Front. Agr. Sci. Eng. 2025, 12(2): 288–307

REVIEW

Advancing agriculture with machine learning: a new frontier in weed management

Mohammad MEHDIZADEH (✉)[1,2], Duraid K. A. AL-TAEY[3], Anahita OMIDI[4], Aljanabi Hadi Yasir ABBOOD[5], Shavan ASKAR[6], Soxibjon TOPILDIYEV[7], Harikumar PALLATHADKA[8], Renas Rajab ASAAD[9]

1 Department of Agronomy and Plant Breeding, Faculty of Agriculture and Natural Resources, University of Mohaghegh Ardabili, 5619913131, Ardabil, Iran.
2 Ilam Science and Technology Park, 6939177157, Ilam, Iran.
3 Department of Horticulture, College of Agriculture, University of Al-Qasim Green, 00964 Babylon, Iraq.
4 Department of GIS and Remote Sensing, Faculty of Geography, University of Tehran, 1417935840, Tehran, Iran.
5 Medical Laboratories Techniques Department, Al-Mustaqbal University College, 51001 Hillah, Iraq.
6 Erbil polytechnic university, Technical engineering college, information system engineering department, 44001 Erbil, Iraq.
7 Department of Fundamental Economics, Tashkent State University of Economics, 100066, Tashkent, Uzbekistan.
8 Manipur International University, Manipur 795140, Imphal, India.
9 Department of Computer Science, Nawroz University, PO BOX 77, Duhok, Iraq.

KEYWORDS

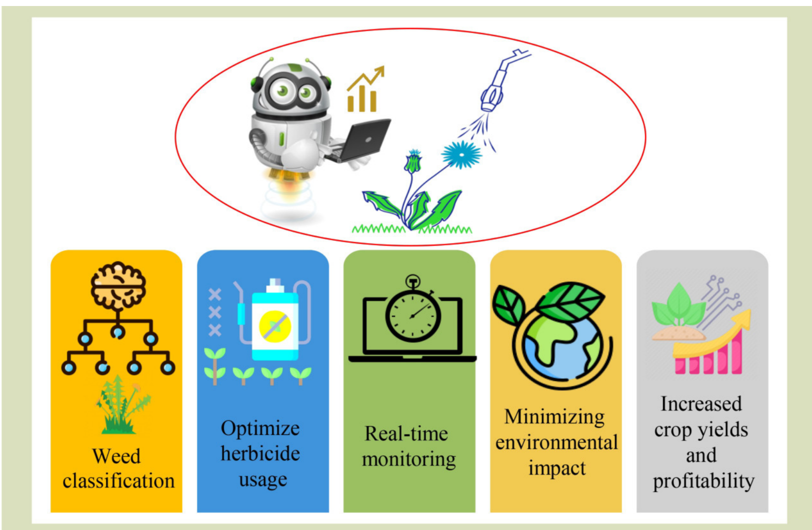
Weed management, herbicides, machine learning, agricultural practices, environmental impact

HIGHLIGHTS

- Machine learning offers innovative and sustainable weed management approaches.
- Herbicide use and environmental impact can be reduced through machine learning.
- Machine learning models can classify weed species and optimize herbicide usage.
- Real-time monitoring of invasive species is possible with machine learning.

Received January 20, 2024;
Accepted April 7, 2024.

GRAPHICAL ABSTRACT



ABSTRACT

Weed management is a crucial aspect of modern agriculture as invasive plants can negatively impact crop yields and profitability. Long-established methods of weed control, such as manual labor and synthetic herbicides, have been widely used but come with their own set of challenges. These methods are often time-consuming, labor-intensive, and pose environmental risks. Herbicides have been the primary method of weed control due to their efficiency and cost-effectiveness. However, over-reliance on herbicides has led to environmental contamination, weed resistance, and potential health hazards. To address these issues, researchers and industry experts are now exploring the integration of machine learning into chemical weed management strategies. As technology advances, there is a growing interest in exploring innovative and sustainable weed management approaches. This review examines the potential of machine learning in chemical weed management. Machine learning offers innovative and sustainable approaches by analyzing large data sets, recognizing patterns, and making accurate predictions. Machine learning models can classify weed species and optimize herbicide usage. Real-time monitoring enables timely intervention, preventing invasive species spread. Integrating machine learning into chemical weed management holds promise for enhancing agricultural practices, reducing herbicide usage and minimizing environmental impact. Validation and refinement of these algorithms are needed for practical application.

1 Introduction

Weed management is a critical aspect of modern agriculture, as invasive plants can significantly impact crop yields and profitability[1]. Long-established methods of weed control, such as manual labor and herbicides, have been widely used in the past. However, these methods can be time-consuming and labor-intensive, and often pose environmental risks[2,3]. As technology continues to advance, there is a growing interest in exploring innovative and sustainable approaches to weed management.

In recent years, machine learning has emerged as a powerful tool in various domains, revolutionizing ways to solve complex problems. Its ability to analyze vast amounts of data, recognize patterns and make accurate predictions has led to novel applications in numerous industries[4]. Agriculture, in particular, has witnessed the potential of machine learning algorithms to optimize various processes and enhance productivity.

Weeds, unwanted plants that compete with cultivated crops for resources, present a constant challenge for farmers worldwide[5]. Since their development in the 1940s, synthetic herbicides have become the primary method for weed control due to their efficiency and cost-effectiveness. However, the indiscriminate use of herbicides have led to environmental contamination, resistance development, and health damage[6–8]. To address these issues, researchers and industry experts have begun exploring the integration of machine learning into chemical weed management strategies. By leveraging the power of computational algorithms and advanced data analysis techniques, machine learning algorithms can provide valuable insights into optimizing herbicide usage, reducing environmental impact, and improving weed management practices[9,10].

Machine learning models can be trained to recognize and classify different weed species based on their visual characteristics, enabling more targeted and precise herbicide application[11]. By analyzing large data sets containing information on weed growth patterns, environmental conditions and herbicide effectiveness, these models can learn to identify optimal treatment strategies for specific weed populations. Additionally, machine learning algorithms can facilitate real-time monitoring of weed growth, allowing for timely intervention, and preventing the further spread of invasive species[12]. The effectiveness of chemical management of weeds using machine learning holds great promise for enhancing agricultural practices, reducing herbicide usage, and minimizing environmental impact. However, further research and development are required to refine these algorithms, validate their performance in various agricultural settings and ensure their practical applicability on a larger scale.

In this review, we summarize the current state of research regarding the integration of machine learning in chemical weed management, exploring the potential benefits, challenges, and future prospects of this innovative approach. By reviewing this emerging field, we aim to contribute to ongoing efforts in developing sustainable and efficient weed control strategies that can positively impact global agriculture.

