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Advancements and developments in the detection and control of invasive weeds: a global review of the current challenges and future opportunities

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Abstract

Weed invasion has become increasingly recognized as a major threat to the practice of sustainable agriculture and the maintenance of natural ecosystems around the world. Without effective and ongoing management strategies, many weed species have the aggressive capacity to alter ecosystem functions and reduce the economic potential of the land into which they have been introduced. Although traditional weed management strategies can be useful in eliminating certain weeds, these approaches can be costly, economically damaging, and laborious and can result in variable long-term success. To further add to these challenges, several weed species have now developed resistance to a range of herbicide modes of action, which, to date, have been the major mechanism of weed control. As a result, it is anticipated that the use of emerging technology will help to provide a solution for the economical and environmentally sustainable management of various weeds. Of particular interest, emerging technology in the areas of weed detection and control (chemical, mechanical, electrical, laser, and thermal) has shown promising signs of improving long-term weed management strategies. These methods can also be assisted by, or integrated alongside, other technology, such as artificial intelligence or computer vision techniques for improved efficiency. To provide an overview of this topic, this review evaluates a range of emerging technology used for the detection and control of various weeds and explores the challenges and opportunities of their application within the field.

Introduction

The intrusion of weeds into agricultural and natural ecosystems is considered as a major driver toward agricultural production loss and biodiversity decline around the world (Kumar Rai 2022; Storkey et al. 2021). Weeds have the capacity to compete against and displace native or desirable species, and without deliberate and ongoing management interventions, they will continue to economically and environmentally degrade the land they have invaded (Kumar Rai 2022; Kumar Rai and Singh 2020). Exacerbating the urgency for efficient weed management, it is anticipated that the global population will reach 10 billion by 2050, and as a result, the global demand for agricultural products is expected to increase by more than 56% during this time (van Dijk et al. 2021). For the agricultural industry to meet such challenges, careful consideration regarding the most economical and environmentally sustainable production methods are required (Westwood et al. 2017). It has also been noted that the influence of climate change, which is likely to result in elevated atmospheric CO_2 levels, higher temperatures, and more variable weather events, will further add to the challenges, particularly in the area of weed management (Clements and Jones 2021; Malhi et al. 2021; Varanasi et al. 2016). These changes will likely impose stronger selection pressures on existing flora and further increase the expansion and impact of several weed species into regions where they may not have previously occurred (Beaury et al. 2020; Clements and Jones 2021; Ziska et al. 2019).

Although conventional weed control methods using herbicides or mechanical devices can provide some level of control, they often show variable success and require repeated, ongoing modifications to provide long-term success (Langmaier and Lapin 2020; Maqsood et al. 2020; Shahzad et al. 2021). A confounding issue is that, given the current reliance on chemical approaches for managing weeds, the repeated use of some herbicides can contribute to the development of herbicide resistance—there are now 269 species reported to have evolved resistance to 21 of the 31 known herbicide modes of action across 72 countries (Benbrook 2016; Heap 2023). Not only is the widespread use of chemicals adding to the potential development of herbicide resistance, but they can also contaminate and pollute the surrounding environment and waterways if they are not appropriately applied to the actively growing plant (Creech et al. 2017; Sankhla et al. 2016). To combat these concerns, innovations in weed management approaches are urgently required to assist land managers with more economical and environmentally sustainable methods of weed control. To address these concerns, it is suggested that the use of a range of emerging technologies will contribute to more sustainable weed management practices. In this regard, this review explores the use of emerging technology in the areas of weed detection and control (chemical, mechanical, electrical, laser, and thermal). It also identifies both the challenges and opportunities of where this technology can be applied in the field or integrated with other techniques such as artificial intelligence or computer vision methods. This information will be of value in identifying future directions and research opportunities in the field of emerging weed technology.

Artificial Intelligence in Weed Management

It is encouraging to recognize that the use of artificial intelligence has shown significant global potential in assisting the agricultural industry, particularly in the field of weed management (Amend et al. 2019; Costello et al. 2022; Fernandez-Quintanilla et al. 2018; Ghatrehsamani et al. 2023). Artificial intelligence can be described as an advanced machine learning system that can emulate the actions of humans, providing alternatives to constant and costly human intervention (Amend et al. 2019; Fernandez-Quintanilla et al. 2018; Ghatrehsamani et al. 2023; Partel et al. 2019). This form of technology has already provided several benefits in the area of weed management and is capable of further assisting, or being integrated with, machine learning systems and robotic devices for improved weed detection and control (Partel et al. 2019). As this area of research is increasingly developing and its full potential has yet to be discovered, the following sections of this review will highlight where artificial intelligence has the capacity to be used alongside a range of emerging technology to assist with improved weed management.

