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Developments in precision weed management systems for precision agriculture

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1 Introduction

In the ever-evolving landscape of agriculture, precision weed management has emerged as a critical frontier in the quest for efficient, sustainable and high-yield crop production. Weeds, a persistent challenge in agriculture, compete for nutrients, water and sunlight ultimately reducing the overall productivity of fields (Zimdahl, 2007).

Weed competition stands as the foremost biotic factor affecting crop yields, surpassing the impact of pests and pathogens. According to Oerke (2006), weeds account for the most significant potential loss at 34% globally, whereas pests and pathogens contribute to lesser extents, with 18% and 16% losses, respectively.

Weed control methods can be grouped into chemical and mechanical (herbicide control and mechanical control), and cultural and physical methods (mulching, cover crops, living mulches, soil solarization, thermal weed control and weed control through grazing). Of these methods, the most common are mechanical methods (often less efficient) and herbicides (known for their

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adverse impact on the ecosystem) and are the most frequently used to manage weeds.

The reliance on pesticides remains a contentious issue, raising health and environmental concerns and thereby underscoring the need for more sustainable agricultural practices. Simultaneously, concerns regarding food safety and the environmental impact of pesticides are driving an increased demand for organic and pesticide-free products. This trend necessitates a shift from pesticide-based weed control methods to more comprehensive weed management strategies, reflecting the agricultural sector's response to the environmental, economic and public demands on production. Innovations such as precision agriculture present potential solutions to these challenges, promoting the adoption of more targeted and site-specific weed management (SSWM) approaches (Christensen et al., 2009).

In 2021, the global use of herbicides reached 1.7 Mt, accounting for app. 50% of the total pesticide use of 3.5 Mt (Statista, 2023), reflecting a high and constant increase in pesticide use, just like the world population and the decrease in usable agricultural area. The FAO estimates that by 2050 the world's population will increase by 34% to 9.1 billion, meaning that food production will have to increase by 70% (FAO, 2009), but between 1961 and 2016, the global cropland area per capita decreased continuously from about 0.45 ha per capita to 0.21 ha, a decrease of nearly 47% (FAO, 2020).

Pesticides are indeed used to increase crop productivity in response to global food demands, yet their extensive use causes contamination of soil, water, and air, and disrupts biodiversity (Sharma et al., 2019; Tang et al., 2021; WHO, 2022). Tang et al. (2021) reported that 64% of the world's agricultural land is at risk of pollution from pesticides with more than one active ingredient and 31% is at high risk. Therefore, it is imperative to reduce the use of pesticides, either through prevention, the efficient use of pesticides or alternatives to their use.

As an alternative to using herbicides, other methods of weed control can be used, such as mechanical, cultural and physical methods (Scavo & Mauromicale, 2020). While these methods may not always suffice to prevent yield loss, they yield mixed outcomes that depend on the application of extensive agronomic knowledge. This expertise is essential for balancing yield preservation with the effective use of alternative weed control strategies. On one hand, these methods avoid the pitfalls of herbicides such as herbicide resistance or contamination of the environment. On the other hand, they can create problems in the soil, such as soil erosion and degradation, reduced nutrient availability and reduced biodiversity. In other words, they can jeopardize the sustainability of crop production and ecosystem services, as well as food security in the long term (Mia et al., 2020; Monteiro & Santos, 2022; Rueda-Ayala et al., 2010; Scavo & Mauromicale, 2020).

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Mechanical weed control has historically been an ecological and sustainable agriculture practice, standing out as the main alternative to the use of chemical herbicides (Kunz et al., 2015; Rueda-Ayala et al., 2010; Van Der Weide et al., 2008). Notably, the adoption of automatic machine guidance systems for inter-row weed hoeing has emerged as an effective method for managing weeds in row crops without relying on herbicides (Kunz et al., 2015). Nonetheless, precise navigation of mechanical tools is crucial to ensure extensive treatment of the field while preventing damage to the crops, which could lead to significant yield losses (Dammer & Wartenberg, 2007; Van Der Weide et al., 2008).

