Review of the cutting edge technologies for weed control in field crops

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Abstract: In 21st century, the rapid increase in population and industrialization not only limits the per capita arable land for crop production but also limits the productive potential of soil and agricultural crops due to the negative impacts of anthropogenic climate change. Besides the abiotic factors of the environment, among biotic factors limiting productivity, weeds contribute the maximum. Due to various limitations in conventional weed control methods, integrated weed management (IWM) practices have evolved for effective weed management in agriculture. In this era of information and technological evolution, artificial intelligence is moving at a faster pace in every sector to address the issues of various dimensions. The use of deep learning, machine learning, and artificial neural networks in AI-enabled robots and unmanned aerial vehicles, along with multi- and hyper-spectral image sensors, make the tools capable enough for quick and efficient weed management for harnessing the ultimate productive potential of different fields crops. No doubt, the IWM practices designed for various crops in different countries in different ecologies have advantages over the individual and traditional approaches to weed control, but the use of these AI-enabled software and tools can save time, resources, money, and labor when used along with the best IWM method. Sensor-based weed identification, mapping, and automation can be done for precise and effective management of weed flora using these modern approaches, which will be environmentally friendly and have a broader scope for achieving global food security.

Keywords: artificial intelligence, food security, integrated weed management, machine learning, nano-herbicide
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1 Introduction

Weed infestations are a constant threat to agriculture, which is the backbone of the world's food production. The existence of weeds poses a significant threat to agricultural yield because they compete with crops for resources, including light, space, water, and nutrients[1]. As a result, this interference interferes with the development and growth of cultivated plants. Additionally, weeds interfere with crops' ability to grow uniformly, which can cause inconsistent crop maturity and complicate harvesting procedures[2,3]. In addition to competing for resources, some weed species are home to pests and illnesses and act as harbours for agricultural viruses that have the potential to destroy entire harvests[4]. The majority of weed research focuses on finding solutions that might mitigate the adverse effects of crop-weed competition. From some of the research, it has been reported that weed competition reduces yields in all major crops worldwide, including wheat (23%), cotton (36%), soybean (37%), maize (40%), rice (37%), and potato (30%). Thus, the most significant biological barrier preventing increased agricultural output is weeds[5]. Furthermore, weeds can reduce the effectiveness of manual and mechanical agricultural techniques, requiring more workforce and resources to eradicate them[6]. Weeds, therefore, have a significant negative economic impact, including decreased crop yields, higher production costs, and the possibility of lower-quality harvests[7].

Herbicides have traditionally served as the primary tool used in weed control, which has led to serious concerns about the environment's long-term sustainability and the safety of food production. Herbicide-resistant weed populations could arise from the careless use of herbicides, requiring the use of more robust and more hazardous herbicides for the environment[8]. Herbicide residues can also linger in water and soil systems, where they may have an impact on human health, aquatic life, non-target plants, and raw food items[9]. Given these difficulties, it is becoming increasingly necessary to adopt more accurate and environmentally friendly methods of managing weeds. This is precisely the area in which artificial intelligence (AI) techniques have become functional.

To effectively manage weeds, minimize adverse effects, and ensure agricultural prosperity, artificial intelligence and cutting-edge technologies must be used. By increasing efficacy, lowering chemical usage, and minimizing residues, artificial intelligence (AI) technology used in weed management seeks to mitigate the

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ecological effects associated with herbicides[10]. This strategy encourages more responsible and sustainable weed control practices in agriculture. AI techniques cover a wide range of technologies, including unmanned aerial vehicles, computer vision, machine learning, deep learning, and remote sensing. Each of these technologies has a unique capacity to address the intricacies of weed spread[11]. The field of weed identification is leading the way in advances in Artificial Neural Networks (ANN)-based Deep Learning (DL), an aspect of Machine Learning (ML)[12]. The use of AI in weed control has significant economic implications. AI aids in resource optimization, particularly in herbicide application and, more specifically, land and labour, by accurately recognizing and targeting weeds[13]. Moreover, robots have brought in a new era of mechanized weed control, providing farmers with a substitute for labour intensive manual labor. With the use of sophisticated sensors and actuators, robotic weeders can precisely navigate fields, minimizing crop damage while selectively pulling weeds[14]. These self-sufficient solutions lessen the physical strain on farmers while also lowering the dangers of environmental contamination and herbicide resistance[15]. Also, the Grey Level Co-occurrence Matrix (GLCM), which provides insights into image texture for better weed detection and classification, is a potential technique in weed management[16]. Through the quantification of pixel connections, GLCM improves the accuracy of weed recognition against complicated backdrops. This introduction addresses opportunities and limitations in the implementation of GLCM and examines its potential to revolutionize weed management tactics[17]. As a byproduct of nanotechnology, nano-herbicides present a revolutionary strategy for controlling weeds with the promise of increased efficacy and decreased environmental impact[18]. These formulations seek to enhance the distribution of herbicides, target specificity, and overall effectiveness by utilizing the unique qualities of nanoparticles[19,20].

Artificial intelligence (AI) and machine learning (ML), in addition to automation, have become formidable instruments in the weed management toolbox[21,22]. Innovations in machine learning, robotic weed eaters, and cutting-edge methods like GLCM and nano-herbicides are revolutionizing methods for sustainability and precision, which are essential for realizing the full potential of the world's agricultural resources[23]. AI-powered systems can optimize weed management tactics with previously unheard-of efficacy by sifting through enormous datasets and identifying complex patterns in crop-weed interactions[24]. These intelligent systems continuously improve their predictive models to maximize weed suppression while reducing the unintended consequences of herbicide use. They do this by adapting to changing environmental circumstances and developing weed populations using iterative learning algorithms[25]. Weed infestations pose a constant threat. Thus, creative and long-lasting weed management techniques are required[26,27]. While relying solely on conventional herbicides causes resistance and environmental issues, combining AI with cutting-edge technology holds promise[28]. Artificial intelligence (AI)-powered weed management systems optimize agricultural productivity while protecting the environment by reducing chemical usage, increasing efficacy, and minimizing environmental residues[29].

2 Literature review

Targeting journals that specialize in pertinent topics, a computerized literature search covering the years 2015 to 2024 was carried out across credible academic publishers, including Elsevier, MDPI, Frontiers, Springer Nature, Bio One, Taylor & Francis, Wiley and ACS. The articles were carefully chosen according to how well they addressed the topic of advanced weed management practices in field crops. With the use of multi- and hyper-spectral image sensors, deep learning, machine learning, and artificial neural networks in AI-enabled robots and unmanned aerial vehicles, the tools are capable of swift and effective weed management, allowing various field crops to reach their maximum productivity potential. Initially, 4713 items were identified in the Google database, later refined to 309 articles after removing duplicates. Further scrutiny led to the identification of 95 pertinent references, supplemented by 208 full-text articles. Sixty full-text articles were excluded based on specific criteria, resulting in 148 articles forming the study's database and serving as references. These comprised 67 papers from the Scopus database, 61 from the Web of Science database, 56 from NAAS, and 24 from other sources for the review (Figure 1).

