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Review

LiDAR applications in precision agriculture for cultivating crops: A review of recent advances

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ABSTRACT

In recent years, Light Detection and Ranging (LiDAR) technology has been one of the most innovative subjects in laser scanning, remote sensing, and object detection systems. This technology may be popular because it can pinpoint structures or zones of interest in millimetre detail. It can also highlight variations and irregularities, such as surface degradation and vegetation growth. This paper presents a review of the specialised literature on LiDAR systems applied to precision agriculture; specifically, in cultivating crops. First, some preliminaries of LiDAR systems according to the mode of transport used, considering terrestrial, mobile, and aerial laser scanners, are given. Subsequently, a well-organised taxonomy of recent LiDAR applications based on the activity being performed is presented. Here, the following four categories are considered: (1) crop-related metric estimation, (2) tree and plant digitisation, (3) vision systems for object detection and navigation, and (4) planning and decision support. Lastly, we discuss some current trends and research challenges in applying LiDAR technology to cultivation activities in accordance with the state-of-the-art literature.

1. Introduction

State-of-the-art studies report that current agricultural techniques will hardly cover the demand for food by 2050 (Tripathi et al., 2019). This is the reason behind the increasing interest of governments and researchers worldwide in applying technology to agriculture. The term most commonly used to describe these trends is Agriculture 5.0. The objective is that agriculture should benefit from applying big data, the Internet of Things (IoT), and artificial intelligence (AI). A great variety of recent studies have examined vision systems, such as RGB cameras, photogrammetry techniques, stereo cameras, and Light Detection and Ranging (LiDAR) technology. LiDAR technology was conceptualised in the mid-1960s, but it was not until the 1970s that the first version of LiDAR was developed in the USA, Canada, and Australia (Irish and Lillycrop, 1999). LiDAR is a remote sensing technology that uses a pulsed laser to measure ranges (variable distances). These pulses are commonly combined with information recorded by airborne systems to generate highly accurate 3D models (cf. Wang et al., 2018).

LiDAR systems base their measurements on using the speed of light. Because light travels at a constant and known speed, LiDAR systems can calculate – with significant accuracy – the distance between the collision point and the sensor that emitted the pulse. LiDAR systems periodically trigger light pulses and build up a map of the environment from a series of detected collisions. It should be noted that LiDAR systems are equipped with more than one laser pulse, which influences the performance of the system. For example, companies such as Velodyne and SICK use sensors that are equipped with from 16 to 128 channels. Other essential performance features include the operating range, the estimated error, and the scanning frequency. In these sensors, the coordinates of the light collisions are stored in a file that is commonly called the 'point cloud'. These points are represented in a 3D space.

At first, LiDAR systems were little used because they were very expensive. However, over time, the cost of investment in these systems has become cheaper and this has allowed LiDAR technology to be used in many applications. For example, LiDAR technology has been used to estimate the depths of the seabed using a bathymetric LiDAR sensor (e.g. Janowski et al., 2022; Specht et al., 2022; Wang et al., 2022); to obtain a perspective of the environment using 360° LiDAR sensors in autonomous vehicles (e.g. Bhat et al., 2021; Chen et al., 2021; Kamble and Kharche, 2021); to detect areas that are prone to flooding based on digital elevation models (e.g. Persiano et al., 2021; Blatrix et al., 2022); to predict landslides by identifying the morphological characteristics of the surface (e.g. Ilesanmi et al., 2021; Stumvoll et al., 2021; Zhou et al., 2022); to detect environmental problems based on atmospheric studies using sensors such as Doppler LiDAR, Raman LiDAR and Differential

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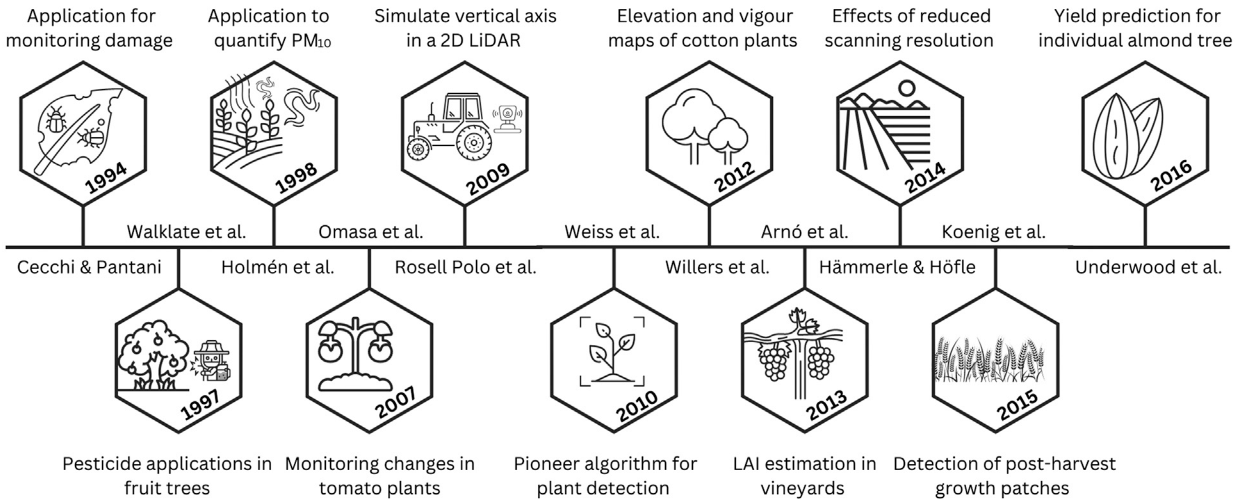

Fig. 1. Timeline of the breakthrough antecedents published from 1994 to 2016.

Absorption LiDAR (e.g. Lin and Liu, 2021; Shemanin et al., 2021; Gaudet et al., 2022); to establish the shape and magnitude of a surface in geodesy (e.g. Berrino et al., 2021; Rodriguez Padilla et al., 2021; Akiyama et al., 2022); to generate cartographic data (e.g. Barragán et al., 2016; Maderal et al., 2016; Rincón and García, 2019); to help prevent forest fires by analysing the structure of the vegetation and the state of the shrub layer in a forest (e.g. Fernández-Álvarez et al., 2019; Xian et al., 2020); to generate digital models that allow the automation of many tasks, from soil preparation to crop management and harvesting in agriculture (e.g. Torres-Sánchez et al., 2015; Tsolakis et al., 2019; Moreno et al., 2020). In this paper, we are interested in LiDAR's application in precision agriculture for cultivating crops.

In the 1990s, several studies started to make incursions into agriculture using LiDAR technology. One of the oldest applications dates back to 1994, in Europe, where LiDAR was used to monitor vegetation for the early detection of stress and damage (Cecchi and Pantani, 1994). During 1997 in the United Kingdom, Walklate et al. (1997) measured top fruit tree canopies for pesticide applications using a LiDAR system. In addition, a LiDAR application to quantify PM_{10} emissions from agricultural non-point sources was reported in 1998 (Holmén et al., 1998).

The 2000s saw the inception of the use of LiDAR systems to obtain 3D tree structures. In 2007, Omasa et al. (2007) proposed a LiDAR system to monitor changes in the structure of tomato plants. In addition, Rosell Polo et al. (2009) proposed adding a kind of elevator on a tractor to simulate a vertical axis in a 2D LiDAR sensor to estimate the 3D structure of apple trees, pear trees, and grape vines, using AutoCAD. Another breakthrough that increased the popularity of LiDAR technology was its use as an object detection system for crop scouting, where it was used to detect and classify plant species. Weiss et al. (2010) presented a pioneering algorithm for the detection and classification of plants using a point cloud that was obtained with a low-density LiDAR system. Following this pivotal study, the use of AI techniques with LiDAR systems became more popular in agriculture.

Then, in the 2010s, several LiDAR applications for crop mapping emerged. Willers et al. (2012) proposed a LiDAR application to create vigour and elevation maps of cotton plants, which are potentially helpful for maintenance tasks in this type of crop. Considering that one of the most widely used indices in viticulture is the Leaf area index (LAI), Arnó et al. (2013) decided to evaluate the feasibility of a tractor-mounted LiDAR system to estimate LAI because this index can provide an indirect method to determine grape yield and quality. In 2014, Hämmerle and Höfle (2014) presented a study to evaluate the effects of reducing the density of the point cloud in crop surface models. Similarly, in 2015, Koenig et al. (2015) compared three classification algorithms to predict the total mass of the barley when it will be harvested. Lastly, Underwood et al. (2016) in 2016 presented a mobile terrestrial scanning system for almond orchards to map the distribution of flowers and fruit to make it possible to predict the yield of individual trees. Fig. 1 depicts the timeline of the breakthrough antecedents that were referred to above, which were published from 1994 to 2016.

LiDAR technology is now used in a wider range of cultivation-oriented LiDAR applications; for instance, it has been used to detect fruits, estimate and monitor tree structures, detect urine patches in pastures, and prune fruit trees.

In the majority of the cultivation-oriented LiDAR applications, descriptive statistics (mostly percentiles) are used to process the point clouds (e.g. Yuan et al., 2018). Given the accuracy of LiDAR systems, using this type of strategy is useful when only one calculation on the crop is required. Meanwhile, clustering techniques are used for more elaborate applications; for instance, obtaining the features of tree canopies (e.g. Wu et al., 2020; Zhou et al., 2020), and detecting fruits (e.g. Gené-Mola et al., 2020). Voxelisation is another popular technique in LiDAR applications, where it is used in applications whose main objective is to create a digital representation of the crop that is as close as possible to reality (e.g. Lau et al., 2018). Lastly, it is common to use licensed software that incorporates these techniques for processing point clouds; among the most popular are CloudCompare (e.g. Hadas et al., 2019), MatLab (Matrix Laboratory) (e.g. Husin et al., 2020), and ROS (Robot Operating System) (e.g. Dhami et al., 2020).

This paper contributes by presenting a systematic review of the state-of-the-art literature on LiDAR systems intended to aid in cultivating crops. We only considered research studies published in the last five years – specifically, from 2017 to 2022 (November) – because this technology is constantly evolving (cf. Walsh, 2022). The studies are classified into a well-organised taxonomy, which enables us to identify current trends and discuss the research challenges. This paper is structured as follows. Section 2 presents some preliminaries concerning terrestrial, mobile, and aerial laser scanners. Section 3 reviews the literature and classifies the studies according to the activity being performed. Section 4 discusses some concluding remarks, stressing current challenges and trends in this field of applications.

2. Background: Terrestrial, mobile, and aerial laser scanners

LiDAR systems in agriculture can be classified into three categories according to how they are transported while scanning (Wang et al., 2018). The first one is aerial LiDAR (Airborne Laser Scanner, ALS), where the LiDAR system is mounted on an unmanned aerial vehicle (UAV). The second one is terrestrial LiDAR (Terrestrial Laser Scanner,

Table 1
ALSs applied to automate tasks in precision agriculture.

Task	LiDAR sensor	Performance
Health monitoring	LiDAR VLP-16 (e.g. Dhami et al., 2020) LiDAR RIEGL VUX-1UAV (e.g. Zhou et al., 2020)	Operating range: 100 m, error: 30 mm, scanning frequency: 5–20 Hz Operating range: 1.5–1,415 m, error: 5–10 mm, scanning frequency: 1200 Hz
Height monitoring	LiDAR VLP-16 (e.g. Liu et al., 2020) LiDAR LMS511-10100 PRO (e.g. Zhang et al., 2021) LiDAR RIEGL VUX-1UAV (e.g. Ivushkin et al., 2019) LiDAR HDL-32 (e.g. Maimaitijiang et al., 2020)	Operating range: 100 m, error: 30 mm, scanning frequency: 5–20 Hz Operating range: 40 m, statistical error: 6–14 mm, systematic error: 25–50 mm, scanning frequency: 25–100 Hz Operating range: 1.5–1,415 m, error: 5–10 mm, scanning frequency: 1200 Hz Operating range: 80–100 m, error: 20 mm, scanning frequency: 5–20 Hz
Inventory estimation	LiDAR HDL-32E (e.g. Hadas et al., 2019)	Operating range: 80–100 m, error: 20 mm, scanning frequency: 5–20 Hz
LAI estimation	LiDAR VLP-16 (e.g. Zhang et al., 2020) LiDAR HDL-32 (e.g. Maimaitijiang et al., 2020)	Operating range: 100 m, error: 30 mm, scanning frequency: 5–20 Hz Operating range: 80–100 m, error: 20 mm, scanning frequency: 5–20 Hz
Estimation of soil properties	IGI LiteMapper laser system (e.g. Florent et al., 2019) LiDAR Quanergy M8 (e.g. Trepekli and Friborg, 2021)	Operating range: 250–1900 m, error: 15–20 mm, scanning frequency: 100–1800 kHz Operating range: 100 m, error: 30 mm, scanning frequency: 5–20 Hz
Estimation of pesticides	LiDAR RIEGL LMS-Q 1560 (e.g. Wu et al., 2020)	Operating range: 2,700–5,800 m, error: 20 mm, scanning frequency: 200–800 kHz
Estimating yields	LiDAR VLP-16 Puck-Lite (e.g. Sofonia et al., 2019)	Operating range: 100 m, error: 30 mm, scanning frequency: 5–20 Hz
Detecting trees	LiDAR VLP-16 (e.g. Itakura and Hosoi, 2018)	Operating range: 100 m, error: 30 mm, scanning frequency: 5–20 Hz
Applying fertiliser	LiDAR VLP-16 (e.g. Shendryk et al., 2020)	Operating range: 100 m, error: 30 mm, scanning frequency: 5–20 Hz
Forecasting production	LiDAR VLP-16 (e.g. Masjedi et al., 2020)	Operating range: 100 m, error: 30 mm, scanning frequency: 5–20 Hz

TLS), where the LiDAR system uses a stationary stand for scanning (e.g. a tripod); consequently, multiple scans at different locations are necessary to obtain a complete point cloud. The last one is mobile LiDAR (Mobile Laser Scanner, MLS), which is more versatile in terms of the vehicle on which it can be mounted (e.g. it can be mounted on a tractor, on a car, on a backpack, or it can be even held by a person walking).