Weed Detection Methods

It is widely agreed that the early detection and control of a weed is a critical step within a weed management program to help reduce its long-term impact on the surrounding environment (Roslim et al. 2021). To assist in this task, recent developments have identified several data and imagery detection methods that can improve the time taken to identify and control a weed within the field (Esposito et al. 2021; Mohidem et al. 2021; Singh et al. 2020). Of the identified weed detection methods within the literature, the most promising that have been recently developed or that are undergoing further research for improvement include the use of (1) unmanned aerial vehicles, (2) all-terrain vehicles, (3) field robotics, (4) remote sensing, (5) proximal sensing, (6) plant signaling methods, and (7) crop genetic modification (Table 1). A common challenge when using certain detection methods such as unmanned aerial vehicles, all-terrain vehicles, and field robotics is their unintentional movement when capturing data or imagery. This movement, often caused by the wind or vehicle motion, increases the risk of motion blur, which can limit the quality of data and imagery and limit the success of deep learning models analyzing the data (Genze et al. 2023). To address this issue, research by Genze et al. (2023) has proposed the use of a deblurring segmentation model known as DeBlurWeedSeg, which has shown to successfully mitigate motion blur when detecting weeds such as common lambsquarters (*Chenopodium album* L.) in grain sorghum [*Sorghum bicolor* (L.) Moench]. Although this model shows promising signs of reducing motion blur and increasing detection, further factors such as crop and weed height, the type of weed species, and environmental conditions all need to be considered due to their potential influence (Genze et al. 2023). If these factors can be accounted for, or if additional models, data, or imagery can be integrated, then it may be possible to mitigate the influence of motion blur, although further investigation into this combination across a range of crop–weed scenarios would be required.

A common aspect of these detection methods is their ability to capture high-quality data and imagery within the field (Coleman et al. 2023; Esposito et al. 2021; Lati et al. 2014; Mohidem et al. 2021; Pallottino et al. 2019; Su 2020; Sujaritha et al. 2017; Weiss et al. 2020). To achieve this, the use of specialized cameras systems or sensors are required, which will often include the use of hyperspectral imagery, multispectral imagery, red-green-blue or VIS (visible) imagery, satellite imagery, thermal imagery, and 3D stereo imagery (Esposito et al. 2021; Rosle et al. 2022; Su 2020; Xia et al. 2015; Table 2). The most commonly used system is the red-green-blue imagery system, as it is a low-cost operational option that can calculate different vegetation indices to distinguish between crop and weed species (Su 2020; Xia et al. 2015). Although this system has the capacity to effectively identify various weed species, it requires significant geometric plant data abilities to confidently recognize a range of species with high-level accuracy (Su 2020; Xia et al. 2015; Xu et al. 2021). To improve its efficiency in situations where crop and weed species appear geometrically similar, it is suggested that the use of multimodal information that uses red-green-blue imagery with depth information will help to improve weed detection accuracy (Xu et al. 2021, 2024). This approach has been referred to as the WeedsNet system, and Xu et al. (2024) demonstrate that the use of multimodal information has the potential to complement red-green-blue imagery in accurately detecting several grass and broadleaf weeds in a wheat (*Triticum aestivum* L.) crop. In this regard, such technology may have the potential to complement red-green-blue imagery systems in other agricultural settings, although this developing technology would require further detailed investigation in a range of other crop situations to determine its applicability and effectiveness in the field.

Another scheme known as the multispectral system has proven to be a powerful alternative to the red-green-blue imagery system, as it can capture and calculate a wider range of vegetation indices and spectral band wavelengths (Esposito et al. 2021; Lara et al. 2020; Lu et al. 2020). In a similar way, hyperspectral sensor camera systems are also powerful, being able to record thousands of radiometric narrow-band images from hundreds of spectral band wavelengths (Esposito et al. 2021; Su 2020). Although hyperspectral imagery has the potential to provide high accuracy in identifying several weeds, research has identified a range of inconsistencies, including insufficient feature extractions and calibration issues that limit its repeated accuracy (Diao et al. 2023; Peleg et al. 2005). It has also been noted that multispectral and hyperspectral systems often take a long time to calculate and collect data accumulation, as well as requiring specified [tailored] algorithms for analysis. As a consequence, there is an increase in the challenges and time taken to produce detailed precision weed maps (Zou et al. 2021). To attend to some of these issues, it has been suggested that the use of specialized models or machine learning techniques can provide further enhancement and

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Table 1. Benefits, challenges and limitations of various weed detection methods