Various methods have been employed to facilitate mechanical intra-row weeding, including measurement of crop height and diameter, as well as the utilization of real-time kinematic global navigation satellite systems (RTKGNSS) (Wang et al., 2019). These methods help accurately locate crops in real-time, minimizing the risk of damage during the weeding process.

A more sustainable approach to weed management, which aims to mitigate the impact of conventional weed control methods, incorporates both ecological principles and innovative technologies (Korres et al., 2019; Sims et al., 2018). This approach encompasses a range of weed control options, including the integrated weed management (IWM) option. IWM is based on combining various weed control strategies (agronomic, physical, mechanical and chemical) within a system, rather than relying on a single method, (Chauhan, 2020; Esposito et al., 2021; Young & Pierce, 2014). The goal of IWM is to maintain and increase agricultural production and the farmer's net income by combining the use of preventive strategies, leveraging scientific knowledge, honing management skills, implementing monitoring processes and optimizing control practices (Hartzler & Buhler, 2007).

In line with IWM principles, the developments of precision agriculture (PA) technologies have opened new solutions for more targeted, efficient and environmentally friendly weed management strategies. Especially, the rapid advancement of artificial intelligence (AI) has led to the development of precise and innovative methods for weed detection and the control of implements such as sprayers and hoes used in SSWM strategies (Rai et al., 2023a; Vasileiou et al., 2024). Typically, SSWM comprises four key processes (Figure 1): (i) weed detection using appropriate sensors to collect weed data for real-time operations or generate weed maps and control maps, (ii) decision algorithms to refine the weed control using historical data and the farmer's strategic

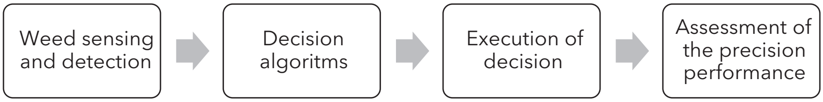

Figure 1 Key processes for SSWM.

preferences, (iii) execution of the decisions using actuators to control a sprayer or a hoe and (iv) assessment of the precision and performance of the applied SSWM (López-Granados, 2011).

In this chapter, SSWM that is currently being used, remote sensing and high throughput imaging of weeds are explored. This is followed by an overview of precision technologies designed for SSWM. The chapter concludes with the advances in SSWM with weeding robots.

2 Understanding site-specific weed management

The emergence of PA was catalyzed by the public' access to GNSS technology, facilitating the guidance of farm machinery and spatial application of fertilizer and pesticides (CEMA, 2017). PA is a concept based on sensing spatial and temporal soil and crop variability and aims at improving crop performance and environmental quality (Monteiro et al., 2021). Following the sensing, PA is characterized by the precise application of inputs to varying conditions in a field. The concept is augmented by farm knowledge systems and the availability of larger amounts of data (Saiz-Rubio & Rovira-Más, 2020). It integrates advanced technology with traditional farming, addressing efficiency, sustainability and innovation.

The advancement of computer power, data storage, the Internet of Things (IoT) and cloud accessibility have revolutionized data collection, storage and processing enabling real-time operations. PA leverages cutting-edge technologies such as sensors, drones, robots, precision machinery and GNSS technology to enhance farmers' productivity, sustainability, and profitability. The effectiveness of technologies hinges on the ability to collect and process data often using AI for high-throughput analyses and decision algorithms.

SSWM is rooted in the principles of PA, a holistic approach that leverages technology to optimize weed management and yields while minimizing the environmental impacts of agriculture. At its core, SSWM aims to identify the spatial distribution and density of the weed species in a field and use this information to target and mitigate weed impact in the crop with surgical precision. This approach reduces herbicide use and negative environmental impact.

