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REVIEW ARTICLE

Advances in site-specific weed management techniques for sustainable crop production

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Abstract

Weeds are amidst the major factors that can adversely affect crop yield. Current weed control methods, such as use of synthetic herbicides and mechanical methods, are widely used and effective, but come with drawbacks like environmental impacts, development of herbicide-resistant weeds and limited labor availability. There is an urgent need to address critical issues such as the use of harmful pesticides, pollution control and the environmental impact on agricultural practices. In recent times, innovative methods have been proposed to address existing limitations and transition toward more ecofriendly weed control approaches. The advancement in automation and information technologies has revealed a new era for weed management, allowing physical and chemical control methods to be tailored for the spatial and temporal variability of weed distributions in agricultural fields. Non-chemical weed control methods could reduce reliance on herbicides and soil tillage. Sensor technologies, including spectral imaging, remote sensing and artificial intelligence (AI), are employed to accurately identify and classify weeds. These classifications are then utilized by automated robots to carry out precise mechanical weeding operations. Additionally, imaging and AI-guided robots, in conjunction with unmanned aerial vehicles (UAVs), can assist in both intra-row and inter-row weeding, alongside targeted patch spraying. Site-specific weed management showed around 50 % saving of herbicides by reducing the application dose. This review examines site-specific weed management technologies, assesses their advantages and provides insights onto their potential implementation in agriculture. Nonetheless, further research is needed to incorporate these technologies into conventional agricultural practices.

Keywords: machine learning; non-chemical weed control; robotics; sensor technologies; UAV

Introduction

The global population has reached 8.1 billion and is expected to cross 9.5 billion by 2050 (1). Current grain production levels are inadequate to feed the growing population and meeting this expected demand could be a mammoth task for mankind (2). This pressured the farming community and forced them to intensify crop production to meet food demands. Besides climate change, decreasing water resources, arable land and the risk from biotic factors are posing an additional challenge (3). Weed incidence is one of the major constraints on world agricultural production. Among the losses caused by biotic factors weeds are at the highest (34 %) followed by pests (18 %) and pathogens (16 %) (4).

Weed management in cropping systems can be categorized into two main approaches: the first relies heavily on the use of synthetic herbicides, while the second emphasizes mechanical, physical and ecological methods to control weed growth. Weed management solely accounts for around one-third of the production cost in field crops (5). Moreover, paucity and cost of labour are also affecting traditional weed management practices.

In recent times, advanced methods have turned up as a potent tool in various fields, transforming ways to manage intricate problems. Specifically, agriculture has witnessed the capability of cutting-edge technologies to optimize various operations, boost sustainability and productivity. Site-specific weed management (SSWM) considers the spatial variability and temporal dynamics of weed populations within the agricultural fields. This approach enables precise targeting of weed control methods to individual weeds or specific patches of weeds. These techniques involve image processing (6), machine learning (7), robotics (8), remote sensing (9) and UAVs. These can offer valuable insights into optimizing herbicide usage, weed detection, weed mapping, reducing environmental impact and improving weed management. Moreover, the increasing emphasis on non-chemical weed management including laser and electrical weed control is driven by the imperative for sustainable farming (10). Laser weeding utilizes autonomous vehicles with lasers and deep learning to precisely target weeds (11), while the Electroherb™ technology employs high-voltage currents to destroy weed cells without leaving residues and thermal method uses the heat to damage or destroy plants by increasing temperatures to 55 - 70°C (12). These methods enhance weed management while minimizing environmental impact. The "many little hammers" (13) means combining various control techniques and technological interventions can improve sustainability and enhance production. Therefore, a new paradigm in weed management is a pressing need in modern agriculture for maintaining environmental sustainability.

In this review, the integration of novel methods in weed management is outlined, investigating the possible benefits, challenges and future prospects of these innovative approaches. By reviewing these surfacing technologies, our goal is to assist current endeavour in developing sustainable and efficient weed management strategies that can have positive impact on global agriculture.

