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Advancements in sensor-based weed management: Navigating the future of weed control

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Abstract: Controlling weed populations in agricultural land is challenging due to various factors, such as soil conditions, crop type, and environmental conditions. Substantial experience is needed to develop a strategy for minimising pressure from weed infestation. For a relatively longer period, weed control was taken care of using herbicides and mechanical and manual weeding. While herbicides simplify weed control, they pose issues like residual effects and the development of herbicide resistance in weeds, necessitating the deployment of alternate smart weed-management technologies. Lately, smart weeding robots and sensor-based site-specific spraying systems have been developed. Sensors as varied as hyperspectral imaging cameras, Global Navigation Satellite System (GNSS), Real Time Kinematics-Global Positioning System (RTK-GPS), optoelectronic, fluorescence sensors, laser and ultrasonic systems can help to improve weed control efficacy when combined with mechanical and spraying robotic systems. Camera-steered mechanical weeding robots and unmanned aerial vehicles are now widely available for weed management. This review focuses on the developments in sensor-based mechanical and chemical weeding, identification of herbicide-resistant weeds, and herbicide effect assessment. This is a comprehensive overview of studies of sensor-based weed-management strategies being adopted worldwide. Furthermore, an outlook towards future sensor-based weed control strategies and necessary improvements are given.

Keywords: patch spraying; precision weeding; resistant weeds; robotic weeding; sensor technologies; UAV; weed mapping

Agriculture supports sustainable livelihood by providing food, pharmaceuticals, textiles, and raw materials for industries through crop production. Yet, weed infestation poses a threat to the sector's productivity due to its competitive nature (Pusphavalli & Chandraleka 2016) as weeds compete with crops

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for essential resources like water, light, space, carbon dioxide and nutrients (Barba et al. 2020; Mahé et al. 2020; Hasan et al. 2021). If not managed properly, the weed seed bank in a field will greatly impact crop productivity and biodiversity (Sodaeizadeh et al. 2012). The global potential crop yield loss without weed control was estimated to be as high as 43% (Oerke 2006). Therefore, properly managing weeds is important for meeting the increasing food production needs (Westwood et al. 2018). Manual and mechanical weeding, herbicide application, sustainable strategies, sensors and machine vision-based weeding are diverse ways to manage weeds.

Resources such as capital, labour, energy and water influence crop production. Labour is a primary and major resource for most weeding operations, especially manual weeding and herbicide application. Srivastava et al. (2020) indicated that in India, agricultural labourers are shifting to the non-agricultural sector, which has reduced the agricultural labour workforce to 30.7 mil. (12%), leading to a 9.3% hike in labour wages (Vaishnavi & Manisankar 2022). This invariably leads to increased cost of cultivation, affecting timely operations and the economics of crop production. In conventional chemical weed control, applying herbicides all over the field increases herbicide usage, weed control costs, and environmental impact due to residual effects.

To overcome these challenges, scientists are working on sensor-guided weed-control strategies. Recent advancements in mechanical weed control have proven to be improved precision-wise and operationally efficient. Improvements in real-time communication between implements and sensor systems have further enhanced the capabilities of mechanical weeding. Various sensors, such as optoelectronic, distance sensors and multispectral cameras for plant detection and image analysis, and Real Time Kinematics-Global Positioning System (RTK-GPS), Global Navigation Satellite System (GNSS) for navigation, offer a range of options to enhance the effectiveness of weed control when integrated with mechanical systems (Machleb et al. 2020). Also, integrating sensors on unmanned aerial vehicles (UAVs) and ground-based mechanical systems has introduced a new mode of weed management. Combining UAVs with hyperspectral cameras, real-time kinematic global navigation satellite system (RTK-GNSS)-controlled sprayers, and other already existing technologies, along with the application of GIS and GPS, has made it possible to implement site-specific weed control (Gerhards et al. 2007; Loghavi & Mackvandi 2008; López-Granados et al. 2016). This paper gives an overview of the development and application of sensor-guided weed control technologies. This necessitates highlighting the identification of herbicide-resistant weeds (Wang et al. 2016; Huang et al. 2017) and assessment of herbicide effect with sensor system. Also, the promising results achieved with the number of sensors and navigation systems associated with machine vision and the need for further improvements in weed management with sensors are described.

SENSORS AND THEIR MECHANISMS

Sensors like spectrometric, optoelectronic, fluorescence, and distance sensors play an important role in the identification of weeds and discrimination between weeds and crops. Spectrometric sensors like multispectral and hyper-spectral sensors measure reflection intensities of the electromagnetic spectrum, from ultraviolet (UV) to near-infrared (NIR). The spectral resolution varies with the sensor. Plants absorb specific light wavelength due to photosynthetically active compounds or other pigments in leaves (Gitelson & Merzlyk 1997; Moshou et al. 2002; Ustin et al. 2002, 2004; Asner et al. 2005; Noble et al. 2012). Most sensors measure visible and NIR light for weed detection, calculating vegetation indices like the Normalised Difference Vegetation Index (NDVI) from spectral data (Zhu et al. 2008). Spectrometers are capable of distinguishing between plants and soil; they can differentiate between various plant species.

Optoelectronic sensors concentrate on a limited number of specific spectral bands, typically one or two, and are designed to operate within the red (R)/NIR spectrum. Their primary emphasis lies in discerning plant presence and absence, achieved by measuring indices closely associated with plant coverage values (Sui et al. 2008). Commercial sensors of this type operate with the same spectrum to derive an index comparable to NDVI (Peteinatos et al. 2013). Weed seeker® 2 (Trimble Inc., USA) is a commercial automatic spot-spray system that applies herbicide only when the sensor detects a weed; advanced optics and processing power enable the sensor to detect and eliminate weeds. This technology helps to reduce the cost of weed control and chemical use by up to 90% (Trimble Agriculture 2024).