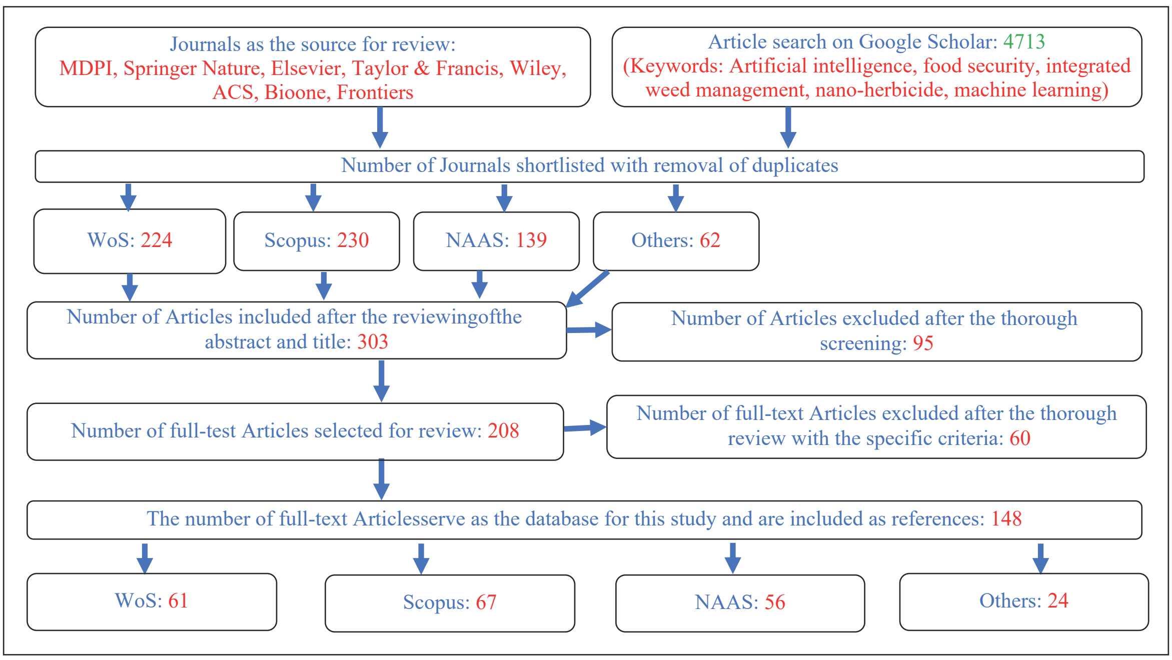

Figure 1 Methods for the selection of articles for review

3 Weed flora under major field crops

Weed infestation and flora are significantly driven by crop type, cropping system, weed seed bank, and crop management practices. They are also impacted mainly by crop rotation and the sequence in which the crops are seeded[30]. To increase crop yield, a crop sequence that can control the related weed flora or infestation is needed. Crop rotation and crop sequence diversification may aid in weed control and sustain soil fertility[31]. The physiological, morphological, and anatomical adaptability of wild species, including weeds, is a distinguishing characteristic that makes them more resilient to environmental stresses than agricultural species[32]. Jungle rice (*Echinochloa colona*), barnyard grass (*Echinochloa crus-galli*), purple nutsedge (*Cyperus rotundus*), rice flat sedge (*Cyperus iria*), rice umbrella plant (*Cyperus difformis*), and goosegrass (*Eleusine indica*) are the weed species causing economic concerns despite the wide variation in rice establishment[14]. Additionally, the sorghum-wheat farming system benefited the fat hen (*Chenopodium album*). In contrast, the rice-wheat cropping system preferred the common goosefoot (*Chenopodium* sp. L.), broadleaved dock (*Rumex obtusifolius*), and salt marsh (*Salicornia spp.*). The fallow-wheat cropping system also favoured salt marsh, broad-leaved dock, yellow sweet clover (*Melilotus officinalis*), rabbit foot grass (*Polypogon monspeliensis*), perennial sow thistle (*Sonchus arvensis*), corn spurry (*Spergula arvensis*), and bermuda grass (*Cynodon dactylon*)[33]. A rice-wheat cropping system has also reportedly been shown to encourage grassy weeds while suppressing broadleaved weeds[34]. In addition, weeds interact with the environment's other biological components, giving pests a place to hide out that might affect nearby crops, such as insects, fungi, and bacteria[35,36]. For instance, in crops like wheat (*Triticum aestivum* L.), oats, and barley (*Hordeum vulgare* L.), wild oats (*Avena fatua* L.) can harbour the etiological agents of the powdery mildew, Altamira (*Parthenium hysterophorus* L.) may serve as a secondary host of the common hairy caterpillar (*Diacrisia obliqua* Walk.)[37] and the root-knot *Meloidogyne graminicola* may live on *Cyperus rotundus*, which can facilitate its proliferation in the field[38]. The troublesome weeds found in black gram and green gram were *Cleome viscosa*, *Celosia argentea*, *Commelina benghalensis*, *Vicia sativa*, and *Triathema portulacastrum*[39]. The most prevalent weeds in chickpeas were *Anagallis arvensis*, *Cyperus rotundus*, *Polygonum plebejum*, *Phalaris minor*, *Chenopodium album*, and *Cyperus rotundus*[40]. In the winter, both irrigated and rainfed pulses include scarlet pimpernel (*Anagallis arvensis* L.), lamb's quarters (*Chenopodium album* L.), and *Fumaria parviflora* (Lam.)[41].

4 Reductions in yield caused by weeds in various crops

In current input-intensive agricultural systems, maximizing productivity by minimizing the negative impacts caused by biotic and abiotic variables is very crucial. Weeds are considered the most biological impediment to agricultural productivity in both industrialized and underdeveloped countries. A range of weed species, some of which may have significantly differing competitive capacities, nearly always contribute to the yield loss brought on by weeds[9]. In general, weeds, along with diseases (bacteria, fungi, etc.) and pests (rodents, insects, nematodes, birds, mites, etc.), provide crops with the most significant potential yield loss. More than 2.1×10^9 t of grain are produced globally at present. If weed causes a 10% overall yield loss, then 2×10^8 t of grain output will be lost altogether[13]. The output of grains would rise by 1×10^8 t, and this loss could be cut in half, which might help to end world hunger. Among the factors that influence the yield losses in crops brought on by weeds are weed type, weed emergence time, crop type, and weed density (Table 1). Weeds can cause a 100% yield loss if they are not managed[13]. According to Gharde et al.[9], weeds caused yield losses of 36% in groundnut (*Arachis hypogaea* L.), 31% in maize (*Zea mays* L.), 25% in soybean (*Glycine max* (L.) Merr.), and 19% in wheat (*Triticum aestivum* L.). Herbicides can control weeds up to a point, but subsequent weed flushes during the growing season due to the variable dormancy of weed seeds present in different layers of weed seed banks, which provides additional difficulties for farmers. Despite its detrimental impacts on the environment, weed control is incredibly challenging for marginal farmers due to the high cost of herbicides, their unavailability at the right time, and a lack of technical knowledge. Therefore, under an integrated weed management (IWM) strategy or with advanced technologies, it is necessary to integrate a wide range of approaches, including cultural, mechanical, and chemical methods[9], along with automation using AI tools and suitable sensors working efficiently with the inclusion of machine learning (ML) and deep learning (DL) algorithms.