2 Weed management challenges

2.1 Importance of weed management

Effective weed management is crucial in modern agriculture and is essential for ensuring optimal crop yields, maintaining food security, and safeguarding the environment[13,14]. Weed management strategies are also important for reducing the use of herbicides and preserving soil health. Weed management techniques should be designed for specific needs of the crop and landscape. Additionally, weed control should be monitored regularly to ensure its effectiveness[15]. To maximize the success of any weed control strategy, it is essential to assess the crop and landscape carefully, select the most appropriate techniques, and continually monitor progress.

Weeds compete with crops for vital resources such as water, nutrients, light, and space. If left uncontrolled, weeds can significantly reduce crop productivity, leading to economic losses for farmers and potential food shortages for the growing population[16]. In addition, weeds can also damage the environment and ecosystems, as well as contaminate water resources. Therefore, it is imperative to manage weeds in order to maintain sustainable agriculture. Weed control methods include physical removal, chemical control, cultural practices, and biological control. Integrated weed management (IWM) is the most effective strategy to reduce weed populations and ensure long-term agricultural productivity[17].

Weeds not only compete with crops for resources but also act as hosts for pests and diseases, further exacerbating agricultural challenges[18]. Additionally, certain weed species are known to produce allelopathic compounds that can inhibit the growth and development of neighboring crops[19]. Effective weed management is, therefore, critical for maintaining agricultural ecosystem health and vigor. Thus, it is important to develop strategies to control weeds in order to protect agricultural ecosystems. The subsequent section provides a comprehensive exploration of the limitations associated with standard weed control methods.

2.2 Limitations of standard weed control methods

Standard weed control methods, such as manual labor, mechanical control and herbicides, have been widely used. However, these methods have several limitations that hinder their long-term effectiveness and sustainability. Manual weed control methods, such as hand-weeding or mechanical cultivation, can be labor-intensive and time-consuming, making them impractical for large-scale agricultural operations[20]. The availability of skilled laborers for such tasks is also a challenge in many regions. In addition, manual methods are often not very effective in controlling weeds, as weedy species can quickly adapt to new methods of weed control. Finally, manual methods can be detrimental to the environment, as they may damage the soil and disturb native plant communities[21].

Herbicides have been extensively used for weed control due to their efficiency and cost-effectiveness. However, indiscriminate herbicide use has led to environmental contamination, including groundwater pollution, soil degradation and harm to non-target organisms[22,23]. Also, the repeated use of herbicides can contribute to the development of herbicide-resistant weed populations, further complicating weed management efforts. In addition, herbicides can be toxic to agricultural workers if they are exposed to them without proper protection[24]. Standard weed control methods often lack precision, resulting in the over-application or under-application of herbicides. Over-application can lead to wastage, increased costs and environmental risks, while under-application may fail to adequately control weeds, reducing crop yields[25].

2.3 Need for innovative approaches

Given the limitations of standard weed control methods, there is a need for innovative approaches to weed management that are efficient, sustainable, and environmentally friendly. Innovative weed management approaches aim to minimize the use of herbicides and reduce their environmental impact[26]. By adopting sustainable practices, farmers can preserve soil health, protect water resources, and maintain biodiversity in agricultural landscapes[27,28]. In this regards, non-chemical approaches include mechanical weed control, crop rotations, cover crops, intercropping, the introduction of beneficial organisms, and artificial intelligence-based practices. Adopting sustainable agricultural practices offers farmers numerous benefits, including increased crop yields and reduced reliance on herbicides. These practices not only lead to economic advantages but also generate favorable outcomes for the environment, creating a harmonious balance between economic prosperity and ecological well-being.

Cutting-edge methodologies that harness the power of machine learning and advanced technologies have emerged as game-changing solutions, holding immense promise in enabling precise and targeted weed control strategies. By leveraging these innovative approaches, agricultural practices can benefit from heightened accuracy and efficiency, revolutionizing the way weeds are detected, monitored, and managed within crop cultures. By identifying specific weed species, mapping weed distribution, and predicting herbicide efficacy, these approaches enable farmers to optimize herbicide usage and minimize off-target effects[29–31]. This can significantly reduce the cost of weed control, while also making farming more sustainable. Additionally, these approaches can help farmers reduce the risk of herbicide drift, which can have a negative impact on neighboring crops[32].

Implementing innovative weed management strategies can offer long-term cost savings for farmers. By reducing herbicide usage, minimizing labor requirements, and incorporating efficient technologies, farmers can achieve higher returns on investment and improve their overall profitability[33]. Additionally, farmers can adopt machine learning and predictive analytics to anticipate and respond to the changing needs of their crops. Machine learning can help farmers identify the best weed management strategies for their particular circumstances, enabling them to make informed decisions that optimize their yields and reduce their costs[34]. Meanwhile, innovative approaches to weed management can adapt to diverse agricultural systems, cropping practices, and changing environmental conditions. By using technological advancements, farmers can enhance their resilience to evolving weed pressures and mitigate weed infestation risks[35]. In general, the importance of weed management in agriculture cannot be overstated. Standard weed control methods have limitations that compromise their effectiveness and sustainability. To address these challenges, there is a pressing need for innovative approaches that optimize herbicide usage, reduce environmental risks, and enhance weed management precision and efficiency. By embracing innovative solutions, farmers can achieve sustainable weed control, ensure optimal crop yields, and contribute to a more resilient and productive agricultural sector.

3 Machine learning in weed management

Machine learning is a subfield of artificial intelligence that focuses on the development of algorithms and models that can learn from data and make predictions or decisions without being explicitly programed[36]. In the context of weed management, machine learning techniques are used to analyze large data sets containing information on weed species, environmental conditions, herbicide effectiveness and other relevant factors[37,38]. These data can then be used to identify areas at high risk of weed invasion and develop targeted strategies to prevent or control weed growth. Machine learning can also be used to optimize herbicide application, ensuring that the most effective herbicide is used in the right places at the right time[39]. By analyzing data such as temperature, soil moisture, and soil type, machine learning can predict where weeds are most likely to invade[40]. This information can then be used to target areas where herbicides should be applied and to apply them at the right time to maximize their effectiveness.

Machine learning algorithms are trained using these data sets to recognize patterns and relationships between input variables (such as weed characteristics and environmental factors) and output variables (such as herbicide efficacy or weed presence)[41]. The trained models can then be applied to make predictions or provide recommendations for weed management strategies in real-time[42]. The predictions or recommendations generated by these models can be used to advise farmers on the most effective weed management strategies for their particular situation. Thus, the use of AI-driven models can help farmers make better decisions on weed management[43].

Machine learning algorithms are increasingly being used in agriculture to identify, analyze, and predict various aspects of crop production, including weed management[44]. These algorithms can be applied in various ways, such as weed species recognition, weed density estimation, herbicide efficacy prediction, and decision support systems. By leveraging machine learning, farmers and agricultural professionals can optimize herbicide usage, reduce environmental impact, and improve weed management efficiency and precision[45]. Machine learning can also help identify which weeds are more resistant to herbicides, helping farmers make informed decisions about which herbicides to use and where to use them[46]. In the subsequent subsections, a comprehensive overview of machine learning techniques, offering valuable insights into their wide-ranging applications in weed management is presented. This exploration aims to provide readers with a deeper understanding of the diverse ways in which machine learning can be harnessed to address the challenges and complexities associated with effective weed management.