The primary agronomic objective of weed management is to minimize or eliminate competition between crops and weeds for essential resources such as sunlight, water and nutrients, thereby preventing losses in crop yield. Other important goals of effective weed control include preventing harvesting issues, maintaining the quality of harvested crops and reducing the spread of weeds.

Weed populations in fields typically comprise various species, exhibiting considerable variation in occurrence and density across the field (Gonzalez-Andujar & Saavedra, 2003; Wiles et al., 1992). In densely planted, competitive

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crops like cereals and corn, most weeds struggle to compete and thus have a limited effect on crop yields. However, certain weed species are highly competitive, even in dense crops, and can cause significant yield losses, particularly at high densities.

In row crops, such as vegetables, where the competitiveness of the crop is low, the agronomic goal tends toward the complete elimination of weeds to prevent competition and avoid harvesting problems due to weed infestation. Achieving optimal SSWM in these settings demands high-resolution detection of both crop and weed plants, particularly weeds growing between crop rows.

Timing is another crucial aspect of weed control, especially in the early growth stages of the species. In dense, competitive crops, a low herbicide dose can often tip the balance of competition in favor of the crop during early growth stages (Christensen et al., 2003). Early growth stages also offer better weed detection opportunities due to less leaf overlap from adjacent plants. At later stages, the overlap complicates the detection of low-growing weed species.

For open and less competitive crops, the optimal timing for SSWM is distinct from that in dense crops. The ideal period for weed treatment is after the initial emergence of weeds but before the peak of crop-weed competition. However, in cases of high weed density, multiple treatments may be necessary.

Central to the success of SSWM lies in the integration of data-driven decision algorithms. These algorithms compile and analyze data from multiple sources, such as satellite or drone images, weather forecasts, soil maps and historical crop performance data, enabling farmers to develop strategies for SSWM that address the spatial variation of weed occurrence and density in their fields. However, adopting these advanced technologies introduces the challenge of collecting data that is both coherent and valuable, given that raw data does not possess intrinsic utility (Saiz-Rubio & Rovira-Más, 2020).

Advanced modelling techniques, powered by artificial intelligence and predictive analytics, enable farmers to anticipate weed outbreaks, optimize treatment schedules and forecast the spatial distribution of weeds and their growth patterns with remarkable accuracy. By combining historical data with real-time observations, decision algorithms empower farmers to adaptively manage weed pressure and mitigate the risk of yield losses due to weed infestations.

This increased availability of data can lead to security and farmers' concerns, since this data can be collected and processed without the user's consent, or consent might be given without farmers being properly informed about collected data and its use.

To address farmers' concerns, legislation has been imposed that mandates technology manufacturers to adhere to certain standards when collecting and using data. These regulations promote transparency in how companies are collecting and using data, to foster the trust that boosts the development of technology as Kaur et al. (2022) note, such measures also lead farmers to share data or adopt new technologies.

3 Weed recognition with advanced imaging technologies

The use of images to analyze and identify objects on the ground began with military use in World War I and has spread to various areas, including agriculture (Abdullah et al., 2023). Since the beginning of the 21st century, researchers have explored a broad spectrum of weed-sensing techniques.

Data for weed detection can be gathered with sensors mounted on satellites, piloted aircraft, drones and ground vehicles. Each of these platforms offers distinct advantages and disadvantages for identifying weeds. A major advantage of these platforms is their capacity to integrate diverse sensor technologies, including multispectral, hyperspectral, LiDAR, RADAR and fluorescence sensors (Abdullah et al., 2023; Rai et al., 2023b; Saiz-Rubio & Rovira-Más, 2020). This integration makes it possible to collect rich and detailed data, enabling more precise analysis and mapping of crop and weed density.