5 Existing weed management practices

There are currently two different methods for controlling weeds in agricultural systems: one involves the widespread use of synthetic herbicides, and the other relies extensively on mechanical, physical, and ecological techniques[69]. However, this strategy has had a significant detrimental impact on the health of the environment, people, and animals. According to Lamichhane et al.[70], improper herbicide uses in agroecosystems result in the evolution of herbicide-resistant weeds, particularly those with multiple resistances, impacts on non-target species, the establishment of a replacement weed flora, as well as shifts in a weed population, all of which make herbicide-dependent cropping systems more vulnerable. The current goal of agriculture is to produce crops that are programmed, planned for quantity, and of high quality while protecting the environment. IWM will be used to manage weeds while reducing the use of herbicides and promoting sustainable and environmentally friendly agronomic practices[6]. Therefore, a good understanding of crop-weed competition dynamics, one of the most active areas in weed science research, is essential for an efficient IWM (Figure 2).

As the number of hazards from herbicides at higher doses increases and the availability of labor becomes a limiting factor in weed management, this tactic is gaining in popularity. Taking economics, labor availability, the environment, and other factors into account, an integrated strategy with advanced weed management will outperform the IWM technique[71].

6 Advanced weed management practices

Eliminating weeds is an essential aspect of raising the production of agriculture. The most popular weed management technique at the moment is large-scale herbicide spraying, although this affects the environment negatively[72]. It is, therefore, vital to establish a weeding strategy that uses fewer herbicides. To maximize crop output and minimize the environmental effects, precision agriculture uses technologies that integrate sensors, information systems, and management[73] may be employed. Currently, precision agriculture is used for a variety of agricultural

Table 1 Predominant weed flora in major field crops and reported yield loss

Name of the crop	Predominant weed flora			Yield loss/%	Reference
	Grass	Broad-leaved weed	Sedge		
Direct seeded rice	*Poa annua*, *Digitaria sanguinalis*, *Echinochloa colona*, *Eleusine indica*, *Dactyloctenium aegyptium*, and *Panicum repens*	*Ludwigia parviflora*, *Melochia corchorifolia*, *Alternanthera philoxeroides*, *Alternanthera sessilis*, *Amaranthus viridis*, *Borreria hispida*, *Cassia* sp., *Euphorbia geniculata*, *Ipomoea alba*, *Mollugo disticha*, *Ageratum conyzoides*, *Portulaca oleracea*, and *Phyllanthus niruri*	*Cyperus iria*, *Cyperus Difformis*	50%-91%	[42-44]
Kharif Transplanted Rice	*Echinochloa colona*, *Digitaria sanguinalis*, *Paspalum distichium*, *Leptochloa chinensis*	*Ludwigia parviflora*, *Marselia quadrifolia*, *Alternanthera sessilis*, *Eclipta alba*, *Trianthema portulacastrum* *Commelina nudiflora*, *Hydrolea zeylanica*, *Monochorina vaginalis*	*Cyperus iria* and *Fimbristylis miliacea*	30%-45%	[45-48]
Summer transplanted Rice	*Echinochloa crus-galli*, *Echinochloa glabrescens*, *Panicum* sp.	*Marsilea minuta*, *Jussiaea repens*, *Alternanthera sessilis*, *A. philoxeroides*, and *Commelina* sp.	*Cyperus difformis* and *Cyperus iria*	20%-40%	[49]
Wheat	*Phalaris minor*, *Cyanodon dactylon*	*Trifolium fragiferum*, *Chenopodium album*, *Vicia sativa*, *Solanum nigrum*, *Rumex dentatus*	*Cyperus rotundus*	25%-40%	[50-52]
Maize	*Eleusine indica*, *Dactyloctenium aegyptium*, *Digitaria sanguinalis*, *Setaria glauca*, *Eragrostis major*	*Trianthema portulacastrum*, *Commelina benghalensis*	*Cyperus compressus*, *Cyperus rotundus*	27%-60%	[53-55]
Black gram	*Digitaria sanguinalis*	*Ludwigia parviflora*, *Croton bonplandianum Parthenium hysterophorus*, *Trianthema monogyna*, *Phyllanthus niruri*, *Desmodium triflorum*	*Cyperus iria*	27%-64%	[56,57]
Green gram	*Poa annua* and *Digitaria sanguinalis*	*Melochia corchorifolia*, *Aeschynomene afraspera*, *Cleome viscosa*, *Portulaca oleracea*, *Cassia tora*, *Grangea maderaspatana*		46%-85%	[58,59]
Mustard	*Digitaria sanguinalis*, *Cynodon dactylon*	*Oldenlandia corymbose*, *Trianthema portulacastrum*, *Phyllanthus fraternus*, *Chenopodium album*, *Amaranthus viridis*, *Anagallis arvensis*, *Cleome viscosa*	*Cyperus rotundus*	28%-50%	[60,61]
Sesame	*Echinochloa colona*, *Echinochloa crus-galli*, *Cynodon dactylon*, *Agropyron repens*	*Trianthema portulacastrum*, *Eclipta alba*, *Solanum nigrum*, *Achyranthes aspera*, *Abutilon indicum*, *Acalypha indica*, *Ageratum conyzoides*, *Commelina benghalensis*, *Cyanotis sps*, *Parthenium hysterophorus*, *Phyllanthus maderaspatensis*, *Portulaca oleracea*, *Tribulus terrestris*, and *Xanthium strumarium*	*Cyperus rotundus*	50%-75%	[60,62,63]
Lentil	*Digitaria sanguinalis*, *Cynodon dactylon*	*Croton bonplandianum*, *Gnaphalium indicum*, *Medicago denticulata*, *Anagallis arvensis*, *Spergula arvensis*, *Rumex dentatus*		30%-65%	[64,65]
Cotton	*Chloris barbata*, *Cynodon dactylon*, *Dinebra arabica*, *Eleusine aegyptiaca*, *Panicum repens*, *Pennisetum cenchroides*	*Abutilon indicum*, *Amaranthus viridis*, *Argemone mexicana*, *Boerhaavia diffusa*, *Corchorus trilocularis*, *Celosia argentea*, *Datura metal*, *Digera arvensis*, *Euphorbia hirta*, *Gynandropis pentaphylla*, *Parthenium hysterophorus*, *Phyllanthus niruri*, *Portulaca oleracea*, *Trianthema portulacastrum*, and *Tridax procumbens*	*Cyperus rotundus*	50%-85%	[66,67]
Soyabean	*Digitaria sanguinalis*, *Cynodon dactylon*, *Sorghum halepense*, *Dicanthium annualatum*, and *Eleusine indica*	*Eclipta alba*, *Phyllanthus niruri*, *Physalis minima*, *Leucas aspera*, *Digera arvensis*, and *Croton sparsiflorus*	*Cyperus rotundus*, *Cyperus diformis*, and *Fimbristylis milliaceae*	84%	[68]

processes, such as pest management, fertilization, irrigation, sowing[74], and harvesting[36]. Because of technological advancements in the last ten years in the fields of robots, sensors, computer hardware, nanotechnology, and unmanned vehicle systems, precision agriculture has advanced quickly[75]. These advancements may enable the precise identification of the weeds in the field.

