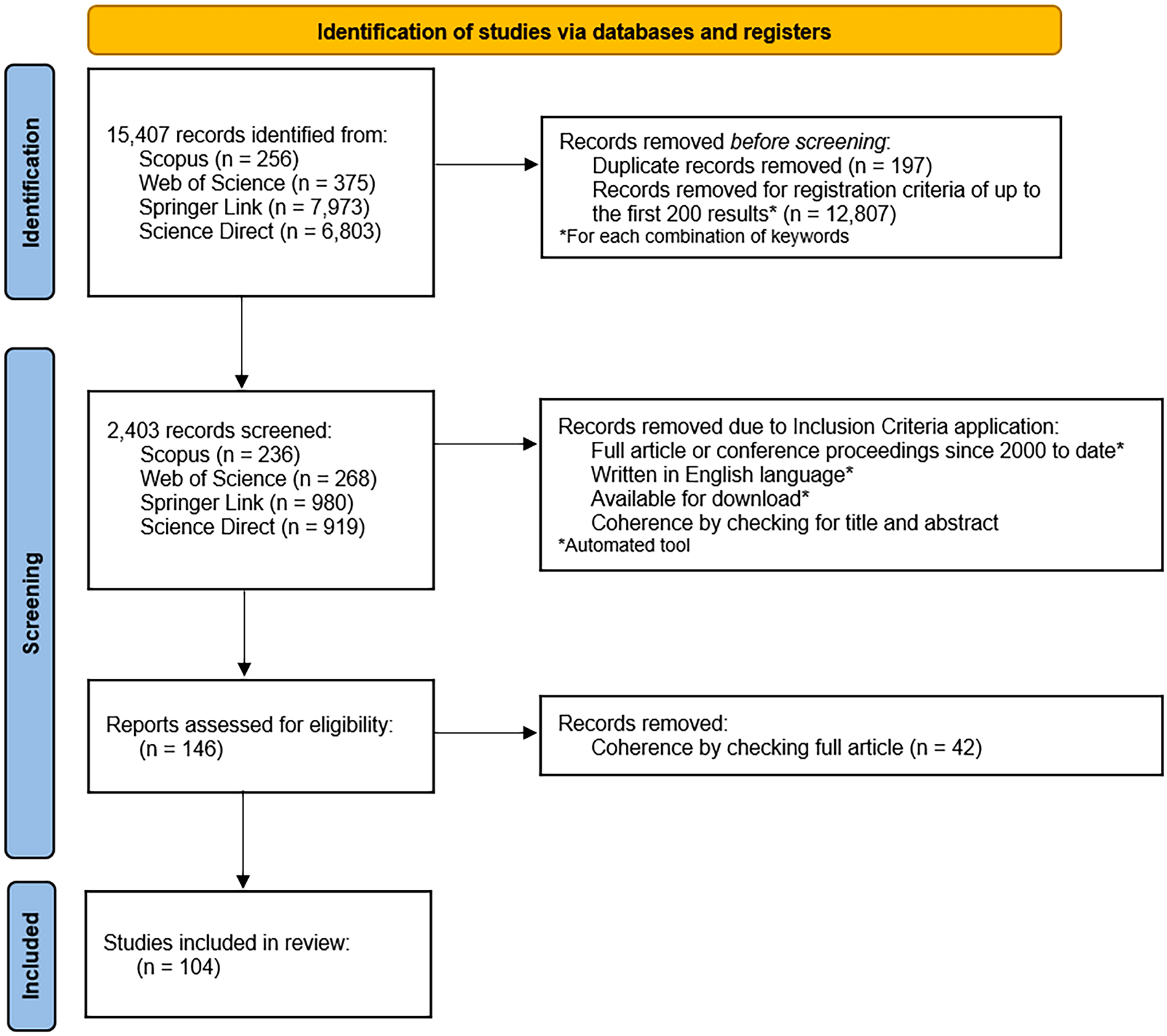

Fig. 6. Summary of the research methodology based on PRISMA guidelines (Page et al., 2021).

Recognising sunflower in open field conditions is a basic approach to extract some information. Firstly, it is important to monitor how long elapses between the phenological stages to allow farmers to plan agronomic operations. Moreover, the screening of each phenological stage enable to easily identify weeds and control them. Sunflower recognition is one of the preliminary investigations to be carried out for germination rate monitoring and early weeds detection (Torres-Sánchez et al., 2015; Jaya Brindha and Gopi, 2022).

Meyer et al. developed and compared unsupervised fuzzy colour index and clustering methods to recognise green plants from soil and residues (Meyer et al., 2004). The intensified fuzzy Gustafson–Kessel algorithm showed good performance on RGB images. Few years later, Ruiz-Ruiz et al. implemented an environmentally adaptive segmentation algorithm to detect plants in four different growing stages (Ruiz-Ruiz et al., 2009). Another study used a pre-trained deep learning network algorithm (AlexNet) for phenological stages classification and sunflower yield estimation through activation maps (Yalcin, 2019). Das Choudhury et al. developed a deep learning tool called FlowerPhenoNet to recognise flowers and produce status reports (Das Choudhury et al., 2022). Deep learning demonstrates high performance and applicability to several flower species.

Lati et al. developed a 3D model to reconstruct sunflower structure due to its evolution during growing season and estimate growth parameters directly from the model (Lati et al., 2013). Authors enhanced stereovision models which allow estimation of plants' parameters regardless of imaging condition. Encouraging results paved the way for further work on this topic, for example the optical system with an image sensor and a processing unit based on Internet of Things technology to track the plant stem growth rate (Nayak et al., 2022). Song et al. worked on automatic extraction of texture and spectral features from multispectral images in different growth periods (Song et al., 2023). A deep semantic segmentation was tested to predict the spatial distribution of sunflower growth stages at pixel level, and it can be useful for experimental fields due to size plots.