Satellite imagery is characterized by a maximum spatial resolution of 30 cm and high spectral resolution, excelling in mapping capacity (ha h^{-1}) but subject to variable image delivery frequencies due to orbital paths and cloud cover (Omia et al., 2023; Wang et al., 2019). Piloted aircraft can provide imagery with both high spatial and spectral resolution. The size and weight of the camera are not constraints for piloted aircraft, allowing the use of larger cameras. For extensive areas, remote sensing often emerges as the most cost-effective strategy. This approach can equip a farm, or even a large region comprising multiple farms, with detailed maps of weed occurrences (Christensen et al., 2009; Liu, 2023; Reedha et al., 2021; Wu et al., 2021).

Drone imagery from low altitudes provides high image resolution (approximately 0.01 m) and considerable flexibility regarding the timing of image capture. This high resolution facilitates the detection of sparse weed populations, crucial in SSWM (Esposito et al., 2021; Mohidem et al., 2021). Flexibility in image acquisition enables the capture of images at times when the differences between crops and weeds are most pronounced.

Proximal sensors mounted on in-field machinery, such as harvesters, tractors, ATVs and robots, can detect weeds with potentially submillimeter resolution (Peteinatos et al., 2014). However, this high resolution leads to sparser sampling compared to airborne systems. Consequently, the potential accuracy in detecting and classifying early stage of weeds at high resolution may be compromised by the necessity to interpolate between sample points.

Common ground-based real-time sensors include spectrometric sensors, optoelectronic sensors and RGB-NIR imaging sensors. Spectrometric sensors, also known as spectrometers, gauge reflection intensities across multiple wavelengths, offering ample data to distinguish between vegetation and soil. However, they can face challenges in differentiating between species, particularly during early growth stages when crops and weeds exhibit similar reflectance characteristics (López-Granados, 2011; Peteinatos et al., 2014).

Multispectral and hyperspectral image sensors mounted on drones or ground-based vehicles have proven to be effective in detecting weeds and differentiating species. This technology provides valuable information not captured by RGB cameras or the human eye. Particularly, hyperspectral imaging, with its extensive range of spectral bands compared to multispectral sensors, has become a powerful platform for classifying weed species (Esposito et al., 2021). Hyperspectral imaging therefore has notable potential for automated in-field discrimination of individual plant species.

Field demonstrations of hyperspectral imaging have shown promising results in lettuce (*Lactuca sativa* L.) and tomato (*Lycopersicum esculentum* Mill.) crops, achieving pixel-level recognition rates of over 75% between species and crop vs. weed discrimination rates of over 90% (Fennimore et al., 2016). For example, Zhang et al. (2009) developed a hyperspectral imaging system coupled with a micro-spray heated oil application system for weed control within tomato seed lines during early growth stages. The system accurately identified 95%, 94% and 99% of tomatoes, black nightshade and pigweed, respectively. This technology offers advantages such as less computing power compared to shape-based pattern recognition, resistance to visual occlusion of leaf margins and the ability to customize spray applications of multiple herbicidal materials based on weed species. However, a drawback of this method is the need for a multi-season calibration process (Żelazny & Licznar-Małańczuk, 2018).

By accurately identifying the occurrence and density of the weed populations in a field, farmers can target weed control with site-specific herbicide applications or mechanical weed control methods, while minimizing the use of chemicals and reducing overall input costs. Furthermore, the ability to monitor weed growth over time before and after treatment enables farmers to assess the effectiveness of SSWM strategies.

Detecting weeds in crops from images is, by nature, a complex problem due to the similar characteristics of weeds and crops such as colour, morphology and texture evolving throughout growth. Identification as a weed can also vary depending on the context, i.e. a crop plant can be considered a weed in one crop context and may not be seen as such in another. Beyond mere identification, recognizing the species is crucial for applying precise measures and the appropriate type of herbicide and dosage.

As agricultural production continues to evolve, the precise differentiation between crops and weeds becomes increasingly important to ensure precise weed control. In recent years, several researchers have employed various

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computer vision techniques to accomplish this task (Wu et al., 2021) which can be categorized into three main types: (1) classifying images as either crops or weeds, (2) detecting or localizing weeds within images and (3) segmenting images to create semantic weed maps. These tasks correspond to three fundamental problems in computer vision: image classification, object detection and semantic segmentation, respectively (Dang et al., 2023).