7 Artificial Intelligence (AI)

Artificial intelligence (AI)-enhanced technology is currently being used in agriculture, with significant enhancements in crop productivity and weed identification[76]. Traditional approaches of weed control are not sustainable in long run due to involvement of higher input cost and lowered effectiveness of the process. Agricultural organizations, farmers, and research institutions are now implementing measures to ensure precision and improve accuracy in weed detection, and many technical tools and gadgets are used in conjunction with artificial intelligence concepts. The best method for preventing seed spread is early weed control[23]. In places with dense vegetation, AI-based approaches, as opposed to shape-based machine vision, may successfully identify weeds at this stage and tell them apart from agricultural crops[77]. The adoption of AI-based weed control, intelligent systems, and robots are now restricted to early adopters because the range of plants that can be recognized based on spectral features is limited or because the precision based on species or geocoordinates is insufficient to safeguard the crop plant[24]. AI is employed in a robotic system for weed control in a variety of ways, including operation control, trajectory planning, data management, weed dispersion prediction model, data sharing, and more[23]. AI is also used in differentiating processes (image processing) in the system (Figure 3). It significantly reduces the usage of herbicides, paving the way for sustainable agriculture, environmental protection, consumer health improvement, and lowing production costs. It also has a significant impact on how successfully herbicide resistance is managed and controlled[23]. However, it has the benefit of being able to respond quickly; it enables real-time robotic weed control devices to operate Eli-Chukwu[78], making it a solution to the problems facing agriculture in the future (Figure 4).

8 Robotics

Agriculture is entering a new era of sustainability, efficiency, and accuracy with the use of robotics in weed control. Robotics is very necessary to build a weeding strategy that uses fewer pesticides. Since early weed identification and management are

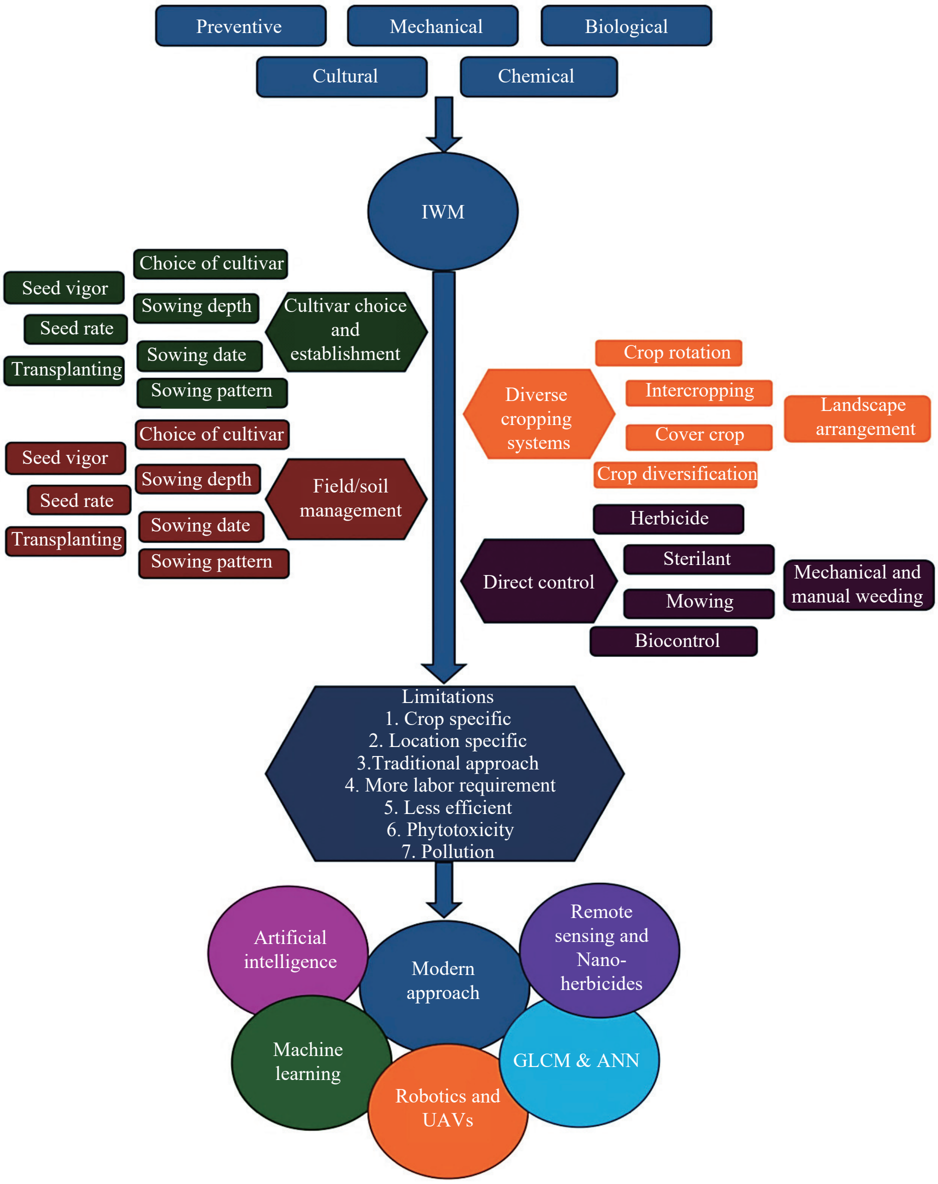

Figure 2 Existing and modern approaches to weed management

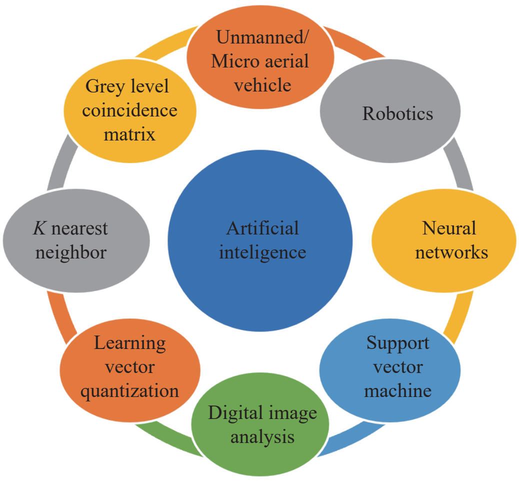

Figure 3 Artificial intelligence/machine learning for advanced weed management

crucial, current weed robot designs are based on real-time image detection using multi- and hyper- spectral sensors. Traditional weed management techniques are being revolutionized by robotic technology, which ranges from self-driving cars to robotic arms with sophisticated sensors. Robotic weed control application has provided satisfactory outcomes, lowering the usage of herbicides to as little as 5%-10% in compared with blanket spraying[79]. Robotics has a wide range of implications for managing weeds in many areas of agricultural operations. The advent of fleets of autonomous robots capable of carrying out a variety of agricultural tasks has prompted years of research on the whole robotization of the agricultural ecosystem[80].

Groups of small, inexpensive robots can be utilized more efficiently and affordably in organic farming and row crops with high value and low controlling weeds thresholds. For accurate spot spraying in specific crops, a number of spraying robot prototypes have been built and studied[81]. A visual system that can identify and locate the crop's location is necessary for the development of an autonomous weeding machine. Such a vision system needs to be able to identify the precise location of the plant stem and protect it while controlling weeds. Induction of visual system in robots can efficiently remove the broad-leaved weeds in cereal field by taking and analyzing near-ground images to identify the weeds[82,83].