3.1 Overview of machine learning techniques

Machine learning as a subset of artificial intelligence has the potential to revolutionize agriculture weed management[47]. Chemical management of weeds, which involves herbicides, is crucial to modern farming practices. However, the effectiveness of these chemicals can vary widely depending on various factors such as soil type, weather conditions, and weed species[48]. Machine learning can help farmers predict future weed growth so they can adjust their weed management strategies accordingly. This can help maximize chemical weed management effectiveness while minimizing costs and environmental impacts. A machine learning algorithm can be trained to identify weed species from satellite imagery and predict when they will appear, allowing farmers to plan herbicide applications accordingly[49].

Various types of machine learning can be used to manage weeds. Supervised learning is one of the machine learning techniques which involves training a machine learning model using labeled data[50]. In weed management, labeled data could include information about the type of weed such as weed species, growth habit (broadleaf or grass), life cycle (annual or perennial), the chemical applied, and its effectiveness. The model can then predict the effectiveness of a particular chemical on a specific weed in a new environment[51]. This approach can help farmers make informed decisions about which herbicides to apply and when to apply them. These algorithms can be used for tasks such as weed species recognition, where images or sensor data of weeds are labeled with their corresponding species[52]. Popular supervised learning algorithms include decision trees, random forests, support vector machines (SVMs) and neural networks[53]. Rasti et al.[54] introduced a supervised image classification method to identify weeds in densely populated crop fields. Through an evaluation of the scatter transform algorithm, as well as single scale and multiscale techniques including Local Binary Pattern (LBP), Gray Level Co-occurrence Matrix (GLCM), Gabor filter, and convolutional neural networks (CNNs), can achieve an accuracy rate of 85%.

Unsupervised learning trains machine learning models with unlabeled data[55]. Unlabeled data in weed management may include information about the characteristics of different weed species or herbicide properties[56]. It is then possible for the model to identify patterns and relationships that humans may not see in these data. Researchers can use this approach to develop new herbicides or optimize existing ones based on their chemical properties[57]. Clustering algorithms, such as k-means and hierarchical clustering, are commonly used in unsupervised learning[58]. Also, this approach can be used to identify the most effective times for weed control, such as when certain chemicals are most effective against weeds. In addition, it can help researchers develop strategies to control the spread of weeds.

Reinforcement learning technique involves training a machine learning model to interact with an environment and learn through trial and error[59,60]. In weed management, reinforcement learning could involve simulating different scenarios for chemical applications and measuring their outcomes[61]. The agent learns to take actions (e.g., herbicide application and manual weeding) based on feedback received from the environment, optimizing long-term rewards such as weed control efficacy. The model can then learn which scenarios are most effective and adjust its behavior accordingly. This approach can help farmers optimize herbicide use by applying them only where they are most needed[62].

Deep learning is the process of developing a machine learning model using neural networks with multiple layers[63]. Deep learning models are trained on large amounts of data, allowing them to recognize patterns that would have been difficult to detect using standard machine learning models[64]. This makes them ideal for tasks that require high accuracy and specificity, such as identifying weeds[38]. In weed management, deep learning could involve training a model to recognize different weed species based on their visual characteristics or DNA sequences[65]. Deep learning algorithms, such as CNNs, are particularly effective at image recognition tasks. CNNs can be trained to identify and classify weed species based on visual characteristics[66]. The model can then predict which weeds will be most responsive to a particular herbicide or suggest alternative methods of controlling them[67]. This approach can help farmers make more precise and targeted weed management decisions. These machine learning techniques have the potential to significantly improve chemical weed management by providing farmers with more accurate and timely information about which herbicides to use and when to apply them[10].

3.2 Applications of machine learning in weed management

The use of machine learning algorithms in weed management offers innovative approaches to optimize herbicide use and improve weed control practices. Among the most important uses of machine learning for weed management are the identification of weed species, the estimation of weed density, the prediction of herbicide efficacy, decision support systems, and the mapping and monitoring of weed populations[11,68].

Machine learning algorithms are capable of recognizing and classifying weed species according to their visual characteristics[69]. Thus, farmers can utilize proper equipment for selectively apply herbicides to specific weed species, minimizing chemical use. Images or remote sensing data can be analyzed by machine learning algorithms to estimate weed density and distribution within a field[70]. Herbicide application rates can be optimized based on this information, ensuring effective weed control and reducing the amount of chemicals applied. To predict the efficacy of different herbicides against specific weed populations, machine learning algorithms can analyze historical data on herbicide applications, weed species, environmental conditions, and crop growth[37]. It is possible to determine what herbicide is the most effective for weed control based on this information.

In addition, it is possible to integrate machine learning algorithms into decision support systems that provide real-time weed management recommendations[40]. These algorithms generate alerts and suggest appropriate intervention strategies by continuously monitoring field conditions, enabling timely and targeted weed control. Using machine learning algorithms, weed maps can be generated from satellite images or drone data, highlighting areas with high weed density[71]. In this way, herbicides can be applied precisely and weed growth can be monitored in real time. As shown in Table 1, machine learning models have a major role in the weed management process.

Table 1 Effect of machine learning models on weed management practices

Method	Model	Aim	Result	Reference
Weed classification	RF classifier model	Classify carrot plants and weeds from RGB	Achieved an average classification accuracy of 94%	[72]
	Bayesian unsupervised classification model and morphological analysis	Separating crops from weeds	Achieved 85% accuracy on segmenting of the weeds without any prior knowledge of the species present in the field	[73]
	Machine learning and handcrafted image processing	Classifying common weeds in corn field	Highly successful with a few weed species in distinguishing each other	[74]
	Unmanned aerial vehicles (UAVs) imagery	Weed classification	The model successfully classified *Lithospermum arvense*, *Spergula arvensis*, *Stellaria media*, *Chenopodium album*, and *Lamium purpureum* in that field	[68]
	Faster region-based convolutional neural network (CNN)	Weed classification on sugarcane, spinach, pepper and banana trees	As a result of implementing the model, the classification accuracy was 97%, weed precision was 95%, weed recall was 99%, and the F1 score was 99% for 242,000 epochs	[75]
Weed detection and identification	Deep learning-based weed detection model (YOLO models)	Weed detection and management in different crops	The model has achieved an accuracy of 98.88% by calculating the number of correctly predicted weeds in the unseen data set	[76]
	Deep CNN models	Identification of weeds present among the bell pepper field	The overall accuracy of the selected models for weed identification varied from 95% to 98%	[77]
	Deep learning detection models (YOLOv3, YOLOv5, and Faster R-CNN)	Weed species identification in fields and lawns	The average accuracy of detection under the same training parameters was about 92%	[38]
	Neural network implemented through the PyTorch framework	Weed detection in wheat crops	The accuracy of weed removal from wheat crops ranged from 0.89 to 0.91	[78]
Weed mapping and spatial distribution	Deep learning techniques on UAV-derived RGB and multispectral imagery	Discern weed infestations in winter wheat crops	Provide accurate predictions (model accuracy > 0.9 on true out-of-bag data)	[71]
	Aerial multispectral imaging and deep neural network	Semantic weed mapping in sugar beet fields	The model significantly helps in discriminating between crops and weeds by segmenting out vegetation in the input images	[79]
	Automatic random forest-OBIA algorithm using UAV imagery	Early weed mapping between and within crop rows	UAV imagery combined with RF-OBIA allows rapid and accurate weed mapping within and between crops	[80]
Optimization of herbicide application	Hyperspectral imaging	Evaluation of crop damage of the non-glyphosate resistant corn plants from glyphosate	The model serve as a basis for determining the severity of crop damage from glyphosate	[81]
	Drop-on-demand robotic system	Optimizing weed management in vegetables	The system optimized control the weeds with as little as 7.6 μg glyphosate or 0.15 μg iodosulfuron per plant	[82]
	High-resolution melting and RT-qPCR probe assays	Detection of target-site mutations conferring glyphosate resistance in Perennial Ryegrass	The model had acceptable ability to rapidly detect the target-enzyme mutations at codon 106 in the EPSPS gene in *Lolium perenne*	[83]