The bird's-eye view (BEV) is one of the most popular techniques to visualise point clouds in ALSs: it simulates a bird's view when flying. For example, Itakura and Hosoi (2018) used BEV to count trees with an ALS. Moreover, this type of LiDAR can also be used to estimate plant height (e.g. Liu et al., 2020; Zhang et al., 2021) and the properties of the soil (e.g. Cassidy et al., 2019; Florent et al., 2019), and to monitor tree health (e.g. Dhami et al., 2020; Zhou et al., 2020). However, a wider variety of ALS applications can be found in the literature.

Table 1 lists cultivation-oriented tasks that use ALSs. The first column indicates the task, the second column indicates the LiDAR sensor that was used to collect the data, and the third column presents the performance of the sensor. Not all suppliers provide the same specifications in the data sheets. Therefore, we have selected the following relevant features: operating range, (statistical/systematic) maximum error, and scanning frequency. According to Table 1, the (Velodyne) VLP-16.[1] (updated as the 'Puck' series) is the most common LiDAR sensor that is used as an ALS, followed by (Velodyne) HDL-32[2] The addressed tasks include:

- Making estimations of tree health, tree height, tree inventory, LAI, soil properties, and crop yield.
- Tree detection.
- Planning, including forecasting production and applying fertiliser.

On the other hand, TLSs and MLSs have become increasingly popular because they have a higher spatial resolution, allowing a more detailed and accurate characterisation of crops compared to ALSs (Wu et al., 2019). Table 2 presents a list of the state-of-the-art studies applied to crop cultivation using TLSs/MLSs (its columns should be interpreted as in Table 1). Here, the technical specifications of TLSs and MLSs are put together because they are basically the same sensors, but with a different support. In Table 2, the scanning speed is provided when the scanning frequency was unavailable. According to Table 2, the variety of LiDAR sensors is broader. Although no sensor dominates this list, the applications of the following LiDAR sensors stand out: (SICK) LMS400,[3] (SICK) LMS111,[4] (Hokuyo) UTM-30LX,[5] (FARO) Focus X330,[6] (SICK) LMS511,[7] and (Velodyne) VLP-16. According to the state-of-the-art literature, TLSs and MLSs have been applied to a wide range of activities that are connected to crop cultivation (see Table 2).

LiDAR systems can be used for measuring crop features and the properties of the soil, digitising orchard plants, detecting objects (e.g. fruits, plants, and trees), and planning agricultural activities. ALSs have chiefly been used to monitor activities in orchards because they are mostly used from a BEV perspective. This may limit their use to only obtaining information on tree canopies. However, ALSs have been used as navigation systems for UAVs (Hu et al., 2018), to maximise production in sugar cane cultivation (Shendryk et al., 2020), and to detect and classify domes covering different types of orchards (Tiwari et al., 2020). The use of LiDAR systems for agricultural activities started with ALSs, which has led to there being more algorithms to process point clouds from a BEV perspective. Although the limitations of the BEV perspective may be mitigated with double return (or even triple return) LiDAR systems, this implies a significant increase in the acquisition cost for this type of system.

[1] https://velodynelidar.com/products/puck/
[2] https://velodynelidar.com/products/hdl-32e/
[3] https://www.sick.com/mx/en/detection-and-ranging-solutions/2d-lidar-sensors/lms4xx/lms400-2000/p/p112350
[4] https://www.sick.com/it/en/detection-and-ranging-solutions/2d-lidar-sensors/lms1xx/lms111-10100/p/p109842
[5] https://hokuyo-usa.com/products/lidar-obstacle-detection/utm-30lx
[6] https://www.faroandina.com/pdfs/FARO_Focus3D.pdf
[7] https://www.sick.com/us/en/detection-and-ranging-solutions/2d-lidar-sensors/lms5xx/c/g179651

Table 2
TLSs and MLSs applied to automate tasks in precision agriculture.

Task	LiDAR sensor	Performance
Estimation of dry matter	Leica ScanStation P30 (e.g. Wijesingha et al., 2019)	Operating range: 120 m, error: 3–6 mm, scanning speed: Up to 1,000,000 points per second
	LiDAR LMS400 PRO (e.g. George et al., 2019)	Operating range: 3 m, statistical error: 3 mm, systematic error: 4 mm, scanning frequency: 300–500 Hz
Health monitoring	LiDAR FARO Focus X330 (e.g. Ziliani et al., 2018)	Operating range: 30–330 m, error: 2 mm, scanning frequency: 97 Hz
	LiDAR Puck (VLP-16) (e.g. Yuan et al., 2018)	Operating range: 100 m, error: 30 mm, scanning frequency: 5–20 Hz
	LiDAR LMS111 (e.g. Vidoni et al., 2017)	Operating range: 20 m, statistical error: 12 mm, systematic error: 30 mm, scanning frequency: 25–50 Hz
Inventory estimation	LiDAR LMS111 (e.g. Krus et al., 2020)	Operating range: 20 m, statistical error: 12 mm, systematic error: 30 mm, scanning frequency: 25–50 Hz
	LiDAR FARO Focus X330 (e.g. Malambo et al., 2019)	Operating range: 30–330 m, error: 2 mm, scanning frequency: 97 Hz
Canopy structure estimation	LiDAR LMS400-2000 (e.g. Wu et al., 2019)	Operating range: 3 m, statistical error: 3 mm, systematic error: 4 mm, scanning frequency: 300–500 Hz
Estimation of nitrogen levels	LiDAR LMS400 (e.g. Colaço et al., 2021)	Operating range: 3 m, statistical error: 3 mm, systematic error: 4 mm, scanning frequency: 300–500 Hz
Application of pesticides	LiDAR RIEGL VZ-400 (e.g. Wu et al., 2020)	Operating range: 160–600 m, error: 3–5 mm, scanning frequency: 100–300 kHz
	LiDAR VLP-16 (e.g. Zhou et al., 2021)	Operating range: 100 m, error: 30 mm, scanning frequency: 5–20 Hz
Monitoring plant growth	LiDAR LMS511 PRO SR (e.g. Sun et al., 2018)	Operating range: 80 m, statistical error: 6–14 mm, systematic error: 25–50 mm, scanning frequency: 25–100 Hz
Estimating production	LiDAR RIEGL LMSZ210ii (e.g. Murray et al., 2020)	Operating range: 100–400 m, error: 10–15 mm, scanning speed: Up to 10,000 points per second
Estimating volume	LiDAR UTM-30LX-EW (e.g. Martínez-Casasnovas et al., 2017)	Operating range: 30 m, error: 30–50 mm, scanning frequency: 40 Hz
Estimating yield	LiDAR LMS400 PRO (e.g. Ghamkhar et al., 2019)	Operating range: 3 m, statistical error: 3 mm, systematic error: 4 mm, scanning frequency: 300–500 Hz
Tree structure digitisation	LiDAR RIEGL VZ-400 V-Line 3D (e.g. Lau et al., 2018)	Operating range: 5–1000 m, error: 10–15 mm, scanning frequency: 30–300 kHz
	LiDAR LMS111 (e.g. Moreno et al., 2020)	Operating range: 20 m, statistical error: 12 mm, systematic error: 30 mm, scanning frequency: 25–50 Hz
	UTM-30LX (e.g. Westling et al., 2018)	Operating range: 30 m, error: 30–50 mm, scanning frequency: 40 Hz
Tree foliage digitisation	LiDAR LMS221 30206 (e.g. Pfeiffer et al., 2018)	Operating range: 80 m, statistical error: 10 mm, systematic error: 35 mm, scanning frequency: 75 Hz
	LiDAR FARO Focus X330 HDR (e.g. Jin et al., 2018)	Operating range: 30–330 m, error: 2 mm, scanning frequency: 97 Hz
	LiDAR LMS111 (e.g. Berk et al., 2020)	Operating range: 20 m, statistical error: 12 mm, systematic error: 30 mm, scanning frequency: 25–50 Hz
Fruit detection	LiDAR Puck (VLP-16) (e.g. Gené-Mola et al., 2019, 2020)	Operating range: 100 m, error: 30 mm, scanning frequency: 5–20 Hz
	LiDAR LMS511 (e.g. Tsoulias et al., 2020)	Operating range: 80 m, statistical error: 6–14 mm, systematic error: 25–50 mm, scanning frequency: 25–100 Hz
Crop navigation	LiDAR UTM-30LX (e.g. Velasquez et al., 2020)	Operating range: 30 m, error: 30–50 mm, scanning frequency: 40 Hz
	LiDAR LMS400 (e.g. Nguyen et al., 2021)	Operating range: 3 m, statistical error: 3 mm, systematic error: 4 mm, scanning frequency: 300–500 Hz
Wild plant detection	LiDAR UST-10LX (e.g. LeVoir et al., 2020)	Operating range: 30 m, error: 40 mm, scanning frequency: 40 Hz
Applying fertiliser	LiDAR LMS511 PRO-HD Type 20100 (e.g. Roten et al., 2017)	Operating range: 80 m, statistical error: 7–9 mm, systematic error: 25–35 mm, scanning frequency: 25–100 Hz
Pruning	UTM-30LX (e.g. Westling et al., 2021)	Operating range: 30 m, error: 30–50 mm, scanning frequency: 40 Hz

TLSs and MLSs have increasingly been used for crop maintenance and are even an important part of software development to support decision making in agriculture. This is a consequence of the versatility with which they can be manipulated within the crop. A representative example is the development of systems to optimise the use of pesticides and fertilisers (as observed in Table 2). However, TLSs are far from being satisfactorily applied in routine tasks because of the frequent relocation of the sensors. Although MLSs mitigate this drawback, they are still limited by the speed at which they can be operated to obtain efficient point clouds. For example, Roten et al. (2017) used an MLS to detect urine patches but the maximum speed at which the vehicle could move without affecting the point cloud was 1 km/h. This deficiency has a major impact on the quality of the data acquisition, as well as on activities that aim to digitise the crop. Although the speed to complete the task can be improved by increasing the sensor's performance (number of channels, scanning speed, scanning frequency, operating range, and so on), this also increases the acquisition costs. The application of LiDAR systems to crop cultivation can be made more efficient by using hybrid systems, such as the one proposed by Pretto et al. (2021). In this work, the authors used an ALS and an MLS to develop an autonomous vehicle to detect and prune wild plants in the crop. These applications could combat the disadvantages that each LiDAR system has separately.

Tables 1 and 2 only provide a technical reference on the LiDAR sensors that have been used to automate tasks in cultivating crops. However, Section 3 will discuss the state-of-the-art studies in more detail, grouping them by kind of application.

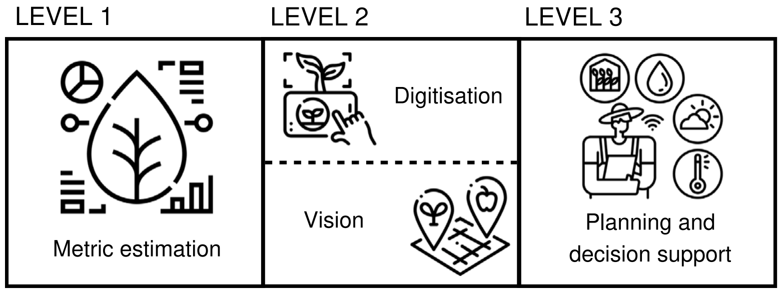

Fig. 2. Taxonomy based on the level of support to perform activities in cultivating crops.

3. Recent LiDAR applications in precision agriculture for cultivation

In this section, pertinent state-of-the-art studies are described and classified. The taxonomy is based on the level of support the LiDAR applications provide to farmers. This taxonomy arose from an analysis of the features of these studies, which allowed us to observe that they can be grouped into the following classes: metric estimation, digitisation, vision, and planning and decision support. Fig. 2 presents the three levels that this review considers.

The first level is ‘metric estimation’, which contains the studies that use LiDAR technology to estimate crop features and soil properties. Here, most LiDAR applications focus on monitoring a variable that is connected to crop efficiency; for example, in sorghum cultivation, the plant height is decisive for the farmer because this variable is linked to the yield. These LiDAR applications also focus only on cleaning and making an interpretation of the point cloud to deliver useful information that should make sense to the farmer. Section 3.1 presents the state-of-the-art literature on ‘metric estimation’.

The second level is related to the creation of abstractions of the real world. Here, there are two clearly differentiated kinds of application: digitisation and vision. Section 3.2 reviews the LiDAR applications for crop digitisation. It is clear that cleaning techniques are also used and metric estimations must be obtained, such as in the studies presented in Section 3.1. However, this is not the main focus of these applications. Indeed, they focus on creating a 3D digital model of the crop that is as close to reality as possible. For example, in fruit growing, LiDAR applications focus on improving digitisation techniques to make accurate representations of the tree structure because this will allow the farmer to evaluate *a priori* different characteristics of the tree, such as the passage of sunlight to the centre of the canopy.

Section 3.3 presents the studies that have used LiDAR technology as an artificial vision system. The essential point here is to identify the type of object that is visualised through the point cloud. A clear example is the detection of apples. This fruit can be detected through clustering techniques, identifying those groups of points in the cloud that represent apples. This means that artificial vision applications do not seek an accurate 3D digital representation but they do aim to identify patterns in the point cloud that arise when scanning different objects and identify them for specific purposes.