Detection method	What is it?	Benefits	Challenges/limitations	Reference
Unmanned aerial vehicles	The use of aerial devices to collect data and imagery, such as an aircraft or drone	• Can be used in difficult to access terrain • Can be automated with GPS or sensory system • Can be used in variable weather conditions • Quick method to cover large areas	• Limited battery life • Prone to motion blur • Requires a skilled operator or GPS navigation system • Influenced by wind • May not be practical in all agricultural settings (e.g., orchards)	Anderegg et al. 2023; Esposito et al. 2021; Mohidem et al. 2021
All-terrain vehicles	The use of a ground vehicle to collect data and imagery	• Data and imagery collected closer to the plant. • Can be used in variable weather conditions • Can be automated with GPS or sensory system	• Limited access to certain areas • Slow process to cover a large area • Prone to motion blur • Limited movability around sensitive areas	Coleman et al. 2023; Laursen et al. 2017
Field robotics	The use of robotic devices such as small autonomous vehicles	• Flexible movability (between crops or sensitive areas) • Can provide high-quality data and images (closer to the plant) • Can be used in variable weather conditions • Can be used alongside some control methods	• Large devices have limited access to certain areas. • Limited battery life if not integrated with another power source • Some devices are bulky and expensive. • May diverge from a planned path if GPS systems or pathways are not accurate	Francoeur-Leblond 2006; Sujaritha et al. 2017
Remote sensing	Classification of a plant/weed using distinct spectral signatures from satellite imagery or imagery data from a distance	• Provides accurate crop and weed density maps • Data can be obtained instantaneously (in the field of view). • Nondestructive method to monitor vegetation	• Requires high-resolution data and satellite imagery • Timing of data collection is critical (may be influenced by weather patterns).	Lamb and Brown 2001; Sishodai et al. 2020; Weiss et al. 2020; Xue and Su 2017
Proximal sensing	Classification of a plant/weed using field-based sensors close to the plant	• Data can be obtained almost instantaneously. • Can provide high spatial resolution • Provides data and imagery from different angles rather than just from above the plant	• Variable lighting or weather conditions may influence results. • Spatial resolution will depend on the distance from and proximity of the sensor to the plant.	Pallottino et al. 2019; Rançon et al. 2023
Plant signaling methods	Uses exogenous fluorescent signals on crop plants to help differentiate them from other species	• Generally not influenced by environmental factors • Fluorescent markers naturally break down • Differentiates between crop plants and weeds	• If a plant does not display high enough fluorescent markers, it may be identified as a weed. • Markers may break down before certain weeds emerge.	Andújar et al. 2018; Longchamps et al. 2010; Su 2020
Crop Genetic Modification (e.g., crop coloring)	Genetically modifies a crop species, allowing it to express certain characteristics that can be detected more easily by imagery	• Increases imagery detection and classification between a crop and weed species • Consistent accuracy in detection	• Limited research in this field for a range of crop species • Genetic modification of a crop may be redistricted due to regulations. • If plants do not have the modification, they may be detected as a weed, resulting in crop loss.	Lati et al. 2014

detection efficiency (Murad et al. 2023). In this respect, a range of techniques have been developed to assist in this area, with some examples including the use of (1) artificial intelligence-based image analysis (Aitkenhead et al. 2003; Haq et al. 2023); (2) deep learning systems and algorithms (such as artificial neutral networks, convolutional neutral networks, deep neutral networks) (Hasan et al. 2021; Murad et al. 2023); (3) image processing techniques (including clustering, generative adversarial networks, Hilbert transformation, histograms of gradients, linear iterative, local binary patterns) (Murad et al. 2023; Nixon and Aguado 2019); and (4) machine learning systems and algorithms (such as adaptive boosting, artificial neutral networks, decision trees, k-nearest neighbor, and support vector machines) (Murad et al. 2023).

Chemical Control

Recent developments in the field of chemical control have shown promising signs in improving the management of a range of weed species around the world (Amend et al. 2019; Ghatrehsamani et al. 2023; Roslim et al. 2021; Table 3). One area in particular that has been shown to be of assistance in this field is the use of autonomous chemical control, which allows for a weed to be

Table 2. Benefits, challenges and limitations of various imagery and sensor systems for weed detection