4 Weed species identification using machine learning

Machine learning is used to automatically identify and classify different types of weeds in agricultural settings using different techniques and models[46]. To analyze and interpret weed-related visual data, including images and spectral information, machine learning algorithms are used, particularly those in the computer vision domain[84]. These algorithms can detect and classify weeds based on their visual characteristics. They can also identify weeds in crop fields with high precision and accuracy, helping farmers manage their crops more effectively.

Machine learning could revolutionize agricultural weed identification. For this, there are several key steps involved, including data collection and preprocessing, machine learning model selection and performance evaluation metrics[52]. These identification systems are being researched to enhance their robustness, accuracy and real-world applicability. Thus, machine learning looks to be a promising tool for agricultural weed identification. This section comprehensively covers the crucial aspects of weed species identification using machine learning. It provides valuable insights into the data collection and preprocessing stages, as well as the selection and evaluation of machine learning models. Based on image processing, Fig. 1 shows weed detection procedures.

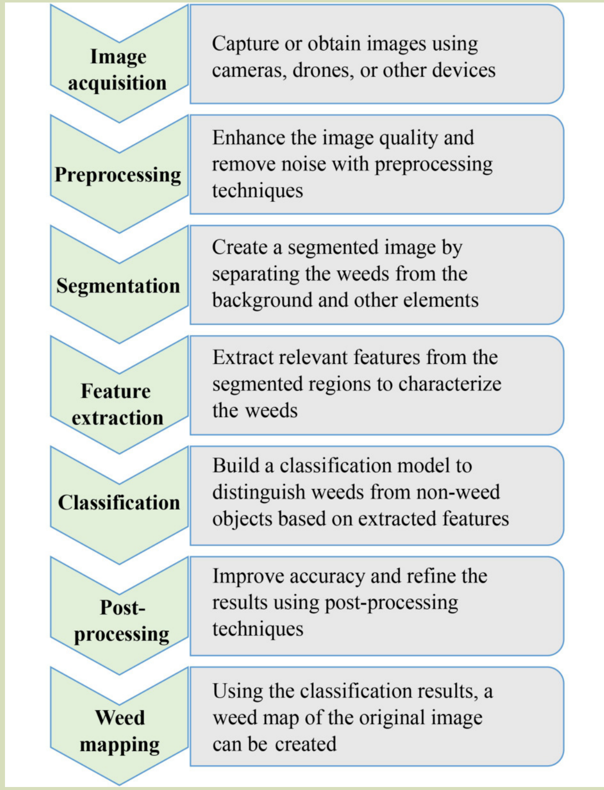


Fig. 1 Weed detection procedures based on image processing.

4.1 Data collection and preprocessing

It is crucial to collect high-quality images of various weed species. Ideally, these images should be taken at different growth stages, under different lighting conditions and with different backgrounds. They should also be of different types, including annuals, perennials, and biennials. Additionally, high-quality images should be taken from multiple angles to provide the best view of each species.

For supervised learning, each image must be labeled with its corresponding weed species. Domain experts are required for this process, which can be time-consuming. For model training, data augmentation techniques (e.g., rotation, flipping, and scaling) can be applied to the images in the next step in order to increase the diversity of the data set. It may be possible to speed up the convergence of the model by normalizing pixel values to a common scale (e.g., 0 to 1). A final step is to divide the data set into training, validation, and test sets to assess how well the model generalizes. With these steps, the model can be trained, validated, and tested, which can be used for successful predictions.

4.2 Machine learning models for weed species identification

CNNs have proven highly effective at image classification tasks. Common architectures, such as visual geometry group (VGG), residual network (ResNet), and custom-designed networks, may be used for weed identification[85–87]. A VGG network-based model was proposed by Fu et al.[88] for weed identification in fields. In real fields, the accuracy of weed detection was over 80% using Kaggle images.

A pre-trained model on a large data set (e.g., ImageNet) can be fine-tuned to identify weed species[89]. In addition to binary classification, SVMs can also be used for multiclass classification[90]. A VGG-SVM model was proposed to identify rapeseed plants and weeds with 99.2% accuracy in training and 92.1% accuracy in testing[90]. For classification, feature vectors extracted from images can be fed into SVMs[91]. It may be possible to improve performance by using advanced architectures such as capsule networks or attention mechanisms in addition to CNNs[92].

5 Weed spatial distribution analysis

Analyzing weed spatial distribution involves determining how weeds are arranged and spread across an area[93]. Commonly, weed mapping involves manual observation and sampling, which can be time-consuming and inaccurate[94]. The use of machine learning techniques provides a more accurate and automated method of analyzing the spatial distribution of weeds[95]. Nyamekye et al.[96] assessed the spatial and temporal variation of aquatic weeds in the Lower Volta River using machine learning. Their study demonstrated that combining remote sensing data with machine learning can be used to provide spatial and temporal distributions of aquatic weeds such as water hyacinths. Using remote sensing technologies, such as satellite imagery and unmanned aerial vehicles (UAVs), enables high-resolution aerial data. Machine learning algorithms can process these data to identify and map weed infestations across large agricultural or natural landscapes[97]. Geographic information systems (GIS) also make a crucial contribution to weed spatial distribution analysis by offering an effective framework for integrating diverse data sources[98]. Machine learning algorithms can be applied to GIS data to create detailed maps illustrating weed distribution patterns. This technology can provide a comprehensive view of the entire area, allowing researchers to identify areas of high weed infestation and target control measures. Thus, GIS and remote sensing provide an efficient tool for understanding weed infestation patterns and deploying targeted control measures. This section introduces the spatial distribution analysis of weeds, followed by the development of predictive models for estimating weed distribution, then explores the application of machine learning techniques for spatial analysis, enhancing the understanding of the underlying patterns and factors driving weed distribution.