3.1.3. Water stress management

Only in recent years the rationalisation of water has begun to be a hot topic, also because of the public concern for it. Precision agriculture tools enable to control irrigated crops and schedule irrigation interventions adapted to the needs of crops avoiding water waste.

López-Granados et al. used an handheld spectroradiometer to find differences between irrigated and non-irrigated crops (López-Granados et al., 2010). Authors suggested to consider red, green, blue and near infrared wavebands to calculate useful vegetation indices related to water content. Taghvaeian et al. analysed the relationship between canopy temperature and water stress (Taghvaeian et al., 2014). The simple degrees calculated above non-stressed indices resulted to be sufficient to schedule irrigations. Vergni et al. have drawn up a new

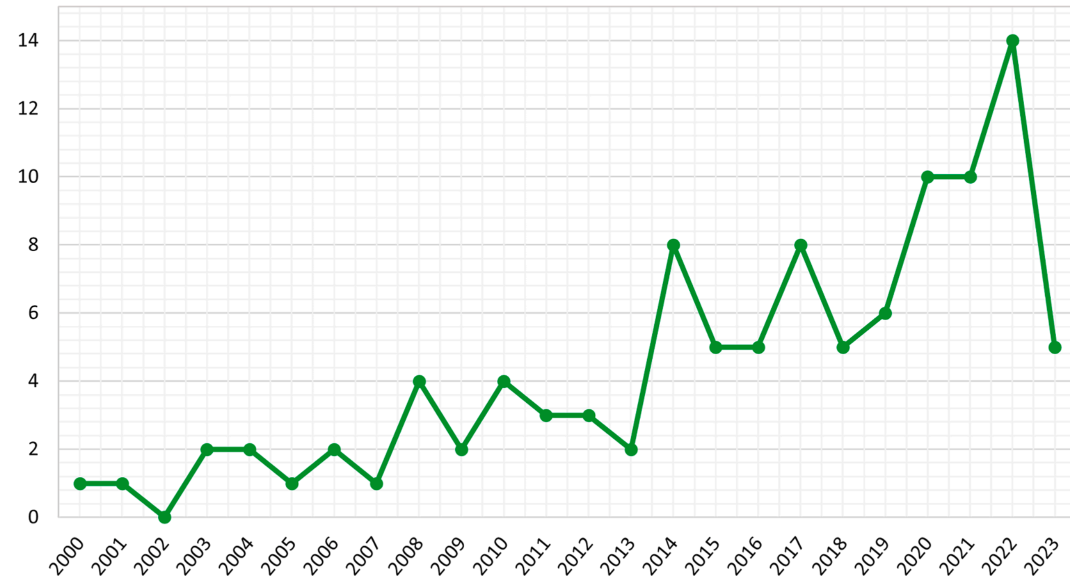

Fig. 7. Number of scientific papers published since the 2000s about precision agriculture applied to sunflower crops. The interest in the topics discussed in the systematic literature review is increasing. Articles published in 2023 seem less numerous than in previous years but refer only to the period from January to March (last accessed on 07 March 2023).

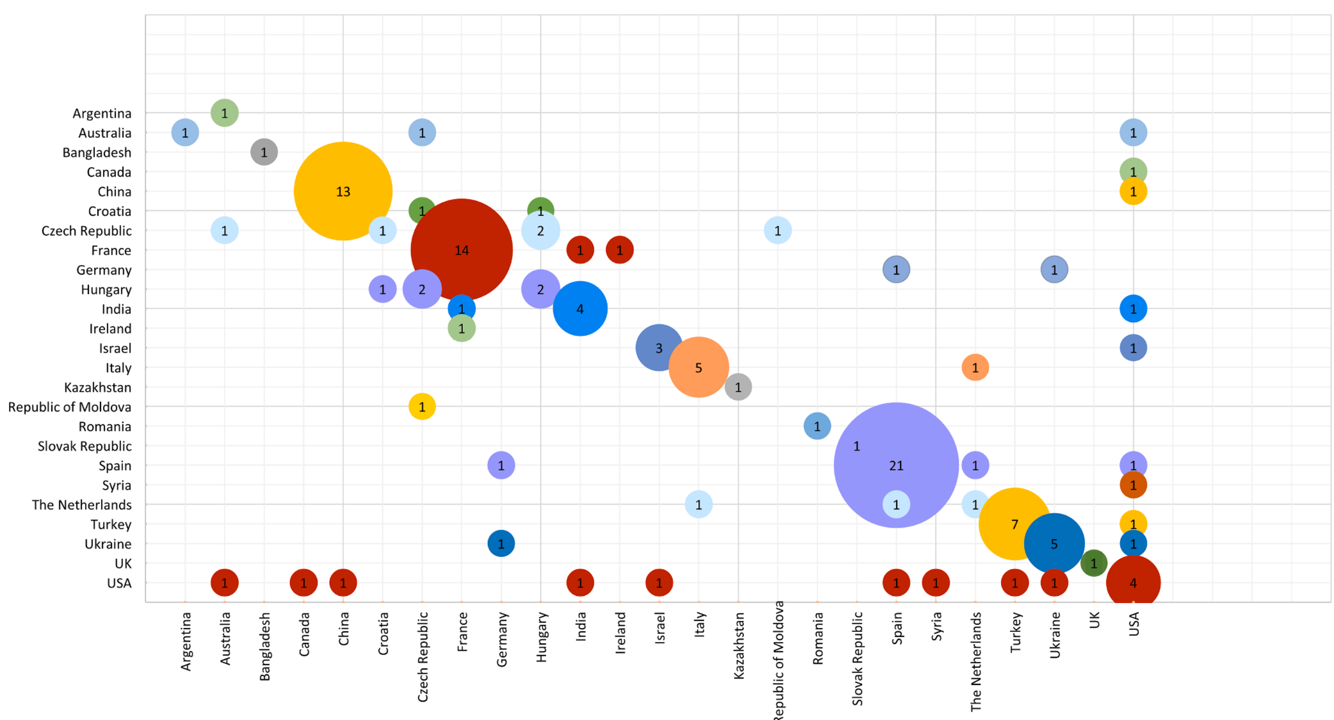

Fig. 8. The bubble chart clarifies which countries are involved in research on precision agriculture applied to sunflower crops. The research teams that worked most on the topics discussed came from Spain, France, and China. The other interesting aspect is that there are numerous collaborative works by researchers affiliated with research institutes from 2 or 3 countries.

index, the Standard Deficit Distance Index (SDDI), that considers how the water deficit is distributed over time and at what severity level (Vergni et al., 2021). This kind of data analysis is crucial to evaluate the drought impact on agriculture and to act accordingly.