They obtained up to 96% eliminating weeds and more than 80% accurate picture classification with only crop loss of 10%. These consist of weed-specific spraying systems and imaging

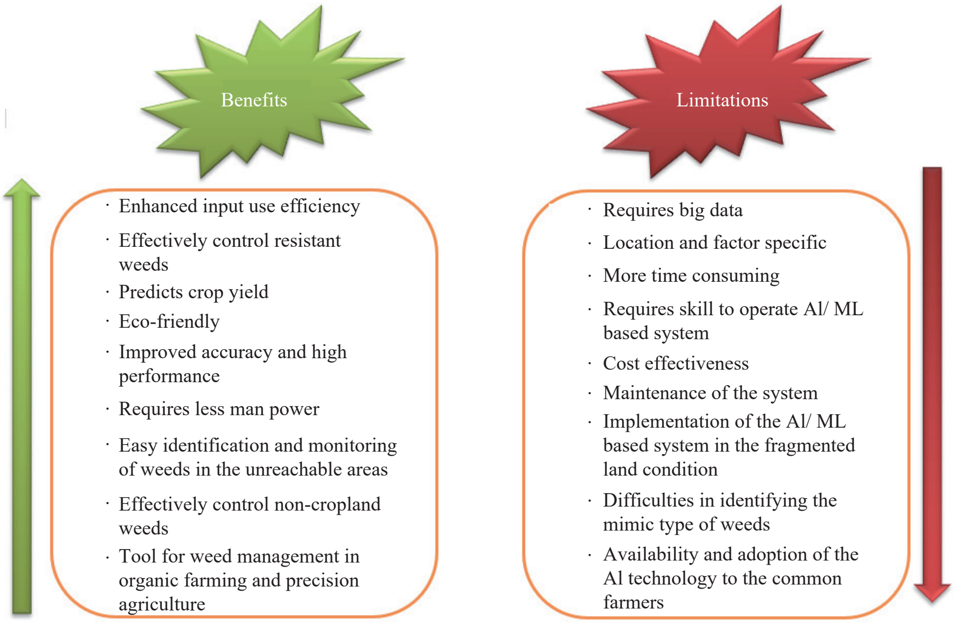

Figure 4 Benefits and constraints of using AI/ML in weed management

technologies that can discriminate between crops and weeds. Several robots have been designed for physical weed management employing hoeing blades, laser, high voltage, and flame in addition to these spraying robots. They distinguish in the intra-row area between the crop and the weeds and target specific weeds[41]. Using the texture properties of weed species, weed species may be distinguished with 93% and 85% classification accuracy for grass and broadleaf, respectively. Grasses and broadleaved weeds were identified using textural image analysis[84]. The effectiveness of robotic cultivators in reducing the need for manual weeding may be demonstrated by a comparison of robotic weed control and manual weeding[85] (Figure 5). As these robots become more affordable and technologically advanced, their ability to remove weeds will also increase.

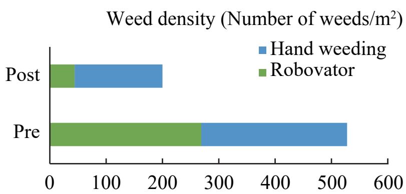

Figure 5 Pre-and post- weeding comparison between robovator and hand weeding[85]

9 Remote sensing

Mapping crops or weeds is one of the most effective ways to manage crops and weeds in agroecosystems to maximize productivity. Because weed populations vary geographically across crop types, mapping weed infestations in annual crops has consequences for managing weeds differently at each site, using herbicides specifically where needed, and studying weed ecology in general. In order to assess the biomass, chlorophyll, and nitrogen (N) contents at a discrete moment, remote sensing techniques like thermal infrared (IR) sensors and light detection and ranging (LiDAR) technology have shown astounding results in monitoring vegetation canopy temperatures and heights[86]. In the agricultural sector, remote sensing has also been widely used to map and identify weeds[87]. A variety of disciplines, including spectroscopy, optics, computers, photography, satellite launch, electronics, and communication, are combined in the multidisciplinary science of remote sensing systems (Figure 6). In remote sensing photography, the digital reflectance value at each pixel results from the integration of spectral contributions from each scene of the element; for example, the scene component of soil, shadow, and crop species are used for weed mapping[88].

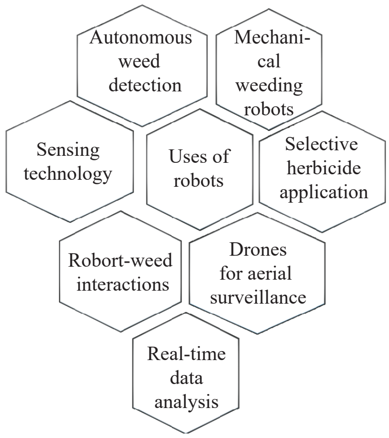

Figure 6 Applications of robotics in advanced weed management

10 Agricultural use of multispectral and hyperspectral remote sensing imagery

Precision agricultural farming technology advances, including variable rate equipment, GPS, and GIS, provide the means to use data from multi-spectral images to manage issues[89]. Multi-spectral images are produced by sensors that detect reflected energy within many distinct bands of the electromagnetic spectrum[23]. Multispectral cameras and superior imaging capabilities are crucial in transforming weed control techniques. These cameras, which use a variety of electromagnetic spectrums or wavelengths to record information beyond human sight, enable detailed examination of vegetation. Multispectral cameras are very good at identifying differences in the reflectance and absorption of light by various plants, which is helpful in managing weeds. Multispectral cameras allow for the construction of precise maps of vegetation by gathering data in certain bands, such as red, green, blue, and nearinfrared. These maps make it easier to precisely identify and map weed infestations since they are frequently complemented with indexes such as the Normalized Difference Vegetation Index (NDVI). Different plants have different spectral signatures that help differentiate undesired weeds from crops[90].

Multispectral imaging is used for more than just identification; it also informs focused intervention tactics. The development of multi-sensor information fusion in agriculture must align with the needs of modern agricultural machinery as it is an advanced, multidisciplinary technology[91]. Using this technique, farmers may produce prescription maps for targeted herbicide application, maximizing resource efficiency and reducing the environmental effects. Furthermore, multispectral cameras aid in the monitoring of crops' general health by enabling the early identification of stress or disease. Multispectral cameras provide farmers with relevant information when combined with precision agriculture technology like GPS and GIS, encouraging a more effective and sustainable approach to weed control in agriculture[90]. Many low-cost, high-performance innovative sensors are now being developed, examples include the StereoLabs ZED stereo camera and the Intel D435 stereo camera. These cameras made up of two camera modules, imitate human stereo vision, open the way to the potential of target recognition for agricultural machines based on depth and stereo vision[89,91]. Multi-sensor information fusion has become essential for intelligent robots in artificial intelligence due to developments in computer technology, sensor functionality, and information fusion technology.

This method maximizes the performance of agricultural machinery environmental perception systems and improves the accuracy of environmental perception. As a result, it effectively promotes the growth of intelligence and informatization within the agricultural machinery sector by guaranteeing the stability and safety of unmanned agricultural machinery during operation[91].

Target detection and classification are the main tasks of hyperspectral remote sensing imagery, which differs from multispectral photography due to its high-resolution and high-interest targets[92]. Moreover, hyperspectral data aids in understanding the physiological status of vegetation, providing insights into plant stress, nutrient deficiencies, and overall health. Early detection of such indicators allows for proactive weed management strategies, minimizing the impact of invasive species on crop yields. In order to detect weeds using hyperspectral remote sensing, Yang et al.[93] studied image segmentation between crop and weed in a soybean field. They found that this method could discriminate between soil and plant with a high degree of accuracy (99.9%).