Lastly, the third level is ‘planning and decision support’. These studies simultaneously apply strategies from the previous three classifications (i.e. metric estimation, digitisation, and vision) to develop more robust solutions to support farmers in making decisions. For example, to prescribe pruning structures in fruit farming, it is necessary to obtain a 3D digital model (as close to reality as possible) of the trees, from which estimations (e.g. the tree height) can be obtained. The branches of the tree must then be detected to get a hierarchy of branches. Then, metaheuristic algorithms are used to manipulate the branches in the tree’s structure and suggest to the farmer which branches need to be pruned to improve the efficiency of the tree. This is the single level that entails the search for prescriptions or recommendations. Section 3.4 reviews the studies that have developed software for planning and decision support in agriculture.

3.1. Metric estimation

It is essential to estimate metrics in agriculture to monitor the state of the crop. Usually, these calculations are related to biomass. This information gives the farmer an insight into the health of the crop and then they can project the yield. For example, by knowing the biomass of sorghum (especially the height of the plant), a farmer is enabled to recognise when the plant changes from a vegetative to a reproductive state. Detecting this change is important because the amount of nutrients needed may be predicted in advance by the farmer. The proposal of Maimaitijiang et al. (2020) is a clear example of the importance of making this kind of estimation. The authors used an ALS to monitor a crop of sorghum at different stages. Their objective was to provide the farmer with key information about the growth and productivity of the sorghum. To deliver this information after scanning the crop with the ALS, they processed the point cloud to estimate the height and the LAI. Similarly, Li et al. (2022) used an ALS to estimate the LAI in a field of maize more efficiently in comparison with the manual method.

Considering the importance of making estimations periodically, Vidoni et al. (2017) developed a semi-autonomous vehicle to monitor vineyards. They equipped this vehicle with two MLSs to scan the vineyards to assess the volume and shape of the plants. This was achieved through an algorithm that they developed, which is based on the Normalised Difference Vegetation Index (NDVI) and thickness of the branch. The NDVI allows values to be obtained about the properties of the tree canopy. Another clear example is the application of Sun and Li (2017) to the cultivation of cotton. These authors used an MLS to monitor plant growth in different seasons of the year. Similarly, this same type of LiDAR system has been applied to estimate the biomass of strawberry plants, which is essential to forecast the growth over time (Saha et al., 2022). Meanwhile, Palacios-Rodríguez et al. (2022) used an ALS to measure the biomass of carobs and employed allometric techniques to estimate the carbon accumulation in this type of crop in southern Spain. Nevertheless, this classification is not only focused on measuring the plant biomass but it is also important to estimate the properties of the soil. For example, Florent et al. (2019) used an ALS to estimate the soil moisture and prevent water-logging. Another important feature in soil nutrient management is to know the level of phosphorus because it could represent a risk to the water quality. With this objective in mind, Cassidy et al. (2019) used an ALS to analyse this feature in crops and prevent the risk of high levels of phosphorus in the soil.

LiDAR technology for agricultural maintenance activities is the estimation-oriented application that has been most broadly explored in the scientific literature. For example, it has been applied to several activities for a wide range of crops, including orchards, with different types of soil and climate. For instance, an MLS is an alternative to conventional techniques to estimate the tree volume of an olive grove (Martínez-Casasnovas et al., 2017). Also, estimating the characteristics of the canopies of almond trees helps to determine the areas that need maintenance (Sandonís-Pozo et al., 2022). Measuring the height of wheat via traditional ways is physically demanding and highly sensitive to human error. However, this estimation is important for this type of crop because it indicates the yield and the weather resistance (Yuan et al., 2018). Yuan et al. (2018) used an MLS to scan a wheat field and estimate the heights of the plants. Meanwhile, Ziliani et al. (2018) and Gao et al. (2022) focused on the heights in a field of maize. This metric allows determining the general state of the health of this type of plant. A similar study was conducted by Zhou et al. (2020), who used an ALS to monitor the growth of maize and analyse the effects of climate on this plant in the lodging season. It is also necessary to monitor the growth cycle in sugar cane cultivation to make yield estimates. Consequently, Sofonia et al. (2019) used an ALS to monitor the growth of sugar cane in Australia. The purpose was to find the relationships between height, biomass, and yield. The traditional technique to estimate the yield and growth rate of grass is inaccurate and expensive (Ghamkhar et al., 2019). So, as an alternative, Ghamkhar et al. (2019) proposed using an MLS to do this efficiently. They were the first, when compared with the traditional technique, to obtain results that can be put into practice. Dhami et al. (2020) used an ALS to estimate the height of a soybean plant from a BEV perspective, which is crucial to understanding the health of the crop. A distinctive feature of this research is that even individual plants can be obtained in the point cloud. According to Liu et al. (2020), the use of ALSs for analysing the height of cotton could become of the utmost importance because it is essential information to facilitate the mechanised harvesting of cotton. Similarly, Zhang et al. (2020) used an ALS to calculate the plant height for canola, pea, chickpea, and camelina.

LiDAR technology has also been used to inventory the trees in an apple orchard by measuring the dimensions of the canopies from the BEV (Hadas et al., 2019). Another LiDAR inventory application was developed by Malambo et al. (2019), where the authors used an MLS to count sorghum panicles and also obtain information about the dimensions of the panicles. An interesting challenge is to inventory cabbages because their size makes it difficult to distinguish them from the ground in the point cloud. Nevertheless, Krus et al. (2020) used two MLSs to determine the production inventory of a cabbage field.

One of the advantages of the LiDAR system compared to multispectral imagery for LAI estimation is that the LiDAR system only requires a single prediction variable (Zhang et al., 2022). The LAI is an important metric to monitor in agriculture because it allows an estimate to be made of the photosynthetic capacity of plants and trees. Moreover, it helps to understand the relationship between biomass and yield under different climatic conditions. For example, Zhang et al. (2020) decided to use an ALS to estimate the LAI in a bean field. Likewise, Pagliai et al. (2022) compared three inputs to understand the LAI in viticulture. These inputs are mobile applications (iPad), aerial acquisition, and MLS. The point cloud is obtained in all of them. However, the first two used Pix4D software to generate the point cloud from a series of images. What is important to highlight about that research is that the LiDAR system allowed better automation of the collection of the point cloud because, when installed on farm tractors, the scanning could be made during maintenance activities. It also involved fewer steps to estimate the LAI. Another feature of the LAI is that it helps to assess water requirements, disease, and the yield of the crop (Kulkarni and Honda, 2020). Some authors have used LiDAR systems to estimate the LAI. For example, Yun et al. (2019) developed an algorithm to process the point cloud from three perspectives (i.e. bottom of the tree, diagonal to the tree, and BEV) to extract the leaf structure in the tree canopy. They used these three perspectives to achieve an accuracy of 90%. Furthermore, the LAI can be used to extract features of the structure of the canopy for canola plants (Wu et al., 2019). Another exciting study for LAI estimation is that of Gu et al. (2022), who used an MLS to estimate LAI during LiDAR movement in apple trees with a thick canopy.

Similarly, the estimation of Dry Matter (DM) is important in forage crops because it is related to ruminant nutrition. However, this is a task that requires laborious, destructive, and inaccurate methods. George et al. (2019) proposed using an MLS to estimate the DM in grassland in Canterbury. They scanned this crop 8 times before mechanical defoliation for better results. Another application to DM estimation can be found in Wijesingha et al. (2019). In that research the authors scanned the biomass of a grassland with a TLS. They then extracted the canopy height and used this metric to estimate the DM. Grasslands constitute a large part of German agriculture, which depends on these grasslands to cover the feed demand of ruminants and other industrial services. Consequently, it is necessary to determine the grass yield and quality in a timely manner. However, this estimation is very challenging to make with only one sensor because of the heterogeneity of the grass (Wachendorf et al., 2019). Wachendorf et al. (2019) conducted a study using a spectral camera and an ALS to perform this task. The authors concluded that a similar error is still obtained when using the traditional method, so it is necessary to continue improving this type of application.

An important factor to be known in fruit growing is the tree structure. However, information on tree structures is limited. Thus, Murray et al. (2020) proposed the use of a TLS to scan apple trees and find the metrics for the tree structure to estimate the yield. An important challenge demanding more precision is to make estimations concerning the canopy structure of the trees because this would allow their pesticide requirements to be estimated. For example, Sultan Mahmud and He (2020) used an MLS to make estimations of the canopies of apple trees to calculate the pesticide required to reduce the environmental impact of the overuse of these chemicals. However, the authors concluded that an MLS is not yet accurate enough to extract the characteristics of the canopy. Wu et al. (2020) found that it is better to use an ALS for this because it allows better extraction of these characteristics from this perspective. The authors extracted the volume and the maximum canopy height of macadamia, avocado, and mango trees. Given the popularity of LiDAR systems, which is due to their accuracy in measuring the dimensions of objects, Husin et al. (2020) used this technology to scan palms to identify their levels of disease (the characteristics of the crown are related to the health of the palm).

Crop biomass is an important aspect to consider because it is related to the levels of nitrogen in the crop. Colaço et al. (2021) used an MLS to calculate the biomass of a wheat grassland. A good water supply is important for any type of crop. In Minnesota, an ALS was used to detect the watersheds left by the rivers and to map them so that farmers can make decisions about the location of their crops (Srinivas et al., 2020).

It is important in agricultural monitoring activities to have an overview of the behaviour of the crop. In this type of application, the algorithms are basically focused on cleaning the noise from the point cloud to make it easier for the farmer to interpret it. In this regard, surface mapping is important because it helps the user to make decisions on the whole crop. An example is the application of an ALS to create surface roughness maps of an agricultural field with crops and trees so that the farmer can appreciate the overall plant growth by looking at the map (Trepekli and Friborg, 2021). In particular, the use of descriptive statistics to filter wheat plants (e.g. Yuan et al., 2018) by means of height percentiles is predominant. Another essential factor to monitor in agriculture is the tree belts surrounding crops, as they reduce the negative environmental impact of agriculture and increase agricultural productivity (Nowak et al., 2022).

Clustering techniques have also been used to estimate crop characteristics. The RanSaC (Random Sample Consensus) and Euclidean clustering methods have been used to monitor the growth of cotton (Sun and Li, 2017). Another application in which clustering techniques have been used, taking into account the crop density, is to estimate the characteristics of sorghum panicles (Malambo et al., 2019). Other studies have used voxelisation techniques to calculate the amount of nitrogen needed by the crop (Christiansen et al., 2017). In this application, Christiansen et al. (2017) used the Point Cloud Library (PCL) from ROS to calculate the level of nitrogen as a function of the plant height chiefly. In addition, Colaço et al. (2021) used ROS to

Table 3
LiDAR applications for metric estimation in cultivating crops.

Study	Metric/index to be estimated	Crop	Strategy	Software	Type of LiDAR
Sultan Mahmud and He (2020)	Canopy density	Apple	M-estimator sample consensus	MatLab	MLS
Main findings:	• The 3D-based algorithm was more efficient than the 2D-based algorithm for assessing the point density of a tree canopy. • Alignment during scanning is essential to avoid the error caused during experimentation.				
Pending challenges:	• In this study, only the indicated canopy points are calculated. However, this number of points does not provide accurate canopy information. • It is necessary to establish a relationship between the number of points and the number of leaves in future work.				
Husin et al. (2020)	Canopy parameters	Palms	Classification, Linear model, Otsu's algorithm	MatLab, SCENE, Paint, AutoCAD, JMP	TLS
Main findings:	• The point cloud generated with TLS provided accurate characteristics of oil palm trees for disease detection. • The results from the statistical analysis revealed that the number of fronds was the best single parameter for detecting basal stem rot. • The linear model's parameter combination consisting of the number of fronds, frond angle, and canopy strata at 200 cm from the top was the best model compared to other combined parameter models.				
Pending challenges:	• The LiDAR-based approach seems to be unable to scan a plantation area with a single scan at a significantly lower cost.				
Sandonís-Pozo et al. (2022)	Canopy parameters	Almond	Clustering, Statistics	RStudio	MLS
Main findings:	• Canopy parameters related to height, width, cross-sectional area and porosity of the canopy along the rows offered a high correlation, especially with NDVI. • This methodology could be interesting as an input to building a model approach to simulate crop growth and better estimate yield production.				
Pending challenges:	• The methodology employed can be applied to other crops with hedgerow cropping patterns. • The mapping of canopy parameters can be extended to more extensive orchards.				
Wijesingha et al. (2019)	Canopy surface height	Grass	SFM, Statistics, Regression	Leica Cyclone 3D, Agisoft PhotoScan Professional, R	TLS
Main findings:	• Overall, 3D point cloud models from the Structure From Motion (SFM) UAV models were slightly outperformed by models with point cloud data from a TLS. • The results of this study demonstrated that the fresh biomass (FB) and dry biomass (DB) of grassland can be estimated using the canopy surface height (CSH) derived from the SFM and the point cloud data. • The accuracy of the prediction in species-poor grasslands is higher than in diverse and heterogeneous canopies.				
Pending challenges:	• The combination of the CSH and spectral data from UAV-borne imagery should be tried. • The performance could be improved by using a digital terrain model developed by the SFM on board the UAV, which would act as a reference layer to derive the CSH.				
Vidoni et al. (2017)	Canopy thickness	Vineyards	Interpolation, Early Disease Algorithm, Statistics	MatLab, LabView, ByeLab	MLS
Main findings:	• The ByeLab system showed significant outdoor performance, allowing early detection of diseases in vineyards.				
Pending challenges:	• The efficiency of the measurements under non-ideal terrain and atmospheric conditions should be evaluated.				
Wu et al. (2020)	Crown parameters	Avocado, macadamia, mango	CANUPO segmentation	CloudCompare, RiSCAN PRO, ArcGis	ALS and TLS
Main findings:	• The results showed that ALS data could accurately measure parameters of the structure of the crown (area, height, and volume). • This study provided information to growers and horticultural industries on the capability and accuracy of LiDAR systems.				
Pending challenges:	• A limitation of this study is that only 7 trees were used for the measurements of the crown structure using TLS. • Future experiments should be based on larger sample sizes.				
Srinivas et al. (2020)	Elevations	Maize, soybeans	Revised Universal Soil Loss Equation, Fixed area threshold	ArcGIS, ACPF	ALS
Main findings:	• This study developed a novel decision support framework using three watershed modelling tools to analyse conservation farming practices. • Results showed that 537 profitable practices, such as grassed waterways, produced an 8.5% reduction in nitrogen. • River basin planning and implementation decisions can be made more easily, quickly, accurately and cost-effectively.				
Pending challenges:	• Work needs to be done on how to communicate field-scale maps to landowners. • Work needs to be done to obtain more specific field data to improve estimates.				
Florent et al. (2019)	Elevations	Crops in Nyírbátor	Interpolation	ArcGis, IBM SPSS	ALS
Main findings:	• The results demonstrated the benefits and advantages of using LiDAR to prevent possible waterlogging and search for hydrological soil characteristics. • The digital elevation model (DEM) and runoff line would improve irrigation planning and water use efficiency. • The available soil water is lower in the deeper layer.				
Pending challenges:	• Computational intelligence methods could provide better results than interpolation.				
Cassidy et al. (2019)	Elevations	Grass	XXL	SAGA GIS	ALS
Main findings:	• This study indicated that the phosphorus carrying capacity of the soil above the agronomic optimum was 15% of the area of the individual sub-catchments. • Catchments can hardly transport hydrologically sensitive areas in soil with phosphorus above the agronomic optimum (1.5%).				
Pending challenges:	• Less intensive agriculture would be necessary to fulfil water quality requirements; otherwise, less ambitious thresholds should be considered to fulfil irrigation redistribution.				