Imagery system	What is it?	Benefits	Challenges/limitations	Reference
Red-green-blue or VIS (visible) imagery	Uses a digital camera that is equipped with a red, green, and blue filter with an image sensor	• Low operational cost • Easy to use and often readily available • Often a quick method of weed detection • Can be integrated with machine learning for improve accuracy	• Requires significant geometric plant variations for accurate detection • May not be suitable for all agricultural settings (e.g., when crops appear similar to a weed species)	Park et al. 2016; Su 2020; Xu et al. 2021
Hyperspectral imagery	Captures data and imagery from a series of signals with continuous channels of narrow spectral bands	• Rapid classification of a plant species • Can also be used for other purposes (e.g., mapping of soil conditions) • Records hundreds to thousands of radiometric bands • Can be integrated with machine learning systems	• Can have complexities with radiometric calibration • Expensive to use • Often a much larger system that may require specialized devices for field application • Can only detect certain bands at a given time	Che'Ya et al. 2021; Esposito et al. 2021; Lu et al. 2020; Peleg et al. 2005; Scherrer et al. 2019; Su 2020
Multispectral imagery	Captures data and imagery from discrete bands across a broad spectral signal	• Powerful operation that can calculate a wide range of vegetation indices • More powerful then red-green-blue imagery systems • Can be integrated with machine learning systems	• Expensive to use • Often a much larger system that may require specialized devices for field application • Sometimes has a lower resolution then red-green-blue systems, therefore needs to be used closer to the grounds surface (e.g., lower altitude using UAVs)	Esposito et al. 2021; Lu et al. 2020; Mazzia et al. 2020
Satellite imagery	Captures images above the plants using satellites	• Quick method to collect data and imagery	• Influenced by cloud or weather patterns • Does not provide the most detailed imagery or data	Weiss et al. 2020
Thermal imagery	Captures imagery based on the surface temperature of a plant	• Can also be used for other purposes (plant stress, moisture stress, herbicide resistance) • Can be integrated with other methods such as remote sensing for improved accuracy	• Not always consistent • Can be influenced by environmental factors • May only be suitable for certain situations	Eide et al. 2021; Xu et al. 2023
3D stereo imagery	Uses a range of imagery (red-green-blue, LiDAR, spectroscopy, thermal, and ultrasound) to detect and weed species in three dimensions	• Capacity to create 3D models of plant characteristics • Can provide high-quality data and imagery with high resolution (can be expensive)	• Relies on a range of imagery systems • Time and cost of this method needs further investigation. • Highly complex due to different plant structures, therefore further automatic programs needed	Andújar et al. 2011, 2018

selectively targeted and sprayed, reducing off-target damage and the need for large-scale or widespread applications (Partel et al. 2019). These benefits can reduce excess herbicides leaching into the soil or into surrounding waterways, while also having the benefit of reducing the cost of materials and labor needed to treat a field each season (Balafoutis et al. 2017; Partel et al. 2019). While a range of autonomous chemical control options are currently available or under development for the control of various weed species (Table 1), it has been noted that most of these chemical devices have been tested or designed to be used within cropping systems, all of which generally have heterogeneous weed distributions that occur at a range of levels (Allmendinger et al. 2022). In this regard, this technology may be difficult to use within natural ecosystems and is problematic in difficult-to-access terrain or regions with varying levels of weed infestations. As such, the use of a range of weed detection methods and imagery or sensor systems discussed earlier in this review may have the potential to assist in this area. Of particular interest, integrating such methods may enable more accurate detection and subsequent control of a weed in areas where it may appear geometrically similar to a crop or native species (Ghatrehsamani et al. 2023; Partel et al. 2019), although this area of research would require specific investigation relating to each scenario.

Herbicide-Resistance Management

It has been claimed that the use of artificial intelligence and specialized camera systems have the potential to assist in the field of herbicide-resistance management in agroecosystems (Amend et al. 2019; Ghatrehsamani et al. 2023; Picoli et al. 2017; Roslim et al. 2021). With the growing concern of more frequent occurrences of herbicide resistance, it is important to quickly

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Table 3. Examples of autonomous chemical weed control devices reported within the global literature.[a]

Product name	Brand/company	How does it work?
ARA	Ecorobotix	Uses Convolutional neural network (CNN)-based detection with multi-camera vision to spot spray weeds
Avirtech-MIMO	Avirtech	Uses 4D radar imaging and unmanned aerial vehicles to map and patch spray weeds
AutoWeed	AutoWeed	Uses deep learning machine technology fitted with high-resolution cameras to detect and spot spray weeds
Bilberry	Bilberry	Uses red-green-blue imagery systems with an artificial intelligence–based detection system for spot spraying
EcoPatch	Dimensions Agri Technologies	Uses red-green-blue imagery with an artificial intelligence–based detection system for spot spraying
FD20	Farmdroid	Uses Real time kinematics - Global Positioning System (RTK-GPS) systems to record the precise location of crop seeds and spot sprays weeds
Greeneye	Greeneye Technology	Uses red-green-blue imagery with an artificial intelligence–based detection system for spot spraying
H-sensor	Agricon	Uses a bi-spectral camera with artificial intelligence–based detection to identify weeds
Kilter AX-1	Kilter Systems	Uses RTK-GPS to detect and selectively spray weeds
Ladybird	University of Sydney	Uses a hyperspectral and thermal camera to detect and sport spray weeds
Robotti	Agrointelli	Uses deep learning systems and RTK-GPS autonomous systems and a LiDAR camera
See and Spray	Blue River Technology	Uses red-green-blue imagery with a CNN-based detection method to spot spray weeds.
Smart Spraying	BASF, Bosch, Amazone	Uses bi-spectral cameras to identify weeds and spot sprays them
Weed-It	Weed-It	Uses a blue LED spectrometer to detect green vegetation
Weedseeker	Trimble Agriculture	Uses infrared sensor technology with a high-resolution spectrometer