Miner et al. proposed and tested a low-cost sensor to detect sunflower water consumption aimed at better crop management (Miner et al., 2017). Sánchez et al. proposed an alternative method to the conventional lysimeter to measure the crop coefficient of sunflower (Sánchez et al., 2014). Kovár et al. assessed infrared thermography to study the efficiency of water use according to the distribution of biologically active preparations (BAPs) (Kovár et al., 2016). Results show that BAPs positively affect oil content, yield, and the sensitivity of stomata to environmental stress. Sreelash et al. demonstrated an interest in crop model inversion to estimate available water capacity (Sreelash et al., 2017). Authors conclude that the quality of estimation depends on many variables but, in any case, provides encouraging results to deepen the topic.

Table 3
Scientific papers focused on the application of precision agriculture strategies on sunflowers. Aims are reported in the first column corresponding to the five main topics. Then, each referenced article was divided according to the input data provided (i.e. ground-based measurements or aerial images) and the main algorithms used for data analysis.

Aims	Input	Algorithms*	References
Crop management	Ground-based data	Simple light-use efficiency model	(Gamon et al., 2001)
	Yield-mapping system	K-mean clustering	(Perez-Quezada et al., 2003)
	Ground-based data and visible-NIR images (FieldSpec Handheld Spectroradiometer)	Least Significance Difference Test	(Turhan et al., 2008)
	Ground-based data	ANN	(Dai et al., 2011)
	Multispectral images (Tetracam ADC Lite)	Maximum Likelihood Classification	(Vega et al., 2015)
	RGB images (Sony DSC-S930)	Green Crop Tracker	(Karakus and Karabork, 2017)
	Ground-based data	n/a	(Monzon et al., 2018)
	MODIS images	Linear regression	(Lykhovyd, 2021)
	Ground-based data and Landsat images	Fuzzy c-means clustering	(Ali et al., 2022)
	Sentinel-1 and RGB (Sony Xperia XZ2 Premium) images	Regression analysis	(Lykhovyd et al., 2022)
	Yield-mapping system and Sentinel-2 images	RF Regression	(Amankulova et al., 2023)
	Ground-based data	Physical-based and machine learning model	(Lei et al., 2023)
Monitoring of phenological stages	RGB images (Kodak Digital Science DC120)	Fuzzy clustering	(Meyer et al., 2004)
	RGB images (Benq DC310 and Epson L410)	Environmentally Adaptive Segmentation Algorithm	(Ruiz-Ruiz et al., 2009)
	RGB images	3D plant reconstruction model	(Lati et al., 2013)
	RGB (Olympus Pen E-PM1) and multispectral (Tetracam Mini MCA-6) images	OBIA	(Torres-Sánchez et al., 2015)
	RGB images	CNN	(Yalcin, 2019)
	RGB images	CNN	(Jaya Brindha and Gopi, 2022)
	Ground-based data	n/a	(Nayak et al., 2022)
	RGB images (LemnaTec Scanalyzer 3D)	DNN	(Das Choudhury et al., 2022)
	Multispectral images (Tetracam Micro-MCA)	Deep semantic segmentation classification	(Song et al., 2023)
Water stress management	Visible-NIR images (FieldSpec Handheld Spectroradiometer)	Multilayer Perceptron and Radial Basis Function	(López-Granados et al., 2010)
	Thermal Infrared images (Apogee SI-211)	Energy balance model	(Sánchez et al., 2014)
	Thermal Infrared images (Apogee SI-121)	Regression analysis	(Taghvaeian et al., 2014)
	Thermal Infrared images (EasIR-4)	Pearson's correlation	(Kovár et al., 2016)
	Ground-based data	Bayesian models	(Sreelash et al., 2017)
	Sap floe sensor	n/a	(Miner et al., 2017)
	Ground-based data	Pearson's correlation	(Vergni et al., 2021)
Weed management	NIR spectra (NIRS System 6500)	Analysis of variance and Duncan's Multiple Range Test	(Jurado-Expósito et al., 2003)
	Ground-based data	Spatial nonparametric regression model	(Francisco-Fernández et al., 2006)
	RGB and multispectral images (RMK TOP-15 + Zeiss objective)	Evolutionary Product Unit Neural Networks	(Gutiérrez et al., 2008b)
	RGB and multispectral images (RMK TOP-15 + Zeiss objective)	Evolutionary Product Unit Neural Networks and Logistic Regression	(Gutiérrez et al., 2008c)
	Ground-based data	Kriging	(Jurado-Expósito et al., 2009)
	RGB images (PANASONIC DMCLX1 + Leica DC VARIO-ELMARIT 1:2.8–4.9/6.3–25.2 ASPH)	Generalized Softmax Perceptron and Posterior Probability Model Selection	(Arribas et al., 2011)
	Fluorescence images (Open FluorCamFC 800-O)	Analysis of variance	(Pérez-Bueno et al., 2014)
	RGB (Olympus Pen E-PM1) and multispectral (Tetracam Mini MCA-6) images	Unsupervised, semi-supervised and supervised techniques	(Pérez-Ortiz et al., 2015)
	RGB images (Olympus Pen E-PM1)	OBIA	(Pérez-Ortiz et al., 2016)
	RGB images (Sony Alpha 7R Mark4)	CNN	(Peteinatos et al., 2020)
	MARS Crop Yield ForecastingSystem (MCYFS)	Feature selection and prediction algorithms	(Paudel et al., 2021)
	RGB images (Sony ILCE-6000) and ground-based data	ANN	(Torres-Sánchez et al., 2021)
Breeding and industrial applications	RGB images (Sony XC-003P)	Unsupervised classification method	(Ducournau et al., 2004)
	Plant-based data	SUNFLO	(Casadebaig et al., 2011)
	Hyperspectral images (CMOS, Thorlabs DCC3240M)	Repeatability Error-Analysis of Variance-Simultaneous Component Analysis	(Ryckewaert et al., 2020)
	RGB images (Canon 650 D)	DCNN	(Kurtulmuş, 2021)