Limitations of Conventional Weed Control

Conventional weed management practices, such as mechanical and manual weeding and the use of herbicides, are widely adopted in agriculture. Nonetheless, these approaches have several limitations and impede their long-term effectiveness and sustainability. Manual weeding methods including mechanical or hand weeding are laborious and time consuming, rendering them impracticable for large scale agricultural activities (14). More skilled labour is required and the possibility of damaging crop and plant roots. Besides this, implementation and effectiveness are influenced by edaphic and weather conditions as well as timely operations (15).

Crop husbandry methods like flooding and drainage, smothering crops along with adjusting irrigation time and method have practical difficulty in adoption. These methods are unable to provide immediate and quick weed control. Perennial and problematic weeds cannot be eliminated and kept under suppressed condition (16). Cultural methods are more effective when they are combined and implemented in a multiyear strategy (17).

Herbicide has revolutionized agricultural production with the ease of managing weeds in crop fields. Despite impeccable impact on weed management, their ill effect on the environment cannot be neglected (18). With the adoption of indiscriminate use of herbicide and development of herbicide-resistant crops, the weeds problem now becomes very prominent (19). Herbicide resistance in weeds, weed shift and environmental contamination are all consequences of long-term, consistent application of the same class of herbicides over the same area (5). It is evident from the increase in numbers of herbicide-resistant weeds that technology must keep up with weed evolution and adaptation (2). The drawbacks mentioned above could be overcome with the integration of advanced techniques of weed management (10).

Novel Methods of Weed Management

Novel techniques are based on continuously evolving advanced and innovative methods used for controlling weeds in agriculture. Widespread use of herbicides has necessitated non-chemical methods for weed management. The current rise in ecological awareness, along with increased interest in organic food and the issues related to herbicides has driven the development of chemical free farming.

Weedy patches in the field can be identified by collecting images with drones and further analysis by machine learning (6). Remote sensing is also an effective method for delineating weed patches, where weeds are identified based on the spectral response of the plant canopy (20). Machine learning is a part of artificial intelligence; in weed management, it is used to evaluate large data related to weeds, herbicidal efficacy and environmental conditions (21). These data can be instrumental in locating sites at high potential for weed invasion and developing specific strategies for preventing or controlling weeds (7). Further, several prototypes of robots are developed for patch spraying in specific crop (22) and physical weed control (23).

These advances aim to optimize herbicide usage, reduce environmental impact and enhance sustainable weed control strategies. Most weed research has advanced toward addressing the detrimental impact of interspecific competition between weeds and crops; also, new technology developments may expand this scope while strengthening the sustainability of weed management (24).

Sensor Identification and Classification Technologies

Image processing for effective weed identification

Image processing techniques are crucial in precise weed identification in agricultural fields. Several studies have emphasized the significance of exploiting computer vision methods for weed diagnosis (25). Advanced approaches like Convolutional Neural Networks (CNNs) have shown assuring results in the efficient identification of weeds (26). Moreover, the amalgamation of IoT and machine vision technologies has enabled the advancement of automated systems for precise weed control, enhancing accuracy and reducing computational time (27). These systems typically comprise pre-processing steps, feature extraction using techniques like Circular Mean Intensities and Discrete Fourier Transform (DFT) and the application of deep learning algorithms like CNN for vigorous weed detection. By leveraging these innovative technologies farmers can effectively manage weeds, optimize herbicide use and ultimately enhance crop yield.

Various researchers have suggested the use of advanced approaches utilizing deep learning models such as CNN to increase the precision of weed identification. A system is devised for binary classifier using image features like colour, histogram and HOG, along with a "core zone" algorithm for the location of weed (28). Integration of Faster R-CNN with the Feature Pyramid Network (FPN) for accurate weed detection and effective perception showed accuracy exceeding 95 % (29). The improved weed identification by analyzing different neural network architectures and optimizing the model weights, achieving a high mean average precision of 93.44 % using the Deep Weeds dataset (30). These studies collectively highlight the significance of image processing in advancing weed identification methodologies in agriculture. Also, these methodologies automate the process of weed detection, reducing manual labour and the time-consuming conventional weed control methods.