Satellites or unmanned aircraft are used in remote sensing to collect data. Large-scale crop yield monitoring and area surveying are both ideal applications for satellite-based remote sensing[94]. Small-area assessments using satellite images are imprecise, particularly when it comes to spatial distribution, weed detection, and pesticide harm assessments (Table 2). High-resolution imaging is required for these operations, which is often acquired by closer inspections using human or unmanned aircraft or ground vehicles[95].

11 Unmanned aerial vehicle systems

The usage of unmanned aerial vehicles (UAVs) is presently one of the most successful precision agricultural technologies[108]. Unmanned Vehicle Systems are movable aerial (UAVs) or terrestrial (UTV) platforms that offer a variety of benefits for carrying out and overseeing agricultural tasks[109]. Drone technology has improved at a faster pace recently. Drone application research is frequently carried out in agriculture for a variety of objectives due to the improved flying efficiency of lower-priced consumer drones[23]. According to Hassanein and El-Sheimy[110], the key benefits of UAVs over UTVs are their quicker monitoring/surveying times and ability to navigate well around obstacles, which is essential while operating between crop rows. UAVs may fly over a large area of land in a short period, collecting the photographic data needed to identify weed areas[109]. The primary technologies used for weed patch detection are Red-Green-Blue (RGB), Multispectral, and Hyperspectral cameras, according to a thorough examination of the literature on weed identification by UAVs.

Table 2 Weed patches to be identified using various kinds of cameras

Type of camera	Crop	Weed	Result	References
RGB camera	*Triticum* spp.	*Cirsium arvense*	Discriminate crop vs weeds	[96]
	Hordeum vulgare	*Cirsium arvense*		[97,98]
Multispectral camera	*Zea mays*	*Amaranthus* spp., *Sorghum halepense*, *Chenopodium album*	Discriminate crop vs weeds	[99,100]
	Triticum durum	*Phalaris canariensis, Avena sterilis*		[101]
	Beta vulgaris	*Cirsium arvense*		[102]
Hyperspectral camera	*Triticum* spp., *Zea mays*, *Hordeum vulgare*	*Conyza canadensis, Chenopodium album*	Discriminate herbicide-resistant weeds	[103,104]
	Sorghum sp.	*Amaranthus macrocapus,Echinochloa colona*, *Cyperus rotundus*, *Malva* sp.	Discriminate crop vs weeds	[105]
Hyperspectral camera+Multispectral camera	*Triticum durum*	*Avena fatua*, *Phalaris canariensis*	Discriminate crop vs weeds	[106]
	Cicer arietinum	*Cirsium arvense*	Discriminate crop vs weeds	[101]
RGB camera+Multispectral camera	*Glycine max*	*Amaranthus palmeri*, *Echinochloa crusgalli*, *Digitaria sanguinalis*	Assesment of crop injury from dicamba	[107]
	Helianthus annus	*Amaranthus blitoides, Sinapis arvensis*, *Chenopodium album*	Discriminate crop vs weeds	[106]

Using an automated object-based image analysis (OBIA) framework, the quadcopter UAV model md4-1000, fitted with an RGB or multispectral camera and a global positioning system (GPS), is used to map and identify weeds, crop rows, and bare soil[106]. Before agricultural harvest, RGB cameras can identify green weeds such as *Cirsium arvense* in cereals. When *C. arvense* was prevalent, it accurately detected the categorization of 17%-92% of patches under different environmental conditions[96]. Adjusting dosages to the measured level of weed infestation promotes the decrease of herbicide treatments through automatically operating weed mapping rules. Drone-based spraying has a significant influence on weed control; it suppresses 98% of bedstraw (*Galium aparine*) and Japanese foxtail plants in wheat crops. When using pre-emergence (PE) spraying, areas with higher soil moisture content and lower straw content may observe a 98%-100% weed control effectiveness from the drone. The application of 70% metribuzin at a rate of 0.175 kg a.i./hm^2 in wheat fields using a drone (PoE) and knapsack sprayer (PE) produces the lowest dry weight of monocot and dicot weeds among the various treatments[111]. This integrated strategy is effective in managing weeds after a weed-free treatment, as evidenced by its maximum weed control effectiveness of 74.82% and minimum weed index of 2.78%[112].

UAV testing has less volume and more acuteness than traditional land procedures, it may spray spot or band spray and produce a more continuous vertical droplet coverage, which is advantageous for drift control and reduction[113]. More flexibility and systematization are features of UAV spraying, which boasts a 60-fold efficiency gain over knapsack and boom sprayer approaches[114,115]. The effectiveness of weed control in soybean crops, such as a comparison of boom, drone, and backpack sprayer techniques, now shows the various sprayers' relative operational efficiency, measured as the ratio of the sprayed area to the spraying time (Figure 7). It also offers information on the typical amount of time needed to finish spraying one hectare of agricultural land[116]. Drone technology has revolutionized advanced agriculture with its application to weed detection and pesticide spraying in contemporary fields. By using camera-equipped drones, weed identification efficiency is increased while also allowing for a more systematic and adaptable approach. This results in an astounding 60-fold gain in total operating efficiency when compared to previous approaches. The effectiveness of this airborne spraying method is highlighted by the novel "downwash" effect produced by drone rotors, which further increases the accuracy of herbicide deposition in specified regions[114].

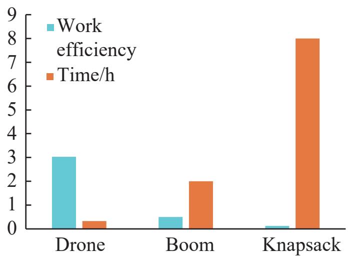

Figure 7 Comparative illustration of the work efficiency and Time/h for the weed management of soybeans using a knapsack, boom, and drone sprayer[114]

12 Neural networks

Artificial neural networks (ANNs) are becoming more potent instruments in the field of advanced weed management, providing creative answers to the problems related to weed control in agriculture. Inspired by the architecture and operation of the human brain, ANNs are computational models that can recognize intricate patterns and forecast outcomes based on input data. ANNs are used in agriculture, especially for enhanced weed management, to improve decision-making, optimize weed control tactics, and support productive and sustainable agricultural practices[117]. Weed species identification is a significant use of ANNs in proactive weed control. ANNs may be taught to identify and categorize various weed species reliably by utilizing image or sensor data in collaboration with the machine learning (ML) and deep learning (DL) concepts[118]. This feature helps farmers to use focused and targeted weed management strategies, maximizing resource utilization and reducing damage to non-target plants. ANNs enhance their accuracy in weed species identification through ongoing learning and adaptation, which helps to create accurate and successful management plans.