ANN, Artificial Neural Network; CNN, Convolutional Neural Network; DCNN, Deep Convolutional Neural Network; DCNN, Deep Neural Network; RF, Random Forest; OBIA; Object Based Image Analysis.

3.1.4. Weed management

An important slice of scientific publications concerns weed management. Weeds can compromise yield and crop quality. So, farmers need to control them with an efficient strategy. Precision agriculture aims to create prescription maps to design site-specific weed control. This implies both weed monitoring and capability to predict weeds' spread using multi-year data.

Jurado-Expósito et al. used NIR spectroscopy to determine the spectral curves of weeds, sunflower, and wheat stubble (Jurado-Expósito et al., 2003). Spectral window from 750 to 950 nm is considered crucial to distinguish several weeds to sunflower and wheat stubble. Pérez-Bueno et al. were the first to work on multicolour fluorescence imaging both to identify infected plants and to use a non-invasive tool for early diagnosis (Pérez-Bueno et al., 2014).

Francisco-Fernández et al. focused on nonparametric analysis to identify *Convolvulus arvensis* patches and then develop a multi-year map to point out areas at risk for infestation by perennial weeds (Francisco-Fernández et al., 2006).

Gutiérrez et al. worked on *Ridolfia segetum* infestations on sunflower crops to support site-specific management through evolutionary product unit neural networks (Gutiérrez et al., 2008b, 2008c). The same workflow was pursued by Jurado-Expósito et al. through the comparison of two prediction techniques (Jurado-Expósito et al., 2009). Kriging with an external drift, which combines weed density data and digital elevation model, improve the accuracy of precision agriculture maps more than the ordinary kriging, that focuses only on weed density data.

More recent applications in this context have given rise to the use of drones to acquire aerial images with high resolution. Pérez-Ortiz et al. combined multispectral information, vegetation indices, and crop row detection method to train a machine learning algorithm to classify sunflower crop and weeds (Pérez-Ortiz et al., 2015, 2016). To reach the same scope, Peteinatos et al. tested three Convolutional Neural Networks (Peteinatos et al., 2020). ResNet-50 and Xception performed better than VGG16, achieving performance of 97 % and 98 % respectively. Arribas et al. confirmed the potentiality of neural networks and identify essential features for classification which are perimeter, area, the major and minor axis of the best-fit ellipse, and the logarithm of the height-to-width ratio (Arribas et al., 2011).

To improve the effectiveness of herbicide treatments and allow the best choice of active ingredient, it is important to early detect broad-leaf (dicotyledonous) and narrow-leaf (monocotyledonous) weeds. Torres-Sánchez et al. focused on this goal by exploiting the combination of UAV images and neural networks and reached satisfactory results (Torres-Sánchez et al., 2021).

3.1.5. Breeding and industrial application

Precision agriculture techniques applied to sunflower crop involves the entire supply chain, for example, the plant breeding sector or agricultural industries. A group of researchers led by Ryckewaert tested a low-cost sensor to identify sunflower genotypes with great outcomes (Ryckewaert et al., 2020). A multivariate data analysis was tested to assess genotypes with major impact and identify which variables are involved. Casadebaig et al. developed the SUNFLO model to simulate the response of sunflower genotype under different environmental condition (Casadebaig et al., 2011).

A recent research addressed the need for industries to identify seeds based on specific features through deep learning (Kurtulmuş, 2021). Ducournau et al. presented an automated and time-saving process for image acquisition and segmentation (Ducournau et al., 2004). In this case study, the aim was to calculate the germination rate of sunflower seeds.

3.2. Application of remote sensing techniques

Remote sensing techniques are widespread in agriculture to monitor crops due to the spread of aerial platforms and satellites. Deepening remote sensing, four main issues to discuss: crop management, monitoring of phenological stages, water management, and weed management. The goal is to ensure the right information to the farmer and the right tool for field management. To address this challenge, researchers should start with basic information about vegetation towards complex correlations. More details are available in Table 4.

Table 4
Scientific papers focused on the application of remote sensing techniques on sunflowers. Aims are reported in the first column corresponding to the four main topics. Then, each referenced article was divided according to remote sensing technique (i.e. by satellite, drones, or different aerial platform) and the main algorithms used for data analysis.