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Fluorescence sensors measure the wavelength and intensity of fluorescent radiation emitted by leaves of plants in a particular amount of time after they are exposed to radiation for a particular time. Shortly after being exposed to light, the plant emits fluorescent radiation, the wavelength of which is longer than that of the incident light. Depending on the properties of the leaf and its physiological state, the intensity of fluorescence will vary (Cerovic et al. 1999). According to Krause and Weis (1991), plants' emission of fluorescent light is due to the presence of chemical compounds such as chlorophyll, polyphenols, flavonols, and anthocyanins. The presence of anthocyanins and flavonols in the epidermis of the leaves enables the emission of blue-green fluorescence (450 nm) when leaves are stimulated with UV radiation. When chlorophyll a and b are stimulated thus, a fluorescent spectrum in the range of red to far-red (680–700 and 735–750 nm, respectively) is emitted. Multiplex® (Force A, France), MiniVegN® (Fritzmeier Umwelt Technik GmbH & Co. KG, Germany), and PAM® fluorometry (Heinz Walz GmbH, Germany) are some active sensors that measure chlorophyll fluorescence (Peteinatos et al. 2013).

Light Detection and Ranging (LiDAR) and ultrasonic sensors are "distance" sensors as they measure the distance to the target based on the travel time between the target and source. LiDAR sensors use a laser beam for measuring the distance to the target either by the phase difference produced from the emitted laser beam and the reflected one or by the time needed for the laser pulse to travel between the transmitter and the receiver of the sensor, reflected by the target (Ehlert et al. 2009; Rosell & Sanz 2012).

In ultrasonic sensors, based on time of flight, the distance to the target is measured using an ultrasonic pulse, which has been used in weed detection and discrimination. The last echo belongs to the soil, while previous echoes belong to vegetation (Dille et al. 2002; Andújar et al. 2011, 2012a, 2012b). Moreover, higher measurement frequencies of LiDAR sensors make them more precise than ultrasonic sensors (Fernández-Quintanilla et al. 2018). In particular, ultrasonic sensors are readily available, inexpensive, and reliably accurate (99%) between the 100 mm and 10 m range (Tillett 1991).

Imaging sensors are a camera-based sensing system. Red green blue (RGB) camera, NDVI camera and bispectral camera are some of the imaging sensors used to discriminate plants from soil and weeds from crop species. The procedure involves digital image acquisition, image segmentation (subdividing images into regions of similar characteristics), and extracting plant shape, colour, texture, and location features (Peteinatos et al. 2013). With the bispectral camera, researchers managed to achieve high-resolution images and to identify weeds correctly by subjecting the images to three groups (Rumpf et al. 2012) and four groups (Weis & Gerhards 2007) or five (Sökefeld et al. 2007) classification algorithms. As illustrated in Figure 1, using

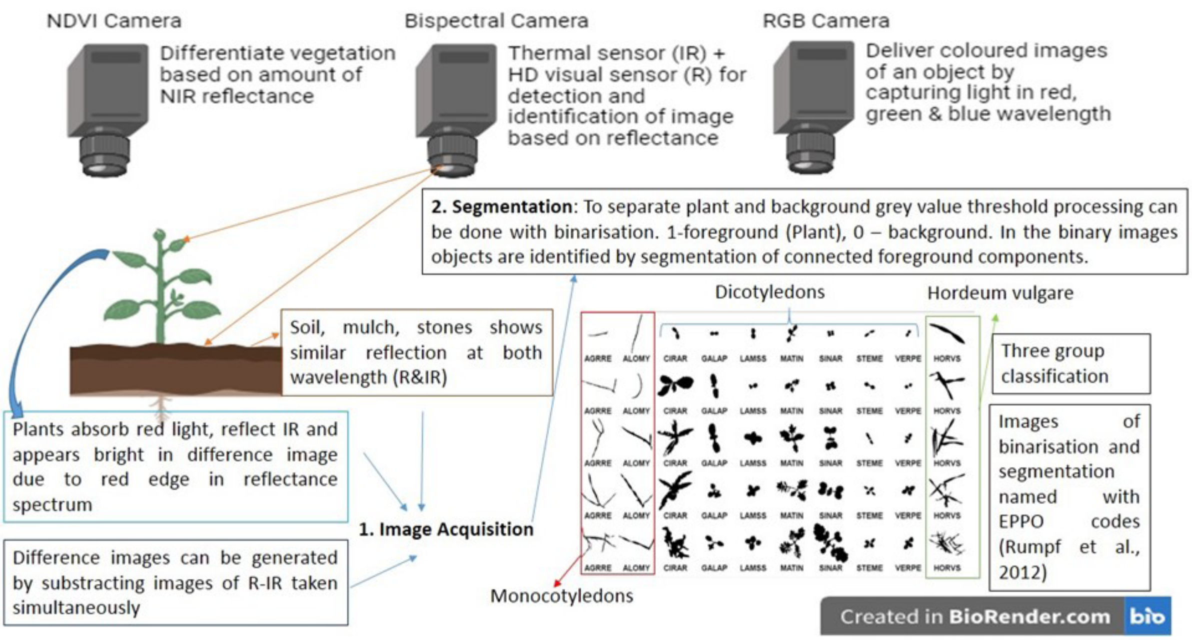

Figure 1. Bi-spectral camera imaging and steps involved in discrimination of weeds