Methods for detecting weeds in the field using computer vision technology primarily encompass traditional image processing and deep learning (Chen et al., 2022; Wu et al., 2021). Machine learning (ML), which is a branch of AI, features algorithms such as support vector machine, decision tree, random forest and K-nearest neighbour classifiers (Dadashzadeh et al., 2020; Gallo et al., 2023; Mwitta et al., 2024; A. Wang et al., 2019; P. Wang et al., 2022). ML can be used to efficiently extract information from videos images, and other visual data and hence perform classification, segmentation and object detection (Gallo et al., 2023). However, these methods require high-resolution samples and graphic processing capabilities and can be costly to implement on agricultural machinery (Wu et al., 2021). Using ML for weed recognition necessitates the extraction of distinct features from weed species including colour, texture, shape and morphology (Chen et al., 2022; Dadashzadeh et al., 2020; Gallo et al., 2023; Mwitta et al., 2024).

Recently, deep learning through artificial neural networks, especially convolutional neural networks has shown remarkable effectiveness in weed identification (Dang et al., 2023; Gallo et al., 2023; Mwitta et al., 2024; Vasileiou et al., 2024).

Despite considerable advancements in imaging and AI processing, identifying weeds in varied and complex natural environments remains a challenge. Critical issues such as fluctuating light and soil conditions, as well as the complications introduced by overlapping leaves and shadows, all of which hinder the achievement of optimal detection results (Liu & Wang, 2021; Mwitta et al., 2024).

4 SSWM technologies

A significant innovation in precision agriculture is variable rate technology (VRT), featuring smart fertilizers, sprayers and machinery that tailor their operations directly to the varying soil and crop conditions within a field or according to a digital map. This adaptability enhances the farm's overall profitability while promoting sustainable practices. Precision weed control has benefited from the integration of VRT with advanced technologies for autonomous vehicles equipped with real-time sensing capabilities. These advances enable instant adjustments in application rates and patterns, ensuring thorough coverage and reducing both herbicide use and potential negative impacts.

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A prerequisite for spatially variable application of herbicides is data about the distribution of weeds within the field (Dammer & Wartenberg, 2007). Two basic technologies can be used for VRT: map-based and real-time-based technologies (Grisso et al., 2011). Map-based VRT modifies the application rate using a digital treatment map, which is made by a decision algorithm. The algorithm integrates data on the spatial presence of weed species, and potential yield loss without intervention, and optimizes the various treatment options such as type of herbicide, dosage or intensity of mechanical treatment (Christensen et al., 2003; Forouzanmehr & Loghavi, 2012; Grisso et al., 2011). In the mapping approach, weed detection, creation of a treatment map, and variable-rate spraying are conducted sequentially (Dammer & Wartenberg, 2007).

The real-time-based VRT method enables variation in the rate of inputs or intensity of a mechanical treatment without the need for prior mapping or data collection This more rapid approach involves on-the-go data collection and processing, with real-time sensors measuring the required properties as they move. All processing is carried out in real-time, utilizing AI techniques as the machinery moves across the field (Forouzanmehr & Loghavi, 2012; Grisso et al., 2011; Rai et al., 2023a).

The sensor method does not always require the use of a positioning system, nor does it necessitate extensive data analysis before implementing variable-rate applications. However, when sensor data is recorded and geo-referenced, it can serve in later SSWM enabling the making of treatment maps for both current and future operations (Grisso et al., 2011).

Both the real-time-based VRT approach and the map-based VRT approach have demonstrated potential, leading to significant yield improvement and reduced environmental impact. Several studies have reported an average reduction of 25% in herbicide use and an increase in yield of 40%. However, it is important to note that the reduction in herbicide use can vary greatly, ranging from 12% to 90% (Fastellini & Schillaci, 2020; Gerhards et al., 2022; Yang et al., 2015).