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Table 3 (*continued*).

Study	Metric/index to be estimated	Crop	Strategy	Software	Type of LiDAR
Zhou et al. (2020)	Height	Maize	Interpolation, SFM, classification	POSPac, RiPROCESS, LIDAR360 software	ALS
Main findings:	• The results demonstrated a higher accuracy of point clouds generated with LiDAR systems than those generated from imagery. • The UAV-LiDAR data reflected the temporal changes of lodged maize plant height and the plant height restoration ability of different lodging types.				
Pending challenges:	• Application in large-scale lodging monitoring is still a difficult problem to solve.				
Yuan et al. (2018)	Height	Wheat	Statistics	LabVIEW, MatLab R2017a, Pix4Dmapper	MLS
Main findings:	• LiDAR demonstrated better results than an ultrasonic sensor. • Simply scanning a section of a plot with LiDAR was sufficient to make an accurate estimation of plant height. • The methodology used is easily adaptable for studies wishing to adopt static measurement.				
Pending challenges:	• In contrast, ALSs could be a more reliable media for assessing wheat height.				
Ivushkin et al. (2019)	Height	Quinoa	Multiple Linear Regression	POSPac Mobile Mapping Suite, RiPROCESS, ArcGIS, IBM SPSS	ALS
Main findings:	• It was concluded that using ALS effectively measures plant salt stress by estimating plant height. • An increased soil salinity significantly affects the height of quinoa plants. • The use of multiple measurement techniques has great potential for monitoring soil salinity.				
Pending challenges:	• Experiments with less salinity should be conducted to reach more valuable conclusions.				
Liu et al. (2020)	Height	Cotton	Classification, PCA, KD-tree, random sampling method	MatLab	ALS
Main findings:	• The coefficient of variation was used to explain the changes in plant height. • Plant height can be an essential reference for the mechanical operations involving this crop. • The maximum relative error of the value measured by the UAV-LiDAR detection system was 12.73%, and the corresponding maximum error was 3.48 cm.				
Pending challenges:	• This approach could be extended by automatically extracting the point clouds for each cotton plant and importing the generated spatial differential parameters.				
Zhang et al. (2021)	Height	Canola, camelina, chickpea, pea	Statistics	MatLab, Pix4Dmapper, QGIS	ALS
Main findings:	• This study demonstrated the efficiency of using ALS for estimating plant height. They obtained correlation coefficients of 0.74 and 0.91. • The use of LiDAR for estimating plant height offered better accuracy than photogrammetry.				
Pending challenges:	• Canopy leaflets affected the generation of the point cloud. • To increase the accuracy of the estimation, an algorithm to remove outliers should be included.				
Gao et al. (2022)	Height	Maize	Seedling detection and fuzzy C-means clustering algorithm	CloudCompare, Scikit-learn	ALS
Main findings:	• A point cloud produced by UAV-borne LiDAR can generate a complete and accurate digital terrain model (DTM) of a maize field at a relatively early stage of growth. • The DTM can be effectively used for bare ground estimation and estimation of the height of individual maize plants to avoid the occlusion problem as the maize grows. • The highest accuracy had an R^2 greater than 0.95, a mean RMSE of 3.63 cm, and a mean MAPE of 1.88%.				
Pending challenges:	• Future work will attempt to improve the quality of the LiDAR point cloud by optimising route settings to extract the number of leaves, leaf area index, and other characteristics of maize growth.				
Hadas et al. (2019)	Height	Apple	Classification, α-shape algorithm	CloudCompare, MatLab	ALS
Main findings:	• This paper developed a robust methodology for point cloud processing that combines three algorithms. • The need for tools to make orchard inventories remotely was addressed with LiDAR technology. • The precision of crown identification, tree height and crown base height was 0.38, 0.09 and 0.09 metres, respectively.				
Pending challenges:	• The uncertainty in identifying crown shapes limited the accuracy of the reference data. • Results with other orchards, species varieties and larger crops should be explored. • The impact of the density of the point cloud and flight height on accuracy needs to be further investigated.				
Dhami et al. (2020)	Height	Soybeans	Clustering, Voxel Filter, Voting Scheme, RANSAC	OpenCV, ROS, PCL	ALS
Main findings:	• A methodology for extracting plant heights from 3D LiDAR point clouds is presented, with a specific focus on plot-based phenotyping environments. • They presented a toolchain that can be used to create phenotyping farms for using in Gazebo simulations. • The algorithm estimated plant heights in a field with an RMSE of 6.1 cm.				
Pending challenges:	• The algorithm should be tested on other types of farms.				
Colaço et al. (2021)	Height	Wheat	Clustering, Statistical Outlier Removal	ROS, CloudCompare, QGIS	MLS
Main findings:	• This was the first report on the use of LiDAR for commercial mapping of a cereal crop. • This system outperformed a commercial active multi-spectral optical sensor's spectral indices and crop height estimation.				
Pending challenges:	• More studies on crop development and their evaluation in different scenarios and complete automation of the data processing are needed. • Further research on technologies for large-scale biomass mapping.				

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Table 3 (*continued*).

Study	Metric/index to be estimated	Crop	Strategy	Software	Type of LiDAR
Christiansen et al. (2017)	Height	Wheat	Voxelisation	ROS, PLC	ALS
Main findings:	• The study introduced a mapping method for observing crops and estimating their current production, volume, plant height, and environmental states. These values are connected to nitrogen treatment strategies.				
Pending challenges:	• Continuous monitoring using ALSs mounted in UAVs is currently impractical because of the low coverage per battery.				
Sun and Li (2017)	Height	Cotton	Clustering	MatLab	MLS
Main findings:	• The correlation between projected canopy area and yield was higher than the correlation between canopy height and yield. • The system used in this research allows the generation of efficient 3D models to measure morphological parameters and analyse growth dynamics.				
Pending challenges:	• If the plant structure is complex (i.e. they are in the mature stage), occlusion effects are present. • Wind is a factor affecting the accuracy of the estimated traits since it might result in blurred point clouds.				
Saha et al. (2022)	Height	Strawberry	Voxel-grid, statistical outlier removal	MatLab, Python, CloudCompare	MLS
Main findings:	• This research provided an approach to estimating plant characteristics and monitoring plant growth. • This approach was able to extract the volumes of the different horizontal canopy layers, which can generate the volume profile of the vertical canopy. • The typical growth pattern of strawberry plants was found in vertical profiles.				
Pending challenges:	• LiDAR sensors could be mounted on a linear transporter close to the ground, which is a feasible tool for monitoring the growth of strawberry plants with better results. • Future work should investigate physiological studies or applications in variable rate management.				
Palacios-Rodríguez et al. (2022)	Height	Carob	Allometric	PHOTOMOD Lite, Global Mapper, Proc SQL	ALS
Main findings:	• This estimation technique for the existence of carbon in carob trees is an alternative to traditional methods because it is a quicker, less costly and more accurate approach. • ALS data allowed the generation of high-resolution maps of carbon stocks, which are essential for forestry.				
Pending challenges:	• The main limitation of this study is related to the quality of the ALS data and its timeliness.				
Ziliani et al. (2018)	Height	Maize	SFM, Ground sampling distances, Regression	ArcGis, Agisoft PhotoScan Professional, FARO SCENE	TLS
Main findings:	• This methodology could reproduce the observed spatial variability of crop height within a maize field at all stages of crop development, with a correlation of up to 0.99 and RMSE of 0.0164 cm. • A resolution of 10 cm produced the best-so-far compromise between accuracy and processing time, providing an acceptable accuracy with a processing time of approximately half a day.				
Pending challenges:	• Further image collection and processing improvements are needed to reduce the bias in UAV-based SFM retrievals. • The overall time needs to be further reduced for real-world applications.				
Yun et al. (2019)	LAI	Apple, mango, rubber, walnut	Cylinder-based approach	MatLab	ALS and TLS
Main findings:	• An approach for measuring total leaf area in canopies is presented, which allows a quantitative assessment of occlusion metrics for various attributes. • When scanning from a single ground position, only 25% to 38% of the leaf surface was recovered.				
Pending challenges:	• With the help of computer graphics algorithms, this approach could be extended to measurements of tree leaf area.				
Gu et al. (2022)	LAI	Apple	BPNN, partial least squares regression	MatLab	MLS
Main findings:	• The residual method was used to remove outliers from the data and eliminate the influence of dense branches and leaves in the canopy. • Comparing the results for R^2 (86.1%) from the obtained models and their ability to predict data revealed that the backpropagation neural network (BPNN) algorithm was better than the other two algorithms.				
Pending challenges:	• In subsequent studies, the influence of canopy thickness needs to be considered.				
Zhang et al. (2020)	LAI	Bean	Statistics, Cloth Simulation Filtering, Beer–Lambert's law	MatLab	ALS
Main findings:	• It was found that the methods for measuring the perpendicular to the swath perform better. • Significant results were presented for LAI and height estimates. This allowed the extension of yield modelling. • Given the similarities in planting with other row crops, this method can easily be applied to crops such as soybeans and sugar beet.				
Pending challenges:	• Future research should focus on expanding the predictor variables for assessing canopy width and LAI.				
Pagliai et al. (2022)	LAI	Vineyards	Statistics	Pix4D, MatLab, VitiCanopy, CloudCompare	MLS
Main findings:	• MLSs were installed on farm tractors to collect the point cloud during field operations. • The tools analysed in this article satisfactorily discriminated (with $R^2 = 0.78$) between areas with different canopy size characteristics.				
Pending challenges:	• Although ALSs allowed rapid mapping of large numbers of hectares, they required trained personnel and specific requirements to comply with national laws. • The main limitations are related to data processing. It is necessary to work on automating the algorithms in the processing steps.				
Zhang et al. (2022)	LAI	Broadacre crops	SfM	LAStools, CloudCompare, Scikit-learn	ALS
Main findings:	• This article strongly supported the potential of UAS-based LiDAR and multispectral imagery to estimate LAI of short broadacre crops. • This article's results encourage its translation into an eventual operational solution for assessing the structure of the crop.				

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Table 3 (*continued*).