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bi-spectral imaging and a three-group classification algorithm, Rumpf et al. (2012) successfully differentiated between monocotyledonous and dicotyledonous weeds, as well as summer barley, achieving a classification accuracy of over 80% across all categories, and notably exceeding 94% accuracy for monocotyledonous plants. Active shape model (ASM) matching and colour co-occurrence method (CCM) are some techniques to identify weeds with RGB imaging. In ASM, shape boundaries are calculated first, and a mean leaf shape model is created to represent the boundary shape of the identified weed. A functional shape description is generated for each recognised object in the identification process. The shape function parameters are subsequently adjusted to align with the reference mean models, and the extent of the required transformation determines the degree of similarity. ASM approaches can address the overlapping issue to some degree (Franz et al. 1991; Persson & Astrand 2008; Swain et al. 2011; Pastrana 2012). The CCM was used by Burks et al. (2002), and the differentiation of weed plant species was achieved based on texture. The RGB colour space was converted to HSI (hue, saturation, and intensity) values during this process. Subsequently, colour co-occurrence matrices were derived from the three HSI channels. A classifier was trained using texture features extracted from these matrices. Burks et al. (2002) attained 100% accuracy in soil classification, while classification accuracy for four plant species (ivyleaf morning glory, large crabgrass, giant foxtail, and velvetleaf) exceeded 90%.

ROBOTIC MECHANICAL WEED MANAGEMENT

Mechanical weeding could be considered a potential alternative for chemical weed control, although it has some issues (Busi et al. 2013) like, the possibility of crop damage due to steering errors (Home et al. 2002; Melander et al. 2006) and its suitability based on external factors. The emerging herbicide-resistant weeds at the global level demand alternate weed management strategies. One such strategy can be the introduction of sensor-guided robotic mechanical weeding. A total of 272 (117 monocotyledons and 155 dicotyledons) herbicide-resistant weed species have been reported globally (Heap 2024). Consideration of the mechanical weeding basic concepts such as treatment timing, frequency, intensity, and factors like crop growth stage, soil moisture and texture, as well as the previous and succeeding weather conditions, are more essential for efficient mechanical weed control (Machleb et al. 2020). Sensor-based (intelligent) cultivators need to possess the capability to recognise either crop row structures or individual crop plants, ensuring an ideal alignment of tools with the crop. The mechanical implement should be directed close to the crop plants to increase the treated field area and prevent the crops from physical damage (Home et al. 2002; Melander et al. 2006).

Agricultural robots have diverse applications in the field, encompassing harvesting and weed control tasks. Their appearance, design, and setup can vary, ranging from modified tractors to compact specialised platforms that autonomously traverse the field to perform specific crop operations (Emmi et al. 2014). Regarding the autonomous removal of weeds using mobile robots, Slaughter and Giles (2008) mentioned certain technical prerequisites, which include weed detection and identification, self-guidance, weed mapping, and precision intra-row weed control. To carry out this challenging task, a sequence of steps is important to locate the exact position of the weed or crop. Robotic systems use two concepts: mechanical weeding and plant care. First, geo-referencing the seeded or planted crop plants using GNSS and recording their locations in a plant map are performed (Pérez-Ruiz & Upadhyaya 2012). Later, a robotic system can employ these data to identify each crop plant and execute the required weeding tasks. With RTK-GPS-referenced seeding, an Intelligent Autonomous Weeder (IAW, Wageningen University) was used for inter-row hoeing in maize, at a driving speed of 0.5 m/s in which no damage to crop plants was observed (Bakker et al. 2010a, 2010b, 2010c). Here, the limitation is the driving speed of 0.5 m/s, which is a slow working speed.

In the early 2000s, inter-row weeding was established successfully with tracking crop rows. To address intra-row weeding issues, Tillett et al. (2008) fitted out the Garford hoeing system with newly designed, half-moon-shaped cultivation blades guided by a vision system for single-crop plant identification. Besides achieving up to an 87% reduction in intra-row weeds, damage to cabbage plants was also avoided. Fennimore et al. (2014) tested the Garford InRow Weeder with hydraulically con-

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trolled rotating discs in celery, bok choy, radicchio, and lettuce, reducing thinning and hand weeding time by 25% for seeded lettuce and achieving 85% reduction in weed densities for transplanted crops. The Garford "Robocrop Guided Hoes" and the "Robocrop InRow Weeder" are now commercially used for weed control in different row crops. Melander et al. (2015) conducted a trial using the Robovator (F. Poulsen Engineering, Denmark) for intra-row weeding in transplanted cabbage and onion. The Robovator employs a machine vision system to identify single-crop plant and knife-like bladed tine pairs for each crop row. No clear differences were observed in weed control efficacy between the conventional method (torsion weeder + harrowing) and the Robovator (smart cultivator). Lati et al. (2016) experimented with Robovator in transplanted lettuce and direct-seeded broccoli. Under moderate to high weed density conditions, the Robovator reduced manual weeding time by 45%. Compared to standard cultivator knives, the Robovator removed 18% and 41% more weeds. These findings highlight the feasibility of sensor-based intra-row weeding and its importance in minimising manual weeding hours. Nørremark et al. (2012) reported a robotic system with a cycloid hoe that carried out mechanical intra- and inter-row weed control using GNSS-reference when moving along crop rows. This combination resulted in high WCE, and large areas of a field, up to 91%, were weeded successfully.

Baerveldt and Åstrand (2002) fitted a forward-looking camera, utilising a grey-level vision system and an NIR filter into a robotic system. This enabled the system to locate rows of sugar beet and identify individual plants. The adaptability of robotic systems for individual crop plant care was thus established. Large weeds like *Rumex* spp. L. or *Cirsium arvense* L. pose challenges in pastures, necessitating hand weeding or herbicide spraying. Adoption of automatic mechanical weeding systems would not only be environmentally significant but could also substantially reduce the need for manual labour. Van Evert et al. (2011) developed an autonomous robot to identify and eradicate *Rumex obtusifolius* L. on a commercially operating farm. They used GNSS to navigate the robot on a predefined path and a camera to identify weeds. With this system, 75% of *Rumex sp*. were removed successfully, with a weed detection rate of 93%.