Looking to the future, traditional weed control methods are likely to be disrupted by the advent of intelligent robotic weeders and drones. These technologies, equipped with cameras, sensors and robotic arms, can autonomously navigate across fields, accurately detecting and applying high-precision treatments to individual weeds, either through herbicides or a physical device. This shift in technology provides numerous benefits to farmers, such as reduced labor costs, a smaller environmental footprint and more precise weed control (Sharma, 2023).

Research in SSWM has focused on critical areas such as image platforms, processing of images with AI, control systems and optimizing the design of sprayers and implements (Gerhards et al., 2022; Mink et al., 2018). Additionally, future intelligent machines will be equipped with autonomous navigation and positioning systems, autonomous control systems, and the ability to perform both inter-row and intra-row weeding (Liu et al., 2023). Studies have shown that automatic machine guidance systems for inter-row weed hoeing have slightly increased the efficacy of weed control compared to conventional mechanical weed control methods (Kunz et al., 2015).

5 Robotic weeding technologies

In the future, agricultural robots will be capable of performing a variety of tasks in the field, from seeding to harvesting including weed control. Their design and configuration will be diverse ranging from a modified tractor to a small specialized platform that autonomously navigates in fields to execute specific operations, tailored to the characteristics of the land and the requirements of the task (Emmi et al., 2014; Machleb et al., 2020; Mahmud et al., 2020). A more advanced approach will be deploying fleets of specialized robots that collaborate on performing operations such as seeding, surveying, weeding and harvesting (Emmi et al., 2014).

The core of a robotic weeder consists of a high-precision guidance system paired with advanced real-time weed sensing and localization technologies. Subsequently, precision weed control tools such as micro-sprayers and mechanical or thermal implements are deployed for targeting treatments. Moreover, an essential component of the system is a mapping feature that records and maps the weeds while also tracking operations and performance (Slaughter et al., 2008).

Autonomous robotic weeders represent a viable option for future SSWM with their application already evident in high-value crops (King, 2017). Weeding in vegetable crops like broccoli, cabbage, field-grown flowers, herbs, lettuce, onions and tomatoes has heavily depended on conventional inter-row hoeing and expensive manual labour, highlighting the potential for robotic weeders. Consequently, the industry is focusing on developing robotic solutions (Melander et al., 2017; Westwood et al., 2018).

According to Peruzzi et al. (2017), four types of robotic weeders are commercially available. These are the Robovator from Frank Poulsen Engineering Aps., Hvalsø, Denmark; Robocrop from Tillett and Hague Technology Ltd., Greenfield, Bedfordshire, UK; IC-cultivator from Machinefabriek Steketee BV, Haringvliet, The Netherlands; and Remoweed from Costruzioni Meccaniche Ferrari, Guidizzolo MN, Italy. Among these, Robovator stands out as the most effective in-row weeding system, especially applicable to organic farming (Mia et al., 2020). The Robovator uses advanced technology to differentiate between crop plants and weeds, by recognizing the crop rows and leveraging the size between crop and weed plants. Field trials with the Robovator have shown promising results. For example in broccoli and lettuce, the Robovator reduced manual weeding by 39% and 27%, respectively, compared to the conventional combination of hoeing and manual weeding (Westwood et al., 2018).

The Australian AgBot II is another robotic weeder that uses an imaging system for weed detection and three mechanical weeding tools: an arrow-shaped hoe, a toothed tool, and a cutting tool (McCool et al., 2018).

The ANATIS robot aids farmers by performing mechanical weeding tasks autonomously. Its rear three-point hitch linkage provides flexibility, enabling it to use various tools for a variety of jobs (CARRÉ, 2024).