Aims	Remote sensing input*	Algorithms**	References
Crop management	A: LiDAR	Regression analysis	(Houldcroft et al., 2005)
	S: SPOT-4/5	Iterative Self-OrganizedUnsupervised Clustering (ISODATA)	(Khan et al., 2010)
	S: Formosat-2	Simple Algorithm for Yield estimates (SAFY)	(Claverie et al., 2012)
	S: SPARC (ESA)	Linear regression	(Delegido et al., 2013)
	S: COSMO-SkyMed	Radiative Transfer model	(Santi et al., 2012; Paloscia et al., 2014)
	S: TerraSAR-X, RadarSat-2, and ALOS	n/a	(Fieuzal et al., 2012; Fieuzal and Baup, 2014)
	S: Radarsat	SVM, DT, and Multilayer Perceptron	(Kussul et al., 2014)
	S: Modis, Landsat-8, Proba-V, Spot-4/5, Radarsat, Sentinel-1	Multilayer Perceptron	(Kussul et al., 2016)
	S: Radarsat-2 and Landsat-8	Multilayer Perceptron	(Skakun et al., 2016)
	S: Landsat-8 and Sentinel-1	CNN, RF, and Multilayer Perceptron	(Kussul et al., 2017)
	S: Chinese HJ-1A/1B	Phenological metrics	(Yu and Shang, 2017)
	S: Chinese HJ-1A/1B	RF	(Yu and Shang, 2018)
	S: Modis	Pearson's correlation and MLR models	(Kern et al., 2018)
	D: Parrot Sequoia (multispectral) on DJI S1000+	Regression analysis	(Tunca et al., 2018)
	S: Landsat-5/7/8	Geostatistical analysis	(Ali et al., 2019)
	S: Landsat-7/8 and Chinese HJ-1A/1B	SVM and RF	(Wen et al., 2019)
	S: Sentinel-2	Supervised modified possibilistic c-means	(Vincent et al., 2020)
	S: Chinese HJ-1A/1B	Hybrid dual-source scheme and trapezoid framework-based ET Model	(Yu and Shang, 2020)
	S: Landsat-8, Deimos, SPOT-5 Take5, Formosat-2, and Sentinel-2	SUNFLO	(Trépos et al., 2020)
	S: Sentinel-2	Linear regression, CNN, and ANN	(Narin et al., 2021)
	S: Sentinel-1/2	Linear regression	(Meroni et al., 2021)
	S: Sentinel-2	CNN	(Tang et al., 2022)
	S: Modis	Robust crop estimation method	(Bognár et al., 2022)
	S: Sentinel-2	Nonlinear least-squares (Levenberg-Marquardt)	(Sadenova et al., 2022)
	S: Landsat-8, Deimos, SPOT-5 Take5, and Sentinel-2	Linear regression, Polynomial regression, RF regressor, and Gaussian process	(Debaeke et al., 2023)

(continued on next page)

Table 4 (*continued*)

Aims	Remote sensing input*	Algorithms**	References
	D: RedEdge MicaSense (multispectral) on house-developed drone	MLR, RF and ANN	(Cui et al., 2023)
	S: Sentinel-1/2	SVM, ANN, CNN, MLR and Extreme Gradient Boosting	(Abdikan et al., 2023)
Monitoring of phenological stages	S: Formosat-2	Mathematical morphology algorithm	(Marais Sicre et al., 2014)
	S: Landsat-8	Regression analysis	(Herbei and Sala, 2015)
	S: Sentinel-1, Spot-5 Take5, Deimos-1, Landsat-8, and Formosat-2	Pearson's correlation	(Veloso et al., 2017)
	D: Tetracam Micro-MCA (multispectral) and DJI Zenmuse X3 (RGB) on DJI Matrice 600	SVM and deep semantic segmentation	(Song et al., 2020)
	D: RedEdge-M MicaSense (multispectral) on DJI drone	RF and DNN	(Li et al., 2021)
	D: Sony ILCE α7RII, DJI FC6310, and Sony ILCE α5100L (RGB) on DJI Matrice 600 Pro	Peak detection algorithm	(Bai et al., 2022)
Water management	S: Landsat-7, Spot-5, GeoEye, IRS-p& LISS III, IRS-R2 AWiFS, and Radarsat-2	Polarimetric descriptors	(Surek and Nádor, 2015)
	S: USDA crop land data	Soil and Water Assessment Tool	(Parajuli et al., 2018)
	S: Modis	MLR and ANN	(Potopová et al., 2020)
	S: Landsat-8, Sentinel-1/2, and Modis	Logistic regression	(Ghazaryan et al., 2020)
	S: Formosat-2, Spot-2/4/5 and Sentinel-2	Simple Algorithm for Yield estimates (SAFY)	(Pique et al., 2020a)
	S: Formosat-2, Spot-2/4/5, Deimos, Landsat-8, and Sentinel-2	Simple Algorithm for Yield estimates (SAFY)	(Pique et al., 2020b)
Weed management	D: Olympus PEN E-PM1 (RGB) and Tetracam mini-MCA-6 (multispectral) on md4-100 drone	OBIA	(López-Granados et al., 2016)
	A: RMK TOP-15 + Zeiss objective (RGB and multispectral images) on plane	Spectral Angle Mapper (SAM) classification method	(Peña-Barragán et al., 2007)
	A: RMK TOP-15 + Zeiss objective (RGB and multispectral images) on plane	Principal Component Regression	(Peña-Barragán et al., 2010)
	A: RMK TOP-15 + Zeiss objective (RGB and multispectral images) on plane	Evolutionary Product Unit Neural Networks and Logistic Regression	(Gutiérrez et al., 2008a)

Table 4 (*continued*)

Aims	Remote sensing input*	Algorithms**	References
	S: Landsat-7, Spot-5, GeoEye, IRS-p& LISS III, IRS-R2 AWiFS, and Radarsat-2	Polarimetric descriptors	(Surek and Nádor, 2015)

**S = satellite; D = drone; A = aerial platform.*
***ANN, Artificial Neural Network; CNN, Convolutional Neural Network; DNN, Deep Neural Network; SVM, Support Vector Machine; DT, Decision Tree; RF, Random Forest; MLR, Multiple Linear Regression; OBIA; Object Based Image Analysis.*

3.2.1. Crop management

Improving agricultural practices has always been a key objective for farmers. Currently, farmers and researchers can use many tools also available for free such as satellite. Satellite images analysis allow to measure vegetative parameters (Santi et al., 2012; Fieuzal et al., 2012; Paloscia et al., 2014), spectral signature of sunflower (Fieuzal and Baup, 2014) and crop classification (Kussul et al., 2017, 2016, 2014; Meroni et al., 2021; Skakun et al., 2016; Tang et al., 2022; Vincent et al., 2020).