Kunz et al. (2015) compared automatic RTK-GNSS or camera-assisted steering with conventional weeding strategies in their field experiment with soybeans and sugarbeets. Automatic hoe guidance was superior to all other methods, resulting in an 89% weed reduction in soybeans and 87% weed reduction in sugarbeets. The increasing driving speeds from 4 to 7 and 10 km/h with automatic steering resulted in no negative impact on the crops. Subsequent field experiments in the same crops led to an 82% reduction in weeds when combining mechanical weeding implements with a camera-steered hoeing frame (Kunz et al. 2016). Similarly, a camera-steered hoe in maize achieved an average weed density reduction of 85% compared with untreated control (Kunz et al. 2018).

Ultrasonic and LiDAR sensors are usually integrated with other sensors to navigate robots or vehicles in the field. Andújar et al. (2012a, 2012b) used ultrasonic sensors to identify high weed infestation patches in crop fields. Similarly, Rueda-Ayala et al. (2015) experimented with ultrasonic sensors for harrowing in maize. This study aimed to adjust tine angles based on weed density, sparing crop plants from unnecessary mechanical stress. As the working intensity of the harrow varied with the angle of tine, steeper angles resulted in high (aggressive) intensity, while gradual adjustments were found to be less intense on both weeds and crop plants. The adjustment of tine angles was achieved by utilising the tractor mounted with an ultrasonic sensor in front, enabling weed detection and facilitating real-time adjustments to the harrow tines. The average effectiveness of weed control was found to be 51%. As this system was meant to be a real-time harrow adjustment system, the system's calibration was necessary concerning the crop stage.

Chandel et al. (2019) also designed a weeding tool with vertical axis rotary mounting and lateral shifting mechanism (LSM). The LSM, driven by an ultrasonic sensor and a single-board computer [ATMEGA 328 (Microchip Technology Inc., USA)], responded in real time to crop height. The overall operating efficiency of the sonar sensor-based intra-row weeding prototype for row crops varied between 80% and 96% when evaluated under different plant spacings, different forward speeds, motor speeds, and operating delays. Andújar et al. (2013) successfully used LiDAR systems to detect and classify weeds in a crop field. Similarly, Reiser et al. (2018) also steered a robot with a laser scanner in the early growth stages of maize rows.

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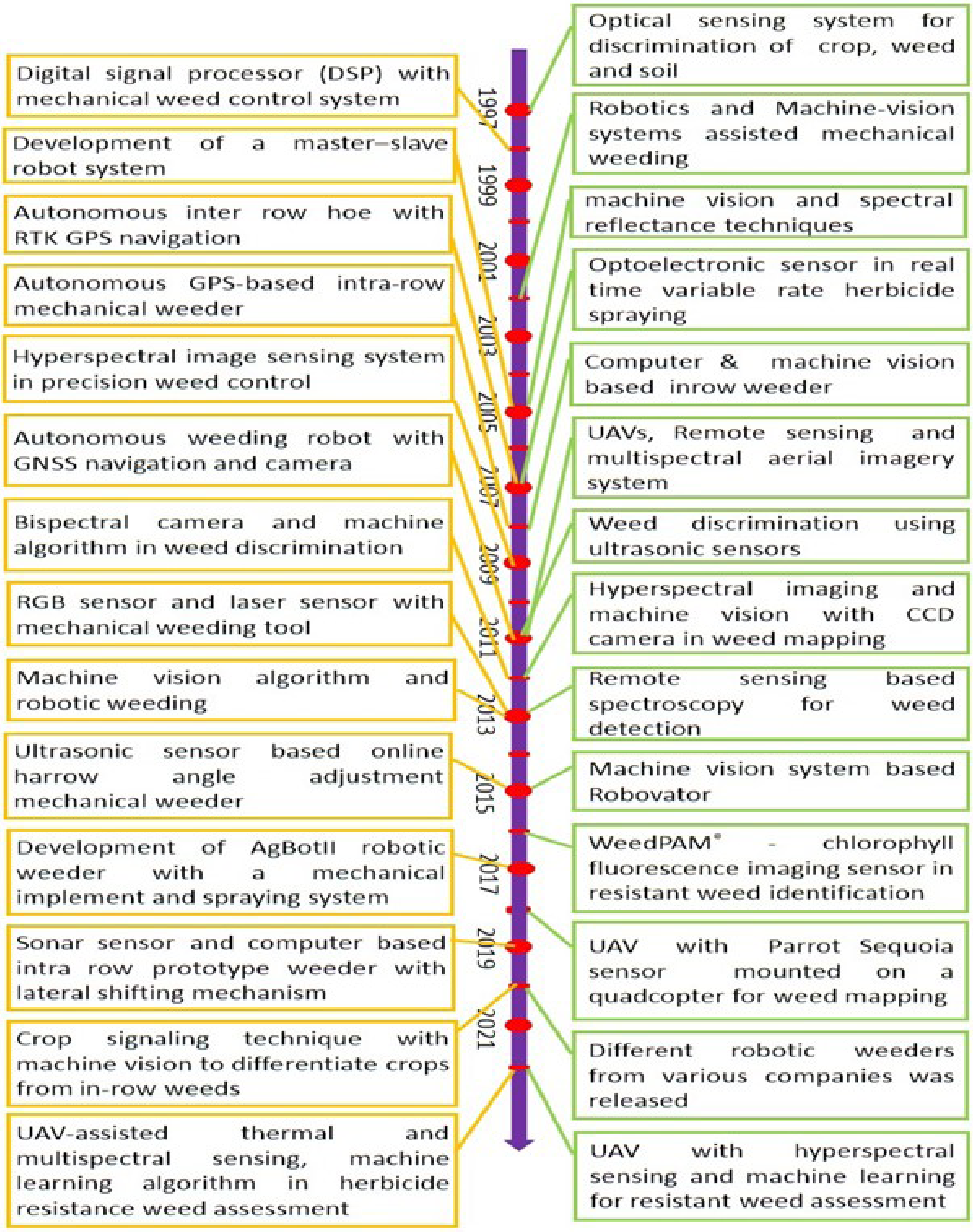