Image processing for weed detection faces many challenges. One major challenge is accurately quantifying treatment efficacy when the entire experimental area is not affected, necessitating techniques like image segmentation (31). Additionally, there is difficulty in distinguishing between crops and weeds with similar morphology under natural field conditions such as occlusion and varying lighting, which can impede the precision of detection (32). Moreover, the automation of plant identification through image processing for phenotyping and weed recognition requires collaboration to overcome the barriers and enhance efficiency, which emphasizes the importance of open-source tools and data sharing (33). Attaining efficient weed detection techniques in agriculture involves combining spatial and spectral information from multispectral images to differentiate between crop and weed pixels, enhancing detection rates and robustness (34).

Machine learning for weed classification

Machine learning emerged as a solution for big data analytics and the problems associated with it such as data acquisition, storage and data processing (35). Its amalgamation with algorithms like k-nearest neighbors (KNN), Random Forest (RF) and Support Vector Machine (SVM) are the most feasible method for managing the weed problem as well as for assessing the patterns for sustainable control (36). Besides this, herbicidal and environmental resistance are also being evaluated, but at complex and organizational levels, interactions occurring at varying scales and orders can significantly increase the level of intricacy that must be addressed (3). Therefore, an effective collection of intelligent and spatially organized strategies becomes necessary. Identifying distinct features and calibration of hyperparameters is necessary for the optimization of the predictive performance of Artificial Neural Network (ANN) in weed detection (37). This data-driven approach enables the acquisition of large amounts of data from sensors such as proximal, airborne and spatial (38).

These algorithms are particularly used for location specific weed management for the improved efficacy of weed detection as well as mitigation (39). Models like ANN can detect weeds with 99.5 % accuracy due to high computational speed, filtering out precarious noise and overall data driven nature (40). It performs non-linear regression and detects weeds in spatial as well as temporal axes for effective management; whereas, in the case of Markov Random Fields (MRF), excess green is employed for weed identification with Red-Green-Blue (RGB) computation (41). This computational model, therefore, forms a spatial autocorrelation attributed to the autonomic aspect of this model to correlate herbicide resistance with weed emergence (42). A classic comparative analysis was reported for multistage scattering transformation on weed classification depicting 96.88 % accuracy by using conversion machine learning techniques and SVM classifiers (43).

The implementation of a modern deep learning-based image approach differentiates monocot and dicot weeds using robot technology, achieving 68.2 % detection accuracy (44). Thus, the study proposes a categorical approach using pixel-wise object-based detection with deep learning VGG-16 Fully Convolutional Network (FCN) technique (45). Additionally, semi-supervised machine learning is being advocated for weed detection due to its increased efficacy. The study conducted using Joint Unsupervised Learning of Deep Representations and Image Clusters (JULE) and Deep Cluster along with a deep network line of VGG-16 and RS Net -50 that showed automated weed classification into predefined classes. The only limitation presented was the inability to determine the precise density of the weeds during imaging (46). To overcome this, index segmentation can be used to differentiate between a weed and its background by comparing pixel intensity with threshold parameters and superimposed crop conditions (47). A diagrammatic view of sensor and application technologies for site-specific weed management is shown on Fig. 1.

Application Technologies

Energy directed methods

Nonchemical weed management is a prominent way of ensuring food security while promoting sustainable agriculture. The shift away from mechanical practices has reduced erosion but increased dependence on herbicides, leading to rising herbicide resistance. To tackle this, alternative weed management methods, such as energy-directed techniques which include electric, thermal and laser weed control should be explored. These techniques transfer various forms of energy to target plants resulting in killing or suppressing the growth of the plant (48).