Yu and Shang performed a multi-year crop mapping involving maize and sunflower based on NDVI time series from Chinese HJ-1A/1B satellite images. Firstly, NDVI data were used to classify crops and investigate phenological features (Yu and Shang, 2017). Then, the study was further developed by introducing random forest model to predict yield (Yu and Shang, 2018). Lastly, evapotranspiration and transpiration were evaluated at pixel level during the growing season (Yu and Shang, 2020).

Pinar and Erpul achieved high Pearson's correlation coefficient using multispectral images based on Pleiades twins (PHR1A-1B) and SPOT-7 satellite due to the correlation of horizontal sunflower leaves with leaf area index (LAI) (Pinar and Erpul, 2019). In addition, they found that NDVI is more suitable for physiology status assessment. Wen et al. developed an automated machine learning method to classify crops over large areas based on Landsat-7, Landsat-8, and HJ-1A/1B satellite images (Wen et al., 2019). Phenology and vegetation parameters were used as input feature for algorithm classification that are random forest and support vector machine. According to Khan et al., combining spatial and temporal satellite data enable the possibility of creating crop maps of large areas supporting policymakers and researchers in devising policies and strategies for food security (Khan et al., 2010).

Biophysical parameters' estimation enables a more realistic interpretation of in-field condition and achieving reliable information on crops. Yield, plant height, canopy coverage, and textural information are usually linked to vegetation indices. In addition, forecasting biophysical parameters is crucial for research and farm business due to the common objective of maximising yield through field analysis. Regarding canopy structure modelling, a simple regression techniques was used to create canopy models through LiDAR (Light Detection and Raging) acquisition (Houldcroft et al., 2005). Abdikan et al. extensively evaluated five regression methods to estimate sunflower crop heights and compared them to scenarios that include NDVI and NDVI-red edge (Abdikan et al., 2023). Results showed that NDVI red edge improves regression model performance.

High spatial and temporal remote sensing data were used in combination with yield prediction models with positive outcomes (Claverie et al., 2012; Kern et al., 2018; Sadenova et al., 2022). Using satellites saves time and covers large areas (Sadenova Marzhan Anuarbekovna et al., 2022). It is also important to study the complexity of variables involved to succeed in early prediction (Debaeke et al., 2023). Tunca et al. found a significant correlation between NDVI data from drones and ground-based spectroradiometer (Tunca et al., 2018).

Ali et al. found that the correlation of simple ratio index and NDVI is the best one to predict yield (Ali et al., 2019). Different research groups focused on yield estimation through time-series, vegetation indices and machine learning application (Bognár et al., 2022; Narin et al., 2021). The major findings are: (i) NDVI performed better than NDVI red edge in most cases; (ii) convolutional neural networks achieved better accuracy of yield estimation; and (iii) sunflowers' inflorescence emergence stage was found to be the best moment for images acquisition and consequently yield estimation. Another interesting study by Trépos et al. found that smoothing LAI data helps to improve yield prediction (Trépos et al., 2020). Delegido et al. found that 674 and 712 nm are specific spectral bands corresponding respectively to the maximal chlorophyll absorption and red-edge region, working with high spatial resolution hyperspectral (Delegido et al., 2013).

Cui et al. assessed soil salinity effects on sunflower crops (Cui et al., 2023). During sunflower growth, a higher LAI values correspond to non-saline plots while its value decrease with increasing in salinity. Moreover, plant height was higher in saline plots. A turning point carried out is the spatial distribution of soil salinity to act in a site-specific way and stem the problem.

3.2.2. *Monitoring of phenological stages*

Monitoring sunflower growth is helpful in identifying crop row orientation because plants can be used as references to more complex analysis. Marais Sicre et al. performed multi-temporal analysis to identify crop row orientations but limits in the application of this method have taken over (Marais Sicre et al., 2014). The explanation is intrinsic to the heterogeneity of the crop. Plant recognition and crop row detection were performed with good outcomes combining threshold segmentation (based on the excess green index) and the Houge transformation using drone images (Bai et al., 2022).

Sunflower growth is deeply linked to vegetation parameters. Herbei and Sala evaluated spectral information based on satellite images to study sunflower crop growth stages (Herbei and Sala, 2015). Three vegetation indices were compared and related to seven phenological phases. NDVI resulted to be faithfully correlated with phenological stages and better able to describe sunflower growth dynamics and variability. Veloso et al. confirmed that NDVI temporal data enable us to describe the growth and senesce period of cultivated sunflowers (Veloso et al., 2017).

In the middle and late growth stage, cultivated sunflower may be affected by a serious disorder known as sunflower lodging. Song et al. enhanced the fusion of multispectral and visible images to acquire information on sunflowers (Song et al., 2020). Then, the support vector machine classification method was used in combination with deep semantic segmentation to recognize lodging patterns with the highest accuracy value of 89.8 %. A similar workflow was implemented by Li et al. concluding that deep learning is more accurate in the detection of lodging patterns than random forest (Li et al., 2021).

3.2.3. *Water management*

As described in Section 3.1.3, water use is a key issue. Parajuli et al. used satellite images to estimate evapotranspiration and calibrate hydrological models (Parajuli et al., 2018). Both studies are based on remote sensing, and the objectives are better water use efficiency and improving irrigation scheduling.

Surek and Nádor worked with satellite time series data to detect sunflower parcels hit by drought in Hungary and found out that the first decade of July is the best time to do it (Surek and Nádor, 2015). Potopová et al. combined agrometeorological data with remote sensing and survey data to explore the relationship between drought and yield losses (Potopová et al., 2020). In recent years, the impact of drought has become increasingly evident and also affects sunflowers. Ghazaryan et al. used a logistic regression to deeply detect the drought impact using a remotely sensed time series (Ghazaryan et al., 2020). Anthesis is found to be particularly sensitive to water stress.

Lastly, according to the global context of climate change, agriculture needs to be more sustainable. To address this challenge, Pique et al. developed the SAFY-CO_2 model for sunflowers by coupling the CO_2 and water modules (Pique et al., 2020b, 2020a). Preliminary results show that the model is accurate at local and landscape scales in estimating biomass, yield, CO_2, and water flux.