5.1 Predictive models for weed spatial distribution

Various environmental factors, historical data and other relevant parameters are used in prediction models to forecast weed spatial distribution[99]. Predictive models developed by machine learning algorithms are particularly useful for improving weed management decisions. These models are reliable and accurate in predicting weed populations and their distribution[100]. They are especially useful for predicting where weeds are likely to appear, so that resources can be allocated accordingly. Additionally, they can help to identify the most vulnerable areas to weed invasion.

Machine learning algorithms, such as random forests, SVMs, and neural networks, can analyze historical data to identify patterns and correlations between environmental variables and weed distribution[101–103]. These models can then predict weed occurrence likelihood in specific areas. Combining multiple machine learning models into ensemble approaches can enhance prediction accuracy. Ensemble models, such as gradient boosting, bagging and stacking, can be applied to develop robust predictions for weed spatial distribution[104].

5.2 Spatial analysis techniques using machine learning

Within geographical data, spatial analysis examines spatial relationships, patterns and processes. To manage weeds more effectively, machine learning techniques offer innovative approaches to spatial analysis[41]. Machine learning algorithms are able to quickly identify patterns in large data sets, which can be used to identify hotspots of weed growth and target those areas for weed control[37]. Additionally, machine learning techniques can be used to model potential weed spread and predict future infestations, allowing authorities to take proactive measures to prevent and control weed growth. The use of machine vision was applied to weed detection in peanut fields by Zhang et al.[105]. As a result, the EM-YOLOv4-Tiny network demonstrated significant efficiency in detecting a single weed image in real-time. Machine learning applications can integrate with precision agriculture technologies, such as automated herbicide sprayers and robotic weed control devices[106,107]. This integration enhances the spatial precision of weed management practices, reducing chemical usage, and minimizing environmental impact.

6 Optimization of herbicide application

The optimization of herbicide application involves a multifaceted approach, considering factors such as timing, dosage, formulation, technology, and environmental responsibility[108]. By adopting precision agriculture practices, using appropriate adjuvants and tank mixtures, and being informed about the latest advancements, farmers can enhance weed control efficacy while minimizing herbicide ecological footprint. A holistic and well-informed approach is essential to achieving sustainable and effective herbicide application in modern agriculture. Farmers should tailor their herbicide application to the unique needs of their farms and the available technologies. They should also monitor their crops closely to ensure successful herbicide application and be aware of the potential risks associated with herbicide use and take steps to minimize their impact[109]. Taking these steps will help to ensure that modern agriculture remains sustainable and effective in the long term. This section and its subsections provide a comprehensive exploration of the optimization of herbicide application. The subsections cover various aspects, including strategies, factors influencing application, and the integration of machine learning techniques. These machine learning approaches encompass predictive modeling, weed species identification, precision application with robotics, decision support systems, weed density and spatial analysis, and integration with the Internet of Things (IoT) and sensor networks.

6.1 Herbicide application strategies

Effective herbicide application is a critical component of modern agriculture and land management practices. Herbicides are essential for controlling weeds, enhancing crop yields and maintaining overall ecosystem health[110]. Strategies for herbicide application should emphasize the importance of precision, timing and responsible use to maximize efficacy while minimizing environmental impact.

Herbicide application strategies are diverse and should be selected based on specific crops, weed species, and environmental conditions[111]. Integrating various approaches, such as pre-emergence and post-emergence applications, along with embracing IWM and precision agriculture, can contribute to sustainable and effective weed control[1]. Careful consideration of timing, herbicide selection, and environmental factors is needed to achieve a balance between optimal weed control and minimizing herbicide ecological impact[112].

Pre-emergence herbicide application is one of the most effective strategies allowing treatment of the soil before weed seeds germinate or seedlings emerge[113]. This strategy prevents weed establishment, offering a proactive approach to weed control. Precise timing is crucial for pre-emergence applications, as herbicides need to be in place before weed germination[114]. This method is particularly effective in annual cropping systems, where planting timing is predictable.

The common strategy for herbicide application is post-emergence, which involves treating weeds after emergence[115]. This strategy allows for more efficient control of existing weed populations. In this strategy, selective herbicides target specific weed species while minimizing harm to non-target species[116]. Proper timing is crucial to maximize post-emergence application effectiveness, as weeds are most vulnerable at certain growth stages.

Another strategy is IWM, which is a holistic approach that combines various control methods, including herbicides, to achieve sustainable and effective weed control[26]. IWM considers ecological, economic, and social aspects of weed management, emphasizing the integration of chemical, biological, cultural, and mechanical control methods[117]. This strategy aims to reduce reliance on herbicides alone and mitigate herbicide-resistant weed populations.

Precision agriculture is the process of using technology, such as GPS-guided equipment and sensors, to optimize herbicide application[118]. This strategy allows for site-specific application, reducing overall herbicide use, and minimizing environmental impact[119]. Variable-rate technology is a key component of precision agriculture, enabling adjustments to herbicide rates based on real-time data[120]. A successful implementation of this strategy requires the introduction of effective and accurate technologies, as well as farmer training.

6.2 Factors influencing optimal herbicide application

Achieving optimal herbicide application is a dynamic process influenced by various factors that encompass the characteristics of both the target weeds and the surrounding environment. Farmers and land managers must navigate a complex interplay of biological, environmental, and technological factors to ensure herbicide effectiveness and sustainability while minimizing the potential negative consequences associated with herbicide use[121]. It is essential to carefully assess the potential for herbicide drift and runoff, as well as the potential effects on beneficial species and non-target organisms[122,123]. Also, farmers should carefully consider the costs and benefits of different herbicide application strategies. An overview of the key factors influencing herbicide application is shown in Fig. 2.

6.3 Machine learning approaches for herbicide optimization

Machine learning in agriculture has improved precision and efficiency. The use of machine learning techniques in herbicide optimization can revolutionize weed management strategies[37]. Through data-driven insights, predictive modeling and spatial analysis, machine learning can help farmers make better decisions, reduce herbicide use, and enhance sustainability[124]. By harnessing the power of predictive modeling, image recognition, robotics, decision support systems, sensors, spatial analysis, and IoT integration, herbicide application strategies can be optimized[125,126]. The