Electric weed control

In electric weed control, the electric current can be delivered to the weed plants by continuous electrode-plant contact or spark-discharge. Both methods are non-selective having an identical mechanism where the current converts into heat energy inside the plant's cell, vaporizing volatile liquid and water (49). This builds up the pressure which results in rupture

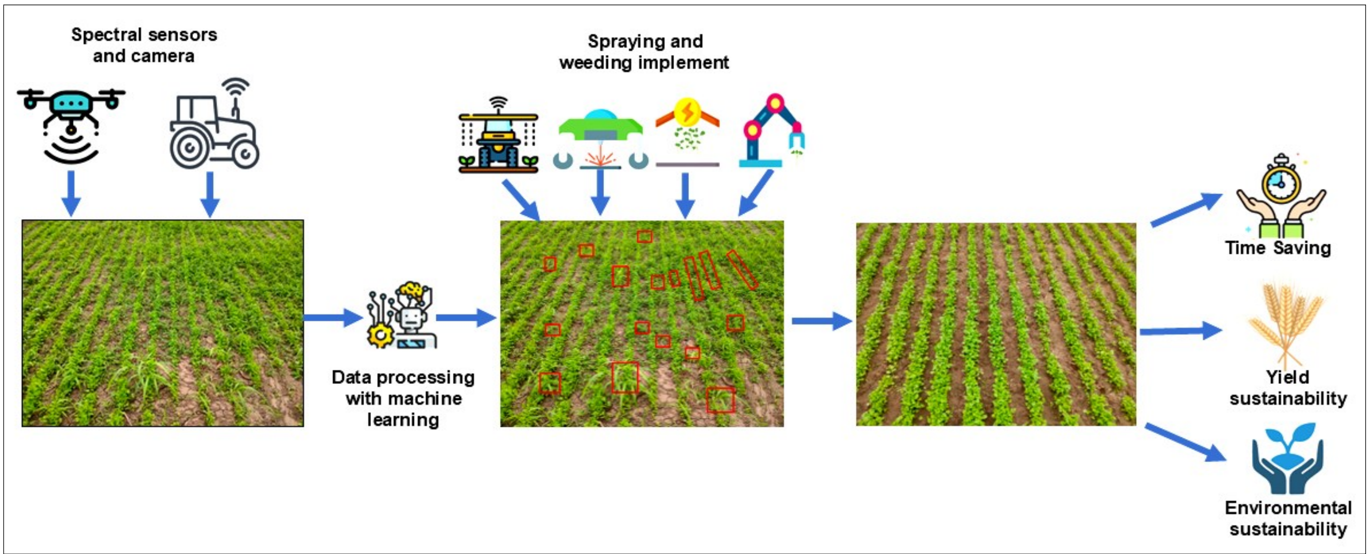

Fig. 1. Sensor and application technologies for site-specific weed management.

of cell membranes in roots and leaves, causing the suppression of growth or plant death. Very few studies have been conducted to compare and evaluate the efficacies of these two application methods. An experiment conducted by applying 0.16 Wh with continuous-contact machinery and prototype spark-discharge, revealed that efficacy depends on site of application of current and not on the method (50).

Field experiments on electric current were reported to be more advantageous at later plant developmental stages, with weed seed viability reduced by 54 % to 80 %. The effectiveness of controlling late-season herbicide-resistant weeds and their impact on crop yield varied based on the timing of intervention and the extent of contact with the crop canopy (51). Electrical applications were more effective than mechanical methods at the early growth stages of weeds. However, the efficacy of the electric weed control decreased with the weed size, due to the greater amount of weed biomass that needed treatment (52).

Since the 1890s, electric weed control has been issued patents; however, despite its potential environmental benefits, conventional or mechanical methods are considered more efficient, economical and less energy intensive (53). Despite the limitations, there has been a surge in developing machinery for electric weed control, as shown in Table 1.