The French company Naio Technologies (Figure 2) offers a range of robots (Oz, Jo, Ted, Orio) designed for different farm sizes and crops including vegetables and vin-yards. These robots employ mechanical techniques for weed control (Naïo Technologies, 2024).

The FarmDroid FD20 (Figure 3) is a fully automatic, lightweight robot designed for use in agricultural settings. It is powered by a solar panel and equipped with high-precision RTK GNSS and sensors, enabling it to accurately mark the placement of crops at sowing and subsequently perform mechanical

Figure 2 Naio Technologies' robots Oz, Jo, Ted, and Orio are shown from top left to right (Naïo Technologies, 2024).

Figure 3 FarmDroid FD20 (FarmDroid, 2024).

Figure 4 Ekobot WEAI robot (Ekobot, 2024).

weed control between and within rows. The precise placement of each seed sown allows for the selective removal of weeds, reducing or eliminating the need for manual weed control. The robot is capable of handling more than 50 different crops and vegetables (FarmDroid, 2024).

Ekobot WEAI (Figure 4) is an autonomous robot system developed by Ekobot, a Swedish company. The electric-powered robot is capable of weeding crops such as onions, beetroots and carrots, covering up to 10 ha. It has mechanical arms to remove weeds between rows and a hoeing system to remove weeds in the rows (Ekobot, 2024).

VITIROVER commercial robots (Figure 5) are small, lightweight and solar-powered. They use mechanical cutting tools to remove weeds and are designed to work effectively under various weather conditions (VITIROVER Solutions, 2024).

Paddy rice fields pose a challenging environment for SSWM. The 4WS K-Weedbot robot tackles this challenge with a high-precision image processing system to navigate and remove weeds without damaging the rice plants (Choi et al., 2015). The AIGAMO-ROBOT is designed for compactness and ease of

Figure 5 VITIROVER commercial robots (VITIROVER Solutions, 2024).

use, powered by batteries and features a tracked locomotion system making it efficient to remove weeds both between and within rows (Mitsui et al., 2008).

The interest in SSWM sprayers has been growing in past decades (Fernández-Quintanilla et al., 2018). SSWM spraying can significantly reduce the amount of herbicide use compared to broadcast spraying of the entire field leading to overuse in areas without weeds. Targeting herbicide application solely to weed-infested areas, cost can be reduced, the risk of crop damage and excessive pesticide residue can be decreased and there can be a potential reduction in drift and leaching of pesticides into the environment (Partel et al., 2019). The success of SSWM spraying relies on a cost-effective weed detection and targeting system, accuracy of the sprayer and control of the spray drift (Partel et al., 2019).

SSWM spraying has shown significant potential for herbicide savings, with reductions ranging from 5% to almost 90%, depending largely on the spatial and temporal distribution of weeds within fields (Berge et al., 2012; Christensen et al., 2009; Jensen et al., 2012; Riar et al., 2011).

The AgriRobot and SAVSAR vineyard robots are designed for targeted pesticide spraying via a human–machine interface (Adamides et al., 2017). The RIPPA and Ladybird robots, along with the more advanced BoniRob, perform precise herbicide spraying. RIPPA and Ladybird are equipped with a hyperspectral imaging system. BoniRob on the other hand uses a combination of cameras, ultrasonic sensors, mechanical tools and herbicide spraying for a comprehensive weed control solution (Bogue, 2016; Underwood et al., 2015; Wu et al., 2020).

The Swagbot robot represents a significant advance in agricultural robotics. Designed for multi-purpose applications, it is capable of performing a range of tasks autonomously including weed identification and spraying, soil and pasture analysis, biomass estimation and even livestock monitoring (Wallace et al., 2019). The goal behind such innovations is to develop standardized and modular robotic systems that can be adapted to meet various agricultural needs (Oliveira et al., 2021).