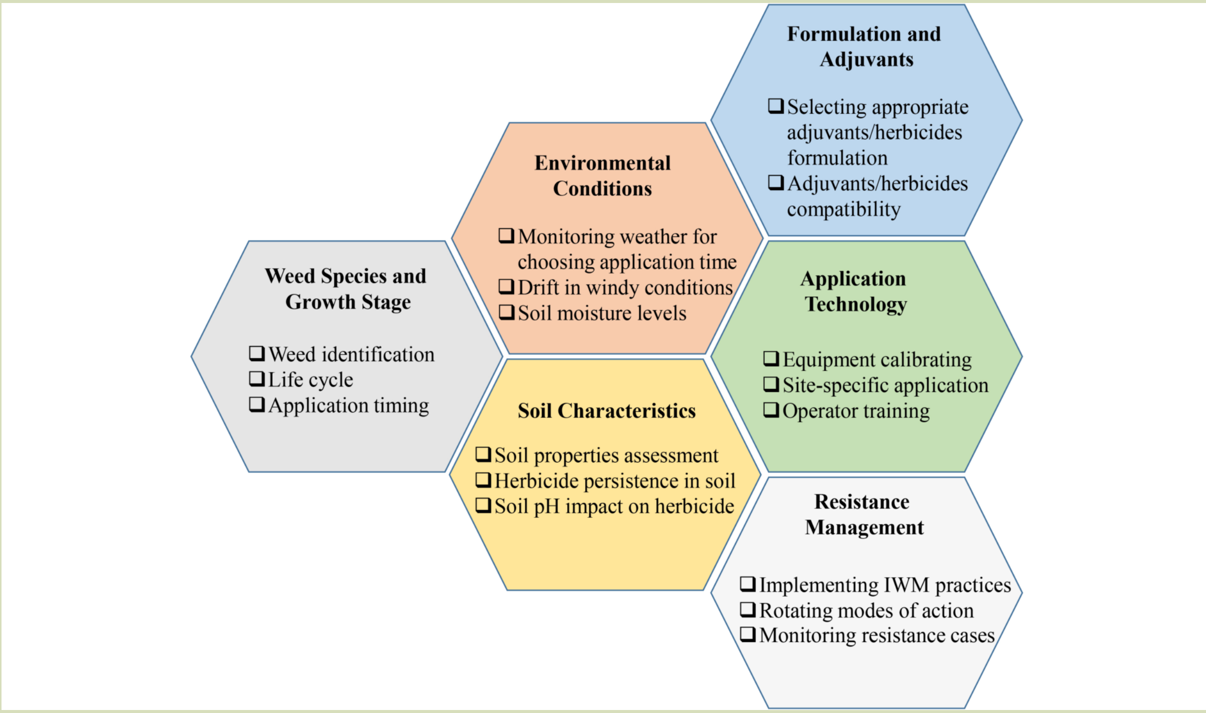


Fig. 2 Key factors influencing optimal herbicide application, along with their critical considerations.

result is improved weed control and a more sustainable and environmentally conscious approach to herbicide use in agriculture. As technology continues to evolve, the synergy between machine learning and herbicide optimization holds substantial promise for the future of weed management in agriculture. For herbicide optimization, various machine learning approaches are used, as explained below. The effectiveness of machine learning models on chemical weed management is presented in Table 2.

6.3.1 Predictive modeling for weed growth

Machine learning excels at developing predictive models for weed growth based on historical data, environmental variables, and crop management practices[141]. Using these models, farmers can anticipate and plan herbicide applications more effectively by forecasting weed emergence and growth patterns. Algorithms, such as random forests and neural networks, can be used to analyze complex data sets to identify correlations and make accurate predictions regarding weed growth under varying conditions[142,143]. Machine learning provides farmers with a powerful tool to optimize herbicide application strategies. The predictive models for weed growth have several primary advantages, including early detection of weed outbreaks, improved timing for herbicide applications, and greater precision for targeting specific weed species[144].

6.3.2 Weed species identification

Machine learning algorithms, particularly image recognition models, have demonstrated success in automating weed species identification[145]. By processing images captured by drones or cameras, these algorithms can differentiate between crops and various weed species in real-time[146]. This capability enables targeted herbicide applications, minimizing the need for blanket treatments and minimizing the impact on non-target vegetation. Additionally, the use of image recognition can reduce labor costs associated with manual identification of weeds[147]. Also, it can help reduce the risk of herbicide drift, which can cause environmental damage. Precision agriculture, real-time decision making, cost reduction, environmental impact, herbicide drift mitigation, increased crop yield, data-driven insights and adaptability are the advantages of these algorithms.

6.3.3 Precision herbicide application with robotics

Integrating machine learning with robotics has led to the development of autonomous herbicide application systems[148]. These robotic systems use machine learning algorithms to navigate fields, identify weeds, and precisely apply herbicides only where needed[149]. By using sensors and real-time data analysis, these robots can adapt to changing field conditions, ensuring optimal herbicide dosage and coverage[150]. This helps reduce chemical usage, protect the environment and

Table 2 Efficiency of machine learning models in chemical weed management

Used model	Aim	Result	Reference
High-resolution hyperspectral imaging acquisition system	Classifying herbicide sites of action	The combination of hyperspectral imaging and machine learning was very effective in rapidly screening and precisely classifying a wide spectrum of herbicides, achieving an accuracy rate of over 80% as early as one day after treatment	[127]
Hierarchical cluster analysis	Assessing New Zealand's herbicide-resistant weed potential	The hierarchical cluster analysis identified eight weed species as high-risk assemblages, including all species known to be herbicide-resistant in New Zealand	[128]
Deep convolutional neural networks (CNNs)	Detection of herbicide weed control spectrum in turfgrass	Training based on the herbicide weed control spectrum demonstrated high accuracy in detecting and discriminating weeds	[67]
Hyperspectral imaging through machine learning	Analyzing the crop damage caused by dicamba on non-dicamba-tolerant soybeans	Hyperspectral imaging captures the spectral response to soybean injury caused by dicamba sprays. An overall accuracy of more than 90% was achieved by the recoverability spectral indices developed	[129]
Robotic system	In-row weed management in vegetables	A 10-fold reduction in herbicide use was achieved by using the robot in the field trial to control all weeds	[82]
Intelligent weeding robot	Intra-row weed management in maize (*Zea mays*)	In actual conditions, 93% accuracy in weed detection was achieved with deep learning, and 90% efficiency in weed removal was obtained by the robot	[130]
Autonomous GPS-based system	Assessing the tilled area for intra-row weed control	With a high level of effectiveness, the system controlled weeds mechanically between and within rows	[131]
Light-activated sensor-controlled sprayer	Weed control in postharvest wheat	In comparison with broadcast sprayers, this system reduced herbicide use by 23% to 55%	[132]
Novel sensor-based method	Evaluation of herbicide efficacy under real field conditions in durum wheat	The method was reported as an effective tool for improving weed management	[133]
Drone-based herbicide application	Effective weed control in rice (*Oryza sativa*)	Herbicide application by drones significantly reduced weed density and weed dry weight, and resulted in the highest grain and straw yield in rice	[134]
RGB (red, green and blue) images from drones	Weed control threshold estimation	The method provided an acceptable estimate of weed cover value	[135]
Drone sprayers	Weed control in soybean (*Glycine max*)	By drone sprayer, Pendimethalin and Imazamox 35% EC + Imazethapyr proved to be more effective than by knapsack or boom sprayer	[136]
Computer vision machine learning system based on stereo vision	Classification and management of rice field weeds	Stereo vision technology, as well as the hybrid ANN-BA classifier developed for increased classification accuracy, demonstrated promising results	[137]
Deep learning CNNs	Weed detection in perennial ryegrass	The use of neural networks was highly effective in detecting *Euphorbia maculata* and *Glechoma hederacea* growing in perennial ryegrass	[138]
Hyperspectral imaging and machine learning	Weeds identification in pastures	Using hyperspectral imaging, four weeds were successfully identified with an overall accuracy of 70% to 100%	[29]
Chlorophyll fluorescence imaging sensor	Identification of herbicide-resistant *Alopecurus myosuroides* populations	95% of classifications were correct when the model detected herbicide stress in weeds	[139]
UV-induced fluorescence sensor	Weed-crop discrimination in corn	Under laboratory conditions, classification success rate was 92%	[140]

maximize crop yields. Site-specific herbicide application, reduction in herbicide usage and costs, and minimization of environmental impact are the main benefits of this algorithm. A robotic herbicide application flowchart is shown in Fig. 3.