[a]Sources: Allmendinger et al. (2022); Amend et al. (2019); Utstumo et al. (2018); Wu et al. (2020); Zhang et al. (2022).

identify and manage invasive populations before they reproduce to form a new generation of resistant plants. One method that has shown promise in the identification of herbicide-resistant plants is the use of thermal imagery assisted by machine learning systems (Eide et al. 2021; Picoli et al. 2017). Research has indicated that thermal imagery can assist in the detection of glyphosate-resistant plants, as treated plants often experience stress and an inhibition of stomatal conductance that leads to reduced photosynthetic rates and increased surface temperatures (Eide et al. 2021; Picoli et al. 2017; Shirzadifar et al. 2020). As a consequence, thermal imagery, assisted by machine learning techniques have the capability of identifying these plants within a field, which can then be controlled by other mechanisms (Eide et al. 2021; Shirzadifar et al. 2020). On the other hand, research by Eide et al. (2021) suggests that when thermal imagery is used in isolation, it is not a completely reliable indicator to predict herbicide resistance, particularly when dealing with herbicides with different modes of action. In this regard, further research into combining thermal imagery with other machine learning techniques may assist in identifying herbicide-resistant weed populations before they can reproduce. It has also been noted that integrating artificial intelligence in real-time image processing may help to assist in identifying herbicide-resistant and susceptible plants by identifying a range of plant and soil characteristics, although this area of research requires further investigation among different herbicides and crop–weed scenarios (Ghatrehsamani et al. 2023). It has also been noted that due to the limited number of new or emerging herbicide modes of action, the integrated use of existing bioherbicides could be another option to increase control efficiency and help reduce potential herbicide resistance in some weed species (Roberts et al. 2022).

Mechanical Control

Robotics and machine learning capabilities have shown promising signs as an emerging method to mechanically control a range of invasive weeds (Fennimore et al. 2016; Oliveira et al. 2021). For example, a study by Bakker et al. (2010) indicated that the use of intelligent autonomous weeders with real-time kinematics global positioning systems can be used to complete interrow hoeing within corn (*Zea mays* L.) crops, with minimal to no damage to the surrounding crop plants. Although this method seems promising, the speeds of such devices are often much slower than traditional methods that often operate at a minimum speed of 4 km h^{-1} or up to 12 km h^{-1} for methods such as harrowing (Bakker et al. 2010; Bowman 2002). Due to these slower rates of speed, some robotic devices may not be able to completely bury or uproot certain weed species in a given time, ultimately allowing them to reestablish (Bakker et al. 2010). This clearly indicates that careful consideration of both the type of weed species and the speed of the mechanical device is needed for the implementation of these methods. Another study by Nørremark et al. (2012) showed 91% success rates in treating various interrow weeds with a robotic cycloid hoe, while research by Kunz et al. (2015) showed that the use of a camera-guided interrow hoeing device (Kult Robocrop®) reduced weed density by 89% in soybean [*Glycine max* (L.) Merr.] crops and 87% in sugar beet (*Beta vulgaris* L.) crops. It appears that camera-guided devices, fitted with machine learning capabilities, can be utilized to help guide the robotic device in targeting specific weeds within these areas, which can markedly improve these methods (Kunz et al. 2015). Such technology may also help to identify weeds that are growing very close to a crop plant and specifically target it or identify and map it for an alternative treatment to minimize potential crop damage.

A study by Van Evert et al. (2011) was associated with the development and testing of an autonomous robotic device to control broadleaf dock (*Rumex obtusifolius* L.) on a commercial farm. The device navigated using global navigation satellite system technology and included a downward-facing camera for plant detection and a mechanical tool with rotating blades that was lowered and activated once the plant was identified (Van Evert et al. 2011). This method was reported to have a 93% detection rate and a 75% success rate in the control of the species. It is anticipated that this method could be used to help decrease the quantity of herbicide needed to treat a field and reduce the costs associated with on-farm labor. Robotic weed control devices can also work in conjunction with other devices, with research by Noguchi et al. (2004) creating a primary and secondary system allowing for several devices to work together.