Study	Metric/index to be estimated	Crop	Strategy	Software	Type of LiDAR
Pending challenges:	• Furthermore, since snap beans only grow up to 0.3–0.6 m in height, the methods in this study should be extensible to other short broadacre crops, such as sugar beets, soybeans, and winter wheat. • It is recommended that future studies evaluate the fusion of LiDAR and multispectral imagery.				
Li et al. (2022)	LAI	Maize	ANOVA	MatLab, SunScan, Agisoft Metashape Professional, Metashape	ALS
Main findings:	• This methodology allowed automatically measuring the LAI with high resolution and fast intensive mapping. • Canopy height measured with 3D point clouds has a relatively strong correlation (up to $R^2 = 0.89$) with the manual measurements. Thus, this methodology allowed cost-effective and high-resolution mapping.				
Pending challenges:	• The correlation of the LAI estimate was low ($R^2 = 0.48$). Therefore, it was an inaccurate estimate of canopy density and LAI. • Further research is needed on improved approaches for data collection related to spatial point cloud density. • Future studies should focus on developing methods with descriptors for further genotype differentiation.				
Maimaitijiang et al. (2020)	LAI/height	Sorghum	Clustering, Random Forest Regression, Statistical Outlier Removal algorithm	Pix4Dmapper, LiDARMill	ALS
Main findings:	• This paper found that the ALS system performed better than RGB photogrammetry on sorghum. This is due to its higher canopy penetration capability. • It maintains its performance regardless of crop size and density.				
Pending challenges:	• Comparing ALS and RGB photogrammetry for other plant traits, such as biomass. • It would also be essential to test these techniques on monitoring crop growth through deep learning.				
Malambo et al. (2019)	Panicle dimensions	Sorghum	Clustering, Otsu thresholding	FARO SCENE, CloudCompare, FUSION/LVD	MLS
Main findings:	• This study served as a proof of concept for a new approach to panicle characterisation (length, width, and height) in sorghum and promoted interest in future developments focusing on phenotyping sorghum panicles. • The overall panicle detection accuracy was 89.3%, with an omission rate of 10.7% and a commission rate of 14.3%.				
Pending challenges:	• It may be impossible to detect panicles within plots due to foliage occlusion. This study could consider denser point clouds, improved data quality, and the development of more robust methods to reach accurate high-throughput phenotyping.				
Trepekli and Friborg (2021)	Roughness length	Potato	Morphological, Classification	Geo-LAS, QGIS, EddyPro	ALS
Main findings:	• This approach can help to make a more accurate spatial representation of the non-linear relationships between canopy features and water dynamics. • The Raupach roughness model is more suitable for simulating time variations. • All morphometric models showed a standard deviation of less than 4.2 cm, ranging from an underestimation by 1.3 cm to an overestimation by 1.9 cm.				
Pending challenges:	• Further research is needed to improve morphometric models in vegetated landscapes to consider the surface drag effects of roughness elements.				
Zhou et al. (2021)	Volume	Begonia	Clustering	PCL, VTK	MLS
Main findings:	• This research proposed a new method based on 3D LiDAR and KD tree to predict crown volume. • The developed method simplified labour consumption and improved measurement accuracy.				
Pending challenges:	• Future work aims to improve the stability and accuracy of the prediction model.				
Krus et al. (2020)	Volume	Cabbages	Classification	SOPAS Engineering Tool	MLS
Main findings:	• Segregation between soil and plants was achieved by using weighted sums and without the additional use of other types of sensors. • An algorithm based on weighted sums had the potential to outperform traditional methods. • The method used does not rely on external sensor readings, e.g. colours.				
Pending challenges:	• Periodic measurements of a single plant could be used to monitor plant development.				
Martínez-Casasnovas et al. (2017)	Volume	Olive	Statistics	CloudCompare, JMP12, ArcGis	MLS
Main findings:	• The tools developed in this study proved to be an excellent solution to quickly and objectively obtain geometric parameters of crop canopies. • The results demonstrated that MLS is an excellent alternative to current research methods for canopy volume estimation.				
Pending challenges:	• It would be interesting in future work to compare MLS and ALS for this type of activity, as users have to choose the most appropriate parameters. • Furthermore, digital maps are also an excellent tool for presenting and analysing the spatial variability of parameters. Further research is therefore needed. • Scanning in the presence of wind is not recommended (still, breezes up to 4 km/h do not significantly alter the estimates).				
George et al. (2019)	Yield	Grass	Regression	Gen Start v18	MLS
Main findings:	• LiDAR sensors helped to remove a critical bottleneck in perennial ryegrass breeding with a real-time and non-destructive estimation, which is valuable. • The results indicated that the estimation of perennial ryegrass yield was satisfactory.				

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Table 3 (*continued*).

Study	Metric/index to be estimated	Crop	Strategy	Software	Type of LiDAR
Pending challenges:	• Seasonal algorithms should be added to correct for the seasonal variation of the dry matter.				
Wachendorf et al. (2019)	Yield	Grass	Classification	Pix4Dcapture, AgriSoft, QGIS, R	ALS
Main findings:	• The objective is to provide farmers with cheap, adequate, timely information to support decision-making. • Thematic crop maps are suggested because they provide low-cost information to support farmers' decision-making.				
Pending challenges:	• Grassland characteristics such as animal droppings are difficult to assess or filter. Deep learning methods could offer interesting insights.				
Sofonia et al. (2019)	Yield	Sugarcane	Not specified	SLAM, Python, Pix4Dmapper, 3DReshaper	ALS
Main findings:	• The results show that LiDAR provided more consistent and significant correlations with the data for the biophysical parameters of sugar cane. • This approach, with some refinements, can be sensitive enough to biophysical parameters to derive predictive models throughout the growth cycle.				
Pending challenges:	• The results suggested that predicting biophysical parameters from photogrammetry is challenging, and further research is needed. • Working closely with farmers to understand their problems will likely improve economic and environmental outcomes.				
Murray et al. (2020)	Yield	Apple	DBSCAN algorithm	Python	TLS
Main findings:	• The data generated by a TLS has excellent potential to inform orchard management due to its accuracy in quantifying structural complexity. • Trees can be classified into management categories based on tree structure assessment with remote sensing techniques.				
Pending challenges:	• Future research suggests using LiDAR to quantify the impacts of pruning on yield because this activity is essential.				
Ghamkhar et al. (2019)	Yield	Grass	Volumetric	MatLab	MLS
Main findings:	• This development offers an accurate, non-destructive and cost-effective estimate for ryegrass. • Real-time volumetric data capture, modelling and analysis software was developed. • It is the first LiDAR-based tool that has demonstrated high accuracy in real-time dry matter quantification with $R^2 = 0.8$.				
Pending challenges:	• A more detailed study of the effects of the environment, management and genotype on precision is needed. • Increasing knowledge about this type of LiDAR sensors can lead to novel programmes in agronomy.				

extract the characteristics of the biomass of a crop of wheat. MatLab has become popular in processing point clouds (e.g. Vidoni et al., 2017; Yuan et al., 2018; Husin et al., 2020). For instance, Otsu's algorithm (implemented in MatLab), has been used to assess the level of disease in palms (Husin et al., 2020). Sultan Mahmud and He (2020) used the M-estimator Sample Consensus (MSaC) algorithm in MatLab to determine the amount of pesticide needed in an apple orchard. The TreeQSM algorithm developed in MatLab is popular for use in quantifying branch architecture (Lau et al., 2018). Meanwhile, other software tools have been used to process point clouds, such as CloudCompare (e.g. Wu et al., 2020; Colaço et al., 2021; Pagliai et al., 2022). Similarly, Sofonia et al. (2019) used software specific to the LiDAR system that they acquired.

Table 3 presents the applications of LiDAR technology focused on metric estimation. It can be seen from this table that most of the applications have been made to estimate characteristics linked to crop production (e.g. height and LAI). In cases where the aim is to monitor the properties of the soil and surface, researchers have opted to use ALS because this type of LiDAR system allows faster scanning and more efficient roughness maps can be obtained from a BEV perspective. Note that plant height and LAI are the features for which most applications oriented towards estimating metrics have been developed with LiDAR systems (indeed, both features are strongly connected to crop health). There is also a great diversity in the types of crops for which applications for health monitoring have been specialised. Table 3 shows that ALSs and MLSs have been used to the same extent to estimate the LAI. However, different software strategies (such as MatLab, statistics, classification, and clustering) have been used.

We have identified a series of processes that are common to those applications of LiDAR oriented towards estimating metrics. Fig. 3 presents a chart that generalises the processes followed by the applications presented in this category. The LiDAR applications to estimate crop features and soil properties perform the following 5 steps: data acquisition, preprocessing, plotting, measuring, and interpretation. Preprocessing is the most challenging step because it entails normalisation, outlier identification, noise cleaning, and global registration (i.e. the coherent merging of multiple point clouds). In Fig. 3, 'plotting' means visualising the point cloud that directly resulted from the preprocessing step in a 3D space (x, y, and z); and 'measuring' means calculating the distances between several identified points; here, software specially designed for point clouds is used (e.g., CloudCompare).

The advantages of using LiDAR technology for metric estimation are that it is not limited by environmental conditions, it has a strong ability to get into the field of crops, and it has significant accuracy in extracting information on the physical characteristics of the crop. However, a strategy must be developed for each type of element to be analysed, or even for each type of crop. Table 3 shows applications that can cover different types of crop to estimate a common metric. One of the disadvantages of ALSs is that the UAV's flight time is short, which makes it difficult to monitor large areas. Another disadvantage is that the crop elements must be scanned repeatedly to improve the accuracy of the point cloud. Lastly, LiDAR systems must work in synergy with other sensors to gain further insight into the status of the crop.

3.2. Digitisation

The idea of digitising real-world objects in three dimensions has been gaining in popularity because of photogrammetry (e.g. Dellaert and Yen-Chen, 2020) and voxelisation techniques (e.g. Lau et al., 2018). Agriculture can greatly benefit from these techniques to digitise trees and crops, mainly using LiDAR technology (cf. Hu et al., 2017). For example, Huang et al. (2022) used a TLS to create a 3D model of bean seeds to qualify the performance traits of bean seeds.

Several LiDAR applications have been used to improve the graphical representations of a crop to enable the farmer to more accurately assess the structure of the plants and trees. For example, Pfeiffer et al. (2018) developed an algorithm that scans the crop with a medium- or high-density TLS to create a 3D representation of trees in production seasons (i.e. with the presence of foliage in the canopy). Bear in mind that the biomass of the crop is an important criterion for making decisions about the crop's health and production. For example, Ao et al. (2022) used Convolutional Neural Networks (CNNs) and morphological characteristics to segment the stem and leaves of maize. The authors tested 40 samples of plants and showed high accuracy (F-score of 0.99). Jin et al. (2018) used a TLS system to create a 3D model of maize biomass by making height estimations and also to manipulate the point cloud to separate the stalk from the leaves, which provided great accuracy in calculating the LAI of the canopy. Similarly, Lin et al. (2022) used a TLS to digitise four varieties of maize; this digitisation

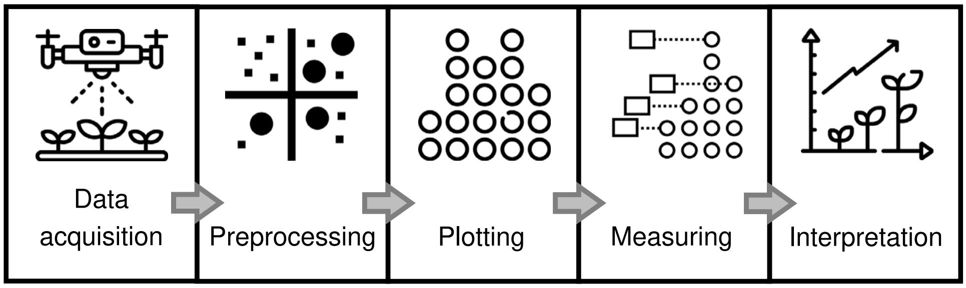

Fig. 3. General design in LiDAR applications for estimating metrics for cultivating crops.

aims to segment plant characteristics. On the other hand, Digumarti et al. (2018) developed an algorithm to automate the segmentation and extraction of the tree structure. They validated the efficiency of this algorithm with beech trees that were scanned with a TLS; in addition, they entered information about the LAI of these trees. In a recent study, Berk et al. (2020) applied LiDAR technology to digitise the foliage of apple trees by separating the leaves from the trunk in the point cloud. Considering the colour of the leaves, it is possible to determine the health of the plants in a crop. Therefore, it is important to digitise this characteristic to provide a more robust 3D model. Recognising these implications, Wu et al. (2018) used a sequence of images taken with a camera and a TLS for the digitisation of the colours of the plants. Hu et al. (2022) proposed a new model called Leaf Area Delaunay Triangulation (LA-DT) for digitising the area of rapeseed leaves.

Pruning is one of the most important activities in fruit growing because the passage of sunlight into the canopy depends on it, which can affect the efficiency of the crop production. This has led several studies to focus on the digitisation of crops to evaluate pruning structures. For example, Moreno et al. (2020) used an MLS to digitise a vineyard and analyse the impact of pruning on this crop. One of the indicators best characterising tree pruning is the percentage of light that is projected onto the ground from the tree canopy. Thus, Westling et al. (2018) used a TLS to digitise trees, which will enable the farmer to evaluate the light energy captured by individual avocado trees. You et al. (2021) used an MLS to create a graph of the structure of a cherry tree. This is a great first step because it can help to develop tools for automating the pruning of fruit trees.

The use of TLSs is predominant in this type of application, in which the aim is to digitise instances of the crop. It is at least plausible that this is because this type of LiDAR system allows a more detailed level of the crops to be examined, thus enabling the creation of efficient point clouds for the representation of the structures in the crop. The voxel-based technique is most commonly used to create 3D models of trees and plants. This technique creates a 3D model from small cubes, called voxels, as a unit of volume. For example, Pfeiffer et al. (2018) used this technique to digitise and analyse the biomass of cherry trees. In addition, Westling et al. (2018) used voxelisation to digitise avocado because they needed to obtain a 3D model of the structure similar to reality to analyse the sunlight index. In TreeQSM, Lau et al. (2018) used a technique similar to voxelisation but used cylinders instead of cubes to create a more representative 3D model of the branches of a tree, along with their hierarchy. The MatLab environment has been widely used for the digitisation of crops. For example, Moreno et al. (2020) used the R2017b algorithm to process the point cloud and to be able to plot the output of this algorithm in a 3D model with the CloudCompare software. Likewise, the MatLab environment has been used to digitise apple trees (Berk et al., 2020). The semantics-guided skeletonisation technique, which is based on the knowledge You et al. (2021) acquired about the way in which cherry trees grow vertically, was used to model topographic constraints and geometric constraints to graph the structure of these trees.

A few LiDAR applications to digitise crops have been found so far, which are shown in Table 4. The dominance of TLSs in this type of application is remarkable. This is due to the flexibility in manipulating the scanning positions with this LiDAR system, which allows getting into the uniqueness of the crops to achieve a more efficient digital representations. It can be observed in Table 4 that most of the applications for digitisation are focused on the tree's structure and most of them aim to assess the impacts of pruning in fruit growing (e.g. vineyards, avocado, and cherry). Furthermore, voxelisation is the most widely used strategy for digitisation and several studies emphasise the detail that can be achieved in a digital model using this strategy.

Fig. 4 generalises the processes followed by the applications presented in this classification. LiDAR digitisation applications perform the following 5 steps: data acquisition, preprocessing, visualisation, evaluation, and reconstruction. The most distinctive feature is the repeated application of the last three steps.