6.3.4 Decision support systems

Machine learning-based decision support systems help farmers make informed herbicide application choices[151]. These systems consider a range of factors, including weather conditions, soil properties and historical data, to recommend the most suitable herbicide, application rate and timing[152]. By providing real-time insights, these systems empower farmers to optimize weed management strategies[153]. The use of this approach may result in a reduction in herbicide resistance development. Additionally, these systems improve decision-making efficiency and tailor recommendations for specific field conditions.

6.3.5 Weed density and spatial analysis

By leveraging data from diverse sources, such as satellite

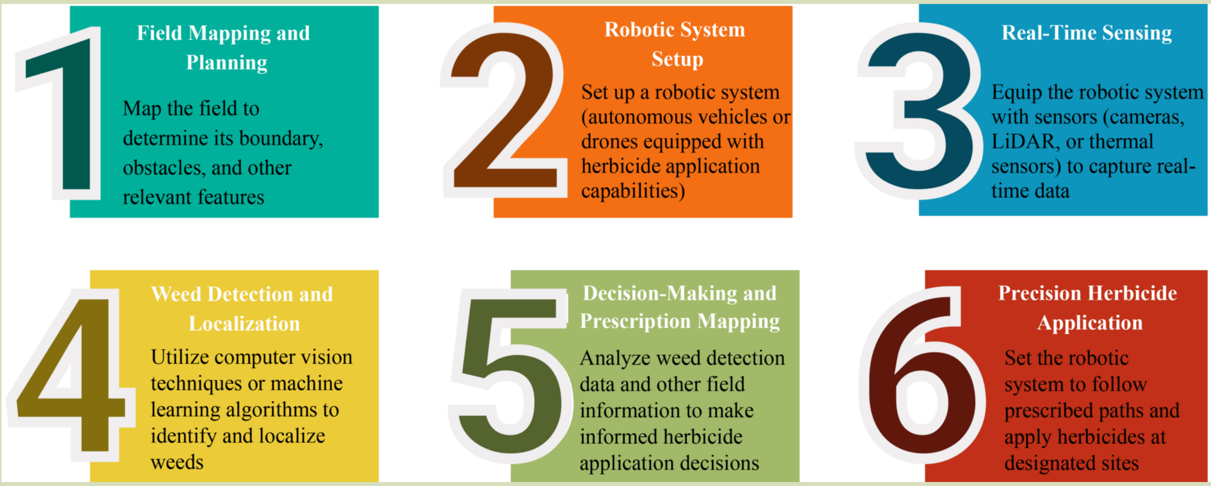


Fig. 3 Flowchart of a precision herbicide application with robotics.

imagery, UAVs, and ground sensors, machine learning algorithms are used to generate comprehensive maps pinpointing areas exhibiting elevated weed density[154]. The integration of these technologies facilitates the accurate identification and mapping of weed distribution patterns across the field. These detailed maps serve as valuable tools for farmers, enabling targeted herbicide applications based on identified weed hotspots[155]. This approach optimizes resource utilization and minimizes the environmental impact associated with indiscriminate herbicide use. The significance of machine learning-driven spatial analysis in providing actionable insights for precision agriculture, offering farmers a strategic and efficient means to manage weed infestations and enhance overall crop productivity[156].

6.3.6 Integration with internet of things and sensor networks

Using data from soil sensors, weather stations and diverse IoT devices, machine learning algorithms are used to dynamically adapt herbicide application plans in response to evolving environmental conditions in agricultural fields[157]. The integration of IoT and sensor networks facilitates uninterrupted monitoring of key parameters, allowing machine learning models to make informed decisions regarding herbicide dosage and distribution. The inherent advantages of this approach include the continuous refinement of weed management plans, leading to a reduction in herbicide waste and the associated environmental impact. Also, the dynamic adaptation enabled by this integrated system contributes to increased efficiency and adaptability in weed management practices[125]. As a result of this approach, IoT technologies, sensor networks and machine learning algorithms are being combined to revolutionize herbicide application in agriculture, making crop management more efficient and sustainable. Figure 4 provides an overview of chemical weed management using machine learning technologies.

7 Benefits and challenges of machine learning in weed management

Machine learning has multifaceted benefits in agriculture. Machine learning algorithms, when applied to weed management, exhibit remarkable precision in differentiating between crops and various weed species, allowing for efficient herbicide applications[158]. Processing data in real-time empowers farmers with immediate insights into weed presence, fostering prompt decision making[159]. Also, adaptability of machine learning models to diverse environments enables efficient weed management in various agricultural settings. Likewise, machine learning has a positive impact through cost reduction through automated weed detection, reducing the need for manual labor and therefore optimizing operations expenses[160,161]. Additionally, targeted herbicide applications driven by machine learning models minimize the environmental impact associated with excessive herbicide use, preserving non-target vegetation[162]. The generated data not only refines current weed management practices but also contributes to a data-driven understanding of weed distribution patterns and the effectiveness of herbicide applications. Overall, the incorporation of machine learning in weed management stands as a transformative approach, offering precision, efficiency and sustainability in contemporary agricultural practices.