Thermal weed control

This method conveys heat from an energy source like spot-flaming, electromagnetic irradiation and steam/hot water application to the plants, increasing on-site temperature. Physical processes influencing heat transfer are convection, conduction and radiation, alongside the absorption by the subsequent material (59). The objective of thermal weed control is to induce lethal effects on weeds. There are various available areas in young plants which include the cotyledons, roots, stems, first leaves or the entire plant. However, perennial weeds with growth points protected at or beneath soil level (e.g., rhizomes, stolons, tubers, or root crowns) are less or not susceptible to thermal methods because the heat does not reach these vital parts of the plant (60).

Flaming has been extensively studied using both tractor -mounted implements and handheld devices; however, it is limited by low selectivity and requires repeated applications for effective weed control (61). Researchers have developed models to optimize tool performance, enhancing energy efficiency. Moreover, several studies have explored biological selectivity by assessing crop tolerance to heat without significant yield loss (62, 63).

Laser weed control

The use of laser-equipped autonomous vehicles for weed management has garnered significant interest (e.g., https://weedbot.eu/; https://welaser-project.eu/; https://carbonrobotics.com/). Artificial intelligence has facilitated swift and accurate location and identification (64), while mirrors can direct lasers towards targeting the apical meristems of weeds (65). Exposing the apical meristem of young plants to laser beam heat can cause severe damage or even death (66). The benefit of using lasers is that they target only a small field area for imposing treatments. Laser beam used 2 mm diameter to manage 75 weeds m^{-2}, exposed less than 0.03 % area (67). As a result, it is most site-specific attainable weed control approach. Laser weeding leaves behind only ashes from the affected plants and the soil remain undisturbed.

Laser weeding results in the formation of ash from incinerated plants, which is primarily composed of phosphorus and calcium, key nutrients for crop development. In contrast, herbicides can evaporate or leach into the groundwater and surface water, posing environmental risks and potentially tainting food and feed. Autonomous laser vehicles require more powerful lasers. As, Plants established from one node rhizomes exhibit highest susceptibility to laser at 3-leaf stage, pursued by 1-leaf stage and 2-leaf stage in *Elymus repens* (L.) Gould (Couch grass) (67). WeLASER project, Futonics developed a 500 W fiber laser source based on Thulium laser technology emitting at a wavelength of 2 µm. This laser system achieved increased weeding capacity, making it ten times more powerful than previous installations (68).

Laser weed seed control might be more appropriate in ploughed fields of row crops like sugar beets and maize than in no-till cropping systems, due to the risk of igniting dry organic material on the soil surface, potentially causing a fire (11).

Robotic uses in weed management

Agribot development has been under study for many years to execute different agricultural operations (69). The technological revolution in agriculture is marked by the processing of huge amounts of data, along with robotization and automatization which paved the way for smart agriculture (70). Over 40 distinct weeding robot models are now available in the market, specifically designed for agricultural crops or fallow applications. Implementation of a tool position correction system for row crops can enhance the speed of weeding by a factor of 1.6 (71). Swift and accurate crop or weed detection is one of the main technologies that allow it to carry out precise weed removal or herbicide application, thereby reducing the risk of crop injury.

Table 1. Examples of the commercially available electric weed control machinery.

Implement name	Mode of action	Countries available	Utility	Reference
RootWave™ eWeeder	Continuous plant-electrode contact	United Kingdom, Netherlands, France and Germany	Orchards, Vineyards and bush fruit	(54)
RAIDEN	Continuous plant-electrode contact	Central and South America	In agriculture (e.g., small plantations, paths, sidewalks and curbs)	(55)
NUCROP	Continuous plant-electrode contact	All Europe	Pre-planting and preemergent weed control as well as the desiccation of cereals, oilseeds and potatoes	(56)
Lightning weeder	Electric-discharge	United States	Weeds are taller than crop plants.	(57)
Weed Zapper	Electric-discharge	United States and Canada	Season and off-season control of weeds closer to crop canopy in field conditions.	(58)