Another device that has been developed as an autonomous mechanical and chemical robot within the agricultural industry is

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Table 4. Common electrical devices commercially developed around the world for weed control

Name	Brand/company	Areas used	Mode of action and use	Reference
Lightening Weeder	Lasco Inc.	United States	Uses spark discharge methods from electrodes mounted onto machinery, generally positioned slightly above the crop plants to target taller weeds	Vigneault et al. 1990
Weed Zapper™ (Annihilator and Terminator Series)	Old School Manufacturing	Canada, United States	Uses several electrodes mounted onto a flexible boom arm with horizontal electrodes above the crop canopy; allows models can be modified and configured for specific use	Schreier et al. 2022
XPower	Zasso™ (XPU and XPS)	Europe, South America	Uses continuous plant electrode contact and can be flexible with its use in a wide range of areas (e.g., under trees, vines or along roadsides)	Slaven et al. 2023
Rootwave™ (PRO and Top Fruit)	Rootwave™	Europe	Uses continuous plant electrode contact with the use of a handheld electric weeder for small spot-spray applications of weeds	Feys et al. 2023

the AgBotII. This device is capable of accurately identifying 90% of the selected species and has shown success in controlling various weeds such as wild oats (*Avena fatua* L.) and common sowthistle (*Sonchus oleraceus* L.). It is a powerful alternative, as it can provide both mechanical and chemical control, allowing an integrated control method, and alternately addressing control mechanisms with each pass (Fennimore et al. 2016; Oliveira et al. 2021). Another device that has been developed for the use of robotic weed control is the BoniRob platform produced by Bosch Deepfield Robotics, which has shown up to 94% success in controlling various weeds (Langsenkamp et al. 2014). This device is capable of identifying and selectively targeting a weed by means of mechanical control (Langsenkamp et al. 2014). Although promising, this technique can be time-consuming and may not be applicable for deeper or heavier clay-type soils, as it is more suitable for sandy light soils (Langsenkamp et al. 2014). In this regard, further investigation on a range of autonomous mechanical devices will need to consider more localized conditions to allow adjustment for greater efficacy in control options. Further investigation will also need to consider (1) which weed species can be mechanically controlled and which will require follow up or integrated methods of control; (2) the accuracy of control to limit potential off-target damage or unwanted soil disturbance, particularly when used alongside planted crops or native vegetation; (3) any potential spread of weeds and their propagules into other areas of the field if the devices are not cleaned or treated appropriately; and (4) the likely change to crop patterns or rows to help facilitate automated cultivation in two directions for improved efficiency (Fennimore et al. 2016; Sharma et al. 2017).

Electrical Weed Control

A range of research studies have shown that electrical weed control has the potential to successfully control various weeds, with several products already being commercially developed for use around the world (Table 4). This method delivers an electrical current to the targeted plant and can be applied by two main methods: (1) the spark-discharge method or (2) a continuous electrode–plant contact method (Slesarev 1972; Wilson and Anderson 1981). The spark-discharge method transfers a brief high-voltage current directly into a plant, while the continuous electrode–plant contact requires ongoing contact between the electrodes and the plant in order to allow a lethal dose of electricity to pass through the foliage, stems, and roots of the plant (Slesarev 1972; Wilson and Anderson 1981). These methods often cause damage to the plant's cells and structures by increasing temperature and vaporizing volatile liquids, ultimately damaging cell membranes (Slesarev 1972; Wilson and Anderson 1981). In some cases, electrical treatment may not completely kill a plant and may only cause damage in some areas, allowing the plant to regenerate over time (Slesarev 1972; Wilson and Anderson 1981). To achieve successful control, several factors need to be considered, such as (1) the type of device used and the amount of energy output for a lethal dose; (2) contact time with the plant; (3) surrounding vegetation, to ensure targeted plants are not shielded by other vegetation; (4) surrounding environmental conditions; and (5) the potential risk of fire (Bloomer et al. 2024; Landers et al. 2016; Lehnhoff et al. 2022; Slesarev 1972; Vigneault et al. 1990; Wilson and Anderson 1981). Of particular interest, research by Schreier et al. (2022) found a strong correlation between the increase of plant moisture content and the decreased level of weed control using electricity on several weed species such as barnyard grass [*Echinochloa crus-galli* (L.) P. Beauv.], common ragweed (*Ambrosia artemisiifolia* L.), giant foxtail (*Setaria faberi* Herrm.), giant ragweed (*Ambrosia trifida* L.), horseweed [*Conyza canadensis* (L.) Cronquist], waterhemp [*Amaranthus tuberculatus* (Moq.) Sauer], and yellow foxtail [*Setaria pumila* (Poir.) Roem. & Schult.], in a soybean-cropping system. In this regard, the use of electrical weed control needs to carefully consider any potential influence from the surrounding environment, as this is likely to influence the success of this method (Lati et al. 2021; Schreier et al. 2022).