Figure 2. Time line of developments in sensor based weeding (1997–2022)

Noguchi et al. (2004) introduced the concept of a robot fleet using a master-slave system, where autonomous vehicles handle all agricultural tasks from planting to harvesting. The master robot handles planning and decision-making, while the slave robots assist in assigned tasks. The robotics and associated high-technologies equipment for agriculture (RHEA) project modifies commercially available tractors to autonomously perform agricultural duties, incorporating multi-level supervision architecture like machine vision for crop row detection and weed, GNSS for navigation, and laser range finders for obstacle detection (Emmi et al. 2014). The tractor from the RHEA project was enhanced by Pérez-Ruiz et al. (2015), incorporating a mechanical and thermal weeding tool.

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The thermal tool (flaming), guided by machine vision, targeted and removed intra-row weeds in maize selectively, while the mechanical tools conducted uninterrupted inter-row hoeing irrespective of weed coverage. With this combination, 90% weed reduction was achieved with no major crop losses. In addition, the RHEA fleet system has also been tested by Conesa-Muñoz et al. (2015) in crops like onion and garlic. The images and work of the Unmanned Ground Vehicle (UGV) with mechanical thermal implements (RHEA-fleet-system) were given in detail by Gonzalez-de-Santos et al. (2017).

Some companies are developing autonomous and semi-autonomous robotic weed-management solutions to reduce the use of herbicides. One such company is Naïo Technologies (France), which has developed a number of robots, including Ted (Vineyard weeding robot), Jo (for Vineyards), Oz (small multi-functional robot), and Orio and Dino for agricultural operations. Navigation of these robots is mostly based on RTK-GPS with a pre-planned path (Naïo Technologies 2024). The company Carré-Made for Agriculture (France) (2020) has also developed a related concept of a robot named "ANATIS". It also performs mechanical weeding autonomously in vegetable farms. However, it is limited to working only in inter-row spaces; intra-row weeds should also be considered. Moreover, a small solar-powered robotic weeder named "Tertill" was developed for weeding in gardens (Tertill 2020), which is a commercially available product. PUMAgri by SITIA is another robotic weeder developed for weeding vineyards (Platform PUMAgri – SITIA 2020) and is equipped to work day and night.

These robotic weeders are designed differently and have varying sizes based on need. Robots of compact size, easy to handle, and of average weight are advantageous in reduced soil compaction. Besides the size and weight, sloping terrain is also an issue for intelligent weeding implements. To cope with this issue, the company Energreen (2024) has developed a number of robots with the capacity to weed and mow on slopes with more than 30° gradient. However, it is not an autonomous robot; instead, it is controlled remotely. Meanwhile, FarmWise's (2020) robot employs deep learning to fulfil the requirements for successful sensor-guided mechanical weeding by capturing and analysing plant images for weed detection and removal. This robust system is suitable for prolonged fieldwork in various conditions. A new similar but solar-powered autonomous robot, the "Farmdroid FD20®", an interesting hybrid robot, combines sowing and hoeing between crop rows, contributing to the concept of autonomous farming. According to their website, Farmdroid can care for 6.5 ha per day and 20 ha per season by working continuously at a speed of 1 km/h (FarmDroid FD20 2020).

Gerhards et al. (2023) evaluated seven robotic weeders in sugar beet and winter oil-seed rape. They reported that 75–83% of herbicide savings were achieved in band-spraying and inter-row hoeing guided by RTK-GPS. Hoeing robots, specifically Farmdroid-FD20®, Farming Revolution-W4®, and KULTi-Select® (with a finger weeder), exhibited remarkable weed control of 92% to 94%. Less than 5% crop stand loss was observed in all the treatments except for the W4-robot. The KULT-Vision Control® inter-row hoeing achieved 80% weed control efficacy with only 2% crop stand loss. However, the hoeing robots, with in-row elements operated at a low working speed of 1 km/h, incurred treatment costs twice as high as broadcast herbicide application and three times higher than camera-guided inter-row hoeing.

SENSORS IN CHEMICAL WEED MANAGEMENT

Herbicides are usually sprayed evenly throughout the fields, even though there is substantial evidence that weeds are more likely to grow in patches or clumps within crop fields (Loghavi & Mackvandi 2008). Real-time sensor-based weed detection enabled the application of variable rates of herbicide, where the weed sensor (optoelectronic sensor – R and NIR lights) was carried by a guide wheel to minimise vibration and connected to the on-board terminal on the tractor to detect small weeds in the cotyledon stage (Dammer et al. 2007). This terminal communicated with a computer, which controlled a field sprayer using a control system (ISOBUS). According to the sensor signal, the application rate was adjusted by a sprayer control system [commercial 4 000 L field sprayer (BBG-Amazone, Germany)]. An average herbicide saving of 24.6% was achieved out of 13 field trials. Dammer et al. (2007) added that, in comparison with conventional application, on average, no yield reduction was caused by sensor-based herbicide application. Similarly, Loghavi & Mackvandi (2008)

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introduced a prototype patch sprayer for precise weed control, integrating DGPS, GIS, and solenoid-activated spray nozzles. Weed positions in the plot were tracked using Ashteck Promark2 DGPS receivers, and with the use of a microcontroller, weed patch locations on the electronic map were retrieved. Results from their experiment confirmed that patch spraying effectively controlled weeds, with significant herbicide (Gramoxin, 10%) savings (69.5%) compared to conventional methods, which recorded mean herbicide spray volume consumption rates of 40 L/ha whereas for patch spray 12.2 L/ha was noted.