Finally, commercial spraying systems such as H-Sensor (Agricon GmbH, Ostrau, Germany) and See and Spray (Blue River Technology, Sunnyvale, CA, USA) utilize artificial intelligence to distinguish between crop plants and various weeds, providing advanced precision spraying capabilities (Partel et al., 2019).

These robots exemplify how automation and AI improve the efficiency and productivity of SSWM. They also highlight the trend toward standardization and modularization in the development of robotic systems.

6 Conclusion

The chapter addresses the pressing need for sustainable solutions in agriculture to balance the dual objectives of reducing environmental impact and maintaining high crop productivity levels by managing weeds to meet global food demand. It emphasizes the critical role of innovative weed management strategies in achieving efficient, sustainable and high-yield crop production. Weeds, as significant competitors for resources essential to crops, necessitate advanced management techniques due to their substantial influence on yield. The chapter then transitions to exploring the evolution from traditional weed control methods towards IWM practices, highlighting the incorporation of precision agriculture and artificial intelligence (AI) technologies for targeted weed control.

Central to the chapter are the four fundamental processes of SSWM: detection of weeds using advanced sensors, decision-making based on different data sources, precise execution of weeding through actuation and rigorous performance evaluation of precision operations. The chapter further elaborates on the integration of diverse technologies, including remote sensing, imaging, machine vision and the deployment of autonomous robots equipped with sophisticated sensors and mechanical tools for weed control.

Moreover, it explores the environmental and economic advantages of precision application technologies like variable rate technology (VRT), which strategically minimizes herbicide usage and environmental pollution by focusing treatment on weed-infested areas within fields. The development and market introduction of intra-row robotic weeders, their efficacy in organic farming and their utility in high-value crops are also examined.

The chapter concludes by affirming the transformative potential of automation and AI in refining agricultural efficiency and sustainability, envisioning a future where smart robotic systems and precision methodologies are pivotal in optimizing crop production with minimal environmental impact.

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8 Where to look for further information

For further information about precision weed management, various scientific journals, textbooks and publications are valuable resources. The *Journal of Precision Agriculture* publishes scientific articles advancing understanding and improving the practice of precision agriculture, including weed sensing and detection. Additionally, journals like *Weed Research*, *Weed Science* and *Weed Technology* publish articles on advanced methodologies and innovations in weed control and management. The journals *Biosystems Engineering* and *Computers and Electronics in Agriculture* provide information about advances in the development of new robotics, vision-based machinery, computer hardware, software, electronic instrumentation and control systems for precision agriculture, including weed detection and control.

The scientific book *Agriculture Robotics* from 2022 (edited by E.I. Sklar, G. Das, and J. Gao) and the chapter "Review of Current Robotic Approaches for Precision Weed Management" (Zhang, W., Miao, Z., Li, N. et al., pages 139–151) assess different weed detection methods and weeder robots used in precision weed management, summarizing recent trends in this area.

Another valuable resource is the book *Approaches for Precision Agriculture* from Springer 2021 (Eds. Kerry R and Escolà A.), particularly the chapter "Sensing for Weed Detection" (Christensen S, Dyrmann N, Laursen MS, Jørgensen RN and Rasmussen J, pages 275–300), which describes the general principles of automated weed detection and demonstrates their application in agriculture with spot-application of herbicides based on automated weed detection using RGB cameras mounted on unmanned aerial vehicles and ground vehicles.

Furthermore, the book *Advances in Integrated Weed Management* from Burleigh Dodds Chapters Online features several relevant chapters, especially the chapter "Advances in Precision Application Technologies for Weed Management" (Lati RN, Gerhards R, Eizenberg H, Matzrafi M, Blank L and Christensen pages 229–254).

For insights into the global agricultural technology industry, FutureFarming .com is a website focused on distributing knowledge and opinions on innovations, market trends, and research. The website provides insights into topics like autonomy, precision farming, data and crop solutions. Future Farming also offers newsletters and detailed buyer's guides highlighting innovative products available for purchase, such as field robots, drones and smart weeders.

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