The literature agrees that using LiDAR systems (with the strategies presented in Table 4) to digitise tree structures allows the creation of 3D models that bear a close resemblance to reality. Moreover, this type of application makes the estimation of wood volume in trees more efficient, which helps to improve the pruning practices in fruit growing. Furthermore, using LiDAR for foliage digitisation allows information about the LAI to be extracted. Unfortunately, the quality of the point cloud to digitise tree foliage is severely affected when wind is present, even after many iterations of the digitisation processes (i.e. visualisation, evaluation, and reconstruction). In this challenging situation, the process of digitising with LiDAR systems is not fully automated.

3.3. Vision

Crop scouting is routinely carried out on a day-to-day basis to analyse the behaviour, from sowing to harvesting the crop. Depending on the size of the crop, scouting can be done on foot or on a vehicle. The basic tasks in scouting are counting trees or plants in the crop, pruning wild plants, sensing the soil's characteristics, counting fruit, and determining the maintenance tasks that will be needed in the crop.

Borowiec and Marmol (2022) used an ALS to detect the edges that delimit the soil extension of crops in the field, and thus keep track of the amount of crop grown. The boundaries were detected using PCA and the Hough transform. It is also important to inventory the number of trees in a crop because this helps to estimate the production and the amount of nutrients needed to maintain the crop. Itakura and Hosoi (2018) used an ALS to count trees from a BEV perspective and obtained an accuracy of 98% when detecting each tree in the point cloud. Likewise, Holmgren et al. (2022) compared the efficiency of tree detection at different heights and concluded that a better resolution in the point cloud is obtained at a maximum height of 150 m, which allowed the authors to detect smaller-than-average trees in low vegetation crops. Wu et al. (2019) compared 5 machine learning algorithms for classifying canola canopy structures and concluded that Random Forest is the algorithm with the best accuracy for classifying canola in the point cloud.

Table 4
LiDAR applications for digitisation in cultivating crops.

Study	Item to be digitised	Crop	Strategy	Software	Type of LiDAR
Wu et al. (2018)	Structure	Plants	RANSAC, Statistical Outlier Removal, α-shape	Agisoft	TLS
Main findings:	• Quality was not only related to LiDAR performance but also the external environment, scanning methods, and the complexity of the plant structure. • α-Shape worked better for plants with large leaves and less shelter between plants.				
Pending challenges:	• It is necessary to conduct rapeseed field trials to verify the versatility of this method. • Point cloud generation had the disadvantages of low automation and increased time. • The integration of multiple technologies for data acquisition would be interesting.				
Lau et al. (2018)	Structure	Eperua, Ormosia	Voxelisation, TreeQSM	RiScan PRO	TLS
Main findings:	• TreeQSM found and reconstructed 95% of the branches thicker than 30 cm. • TreeQSM identified the correct branching order in 99% of all cases and reconstructed 87% of branch lengths and 97% of tree volume.				
Pending challenges:	• This method could reconstruct branches over 40 cm in diameter; below this diameter, its accuracy decreases. • Future work should optimise plot and sampling design to increase the point cloud density on branches and within the canopy.				
Moreno et al. (2020)	Structure	Vineyards	α-shape algorithm	MatLab, LabVIEW, CloudCompare	MLS
Main findings:	• The number of scans significantly affected the relation of the actual biomass with the estimations. • LiDAR demonstrated a higher capacity for branch reconstruction than other types of sensors.				
Pending challenges:	• Work must be done to improve computational processes and point cloud processing. • The information could be used for automatic pruning systems or site-specific fertilisation.				
You et al. (2021)	Structure	Cherry	Skeletonisation, CNN	ROS	MLS
Main findings:	• This article introduced an algorithm that produces a labelled skeleton using topological and geometric priors. • This labelled skeleton also provided semantic information about the different parts of the tree.				
Pending challenges:	• This framework could be used during outdoor field tests on an end-to-end robotic tree trimming system. • It is suggested to increase the generalisation and performance of the algorithm by embedding different methods.				
Westling et al. (2018)	Structure	Avocado	Voxelisation, Radiation absorption model	SLAM	TLS
Main findings:	• This research presented a solar-geometric model for estimating light interception in avocado trees. • Compared to ceptometer energy measurements on the canopy floor, the model obtained $R = 0.854$; this suggests that the model is suitable for decision support systems.				
Pending challenges:	• Trunk or foliage labelling was done manually; so, future work is needed on algorithms to automate this classification.				
Digumarti et al. (2018)	Structure	Beech	Deep Points algorithm	SpeedTree, Unreal Engine, Microsoft's AirSim	TLS
Main findings:	• A method is presented to segment the 3D point cloud of vegetation to create a hybrid model composed of the skeleton of the branches and the segmented foliage, avoiding parametric models. • An average classification accuracy of 91% was achieved on simulated data.				
Pending challenges:	• Thinner branches are still classified as leaves. Strategies to address this problem should continue to be sought.				
Ao et al. (2022)	Structure	Maize	Convolutional neural networks, morphological characteristics		TLS
Main findings:	• The method achieved high accuracy in component segmentation (F-score = 0.8207) and plant segmentation (F-score = 0.9909). • The proposed method extracts accurate information for high-throughput phenotyping and provides helpful information for potential analysis of the relationship between genotypes, environmental conditions and phenotypes.				
Pending challenges:	• Further, evaluate and improve the proposed method.				
Hu et al. (2022)	Structure	Rapeseed	Delaunay triangulation, linear regression, elevation filtering method	PCL, Visual Studio 2022	TLS
Main findings:	• The experimental results showed that the LA-DT estimation errors of the three groups of field rapeseed were all less than 3%. • The LA-DT could accurately estimate the total LA of rapeseed in the target field. • Results showed that appropriately reducing the point cloud density could speed up the running rate and ensure the running accuracy of the model.				
Pending challenges:	• This study further verified the accuracy of the model through experiments on individual rapeseed plants.				
Lin et al. (2022)	Structure	Maize	DBSCAN algorithm, Radius-NN, KDTree	CENE, PCL	TLS
Main findings:	• This method has an average error of only 0.06 rad in direction prediction. • An individual maize segmentation model was established to process the maize point cloud in the field directly.				
Pending challenges:	• Three factors restrict the accuracy of the segmentation and stratification models—the rationality of the segmentation, the stratification method, and the data quality of the target 3D point cloud. • In the future, the researchers plan to test and update this in larger field crop phenotypic experiments.				
Jin et al. (2018)	Tree foliage	Maize	Deep Points algorithm, Median normalised vector growth	Green Valley International LiDAR360, FARO Scene	TLS
Main findings:	• This study was the first to introduce a LiDAR-based stem and leaf segmentation method. • This algorithm had satisfactory accuracy for categorising maize with different heights, compactness, number of leaves and densities. • The method could extract the three-dimensional volume quickly.				

(continued on next page)

Table 4 (*continued*).

Study	Item to be digitised	Crop	Strategy	Software	Type of LiDAR
Pending challenges:	• The authors discuss that this method could promote the development of high throughput phenomics.				
Berk et al. (2020)	Tree foliage	Apple	Trapezoidal method	MatLab	MLS
Main findings:	• Assessing leaf surface and tree spacing with LiDAR allowed more accurate analysis and targeted spraying management. • This LiDAR method for canopy volume proved to be the most consistent digital reconstruction method. • This approach digitally reconstructed the tree canopy of the smaller eight-volume elements.				
Pending challenges:	• Further research should be conducted to improve the leaf area measurement. • Variation in tree age, size or variety is not considered.				
Huang et al. (2022)	Seed	Legume	RANSAC, PCA, Computational Geometry Algorithms Library	PCL	TLS
Main findings:	• This method automatically calculated 34 traits: 11 morphological traits, 11 scale factors, and 12 shape factors. • The high accuracy of the measurements, the low time cost and the ability to handle batch data processing and automatic measurement showed that the method has the potential for legume seed phenotyping.				
Pending challenges:	• The 3D construction method was based on symmetry; so, it had limitations when measuring seeds with irregular geometric shapes. • Future research should explore an effective segmentation method when seeds overlap and stick together. • The authors proposed integrating this method into a hand-held scanning system for real-time measurement.				

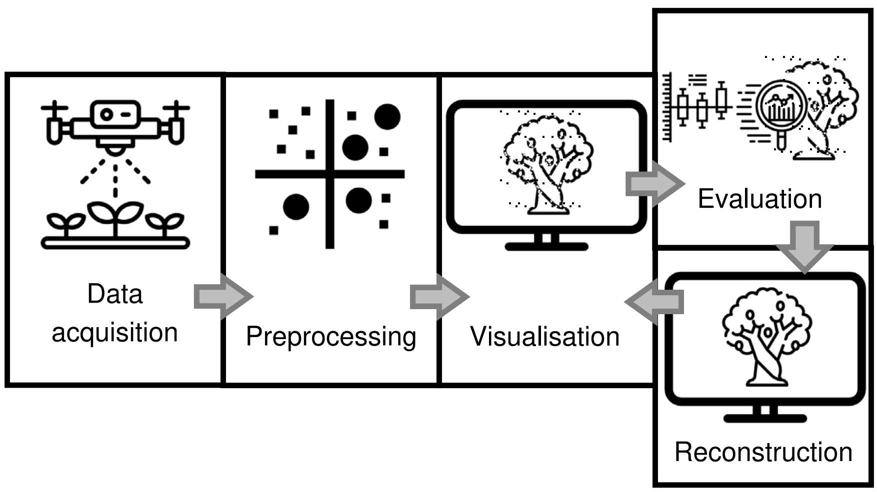

Fig. 4. General design used in LiDAR applications for digitisation in cultivating crops.

Counting the amount of fruit on the trees is directly related to production and is difficult to do manually. For example, counting the number of apples that a tree has produced would be a physically exhausting task because the farmer would have to go tree-by-tree to inventory the entire crop. Gené-Mola et al. (2020) used an MLS to detect and count the apples on a tree with an accuracy of 90%. Another interesting application for apple detection was proposed by Gené-Mola et al. (2019), whose proposal does not depend on environmental conditions to perform this task and can separate those apples that are on a single shoot with an accuracy of 80%. Furthermore, Tsoulias et al. (2020) used an MLS to count the apples on a tree. The difference is that they performed the apple detection after the crop had been scanned. A similar LiDAR application for fruit detection can be found in Tang et al. (2022), who used an MLS to detect fruit on tea trees and estimate oil production. An innovative application of ALSs can be found in Tiwari et al. (2020), who detected and classified the roofs that cover crops to get a notion of which farms are in operation.

LiDAR technology has been used as a computer vision system to drive autonomous vehicles artificially. For example, Hu et al. (2018) used LiDAR as a vision system for a quadcopter to fly through trees. Normally, in rural areas, it is not possible to have a reliable GPS signal. Therefore, Malavazi et al. (2018) used LiDAR technology to map lanes in the crop and aid the navigation of their Oz vehicle. Vehicle navigation in maize fields often presents a significant challenge given the density of their biomass. For this reason, Velasquez et al. (2020) developed a LiDAR-based navigation system for this type of crop to make it practical for the autonomous vehicle to move among the maize plants. LeVoir et al. (2020) used a camera and a low-cost LiDAR device as a vision system to navigate an autonomous vehicle in a maize field in low and high population seasons. In contrast, apple harvesting requires two main tasks to be performed manually: picking and transporting apples. Mao et al. (2022) used an MLS as a vision system for two vehicles to automate these activities. The VineSLAM algorithm is another proposal specialising in a single type of crop (Aguiar et al., 2022). This algorithm uses the point cloud generated by an MLS to map the environment and locate vehicles in a vineyard. Jiang et al. (2022) developed a system to navigate a vehicle in a greenhouse. They used an MLS that generates a point cloud in 3D. However, they merged this information in 2D because this mapping improved the algorithm's efficiency.

Detecting and pruning wild plants in crops is a constantly performed task because the timely pruning of wild plants will prevent them from consuming crop nutrients and promoting the formation of crop-disease pests. An alternative for the detection of wild plants can be found in Pretto et al. (2021), where the authors used two LiDAR systems (ALS and TLS) to detect and automate the pruning of wild plants. LiDAR systems can also be used during crop exploration (i.e. as a computer vision system for vehicle navigation). This vehicle can make estimations of the grass in the crop, thus allowing the navigation of the vehicle (Nguyen et al., 2021). Cruz Ulloa et al. (2021) used a LiDAR system to automate the application of fertiliser by detecting cabbages.

For applications involving fruit or tree counting, machine learning algorithms have mostly been used, such as Euclidean clustering (Reiser

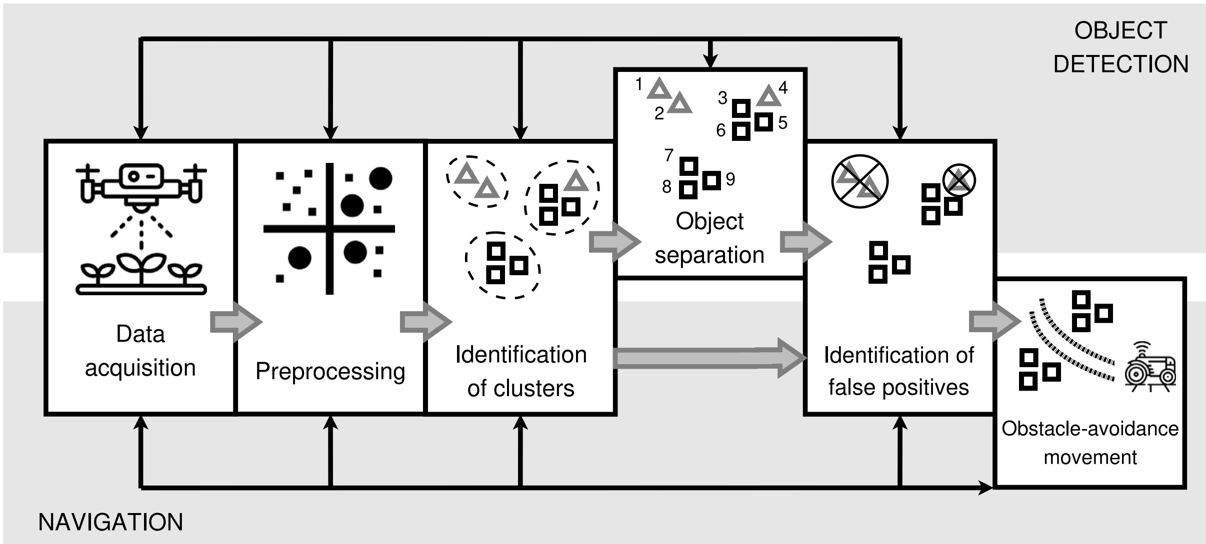

Fig. 5. General design used in LiDAR applications for artificial vision in cultivating crops.

et al., 2018), support vector machines (Gené-Mola et al., 2020), *k*-nearest neighbours (Tsoulias et al., 2020), and *k*-means (Cruz Ulloa et al., 2021). In contrast to these applications, Itakura and Hosoi (2018) used voxelisation to detect and count the trees in a crop. Furthermore, for applications using navigation systems, algorithms such as the graph-based optimisation of Simultaneous Localisation and Mapping (SLAM) (Hu et al., 2018), RANSAC (Malavazi et al., 2018), and H∞ (Velasquez et al., 2020) have been used. The AgriColMap library has also been used to detect wild plants (Pretto et al., 2021).