Staab et al. (2009) developed a precision weed-control system that can autonomously detect, identify, and map weed species in the seedline of directly seeded processing tomatoes. The system utilises a hyperspectral imaging subsystem with a spectral range of 385–810 nm at 1.6 nm resolution and a spatial resolution of 0.4 mm across the seedline. Hyperspectral field images are collected in real time from a continuously moving cultivation sled. An offline multivariate Bayesian classifier was built to determine the type of plant represented in each pixel in the hyperspectral images. Site-specific classifier training significantly improved classifier performance on the field data. It correctly recognised 95% of tomato foliage and over 84% of four weed species: black nightshade (*Solanum nigrum*), lambsquarter (*Chenopodium album*), red-root pigweed (*Amaranthus retroflexus),* and purslane (*Portulaca oleracea*). The hyperspectral imaging system was robust in identifying partially occluded foliage, providing an accurate weed map for species-specific herbicide application.

However, developing a dependable real-time system for weed control is challenging, notably in distinguishing crops from weeds. Raja et al. (2020) introduced a novel technique called "crop signaling", utilising machine vision to differentiate crops from in-row weeds even in complex natural scenarios. The technique involves using machine-readable signaling compounds to create distinct visual features for crop–weed discrimination. They are designed for a vision-based weeding robot with a micro-jet herbicide-spraying system. The proposed algorithm achieves high accuracy in crop (lettuce) detection (99.75%) and weed identification (98.11%).

Similarly, the ONE SMART SPRAY, developed by Bosch (Germany) and BASF (Germany) in 2021, offers a revolutionary approach to weed control. This precise, site-specific sprayer customises herbicide applications without requiring an internet connection. Equipped with high-resolution cameras, it detects weeds in milliseconds, applying herbicides only where needed for optimal efficiency, with over 95% accuracy. It operates day and night, supported by LED lighting, and transfers data post-application to the xarvio® ONE SMART SPRAY module, which creates digital maps to monitor weed growth and resistance. This cutting-edge technology enhances agricultural productivity, profitability, and sustainability (ONE SMART SPRAY 2023). Saile et al. (2022) reported that a combined integrated weed management (IWM) approach using a pre-emergence herbicide application (plot sprayer) and post-emergence sensor-guided (camera-guided harrow and hoe) mechanical weed control in cereal crops offers the 100% weed control efficiency (WCE) and implied that it was the most robust weed management strategy.

Pérez-Ruiz et al. (2015) also enhanced a tractor from the RHEA project by incorporating a patch sprayer (variable rate sprayer for real-time application) and canopy sprayer (air blast sprayer) for pesticide application in groves, woody crops, and orchards. A detailed description and images of the patch sprayer and canopy sprayer system with UGV and UAV for weed mapping can be found in Gonzalez- de-Santos et al. (2017).

Sensor-carrying UAV in chemical weed management. López-Granados et al. (2016) focused on site-specific weed management, applying customised control treatments based on geo-referenced weed-seedling infestation maps generated in two sunflower fields by analysing overlapping aerial images of the visible and NIR spectra. They utilised UAVs equipped with visible or multispectral cameras, flying at 30 and 60 m altitudes to collect pictures. The study involved configuring and evaluating the UAV and sensors for image acquisition and ortho-mosaicking, developing an automatic image-analysis procedure for weed-seedling mapping, and designing a site-specific weed-management program. Object-based image analysis (OBIA) methods successfully matched sunflower rows with ortho-mosaicked imagery and accurately classified them for all flight altitudes and camera types. The OBIA procedure facilitated the computation of herbicide requirements for timely and site-specific post-emergence weed-seedling management.

Martin et al. (2020) investigated the feasibility of using a remotely piloted aerial application sys-

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tem (RPAAS) instead of a backpack sprayer for post-emergence herbicide application. They applied a spray mixture of tap water and fluorescent dye on palmer amaranth (*Amaranthus palmeri*) and ivy leaf morning glory (*Ipomoea hederacea*) using the RPAAS and CO_2-pressurized backpack sprayer. The study found comparable spray efficiency between those sprayers. The adaxial surface had a significantly higher fluorescent spray droplet density for the backpack sprayer. At the same time, the RPAAS showed increased droplets on the abaxial surface due to rotor downwash and wind turbulence generated by the RPAAS, causing leaf fluttering. Such a phenomenon may improve the efficacy of contact herbicides, implying that RPAAS is superior to conventional sprayers.

Abdulsalam et al. (2023) used monocular vision for drones to autonomously detect various weeds and estimate their positions for precision agriculture. It utilises a deep neural network architecture called fused YOLO (you only look once) to classify and detect weeds in images captured by a monocular camera on a UAV following a predefined elliptical trajectory. Weed positions are estimated using an unscented Kalman filter (UKF), and bounding boxes are assigned to determine the exact locations of weeds. Indoor and outdoor experiments validated the effectiveness of this approach in the detection/classification/estimation approach; misclassification and mispositioning errors of weed estimation were minimal. Paul et al. (2023a) reported that applying pretilachlor followed by bispyribac-Na with drones was more efficient in terms of profitability, energy use, and benefit-cost ratio in direct-seeded rice. In addition, UAV application of pre-emergence herbicide (pretilachlor) was more effective during early growth stages for timely weed control without any phytotoxicity to rice seedlings (Paul et al. 2023b).

SENSORS IN COMBINED WEED MANAGEMENT

Bawden et al. (2017) developed an agricultural robot named AgBotII that is integrated with a mechanical implement and spraying system. The robot identified and classified weeds with an RGB camera; based on this information and GPS location, the implement removed the weeds either mechanically or treated them chemically with respect to species of weeds classified by software. The classification achieved a high accuracy of 90%. Wild oats and sow thistle were successfully removed mechanically. The combination of mechanical and chemical weed control strategies in robots could emerge as a potent alternative to traditional control methods. Since it works based on pre-captured and processed image datasets of weeds, there may be a chance of damaging crops. So, further improvement in the machine is needed for commercial use of this implement in fields with crop rows.