It initiates with the involvement of a detection system that locates and differentiates weeds from plants, followed by developing a weed control strategy specific to the production system and cultivation practices based on data gathered by the perception system (72). This ensures precision and efficiency in weed management. Intra-row weeding robots are more sustainable than conventional weeding methods in terms of environmental friendliness and performance (73). Various spraying robot models for precise spot application in distinct crops have been developed and scrutinized (8, 22). Avo (Switzerland), which is used in beans, cotton and rapeseed; Ladybird (Australia), used in lettuce, cauliflower and broccoli; H-sensor (Germany), are a few examples of commercial spraying. Besides, many robots are developed for physical weeding using laser, flaming, hoeing blades and electricity. They aim at single weed at a time and distinguish among crops and weeds within the row space (74).

Even after the substantial costs of robotic weed management, it has become a booming and reliable weed control method with significant potential to reduce the herbicide uses (75). A survey report on the German population shows their willingness to decrease agrochemicals in agricultural production, to accept and invest in advanced agrotechnology to acquire this goal (76). Many challenges persist in robotic weed management that need to be resolved. Even now machine vision-based weeding robots are in their initial stages of development due to system complexity and environmental problems.

UAVs in weed management

UAVs are introduced as an option for environmental observation, acquisition of images and providing high spatial and temporal resolution. Nowadays, UAVs gaining widespread interest in agriculture to aid in decision support and monitoring in various practices like irrigation, fertilization, weed management, etc. (77). Drones are transforming weed control in agriculture through their advanced capabilities in mapping and herbicide application.

Weed mapping is a crucial step in weed management and the most common use of UAVs in precision farming. As the weed population is not uniform throughout the field and is segmented into control areas, each area is subjected to a tailored weed management plan. To accomplish this, a precise weed density map is a prerequisite for accurate and targeted herbicide spraying (9). Creating weed patch maps for herbaceous crops has been difficult using remote sensing methods due to similarities in visual and spectral characteristics between crops and weeds in their initial growth stages (78) whereas, UAV imaging aids in better categorization of early season agronomic circumstances (79).

UAV application for spraying is more effective, standardized and less labour-extensive than a knapsack sprayer as the spraying efficiency was more than 60 % (80). This enables precise targeting of weeds, minimizing herbicide usage and reducing environmental impact. Their rapid deployment and ability to navigate challenging terrains ensure timely treatment of affected areas, making drones a vital component in modern, sustainable farming practices (81). The application of herbicide via drones in green gram reduced herbicide and spray fluid use by 6.9 % and 25 % respectively and addressed the labour shortage as well (82). Spray drones equipped with remote-sensing imagery are used to determine invasive species patches and offer precise control at a reasonable cost. A future unified UAV system that identifies and treats invasive species in a single pass holds promise for early recognition and prompt response in wetland management (83). Various studies emphasized the importance of integrating technology like UAVs into agriculture to meet sustainable development goals. UAV-based herbicide spraying being fast and efficient, promotes sustainable plant protection and crop production; hence, supports the sustainable development goal (SDG) (84).

Remote sensing for targeted herbicide application

Remote sensing technologies, such as UAV imagery and hyperspectral reflectance analysis provide valuable tools for targeted herbicide application in weed management (85). These techniques facilitate the generation of accurate weed distribution maps and the prediction of herbicide response in specific weed species, like *Amaranthus palmeri* (86). Sensor-based harrowing systems equipped with decision algorithms based on field variations can modify treatment intensity for optimal crop selectivity and weed control efficacy (87). Furthermore, remote image processing software like SARI® can estimate precise yield losses, generate herbicide prescription maps and enhance herbicide application efficiency through real-time data analysis (88). By leveraging remote sensing applications, farmers can make abreast decisions on herbicide and optimum dosage, which restrict herbicide resistance evolution leading to efficient weed control and enhanced agricultural sustainability.