3.2.4. *Weed management*

As discussed in the previous subsection, weed management is one of the most important issues in sunflower production. López-Granados et al. confirmed the potential of multispectral or hyperspectral images to recognize the different spectral signatures and consider machine learning a powerful classification method of remotely sensed data (López-Granados et al., 2016).

Peña-Barrágan et al. worked with conventional-colour aerial photographs to capture *Ridolfia segetum* patches (Peña-Barragán et al., 2007). The best performance (overall accuracy = 93–99 %) was achieved with the red/green ratio index in mid-June measurements. In a later study, they also found a relationship between weed infestation rate and sunflower yield (Peña-Barragán et al., 2010). As the infestation rate increases, the yield decreases progressively. Then, Gutiérrez et al. analysed multispectral images and provided a useful tool to predict patches of *R. segetum* through logistic regression-based techniques (Gutiérrez et al., 2008a).

Sunflower is also affected by *Orobanche cumana*, commonly known as broomrape, which is a holoparasite. Broomrape triggers competition for water and nutrients with the host plant: water stress and other physiological alterations can be detected by using remote sensing techniques. Taking up a study cited earlier, Surek and Nádor noted that weed infection could be detected in mid-June with radar images, two months earlier than optical images (Surek and Nádor, 2015).

3.3. *Hyperspectral sensors applied to cultivated sunflower*

Hyperspectral sensors are innovative technologies available for research and farming purpose. Nowadays, they are not so widespread in sunflower cultivation due to their high cost and the lack of knowledge in the potential of data analysis for sunflowers. As detailed in the introduction, it is important to focus on sunflower crop to faces the increasing global demand and farmers challenges. In Table 5 available scientific papers are systematically reviewed based on the instruments used, the wavelengths range and the aims. The systematic research gives four main areas of hyperspectral sensors application that are weed detection,

Table 5
Scientific papers included in the systematic review based on the instruments used and their relative wavelengths range, and the aims achieved by referenced authors.

Instruments	Wavelengths range	Aims	References
ASD HandHeld FieldSpec Spectroradiometer	325–1075 nm	Weed detection	(Pena-Barragan et al., 2006)
SVC HR-1024	350–2500 nm	LAI estimation	(Duan et al., 2014)
UAV-HYPER	350–1030 nm	LAI estimation	(Duan et al., 2014)
FieldSpec Pro-FR Portable Spectrometer	400–1600 nm	Water stress detection	(Rapaport et al., 2017)
FieldSpec Pro-FR Portable Spectrometer	350–2500 nm	Weed detection	(Cochavi et al., 2017)
NEO Hyspex VNIR-1600	400–1000 nm	Disease detection	(Xu et al., 2019)
Raspberry Pi + Picamera	n/a	Weed detection	(Le Ru et al., 2021)
NEO Hyspex VNIR-1600	400–1000 nm	Plant breeding	(Ryckewaert et al., 2021)
Specim-IQ	400–1000 nm	Weed detection	(Atsmon et al., 2022)
4D dual-mode staring hyperspectral-depth imager	500–640 nm	Plant recognition	(Luo et al., 2022)

plant breeding, vegetation parameters estimation and stress detection (including LAI estimation, water stress and disease detection).

The main application of hyperspectral camera found in cultivated sunflowers is weed identification to improve herbicides distribution. Peña-Barrágan et al. conducted a study to find out the difference between hyperspectral reflectance of bare soil, sunflower, and *Ridolfia segetum* considering different phenological stages (Pena-Barragan et al., 2006). Authors worked with an ASD HandHeld FieldSpec Spectroradiometer (Analytical Spectral Devices, Boulder, CO, USA) considering the wavelengths range between 325 and 1075 nm. Best results were obtained with ANVI index and wavelength range of 500–540 nm. Good results led to weed patch construction and the possibility of designing site-specific treatments for the following seasons.

Weed identification through hyperspectral measurement is taken up by Cochavi et al. with a FieldSpec Pro-FR Portable Spectrometer (Analytical Spectral Devices, Boulder, CO, USA) (Cochavi et al., 2017). Measurements were collected in the range between 350 and 2500 nm to recognize *Orobanche cumana* in sunflowers. Results show that hyperspectral imaging enables the early detection of the broomrape spatial distribution. Afterward, Atsmon et al. focused on the early detection of *Orobanche cumana* with the Specim-IQ (Specim Ltd., Oulu, Finland) (Atsmon et al., 2022). Researchers developed a classification model based on logistic regression to identify broomrape with an accuracy of 89 % using a ground-hyperspectral camera working in the spectral range of 400–1000 nm. Another application was performed by Le Ru et al. about phenotyping of sunflower resistance to *O. cumana* through image analysis of sunflower roots (Le Ru et al., 2021).

According to plant breeding objectives and the huge amount of data collected from hyperspectral imaging, Ryckewaert et al. started training a classification model to identify four different genotypes of sunflower (Ryckewaert et al., 2021). Spectral data were acquired by using a lab-line scanning system equipped with the hyperspectral camera NEO Hyspex VNIR-1600 (Norsk Elektro Optikk AS, Skedsmokorest, Norway). Leaf spectral characteristics were captured in the wavelength range between 400 and 1000 nm. Results show that the classification method can predict a large amount of genotype data with precision and recall values, respectively, from 72 % to 84 % and from 63 % to 89 %.

One of the recent applications is the 4D dual-mode staring hyperspectral-depth imager (DSHI) as a non-invasive plant component analysis (Luo et al., 2022). This model is the result of the fusion of reflectance spectra, fluorescence spectra, and 3D spatial data of the observed object. Authors applied the model to distinguish real and plastic sunflowers. The model not only recognised the real flower but also traced the properties of chlorophyll distinguishing an absorption peak at 670 nm in the reflectance spectrum and two absorption peaks at 680 nm and 725 nm in the fluorescence spectrum.