SENSORS IN HERBICIDE EFFECT ASSESSMENT

Non-destructive assessment of herbicide effects may aid integrated weed management. Streibig et al. (2014) tested whether a sensor can detect herbicide effects on canopy variables with a logarithmic sprayer. Nine sensor systems were used for scanning spring barley and oil-seed rape fields sown with varying crop densities and increasing herbicide (tribenuron-methyl & glyphosate) rate 12 days post-spraying at BBCH 25 (growth stage scale) and 42 days after sowing. Comparing ED_{50}s (herbicide efficacy response curve) for crops and weeds derived by sensors concerning their density and herbicide effects was their objective. The sensors revealed changes in canopy colours, height, and density because of herbicide application despite them not being originally designed for such purposes. These findings suggest the potential for future sensor standardisation, benefiting research and development for detecting herbicide effects on crops and weeds during critical canopy development stages.

SENSORS IN HERBICIDE-RESISTANT WEED IDENTIFICATION

WeedPAM® (mobile version of IMAGING-PAM® – a fluorescence sensor), a novel chlorophyll fluorescence imaging sensor, can identify herbicide stress in weeds shortly after treatment. Wang et al. (2016) assessed its ability to differentiate between herbicide sensitive and resistant populations of *Alopecurus myosuroides* at five days after treatment (DAT) with ALS- and ACCase-inhibiting herbicides. Resistance profiles were analysed through standard greenhouse bioassays, whereas the sensor measured the maximum quantum efficiency of PS II on *A. myosuroides* plants. Classification based on the sensor data was confirmed visually at 21 DAT, with 95% accuracy in WeedPAM classifications.

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This ability of WeedPAM (Figure 3) to detect herbicide-resistant *A. myosuroides* populations shortly after treatment can facilitate the selection of alternative weed-control methods within the same growing season.

Huang et al. (2017) created and employed UAV technology to conduct digital imaging in a RGB spectrum as well as colour-infrared imaging over agricultural fields. This was utilised for identifying weed species, assessing crop injury caused by varying doses of dicamba, and detecting and mapping naturally occurring glyphosate-resistant (GR) and -susceptible (GS) weeds. Similarly, Eide et al. (2021) used UAV-assisted thermal and multispectral sensing techniques for the detection of glyphosate-resistant and -susceptible biotypes within a week of herbicide application in a real-field condition due to their potential to detect plants' biophysical characteristics. Spectral reflectance data obtained from different weeds were processed in ArcGIS and with different image classification techniques. NDVI and composite reflectance analysis of multiple spectra 842, 705, and 740 nm gave better accuracy than thermal reflection values. They found that at 8 DAT of herbicide, a commendable classification was achieved with 87.2% accuracy by random trees classifier, among others. Huang et al. (2022) explored the spectral features of glyphosate-resistant and glyphosate-sensitive Johnsongrass (*Sorghum halepense*) plants using the hyperspectral plant-sensing approach and differentiated them with machine-learning algorithms. As mentioned, GR plants were found to have higher spectral reflectance than GS plants. They reported that with this approach, GR Johnsongrass was accurately differentiated from GS Johnsongrass with a classification accuracy of 77%.

MACHINE VISION IN WEED SEED IDENTIFICATION

Manual identification of seeds by specialised technicians is a challenging and time-consuming process. So, implementing computer-based methods for rapid and reliable seed identification and classification becomes important in terms of technical and economic aspects. Internet of Things (IoT) technology in weed seed identification can be valuable in agriculture and crop management. As it integrates image-capturing sensors, data collection and transmission with wireless communication protocols, machine learning algorithms and cloud computing for large datasets, the developed database can be used in future with mobile applications, and web interfaces enabled upgradability will lead to more efficient and precise weed management in agriculture. The automatic systems can utilise seed images to extract classification features related to size, shape, colour, and texture, making machine vision, involving image-processing algorithms and classification methods, an appropriate framework for automated seed identification (Granitto et al. 2005). These authors tested the potential of automatic computer-based systems in terms of reliability and quickness in identifying weed seeds from colour and black-and-white images. Standard image-processing techniques were employed to extract morphological and textural characteristics of seeds as classification features for effective evaluation. The study used a database of 10 310 images representing 236 weed species. They considered implementing a simple Bayesian approach (naive Bayes classifier) and artificial neural network systems (single and bagged) for seed identification. Results indicated that the naive Bayes classifier, with

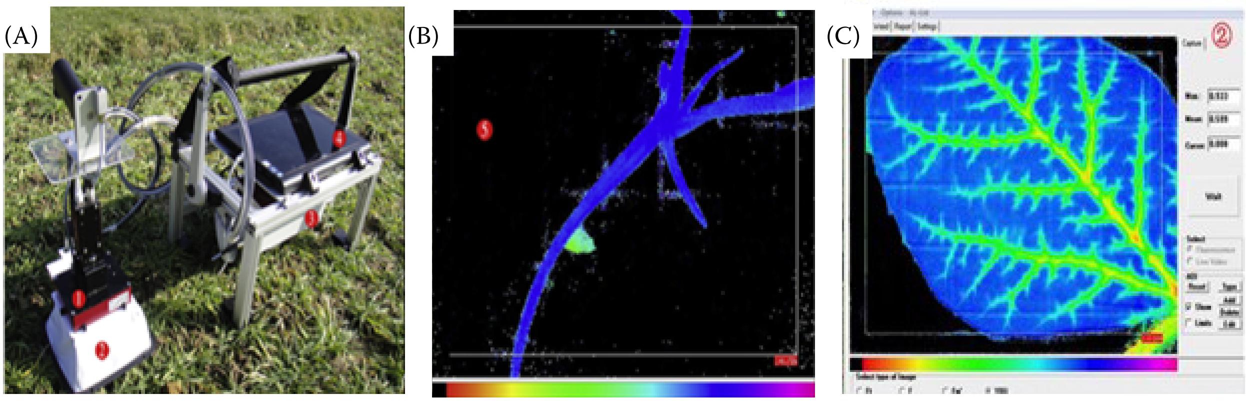

Figure 3. A – the WeedPAM® sensor in the field; B – chlorophyll fluorescence imaging of *A. myosuroides* (Wang et al. 2016); C – chlorophyll fluorescence imaging of herbicide-treated soybean (Wang et al. 2018)