It is clear that electric weed control can be suitable for a range of cropping systems, with research suggesting that it can be successfully used to control a diverse range of species (Bloomer et al. 2024; Landers et al. 2016). Research by Landers et al. (2016) in Brazil and Paraguay used a plant–electrode contact machine (16.6 km h^{-1}) and obtained between 94% to 100% control after 28 d for weeds such as high mallow (*Malva sylvestris* L.), smallflower galinsoga (*Galinsoga parviflora* Cav.), *S. oleraceus*, and wild poinsettia (*Euphorbia heterophylla* L.). On the other hand, only up to 75% success rates were realized when trying to control garden spurge [*Chamaesyce hirta* (L.) Millsp.], thus showing that certain weed species may respond differently to each treatment (Landers et al. 2016). Electrical weed control can also be used to reduce seed development, with an example of the Weed Zapper™ 6R30 (spark-discharge) achieving 54% to 80% reduction in *A. artemisiifolia, A. tuberculatus*, *A. trifida*, *S. faberi*, *S. pumila*, and common cocklebur (*Xanthium strumarium* L.) (Schreier et al. 2022).

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Although there are several benefits of using electrical weed control methods, there are also several risks associated with its use (Bloomer et al. 2024). One drawback of using such methods is the low rate of speed and the considerable time needed to treat large fields (Llewellyn et al. 2016). A potential solution to this challenge would be to integrate this technology with artificial intelligence or machine learning devices to help identify and then treat weeds autonomously (Llewellyn et al. 2016; Machleb et al. 2020). It is also important to consider any potential resistance to electrical weed control (Beckie et al. 2020; Somerville et al. 2017). In particular, some species with higher levels of cellulose or lignin within their cell walls may have a higher resistance to bursting or becoming vaporized; likewise, plants with a hairy, thicker, or waxy epidermis may also be more protected from electrical control (Bauer et al. 2020; Vigneault et al. 1990). Plants that are not completely controlled may regenerate at a later time from their root systems; therefore, careful postcontrol monitoring may be required (Bloomer et al. 2024; Lehnhoff et al. 2022).

Research has suggested that the use of electrical weed control can also impact soil biota, as it may travel through a plant's root system and into the soil or adjacent water, thus potentially affecting the cellular constituents of surrounding organisms (Ruf et al. 2023). The effect of electrical weed control on the surrounding organism will depend on the voltage and length of the application (Ruf et al. 2023). For example, research by Lati et al. (2021) used an application of 0.05 Wh, which resulted in an increase of more than 40 C in the shoots and roots of black nightshade (*Solanum nigrum* L.) and redroot pigweed (*Amaranthus retroflexus* L.), which is likely to influence the surrounding soil conditions. Ruf et al. (2023) also found a reduction in earthworm biomass within the top 25 cm of the soil profile after using the Zasso™ XPower XP300 applicator at 3 km h^{-1} for 2 wk compared with an uncontrolled area. Research has also shown several physical changes to the earthworms from areas that have been treated with electrical weed control, such as a change in skin color, the presence of necrotic tissue, and damage to other cells (Ruf et al. 2023). On the other hand, contrasting results have shown that some macro- and mesofauna can survive in areas treated by electrical weed control and maintain more stable populations compared with other methods such as mechanical control where there are large soil disturbance events (Löbmann et al. 2022). Based on the differences in these findings, it is suggested that localized populations, environmental conditions, or soil types may play an important role in the response of soil biota, and therefore would require localized investigations to determine any long-term effects of this method.

Laser Weed Control

The combination of lasers and various weed detection systems has been shown to be a promising method in weed control, particularly in the early life-cycle stage (Heisel et al. 2002; Rakhmatulin et al. 2021; Wang et al. 2019). These devices have the capacity to be integrated with machine learning devices, including classification algorithms and automated devices for efficient weed control within agroecosystems (Ghatrehsamani et al. 2023; Rakhmatulin et al. 2021). The most commonly used lasers include carbon dioxide lasers, diode lasers, and fiber laser devices (Coleman et al. 2021; Gates et al. 1965; Heisel et al. 2002; Wöltjen et al. 2008). These devices work by emitting an infrared beam that is absorbed by the plant's cells, consequently burning them (Gates et al. 1965; Heisel et al. 2002). Several studies have shown that the use of lasers can be effective in controlling various weeds at different rates, with some examples including *E. crus-galli* at 54 J per plant (Marx et al. 2012) and rigid ryegrass (*Lolium rigidum* Gaudin) at 76.4 J (Coleman et al. 2021). Several other species that have also been severely damaged or controlled using laser weed control include *A. fatua* (Bayramian et al. 1992), cereal rye (*Secale cereale* L.) (Bayramian et al. 1992), tobacco (*Nicotiana tabacum* L.) (Wöltjen et al. 2008), and water hyacinth [*Eichhornia crassipes* (Mart.) Solms; syn.: *Pontederia crassipes* (Mart.) Solms] (Couch and Gangstad 1974). A common trend within the literature shows that each weed species often requires a different contact time or energy dose to be controlled or partially damaged by the use of lasers (Marx et al. 2012; Rakhmatulin and Andreasen 2020). Research has also shown that many of these robotic devices, such as the commercially available LaserWeeder by Carbon Robotics, are often very expensive and very slow, only reaching speeds of 1.6 km h^{-1} (Vijayakumar et al. 2023). For such applications to become more widely available, a time–cost–value analysis may be useful to determine whether this is the most appropriate method for a specific weed situation. Another important consideration regarding laser weed control is its influence on the surrounding soil biota, with long-term data on a range of environments required to examine this influence at a broader range (Khan et al. 2020).