A common deep learning model (DL) used for image identification, video analysis, and natural language processing is the convolutional neural network (CNN)[119]. According to various research, deep convolutional neural networks (CNNs) are effective ways to address the shortcomings of manually generated characteristics when it comes to seed, crop, and weed classification[120]. DL has made significant strides in the past few years in the classification and segmentation of remote sensing data for various applications[121]. When it comes to weed recognition and detection, DL is excellent. When compared to conventional image processing techniques, DL reduces recognition time and ensures accuracy by doing away with the requirement for laborious and ineffective manual feature extraction and just needs the input picture to be cropped to an appropriate size for target detection[122]. Because CNNs can extract and learn feature representation directly from large datasets, they are becoming a more and more preferred technique for remote sensing problems in contrast to traditional machine learning (ML) methods[123]. Large learning capacities are made possible by this, leading to improved accuracy and performance[124]. According to Dyrmann et al.[125], convolutional CNN was used to categorize a group of 22 weed species. A classification accuracy of 82.4% to 88.2% was attained in this investigation. In a similar study, 17 different weed species were identified and categorized in a maize field by Dyrmann et al.[126]. With a total accuracy of 87%, a CNN was utilized to categorize the weed species once they were discovered. Sharpe et al.[127] spray on goosegrass (*Eleusine indica* L.) in greenhouses at the 5-leaf stage using CNN in situ conditions for weed identification. With a mean Average Precision (mAP of 0.9533 for monocotyledonous weeds (*Solanum nigrum* L. and *Portulaca oleracea* L.) and a mAP of 0.9492 for dicotyledonous weeds (*Cyperus rotundus* L., *Echinochloa crus-galli* L., and *Setaria verticillata* L.), RetinaNet has shown remarkable performance in classifying two significant weed groups. The outcomes of discrimination against species that belong to the same family have much promise for the identification of herbicide-resistant species[128]. This object recognition neural network-based approach to weed species detection shows promise for both selective control by distinct weed species and selective control of weeds relative to crops. According to Hu et al.[119] the Mask R-CNN network may be used for a variety of agricultural applications, including as weed identification in oilseed and maize rape fields, as well as crop and weed recognition and weed localization in motorised weeding robots. To accomplish accurate crop and weed segmentation, they have employed ResNet-50, ResNet-101, VGG16, and SegNet as feature extraction networks. SVM is one of the machine learning classifiers that oil seed rape fields utilise to increase the accuracy of picture segmentation. Using SegNet, which is based on ResNet-50, helps speed up the pixel labelling procedure. Robots that gather information from farms have employed the enhanced Res-UNet model for high-precision picture segmentation of weed and sugar beetroot data.

13 Grey level Co-occurrence matrix (GLCM)

One texture analysis technique that is often used in computer vision and image processing is the Grey Level Co-occurrence Matrix (GLCM). Even though it might not be directly related to weed control, it might be used in this sector for things like classifying and detecting weeds. GLCM may be applied to image analysis methods for weed management to extract texture information from images taken in agricultural fields. Then, various plant kinds, including weeds, may be recognized and categorized using these textural properties. Through the examination of the spatial correlations between pixel intensity values in a picture, GLCM may detect minute alterations in texture that could potentially signify the existence of weeds or more vegetation[16].

Since the texture of veins in leaves and leaf surface roughness varies, texture features (representing the spatial distribution of pixels) have recently been demonstrated to be effective in differentiating crops from weeds[16]. GLCM texture operators are the most often reported texture operators for plant discrimination. An improved GLCM was employed by Tang et al.[129] Chowdhury et al.[130] combined texture information with colour to extract feature data to identify roadside weeds. This resulted in good identification and classification results. The correlation of grey values between pixels at a given image space position was represented by the local information of the picture, which was employed by GLCM. Nevertheless, it is unable to utilize the image's global information[131].

The method for managing and identifying weeds using GLCM is shown in this flowchart. Agricultural field photos are first acquired, and then preprocessing operations like contrast enhancement and noise reduction are performed. The preprocessed photos are then used to compute the GLCM and extract texture characteristics. Weed identification and categorization are based on these textural properties. Mapping and distribution studies are carried out based on the discovered weed areas (Figure 8).

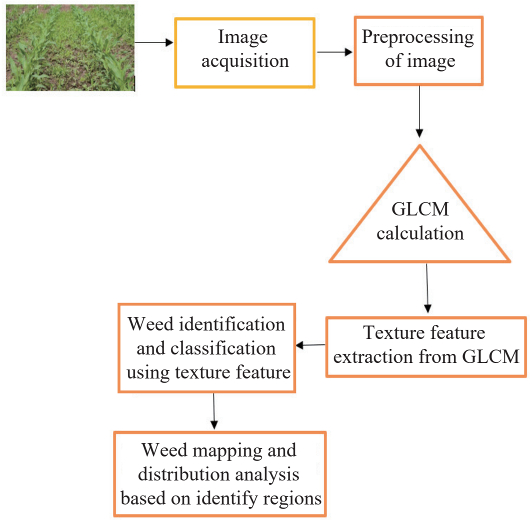

Figure 8 Flow chart for Grey-Level Co-occurrence Matrix (GLCM) for weed identification

14 Nano-herbicides

Utilizing nanotechnology to maximize herbicide delivery, effectiveness, and environmental impact, nano-formulation is a cutting-edge method in advanced weed control. With its creative answers to problems related to the administration of traditional herbicides, this new sector has the potential to transform weed management in agriculture completely. The nano-herbicides are different based on their formulation and mechanism of action (Figure 9). Herbicides with nano-formulations have better solubility and bioavailability, which is a significant benefit. The limited solubility of several herbicides in water presents difficulties that restrict their efficacy. These herbicides can be transported by nanoparticles, which will increase their solubility and improve their dispersion over weed surfaces. Because of the improved effectiveness resulting from this enhanced bioavailability, weed control is possible even at lower doses of active substances. Some examples of nano-enabled herbicides for weed control can be listed in Table 3.

Typically, herbicides are applied via foliar spray, which does not completely eradicate them, particularly for perennial weeds such as *Solanum elaeagnifolium*, *Cynodan dactylon*, and *Cyperus* sp. However, these nano herbicides eliminate the function and structure of the plant-specific chloroplast, prevent lipid biosynthesis, obstruct cell division by obstructing the mitotic cycle, or inhibit the growth of the plants[143]. The nanoherbicides have more adhesive capacity,