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a well-selected set of features, performed excellently compared with the more complex neural network approach. Hardware cost and operational complexity could also be reduced by using morphological and textural characteristics alone as classification features with black-and-white images. The findings suggest that, under specific operational conditions, this approach would result in a relatively minor loss in performance compared to using colour images.

CHALLENGES IN THE USE OF SENSORS

The challenges in combining mechanical weeding and sensor guidance start from the inherent nature of mechanical weeding. Treatment timing varies across regions and soil conditions without assurance that a sensor-guided implementation consistently reduces treatment applications. While machinery equipped with sensors can enhance weed control, not all systems are practical, and downsides may include higher repair and acquisition costs. Autonomous systems need robust accident prevention to avoid field and roadway damage. Market trends favour mostly camera-steering systems in mechanical weeding. Future challenges involve designing robust, lightweight, sustainable sensor-guided weeding implements to address repair delays. Additionally, alternative fuel technology should be considered to reduce pollution in fieldwork, potentially favouring small robots running on solar power over single tractors. Further advancements require a better understanding of mechanical intra-row weed control, AI algorithms for species differentiation, improved actuators, enhanced robot durability, user-friendly interfaces, and collaboration with experts for effective plant species identification. The cultivation system must adapt to facilitate robotic mechanisation in a modern, diverse, and sustainable agro-ecosystem.

Though sensor-based UAVs in weed control offer promising benefits, they have some challenges in adverse weather conditions, such as strong winds, rain, or low visibility, which can hinder UAV operations. Maintaining stable flight conditions is crucial for accurate data collection and weed control. Processing and analysing the vast amount of data collected by UAV sensors require advanced algorithms and computing resources. Integrating real-time data analysis into UAV systems is a challenge that affects the speed and efficiency of decision-making. Limited battery life constrains the flight duration of UAVs. Operating and maintaining UAVs with sensor technology requires specialised skills. Farmers and operators need training to ensure proper use, data interpretation, and maintenance of the UAV systems.

FUTURE PROSPECTS

Transitioning from the traditional "entire field" method to an individual plant scale reduces synthetic herbicide use without compromising weed control. Aerial and ground vehicles carrying sensor systems may be expanded to gather localised field data, enhancing prediction models for sustainable production management. Intelligent cultivators and robots access past data and integrate it into decision support systems for targeted weed strategies. Smart implements may streamline manual adjustments, such as automatic adjustment of camera steered hoe for different spacings in crop rows. Basic weeding tasks may shift to multiple robots with diverse implements in future. Robots may use chemical, mechanical, electrical, and thermal weeding tools on the same platform. An algorithm with the ability to prioritise techniques to be employed based on weed infestation will be developed.

Unmanned vehicles carrying sensors may increasingly be used for precision spraying, delivering herbicides directly to the weeds while minimising exposure to crops and reducing the overall volume of chemicals used. This approach improves weed control efficacy, mitigates environmental impact, and helps fight against herbicide resistance. As unmanned technology matures, fully autonomous vehicles may become more common and capable of conducting surveillance and intervention missions without human intervention. This will save time and reduce labour costs, making weed management more efficient. The future may see UAVs working with ground-based robots, where UAVs identify map weed infestations and ground robots carry out the actual weeding or spraying. This combination could optimise both technologies' strengths for more comprehensive weed management. With a growing emphasis on sustainable farming practices, UAVs and other robotic systems may likely be utilised to apply biological herbicides or natural weed suppressants, further reducing the environmental footprint of agricultural operations.

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CONCLUSION

Sensors play a crucial role in contemporary weed management, aiding in the navigation, identification, and differentiation of crops and weeds. Autonomous weeding robots utilise RTK-GPS and GNSS for precise inter- and intra-row navigation. Machine vision, RGB and hyperspectral cameras are key components for identifying crops and weeds, enabling varied driving speeds and increased precision compared to manual steering. Laser and ultrasonic systems are additional guidance sensors supporting autonomous robots. Small robot fleets are expected to take on repetitive agricultural tasks, while site-specific weed control can be achieved through various spraying systems guided by machine vision and hyperspectral cameras. UAVs equipped with DGPS, GPS navigation, and multispectral cameras effectively identify and map weeds for aerial herbicide spraying, reducing reliance on backpack sprayers. These sensor-based advancements in weed management facilitate spot spraying, leading to higher Weed Control Efficiency (WCE), i.e., reduced herbicide usage and increased control of weed population, and favour early detection of resistant weed biotypes and invasive weed spread through UAV monitoring.

Integrating mechanical and chemical weed control in robots presents a promising alternative to traditional methods. Rather than focusing on crop-specific mechanisation, a broader application of robots is suggested. However, concerns about the commercial availability and affordability of large-sized robots for farmers persist, emphasising the importance of developing machines suitable for medium-sized land holdings. Additionally, studying weed seed banks is crucial, focusing on using sensors for qualitative and quantitative identification and seperation of weed seeds. Early detection of herbicide-resistant weeds through sensor technology is emphasised for improved weed management in the future.

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