Thermal Weed Control

The use of thermal weed control has been successfully integrated within the agricultural industry as a pre–crop emergence technique for weed control (Seaman 2016). Thermal weed control works by emitting quantities of intense heat directly to a targeted plant, which can increase its temperature and thus physically disrupt its cells (Brodie et al. 2019; Seaman 2016). Thermal weed control can often be in the form of a flame, hot oil, steam, or radiation (Brodie et al. 2019). Such technology has been implemented across various agroecosystems for the control of various weeds such as bermudagrass [*Cynodon dactylon* (L.) Pers.], *E. crus-galli*, hairy beggarticks (*Bidens pilosa* L.), ragweed parthenium (*Parthenium hysterophorus* L.), and several *Amaranthus* species (Mutch et al. 2008; Ulloa et al. 2012). Further research has also been used to trial the use of hot foam as a thermal weed control, which has shown success in controlling more than 75% of various species such as little mallow (*Malva parviflora* L.) and wild mustard (*Sinapis arvensis* L.) (Antonopoulos et al. 2023). The impact of thermal weed control is claimed to be more successful on annual species, with the effect on perennial species being more variable due to their more developed and structured root systems or underground rhizomes, which can reshoot if they are not completely damaged (Cisneros and Zandstra 2008). As a consequence, thermal weed control may not be suitable for all weed species and may thus result in surviving weed species creating monospecific stands, all of which can result in the need for further control and resources. For this method to be more widely used with confidence, further investigation on thermal weed control on a range of weed species across different environments would be needed.

The use of radiation-based thermal control, often referred to as microwave radiation, has shown promising results in the control of various weed species (Brodie 2012; Brodie et al. 2019). Under laboratory conditions, Aygun et al. (2017) have shown that microwave radiation energy has the capacity to kill various weed species such as *C. dactylon*, johnsongrass [*Sorghum halepense* (L.) Pers.], *S. nigrum*, and *X. strumarium*. Although this method successful for individual species, each species generally required a different speed and rate of microwave radiation for its effective

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control (Aygun et al. 2017). Further research also suggests that different species respond differently to a changing application and rate of microwave radiation (Brodie and Hollins 2015; Kaçan et al. 2018). In particular, a study in Australia by Brodie and Hollins (2015) identified that wild radish (*Raphanus raphanistrum* L.) required at least 60 J/cm^{-2} for 100% mortality, while *L. rigidum* required 370 J/cm^{-2}. Despite these successes, the use of microwave radiation energy for weed control often requires at least 10 times more energy than traditional methods such as chemical control, which therefore has currently limited its commercial use (Brodie 2012). One solution that could improve this method is its potential use alongside artificial intelligence and automated weed control devices. This could allow for plant detection and specific plant control using microwave energy to limit the need for its use across a large scale, although this method would require further investigation and an economic benefit analysis before it could be confidently used as a key weed control method.

Conclusion and Future Management Considerations

It is clear that the use of emerging technology is helping to shape the future of weed management and control around the world and has provided improved and sustainable alternatives for the detection and control of various weed species. Not only can these advancements in technology improve the way various weeds are controlled, but they can provide long-term economic and environmental benefits compared with traditional methods of weed control. However, despite their current success in agroecosystems, several areas of consideration need to be taken into account for their widespread and long-term application. Regarding the use of weed detection systems, some methods will need to be carefully chosen to ensure they are suitable to the specific environments where they are intended to be used. For example, unmanned aerial vehicles fitted with red-green-blue imagery may provide coverage across a large area, but they might not be suitable to all agricultural settings; for example, orchards or areas where crop and weed patterns appear geometrically similar would not be candidates for their use. In this case, the integration of other methods or imagery and sensor systems will need to be considered for improved accuracy. Artificial intelligence could also provide an additional level of support in classifying imagery. Regarding the use of chemical control and herbicide-resistance management, emerging technology in the detection of weeds has allowed for improved detection rates and subsequent control of a species before it has the ability to produce seeds and further impact the environment. Autonomous mechanical control has also been shown to be a feasible option in controlling various weeds as a nonchemical method of control. Despite promising signs, further investigation will need to consider the cost-benefit of using such devices, as they are often much slower and more expensive than conventional methods, which is also a consideration for electrical, laser, and thermal methods. It is suggested that this approach will become more practical and provide greater confidence in sound weed control strategies with the aid of machine learning systems and the integration of artificial intelligence systems.

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