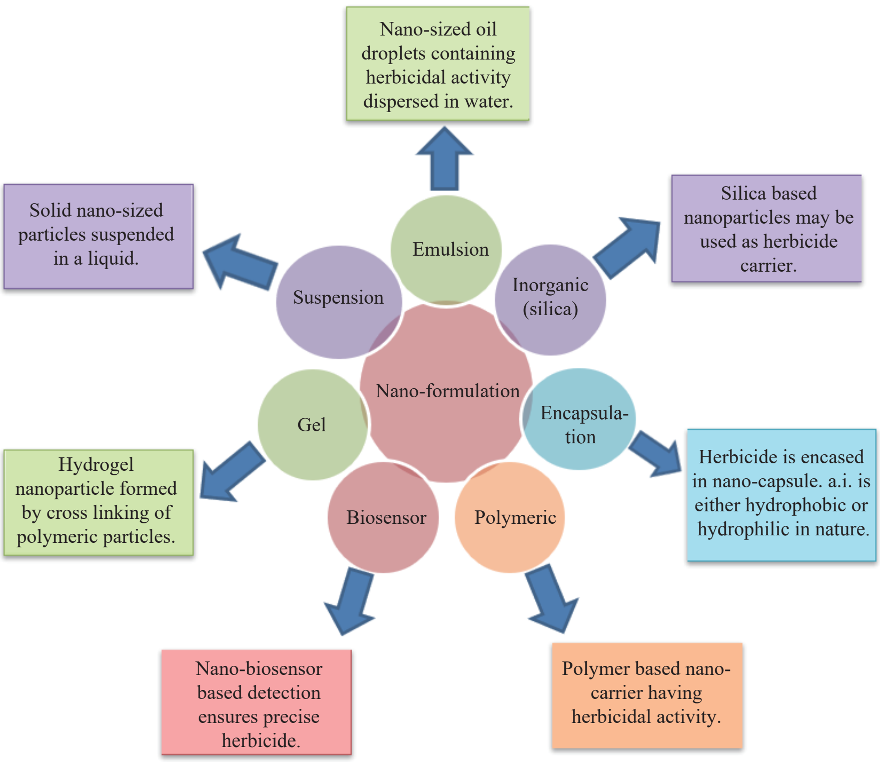

Figure 9 Types of nano-formulation for weed control

Table 3 Some examples of nano-enabled herbicides for weed control

Nanoherbicides	Plant	Findings	References
Nanoemulsion containing glyphosate	*Eleusine indica* (L.)	Size<200 nm; Good biological effectiveness. It is made up of tiny glyphosate droplets that are disseminated in water with the help of stabilisers and surfactants, improving weed target absorption, penetration, and coverage.	[132]
	Asystasia gangetica (L.), *Diodia ocymifolia*, and *Paspalum conjugatum*	Decreased dose and enhanced plant absorption of herbicides.	[133]
Biochar-2,4-D	*Zea mays* L., *Brassica* sp.	The non-target plant was not toxically affected by the nanoformulation. On the other hand, Brassica sp. was eradicated by it, and its herbicidal activity increased. The method demonstrated strong herbicidal effectiveness and a continuous release for around 26 d.	[134,135]
Microemulsion of pretilachor	*Echinochloa crus-galli*	The nanoherbicide enhanced the herbicidal action. It utilises a stable microemulsion system to enhance the delivery and penetration of pretilachor herbicide.	[55]
Nano-hydrogel_ glyphosate	*Oryza sativa* L.; Weeds	The herbicidal activity was enhanced, and the effect on non-target species was decreased using nano herbicides.	[136]
Microemulsion_TM	*Convolvulus arvensis* L.	At low levels of a.i., the nanoformulation shows herbicidal action.	[137]
Nanoemulsion_palm oil and Parthenium hysterophorus L. crude extract	*Diodia ocymifolia*	Reduction in seed germination as a result of small particles.	[138]
PCL_Metribuzin NPs	*Ipomoea grandifolia*	Deliver it to target sites for weed management. When compared to conventional formulations, controlled release, higher solubility, increased stability, and less environmental effect are all present.	[139]
Diquat dibromide@mesoporous silica nanoparticles-SO3	*Datura stramonium* L.	Improved stability, controlled release, and potentially enhanced herbicidal activity.	[140]
Clay-maroquin	*Brassica oleracea* var. botrytis L.	It increases the efficiency and durability of herbicides used to reduce weeds by using clay as a carrier to boost herbicide adherence to plant surfaces and soil particles.	[141]
pH-responsively controlled-release nanopesticide@ Fe3O4 NPs_CS	*Cynodon dactylon* L.	It is a novel formulation designed for targeted pesticide delivery.	[142]

longer contact time, and better spread on the leaves, and they are able to control the release of ions or biomolecules[144,145]. The inclusion of nanomaterials in herbicide formulations will increase the herbicide's absorption and distribution by plants, increase the herbicide's adsorption on clay particles to prevent runoff and possible groundwater pollution or shield the herbicide from environmental hazards, increase the residual activity due to UV or microbial destruction[95]. Micro-emulsions (ME) are nano-formulations that have proven commercially successful so far. One sort of nanotechnology used in pesticide formulation may be seen in these particles, which are generally 10 to 50 nm in size[146]. According to Bhaskar et al.[143], Dhanpal et al.[147], a target-specific herbicide molecule enclosed in a nanoparticle aims for a particular receptor in the target weeds' roots. When the herbicide molecule enters the system, it moves to regions that prevent the breakdown of food conserves in the root system, starving the specific weed plant to death. Nano-encapsulated herbicides in rainfed agriculture will spread after they have received enough moisture so that the instantaneous release of new herbicide molecules would destroy the weed seeds upon receipt of rain[148]. The use of nano-formulations in agriculture is a novel way to improve weed control. These formulations solve long-standing concerns with herbicide application by using nanotechnology, providing improved effectiveness, tailored delivery, less environmental impact, and potential fixes for resistance problems. Nano-formulations have the potential to change the weed control game as research advances by giving farmers efficient, sustainable methods to maximize crop output while reducing environmental damage.

15 Future scope

Weeds, being the most vulnerable pest in agricultural ecosystem, also regarded as "silent killer", its management is an imperative and most daunting task for farmers. The scientific community has done many advances in weed management research i.e., crop specific IWM, herbicide tolerant crops, UAV based application, etc. These technological advances even though have increased the potential of weed control in field, still the adaptation is limited to large and progressive farmers. Inclusion of advanced tools i.e., ML, AI, remote sensing, artificial neural network-based solutions not only help the existing technology perform more precisely but also reduce the input use and improve the produce and quality of crops. Climate change has tremendous negative impacts on agriculture and weed management and leads to development herbicide resistant biotypes and weed flora shift. The use of advanced AI and ML programming will help us to understand the complex system of crop-weed dynamics in better way under various soil and climatic condition in different crop management systems. This will create a sustainable, ecological and economic aspect of weed management in the long run. The feasibility and practical utility of these advanced tools and techniques is yet to be explored. Though several researches are being conducted worldwide based on these advanced tools and programming, their viability in the farmer's field needs to be assessed in terms of handling and economic consideration, as most of the farmers have poor economic backgrounds and low technological soundness.

16 Conclusions

The future of weed control and management in agriculture looks increasingly technological and sustainable. Emerging tools like robots, drones, sensors, AI, and advanced chemistry promise ever-improving efficiency, precision, and environmental stewardship. As sensor and imaging technologies continue to advance, they will provide unprecedented views of crop and weed distributions, even revealing indicators of plant health and stress at the individual level. Paired with geospatial data and machine learning, this will allow prescription maps and tailored management plans tuned to localised conditions across fields and regions. The falling costs and advancing capabilities of robotic weeders will drive rapid adoption as these autonomous machines alleviate the need for manual labour and chemical interventions. Computer vision and AI will enable robotic platforms to differentiate crops from weeds with increasing accuracy, facilitating efficient mechanical removal without herbicides. Chemical options will also continue improving in precision and environmental profile through innovations like nano-herbicides. More targeted formulations and delivery methods will enhance efficacy while reducing dosage rates and off-target movement. Importantly, these tools show the most promise when integrated into intelligent systems, not when used in isolation. Combining cutting-edge chemistry, mechanical intervention, and AI-enabled decision support systems will push agriculture toward sustainability. The outlook is bright for both technological innovation and environmental stewardship in weed control. Farmers now have an expanding toolkit to create tailored, precise, efficient and sustainable crop management plans. The fusion of advances in sensing, data science and mechanical solutions will shape the future of agriculture.

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