Remote sensing for herbicide applications offers several benefits in precision agriculture. It allows site-specific weed control by mapping spatial distribution information of weeds (89) and determining the emergence time of weed species (90). Utilizing smart sensors and UAV imagery for accurate weed identification, leads to reduced herbicide usage and environmental impact (91). UAV-based vegetation indices provide precise estimations of crop injury from herbicide application, surpassing traditional visual ratings in accuracy and consistency (92). By integrating data science and nanosensors, remote sensing methods enhance decision-making processes in herbicide management, potentially reducing chemical usage, minimizing environmental pollution and optimizing crop control strategies. Overall, remote sensing technologies play a crucial role in improving the efficiency and sustainability of herbicide applications in agriculture.

Herbicide uses can be reduced by enabling more precise and targeted weed management strategies. UAVs equipped with imaging sensors can provide high-resolution weed distribution maps (92), allowing site-specific weed management. By integrating UAV imagery for mapping and UAV sprayers, a UAV integrated system (UAV-IS) can efficiently identify and target weedy areas while minimizing treatment on non-weedy areas through variable rate applicator (93). Additionally, the availability of accurate weed distribution maps generated through UAV remote sensing allows for the development of supervised deep learning models for weed detection, leading to more effective and timely herbicide application (94). This integration of remote sensing technology enhances the efficiency and efficacy of weed control measures, ultimately reducing the overall load of herbicides applied in crop production.

Economic aspects and ecological benefits

Nowadays, the acceptance of chemicals in crop protection is declining among people. The presence of residue contamination has now become a globally significant issue. The impacts extend beyond human health, as it contaminates environment, incorporated into the food chain and affect food safety (95). Objectives set by Farm to Fork and Green Deal strategies aim to decrease the overall usage and hazard of chemical pesticides by 50 % up to 2030, encouraging the adoption of more sustainable methods of management (96).

Advanced agriculture technologies are viewed to have the potential to improve agricultural resources and practices (97), hence enhancing productivity and profits of the farm. Replacement of manual labour by robotic weeding will boost productivity (98). A 50 % reduction in herbicide costs due to site specific weed management is reported (99). While implementing advanced techniques many factors like market price, area requirement, annual utilisation and weeding efficiency must be taken into consideration (75). Farmers not only have economic concerns; but also, about the extra tasks that will require more of their technical and IT knowledge (100).

Adoption of novel techniques of weed management in conventional farming can be driven due to ecological benefits, particularly the substantial decrease in the use of herbicides. Decrement in herbicide application leads to diverse ecosystem, supports beneficial organisms hence contribute to resilient agroecosystems. Reduction in costs of herbicides, an alleviation in yield loss and less occurrence of herbicide-resistant weed populations aid in the adoption of these technologies. Moreover, due to robotic weeding, consumption of fuel and carbon will be less and reduced soil compaction which will favour the ecological advantage (75).

Conclusion and Future Prospects

Novel techniques of weed management have the potential to lessen herbicide consumption while boosting sustainability in agriculture and environmental conservation. Both goals are attainable without hampering crop yield or increasing weeding expenses in the subsequent years. Hence, these novel techniques can be treated as an effective and ecofriendly way to attain sustainable development goals. Energy-directed weed control shows promising results and has gained global popularity with several industries manufacturing machines; although its applicability, effectiveness and risks need to be studied extensively. These technologies are still in the early phase of research and require more improvement before being introduced to the farmer's field on a large scale. Moreover, capacity building and support of farmers are necessary to get acclimatized to these technologies for the adoption and accomplishment of the purpose through front-line demonstration and on-farm testing.

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Authors' contributions

LSB carried out writing, including both the review and editing, as well as formulation of the original draft. SR has done the critical reviewing and editing along with conceptualization and supervision. SAF, VR & SM critically reviewed and gave suggestions. All authors read and approved the final manuscript.

Compliance with ethical standards

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