Table 5 presents the applications of LiDAR technology focused on artificial vision. This table shows that clustering has been repeatedly combined with MLSs to detect apples. This may be due to the proximity of the points generated by the collision of the laser pulse with the fruit. In addition, some LiDAR sensors can record the intensity of the reflection, and this intensity is linked to the type of object with which the light pulse has collided. In general, clustering is the most widely used approach to detect fruits and wild plants in agriculture. Additionally, navigation is mainly addressed through LiDAR technology because it allows the vehicle to navigate among the crops with a highly accurate representation of the obstacles in the environment through which the vehicle will move. Although navigation applications have been developed for maize, even though it becomes a dense crop in the production stage, it is still a challenging field in which to navigate.

Fig. 5 depicts the processes followed by the applications presented in this category. Two groups of LiDAR applications for artificial vision are clearly differentiated: object detection and navigation. In general, they share the following processes: data acquisition, preprocessing, cluster identification, object separation (only for object-detection systems), identification of false positives, and obstacle-avoidance movement (only for navigation systems).

In most LiDAR applications for artificial vision, an indirect product can be obtained. For example, in fruit detection, some researchers reported that the characteristics of the crop's geometry can be obtained from the same point cloud. In navigation applications, the height of the crop can be jointly estimated. In addition, LiDAR technology more precisely gives the location of fruits and trees, often with a millimetric error. The quality of the point cloud is not affected by the light conditions in the crop (in contrast to techniques based on image or video processing).

3.4. Planning and decision support

The aim of Agriculture 5.0 is to benefit agricultural production from the use of technology, growing crops in a way that would be more resource efficient and improve production. LiDAR technology allows several crop characteristics to be estimated, such as biomass, wood volume, sunlight, soil properties, and tree structure. These estimations enable the development of technological solutions that support decision-making in the planning of crop maintenance and production activities.

Analysing soil characteristics provides many benefits for planning activities in agriculture. Thus, Estrada et al. (2017) analysed the soil characteristics of plots in Spain with an ALS in combination with satellite information to find irrigation patterns and improve irrigation planning. In another example, ruminants leave urine patches on crop soils while grazing, which helps to nourish the soil with nitrogen in an organic form. In a recent study on urine patch detection (Roten et al., 2017), an MLS was used to detect urine patches on the plots and to estimate the nitrogen supplied by this means. The aim is to suggest that the farmer only acquires the necessary nitrogen by other means.

The biomass in sugar cane helps to estimate the amount of nutrients needed by this type of plant. Consequently, Shendryk et al. (2020) proposed an ALS to estimate the biomass of sugar cane in different seasons of the year to predict their growth and to then plan the amount of fertiliser that needs to be applied to the crop. Another application that focuses on crop biomass can be found in Pan et al. (2022), who developed an artificial network to predict the biomass of wheat by scanning the crop with an MLS. Spreading fertiliser on crops is one of the most important processes in agriculture and is carried out in different seasons, depending on the crop. An exciting application of LiDAR for pesticide application is that of Liu et al. (2022), who developed an autonomous vehicle for pesticide application in fruit tree groves, reducing pesticide application by up to 32.46% compared to traditional pesticide application.

Given that the biomass of sorghum is directly linked to its production, Masjedi et al. (2020) applied multi-temporal predictive modelling to point clouds to estimate the biomass of this crop to forecast the production that will take place during the year. Another application for predicting crop yield is that of Dilmurat et al. (2022): they used the H2O-AutoML framework to combine point cloud and hyperspectral data acquired with a UAV to predict the yield of a maize field, and concluded that combining both sensors yields better results than using them separately.

In Section 3.2 (digitisation), Westling et al. (2018) was cited because they used LiDAR to digitise tree structures, which was necessary to calculate the sunlight entering the canopy of avocado trees. The purpose of working on measuring the sunlight index on these trees

Table 5
LiDAR applications for artificial vision in cultivating crops.

Study	Task	Crop	Strategy	Software	Type of LiDAR
Gené-Mola et al. (2020)	Fruit detection	Apple	Support vector machine, DBSCAN	CloudCompare, MatLab	MLS
Main findings:	• This system detected and located more than 80% of the visible fruit. • A methodology for fruit location and crown characterisation was developed. • The forced air and multi-view utility helped to reduce the number of fruit occlusions.				
Pending challenges:	• Further research should focus on analysing and comparing fruit occlusions in different training systems.				
Gené-Mola et al. (2019)	Fruit detection	Apple	Clustering	CloudCompare	MLS
Main findings:	• The results suggested that the apparent reflectance parameter can help detect apples. • Apple detection through LiDAR showed similar results to those based on RGB; however, it had the advantage of providing direct 3D information.				
Pending challenges:	• The most important limitation of this research is the small data set. • Future work should focus on analysing fruit reflectance under different laser wavelengths.				
Tsoulias et al. (2020)	Fruit detection	Apple	k-nearest neighbours, Sparse Outlier Removal	MatLab, CloudCompare	MLS
Main findings:	• Evaluation of apple bunches on foliated trees over bunches on defoliated trees showed that robustness is affected by fruit size. • The geometry of the fruit influences the accuracy of the detection.				
Pending challenges:	• Further research should be carried out to test the method on different apple cultivars with a less spherical shape and varying surface properties to identify and address possible deviations in geometric and reflectance values.				
Cruz Ulloa et al. (2021)	Fruit detection	Cabbage	Clustering	ROS	MLS
Main findings:	• This article presented the first proof of concept of an integrated robotic system for fertilisation using only LiDAR data. • The proposed method has demonstrated that relative localisation can be reliably established from real-time feature extraction.				
Pending challenges:	• Further research on extracting the main features of the clusters to develop more complex tasks for the robotic arm (e.g. fertiliser application, irrigation, weeding, and harvesting).				
Tang et al. (2022)	Fruit detection	Camellia	Clustering	SCENE	TLS
Main findings:	• The algorithm developed in this research showed better results in oil tea identification than the traditional DBSCAN and maximum–minimum distance clustering algorithm. • The improved method had high stability and repeatability and provided a new reference for other performance estimates.				
Pending challenges:	• The main factors causing uncertainty in the identification process are LiDAR performance errors and errors caused by the environment and target attributes. • Deep learning should be applied in this system to explore the possibility of obtaining better results in the most challenging conditions.				
Mao et al. (2022)	Navigation	Apple	RANSAC	ROS	MLS
Main findings:	• This research developed a navigation system for a harvesting robot with master–slave navigation methods for apple harvesting. • This system met the demands of cooperative operation without collisions.				
Pending challenges:	• The robot could navigate at a maximum speed of 0.5 m/s: if this speed is exceeded, tracking errors occur. • Future work should be focused on the optimisation of the tracking algorithm and the design of PID control rules to increase the efficiency of the robot.				
Velasquez et al. (2020)	Navigation	Maize	$H\infty$	MatLab	MLS
Main findings:	• The main contribution was the design and implementation of an $H\infty$ controller to reduce cross-track error. • Despite environmental disturbances, the navigation system kept the robot centred between the crop rows. • The $H\infty$ controller was tested in three different situations in a maize crop: one in the vegetative stage, and two in the reproductive stage.				
Pending challenges:	• Small robots (smaller than a lane and shorter than neighbouring plants) made quantitative performance analysis difficult.				
Malavazi et al. (2018)	Navigation	Maize	PEARL, RANSAC, RUBY	SIFT	MLS
Main findings:	• The modified PEARL approach developed in this research improved crop detection compared to the classical PEARL and RANSAC-based approaches. • The proposal was tested on both synthetic and real-world case studies.				
Pending challenges:	• Due to the terrain conditions, when the robot used the odometry data, it tended to make errors in the row change. • When the weed is at a higher level than the LiDAR position, the developed approach could not be used to detect the crop.				
Nguyen et al. (2021)	Navigation	Grass	Linear regression	RTKNavi, Mission Planner	MLS
Main findings:	• The DairyBioBot proposed in this paper was the first system developed to autonomously measure perennial ryegrass plants' volume. • Plant volume measured with LiDAR and fresh matter biomass are strongly correlated, demonstrating the usefulness of the DairyBioBot for autonomous biomass estimation in the field.				
Pending challenges:	• Future work should optimise data collection and data analysis with less human effort.				
Hu et al. (2018)	Navigation	Dummy trees	LM, RRT*, SLAM (Hector, Gmapping, Karto)	ROS, MatLab	ALS
Main findings:	• With a lower computational complexity, the system developed in this research can accomplish the tasks even in the presence of many tree-shaped obstacles. • The improvements to the algorithm selected in this research decreased the failure rate by 2.6 times compared to the original algorithm.				
Pending challenges:	• This approach was only tested on simulated trees, using cylinders as obstacles. • The current algorithm was only applied to two-dimensional environments and has little applicability to UAV systems.				
Aguiar et al. (2022)	Navigation	Vineyards	RANSAC, Iterative Closest Point, VineSLAM	ROS	MLS

(*continued on next page*)

Table 5 (*continued*).

Study	Task	Crop	Strategy	Software	Type of LiDAR
Main findings:	• This approach could locate the robot accurately, even in long and symmetrical vineyard corridors. • Localisation is achieved using only three orthogonal half-planes.				
Pending challenges:	• Future research should extend the algorithm's capabilities to extract features with semantic representations. • The algorithm should be tested in a broader range of irregular scenarios.				
Jiang et al. (2022)	Navigation	Greenhouse	Dynamic Kalman filter, SLAM, Dijkstra	ROS	MLS
Main findings:	• The robot navigates at speeds of 0.2, 0.4, and 0.6 m/s. • Adding objects with structured features in the greenhouse environment can improve the robot's positioning accuracy.				
Pending challenges:	• This research only accomplishes simple positioning and navigation of the robots in greenhouses. • Future work plans to use 5G, cloud computing platforms and other models to improve robot efficiency.				
Tiwari et al. (2020)	Roof detection	Greenhouse	Classification	ArcGIS, eCognition Developer, ERDAS IMAGINE	ALS
Main findings:	• This strategy interpreted orthophoto data, measured ground data and LiDAR to classify and map structural features in an agricultural region. • The procedure has an accuracy of 92% for classifying and typing the protected agriculture structures in the study.				
Pending challenges:	• This study could help to understand the pattern of cultivation and its growth. • Data is collected through questionnaires sent to farmers, so it would be beneficial to develop a system to automate this task.				
Holmgren et al. (2022)	Tree detection	Spruce, Scots pine	Clustering	R	ALS
Main findings:	• A higher detection rate of trees is observed using data collected at low altitudes (150 m above ground level). • The 3D crown segmentation method allowed more trees to be detected than a 2D method. In addition, 3D dots allowed the detection of trees underneath other trees.				
Pending challenges:	• Only with the first part of the algorithm, high proportions of stem volume were detected. This is useful information for mapping forest resources over larger areas. It would be interesting to test the LiDAR system under these challenging conditions.				
Itakura and Hosoi (2018)	Tree detection	Ginkgo trees	Voxelisation, SLAM	ROS	ALS
Main findings:	• Trees were detected in the 3D point cloud with high accuracy, and the number of trees and diameter at breast height were estimated. • This method could detect partially scanned trees.				
Pending challenges:	• If the trunk representation was poor, the estimate's accuracy fell below 52%. • The tree detection method should be tested on larger areas of trees.				
Wu et al. (2019)	Canopy structure detection	Canola	Clustering, Classification	PhenoSMART, CloudCompare, MatLab	MLS
Main findings:	• This research showed that the Random Forest algorithm is adequate for canola point cloud classification. • LiDAR-derived height and intensity information enriched the identification of canola features. • LiDAR can be used to differentiate plant parts efficiently.				
Pending challenges:	• Further research is needed to investigate whether the method is adaptable to other types of crops.				
LeVoir et al. (2020)	Plant detection	Maize	Clustering	NAVLAB	MLS
Main findings:	• The solutions developed in this research outperformed most of the current computer vision algorithms used for precision agriculture. • Combining adaptive RGB filtering and inverted linear regression provided higher precision.				
Pending challenges:	• The computer vision system is expected to be sensitive to weather conditions (however, less sensitive than GPS-based approaches).				
Reiser et al. (2018)	Plant detection	Maize	Clustering	ROS, MatLab	MLS
Main findings:	• This research used 2D LiDAR for obtaining georeferenced 3D point clouds of maize plants at different stages of growth and used this information to cluster individual plants. • The contextualised iterative plant clustering method was accurate and reliable with an RMSE between 3.0 and 2.7 cm.				
Pending challenges:	• Discrimination between crops, weeds or other objects is not possible because the described methods do not consider the shape of the objects.				
Pretto et al. (2021)	Wild plant detection	grass-weed	Gaussian Processes, CMA-ES	AgriColMap, MAPLAB, PatchMatch framework, ROS	ALS and MLS
Main findings:	• The main contribution is a robotic solution for precision agriculture combining the aerial reconnaissance capabilities of a UAV with a multi-purpose agricultural unmanned ground vehicle. • The solutions proposed were a breakthrough in robotic systems for precision agriculture, easily applicable to a wide range of robots.				
Pending challenges:	• The implementation of this technology can become quite expensive. The research should be extended to consider low-cost LiDAR sensors.				
Borowiec and Marmol (2022)	Land boundaries detection	Crops in Zimno (village)	PCA, Hough transform, multi-resolution algorithm	MatLab	ALS
Main findings:	• The use of LiDAR proved to be an useful technology in the process of detecting agricultural boundaries. Most of the boundaries were legible in the laser data. • Knowing an additional *z*-coordinate allowed more accurate edge detection in areas where 2D information was ambiguous. • The method developed is helpful for automatic verification and tracking of anomalous information.				
Pending challenges:	• The boundaries of plots cultivated and covered with different plant species should be analysed. This diversity could be challenging because each species can have a different intensity value.				

was to be able to make recommendations for their pruning. Large-scale pruning of fruit trees consists of cutting branches from the trees to make their structure more efficient. With this aim in mind, Westling et al. (2021) extended their research by using an MLS to scan the structure of avocado and mango trees and make pruning suggestions based on the sunlight index (which is 25%). Bohn Reckziegel et al. (2022) also used an MLS to scan cherry trees and make suggestions on pruning structures through the Quantitative Structure Model (TreeQSM) algorithm to improve the efficiency of light passage in the trees.