Hyperspectral data are also used to detect vegetation properties including water stress, nutritional stress, and disease. Duan et al. explored LAI estimation by using an SVC HR-1024 (Spectra Vista Corporation), a field-portable spectroradiometer (350–2500 nm) for *in situ* measurements, and UAV-HYPER sensor (350–1030 nm) for aerial acquisition (Duan et al., 2014). The aim was to evaluate the performance of a model for LAI estimation from hyperdata. Results show that the PROSAIL model is suitable for LAI estimation for all the tested crops, including sunflowers.

Rapaport et al. focused on leaf water content detected through hyperspectral imaging considerable a faster and non-destructive alternative for water status monitoring (Rapaport et al., 2017). The experimentation was carried out with a FieldSpec Pro-FR Portable Spectrometer (Analytical Spectral Devices, Boulder, CO, USA) to acquire images in the wavelength range of 400–1600 nm. The narrow-band WABI (Water Balance Index) demonstrated the ability to monitor water status and track any occurred alteration during sunflower growth.

Lastly, an experiment was conducted to recognize presence/absence of disease in sunflower, focusing on powdery mildew and Septoria leaf spot (Xu et al., 2019). As reported for Ryckewaert et al., spectral data were acquired by using a lab-line scanning system equipped with the hyperspectral camera NEO Hyspex VNIR-1600 (Norsk Elektro Optikk AS, Skedsmokorest, Norway). Subsurface characteristics of leaves are the most interesting feature in disease detection. To help in disease classification, a dataset for classifying sunflower disease through machine learning was published (Sara et al., 2022).

3.4. Vegetation indices built up using hyperspectral data

According to Thenkabail, vegetation indices use spectral information and are widespread to quantify crop variables, such as grain yield, wet biomass (WBM), and LAI (Thenkabail et al., 2000). The article aimed to evaluate the performance of several vegetation indices and crop biophysical variables. For example, the best result for the sunflower crop is given by NDVI1 (band centres and bandwidths are reported in Table 6) both for WBM ($R^2 = 0.59$) and LAI ($R^2 = 0.65$) correlation by using a nonlinear exponential model.

Hyperspectral remote sensing can be used to correlate the impact of boron and irrigation on sunflower growth and productivity (Routh et al., 2019). Routh et al. conducted an experiment by using an SVC HR-1024 (Spectra Vista Corporation) that acquires in the 350–2500 nm spectral range. Hyperspectral data were used to obtain several vegetation indices. Multiple and linear regressions enable us to find which indices can retrieve biophysical parameters, chlorophyll content index, and physiological parameters with high accuracy.

Another topic of this subchapter is the quantification of chlorophyll content. Delegido et al. found that the influence of chlorophyll is related to the reflectance minimum at 670 nm (Delegido et al., 2010). A new index called Normalized Area reflectance Curve (NAOC) was drawn up to estimate chlorophyll content. Based on the correlation with ground measurement, a simple method of estimation was carried out to create leaf chlorophyll maps with a single hyperspectral image.

As well as for open-field applications, HSI is a promising method for plant phenotyping. An example of an HSI application is the indoor phenotyping of a limited number of plants (Sarić et al., 2022). AS reported in the paper, HSI technology can be used to quantify xanthophyll pigments and photosynthetic efficiency under different nitrogen applications (Gamon et al., 1992).

3.5. Correlation between hyperspectral data and crop growth model

After an in-depth analysis, no article matching these research criteria was found.

4. Conclusions and perspectives

The current work represents a compendium of available literature focused on the application of precision agriculture and remote sensing on sunflower crops. An in-depth analysis of the use of hyperspectral sensors was carried out to calculate vegetation indices and build crop growth models.

The first positive outcome is that the published articles are increasing, and if compared to other crops, the research on sunflowers is

Table 6
The setting of NDVI1 band centres (λ_1-λ_2) and bandwidths ($\Delta\lambda_1$-$\Delta\lambda_2$) in nm for different crop variables (extracted from Thenkabail et al., 2000).

Crop	Crop Variable	Band Features	NDVI1
All crops (including sunflower)	WBM (kg/m^2)	λ_1	682
		$\Delta\lambda_1$	30
		λ_2	310
		$-\Delta\lambda_2$	20
	LAI (m2/m2)	λ_1	540
		$\Delta\lambda_1$	20
		λ_2	682
		$-\Delta\lambda_2$	10

still limited to a few research groups. For this purpose, the geographical distribution of the scientific papers gave an unexpected result. Sunflower cultivation is concentrated in a few countries in the central and eastern parts of Eurasia characterised by continental climate (mainly Ukraine and Russia). Most of the scientific production originated from Spain (Mediterranean climate), France (temperate oceanic climate), and China (temperate climate).

Results from analysis of the available literature converge in some crucial points. Crop management is one of hottest topics and mainly involves yield prediction, management zones, crop classification, and the measurement of vegetative parameters. Another in-depth topic is weed management with regard to the recognition of *Ridolfia segetum* and *Orobanche cumana*. Research on sunflower growth has developed primarily due to machine learning allowing the recognition of phenological stages based on images.

Based on the review, hyperspectral sensors are not so widespread in sunflower cultivation, especially to build crop growth models and find correlations with vegetation indices. Future research should focus on the creation of both growth and prediction models. In addition, there are some major topics to explore. Water stress management, evaluation of new hybrids and disease detection are the major challenge to address in future research. What is essential is to find vegetative parameters that can explain the status of the crop with time-saving methods and ready-to-use responses.

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CRediT authorship contribution statement

Luana Centorame: Writing – review & editing, Writing – original draft, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Alessio Ilari:** Writing – review & editing, Validation, Software, Methodology. **Andrea Del Gatto:** Supervision, Resources, Funding acquisition. **Ester Foppa Pedretti:** Supervision, Resources, Project administration, Funding acquisition, Conceptualization.

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.

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