As shown in Table 6, there is a diversity in the applications for planning in agriculture because these types of solutions are more robust to support the farmer in making their crop activities more efficient. For example, ALSs are used to estimate sorghum production, but the approaches differ (cf. Masjedi et al., 2018, 2020). In addition, techniques that recommend the amount of fertiliser to be applied use both LiDAR systems and different strategies to address the problem (cf. Roten et al., 2017; Shendryk et al., 2020). For applications that seek to analyse soil characteristics, algorithms such as RANSAC (Roten et al., 2017) and Maximum Value Composite (MVC) (Estrada et al., 2017) have been used. In addition, artificial networks have been used for biomass estimation (Masjedi et al., 2018); algorithms such as PCA have been used for fertiliser application in relation to sugar cane biomass (Shendryk et al., 2020), and regression models have been used for forecasting the biomass of a crop of sorghum (Masjedi et al., 2020).

The problem of pruning is also addressed here. Most applications for pruning in digitisation only focus on creating a good representation of the tree structure and the farmer is then supposed to evaluate the pruning. However, Westling et al. (2021) made recommendations about the final structure that presents the best efficiency. Voxelisation and TreeQSM have been used to make recommendations on pruning (e.g. Westling et al., 2021; Bohn Reckziegel et al., 2022). All of the applications that are presented in Table 6 involve strategies that have been used for applications of all of the previous categories in this taxonomy.

For these LiDAR applications, the researchers agree that the efficiency of the application is improved by combining different sensors. However, it is more accurate to use the sensors separately for some applications, such as fertiliser application in sugar cane. Meanwhile, it is faster to process the point cloud generated by the LiDAR system compared to photogrammetry for this type of application. Unfortunately, the speed at which the system moves makes it unfeasible to implement these solutions in practice.

4. Concluding remarks

LiDAR technology in precision agriculture can make crop performance estimations more efficient, allowing farmers to make better use of their resources without neglecting the quality of production, promoting the objectives behind Agriculture 5.0. However, their cost is still one of the main limitations to the development of LiDAR applications in agriculture.

Because the adoption of LiDAR technology depends on the task to be performed, we can make the following suggestions based on a review of the state-of-the-art literature:

- According to the type of LiDAR sensor:
  - Mobile Laser Scanners (MLSs) are suitable for tasks such as monitoring and maintenance of crops, detection and classification of objects, estimation of the volume of trees, crop scouting, and navigation. This is due to the ease with which an MLS can enter the crop.
  - Terrestrial Laser Scanners (TLSs) are adequate for digitisation-related activities, like approximating the tree structure or the tree foliage. Pruning is one of the activities where TLSs stand out.
  - The models of LiDAR sensors commonly used as MLSs or TLSs are the following: LMS400, LMS111, UTM-30LX, Focus X330, LMS511, and VLP-16 (a.k.a. Puck).
  - Airborne Laser Scanners (ALSs) are appropriate for tasks such as counting trees, determining irrigation areas, navigation system for quadrators, and monitoring activities in orchards, among others. This is due to their bird's-eye view (BEV) perspective, which is ideal for capturing surrounding objects and their spatial locations. The most commonly used sensor is the VLP-16 model.
- The most popular software tools for processing point clouds in the literature are Point Cloud Library, LiDAR360, and CloudCompare.
- ArcGIS is often used to visualise and process data that results from LiDAR point cloud rasterisation.
- Among the methods used in point cloud processing are: descriptive statistics, which are used for metric estimation; clustering and classification techniques are suitable for both artificial vision and monitoring tasks; and voxelisation techniques are suitable for creating digital representations (such as seeds, plants, tree structure, and tree foliage).

Concerning metric estimation, there is a marked tendency for calculating the Leaf area index (LAI), Normalised Difference Vegetation Index (NDVI) and height. These indices are used to estimate the photosynthetic capacity of the crop, estimate the production, and evaluate the crop's health status. Here, we can say that MLSs are widely used for scanning activities because most autonomous vehicles are terrestrial, which allows them to access the crops easily. Indeed, they are quite popular to monitor height and biomass because these features are strongly related to their yield, soil salinity, and plant health. Also, these estimates help to determine the application of fertiliser and pesticide.

In terms of computer vision, the trend is that LiDAR technology is used in object-detection systems to count fruit on the trees (mainly through MLSs) and estimate crop yields, inventory trees, and detect wild plants in the crop. On the other hand, ALSs are used as a computer vision system for UAVs to perform activities oriented towards estimating metrics involving tree canopy or properties of the soil to generate irrigation and roughness maps.

Regarding digitisation, TLSs are mostly used because they have a higher spatial resolution, which allows a more detailed and accurate characterisation of crops compared to MLSs and ALSs, becoming adequate to digitise complex characteristics (such as tree structure or foliage) and make further estimates based on them.

In regard to planning and decision support, it has had an impact on pruning in vineyards, as well as avocado and mango orchards. Here the trend is to make recommendations for tree pruning structure, detect the branches that need to be pruned, and recommend the pruning structure based on different indices, such as sunlight.

A discussion of the main challenges researchers face when using LiDAR technology follow.

In LiDAR applications for crop monitoring, most MLSs can go at a maximum speed of 1–11 km/h to avoid decreasing the efficiency of the application, which is insufficient in practice. Speed is the main limiting factor when accuracy is the objective in measuring crop characteristics.

Although the use of TLSs predominates for crop digitisation, it is feasible to use an ALS for this type of application. Nevertheless, if the foliage is dense, then it is challenging to digitise the tree from a BEV perspective with a single backtrack ALS.

Variations in leaf colour can represent the state of a tree and the health of a plant. However, in low-cost LiDAR, it is difficult to measure this feature.

Finally, experimentation on the crop increases the cost of doing field research in Agriculture 5.0 and, unfortunately, there are very few repositories containing instances of crops scanned with LiDAR systems.

From these challenges, we identify the following issues that require further research:

Table 6
LiDAR applications for planning and decision support in cultivating crops.

Study	Task to be supported	Crop	Strategy	Software	Type of LiDAR
Shendryk et al. (2020)	Fertiliser application	Sugar cane	PCA	Global Mapper	ALS
Main findings:	• The results of this research were of significant interest for nutrient management programmes for nitrogen fertilisation. • Predicted yield peaks early in the season (100–142 days after harvest), and it decreases as the harvest date approaches.				
Pending challenges:	• Future research should apply the models from this work to predict leaf nitrogen content and biomass with a UAV. • Environmental factors, such as pest occurrence, can affect LiDAR-derived and multispectral measurements.				
Roten et al. (2017)	Fertiliser application	Grass	RANSAC	MatLab	MLS
Main findings:	• This study helped determine the capability and feasibility of using a LiDAR system to detect urine stains created during grazing. • Contour maps of the pasture were accurately detected by asymmetrical urine stains and calculating a percentage of urine area with high nitrogen content.				
Pending challenges:	• Scanning speed (0.65 km/h) was not practical for commercial farming operations.				
Liu et al. (2022)	Fertiliser application	Fruit trees	RANSAC	PCL	MLS
Main findings:	• Compared with traditional spraying, variable-rate spraying applies 32.46% less pesticide, suffers 44.34% less drift and 58.14% less ground loss. • This research found that reducing ineffective spraying is essential for improving the efficiency of the spraying.				
Pending challenges:	• Making appropriate spraying decisions for fruit tree canopy characteristics is a way to improve the efficiency of the spraying.				
Estrada et al. (2017)	Irrigation	Herbaceous, Woody, Grazing	Classification, MVC	The Sentinel-2 Toolbox	ALS
Main findings:	• The algorithm for identifying irrigation patterns yielded an overall accuracy of up to 95%. • This kind of identification of irrigated areas would benefit the EU's Common Agricultural Policy considerably, allowing to its saving significant amounts of money annually.				
Pending challenges:	• Additional data (e.g. very high-resolution images) and field visits are still necessary to correctly determine agricultural characteristics.				
Masjedi et al. (2020)	Production	Sorghum	Multi-temporal predictive models, Regression-based models	Scikit-learn library	ALS
Main findings:	• Geometric features derived from the LiDAR point cloud to characterise the plant structure and chemical features extracted from the hyperspectral data provided the most accurate predictions. • The number of samples in the training set for the prediction was an important factor in determining the accuracy of the predictions.				
Pending challenges:	• It is recommended to collect at least 50 samples. However, if high variability in the biomass data associated with the varieties in the experiments is expected, more samples would be needed.				
Masjedi et al. (2018)	Production	Sorghum	Support vector regression, Multi-layer perceptron	Headwall SpectralView	ALS
Main findings:	• The regression model predicted end-of-season biomass with relatively higher accuracy. • This article used high temporal and spatial resolution remote sensing data to focus on predicting sorghum biomass.				
Pending challenges:	• The use of other inputs derived from remote sensing should be investigated. • Late season values were affected by the complexity of the canopy.				
Pan et al. (2022)	Production	Wheat	BioNet	PointNet, PointNet++, DGCNN, GS-Net, PyTorch	MLS
Main findings:	• A Biomass prediction Network (BioNet) was proposed, which also considered plant structure. • Experiments showed that BioNET improved by about 33% over current state-of-the-art methods.				
Pending challenges:	• Introducing more sensors into the system is desirable to improve prediction accuracy.				
Dilmurat et al. (2022)	Production	Maize	classification and regression	H2O-AutoML	ALS
Main findings:	• UAV platforms incorporated with multiple sensors can provide multi-domain characteristics, the spectrum and texture of the canopy, as well as its structure, thus proving a capable tool for predicting the yield of maize. • UAV-based multisensory data fusion provided performance superior to that of many previous studies concerning the estimation of plant traits and grain yield.				
Pending challenges:	• Yield estimation via UAV-based multisensory data fusion and machine learning should be investigated across various crop types and in different field environments.				
Westling et al. (2021)	Pruning	Avocado, mango	Voxelisation	ACFR, Comma and Snark, SimTreeLS	TLS
Main findings:	• The final results of this research showed the great potential of this framework to be the starting point for automated pruning. • Compared to a tree pruned with current techniques, light distribution improved by up to 25.15% using the framework of this research.				
Pending challenges:	• Research should continue improving the suggestion mechanisms and, in addition, incorporate more agricultural objectives and operations connected to pruning. • The basis of this framework should be extended to provide a commercially applicable pruning suggestion system.				
Bohn Reckziegel et al. (2022)	Pruning	Cherry	Leaf Creation Algorithm, TreeQSM	LaserControl, CloudCompare, MatLab	TLS
Main findings:	• This research contributed to the virtual pruning of tree structures, to be used strategically for the maintenance, planning, and design of tree crop farming systems. • The pruning recommendations for low-intensity treatments presented solutions applicable to real fields.				
Pending challenges:	• The high-intensity treatments produced results that were not applicable in the field, e.g. they removed up to 60% of the tree volume.				

- It is necessary to develop sensors with a more accessible cost for researchers but without – critically – losing the quality of their performance. Conjointly, the researchers should develop approaches that satisfactorily work using low-cost LiDAR sensors to make this technology accessible to farmers.
- One issue that must be addressed when using an MLS is the speed at which a person scans an object because scanning quickly will affect the density of the point cloud. For this reason, it is necessary to develop software that deals with this issue.
- It is necessary to complement the LiDAR systems with other sensors that can capture information, such as leaf colour, to determine tree and plant health status. One way to obtain spectral information for the point cloud is to use a multi-band LiDAR system.
- Regarding foliage-oriented digitisation, the presence of wind significantly affects the accuracy of the employed algorithms because the generated point clouds are blurred. The development of approaches less sensitive to this outdoor condition would be valuable.
- It is necessary to make more repositories containing instances of crops scanned with LiDAR systems publicly available, which would help to mitigate the high cost of the experimentation and promote research in Agriculture 5.0.

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

No data was used for the research described in the article.

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