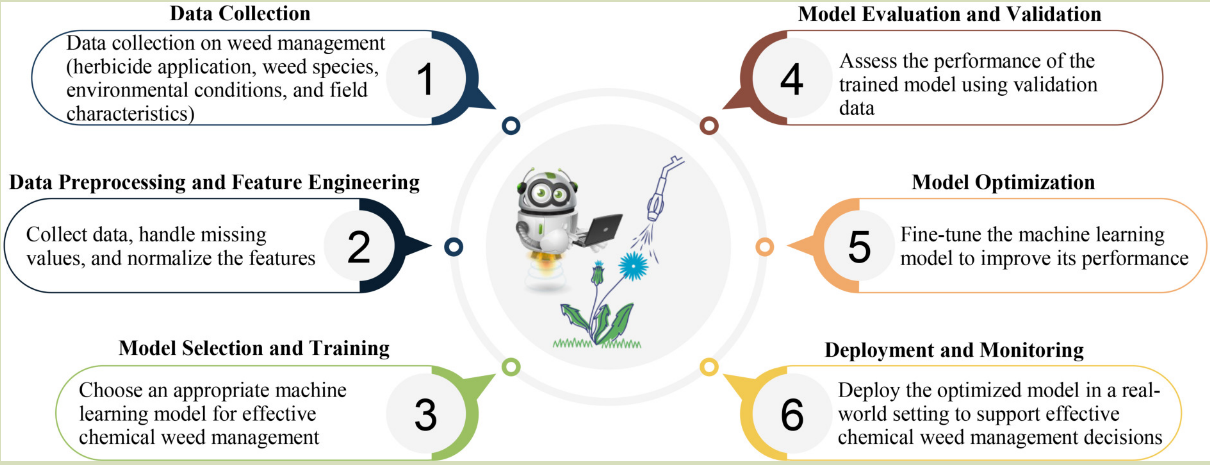


Fig. 4 Overview of machine learning technologies for effective chemical weed management.

A complex landscape of challenges and limitations surrounds the integration of machine learning in weed management[163]. As machine learning applications are adopted for precision agriculture, critical impediments emerge. The foremost challenge lies in the acquisition of high-quality and diverse data sets, indispensable for robust machine learning model training[34]. Addressing the challenge of model generalization requires continuous research and refinement to enhance adaptability across diverse agricultural landscapes. Model generalization across varied environmental conditions and weed species poses a substantial obstacle, requiring nuanced model development strategies. The largely unavoidable risk of bias within training data raises concerns regarding the ethical and unbiased deployment of machine learning-driven weed management systems[164]. The interpretability of complex machine learning models is viewed as a limitation, impacting user trust and comprehension. Additionally, the seamless integration of machine learning technologies with existing agricultural systems necessitates compatibility, underscoring the need for meticulous planning and adaptation.

8 Future directions and research opportunities

As the application of machine learning technologies in precision farming continues to evolve, a diverse potentials and emerging challenges have become evident. Despite the challenges, machine learning models should be considered a way for improving weed detection, classification, and management. The integration of novel data sources, including hyperspectral imaging and advanced sensor technologies, holds promise for refining machine learning-driven weed management accuracy and scope. Future research should also focus on addressing challenges such as model interpretability, biases, and seamless integration with existing agricultural systems. Also, exploring the potential of reinforcement learning and other advanced machine learning techniques can contribute to the development of more adaptive and resilient weed management systems. Emerging technologies and trends in machine learning integration into weed management practices are contributing to more efficient, sustainable, and targeted approaches to weed detection and control. Some notable emerging technologies and trends include advanced sensor technologies, remote sensing and UAVs, data fusion and integration, robotic systems, and precision applications, real-time analytics and decision support systems, biological control and IPM, continuous learning and adaptability, and blockchain technology for traceability. Through these future directions, the weed management in modern agriculture can enter in a new era of innovation, sustainability and efficiency.

9 Conclusions

In conclusion, the integration of machine learning techniques into chemical weed management practices holds significant promise for addressing the challenges associated with standard weed control methods. This review highlights the potential benefits of using machine learning algorithms in weed management, including enhanced precision, reduced chemical usage, and improved sustainability. By leveraging computational algorithms and advanced data analysis techniques, machine learning models can accurately identify and classify weed species, analyze weed spatial distribution, and optimize herbicide application strategies. These capabilities enable targeted and precise weed management, leading to increased agricultural productivity and minimized environmental impact.

However, it is important to acknowledge that further research and development are necessary to refine these algorithms, validate their performance in diverse agricultural settings, and ensure their practical applicability on a larger scale. The limitations of current weed control methods, such as labor-intensive manual labor and indiscriminate herbicide use, necessitate the exploration of innovative and sustainable approaches. Machine learning, along with other emerging technologies, offers a pathway toward more efficient and environmentally friendly weed management.

By considering the current state of research in the field of machine learning in weed management, this review is intended contribute to ongoing efforts in developing sustainable and effective weed control strategies. The optimization of herbicide usage, reduction of environmental contamination and preservation of agricultural ecosystem health are critical aspects that can be achieved through the integration of machine learning into weed management practices. Ultimately, the successful implementation of machine learning techniques in weed management has the potential to positively impact global agriculture and ensure food security in a sustainable manner.

Compliance with ethics guidelines

Mohammad Mehdizadeh, Duraid K. A. Al-Taey, Anahita Omidi, Aljanabi Hadi Yasir Abbood, Shavan Askar, Soxibjon Topildiyev, Harikumar Pallathadka, and Renas Rajab Asaad declare that they have no conflicts of interest or financial conflicts to disclose. This article does not contain any studies with human or animal subjects performed by any of the authors.

REFERENCES

1. Monteiro A, Santos S. Sustainable approach to weed management: the role of precision weed management. *Agronomy*, 2022, **12**(1): 118
2. Nahar K, Baillie J, Zulkarnain N A. Herbicide fate and transport in the great barrier reef: a review of critical parameters. *Water*, 2023, **15**(2): 237
3. Karimi-Maleh H, Ghalkhani M, Saberi Dehkordi Z, Mohsenpour Tehran M, Singh J, Wen Y, Baghayeri M, Rouhi J, Fu L, Rajendran S. Mof-enabled pesticides as developing approach for sustainable agriculture and reducing environmental hazards. *Journal of Industrial and Engineering Chemistry*, 2024, **129**: 105–123
4. Baduge S K, Thilakarathna S, Perera J S, Arashpour M, Sharafi P, Teodosio B, Shringi A, Mendis P. Artificial intelligence and smart vision for building and construction 4.0: machine and deep learning methods and applications. *Automation in Construction*, 2022, **141**: 104440
5. Garg S, Rumjit N P, Roy S. Smart agriculture and nanotechnology: technology, challenges, and new perspective. *Advanced Agrochem*, 2023 [Published Online] doi:10.1016/j.aac.2023.11.001
6. Wołejko E, Wydro U, Odziejewicz J I, Koronkiewicz A, Jabłońska-Trypuć A. Biomonitoring of soil contaminated with herbicides. *Water*, 2022, **14**(10): 1534
7. Montull J M, Torra J. Herbicide resistance is increasing in Spain: concomitant management and prevention. *Plants*, 2023, **12**(3): 469
8. Ojelade B S, Durowoju O S, Adesoye P O, Gibb S W, Ekosse G I. Review of glyphosate-based herbicide and aminomethylphosphonic acid (AMPA): environmental and health impacts. *Applied Sciences*, 2022, **12**(17): 8789
9. Vasileiou M, Kyrgiakos L S, Kleisiari C, Kleftodimos G, Vlontzos G, Belhouchette H, Pardalos P M. Transforming weed management in sustainable agriculture with artificial intelligence: a systematic literature review towards weed identification and deep learning. *Crop Protection*, 2024, **176**: 106522
10. Ayoub Shaikh T, Rasool T, Rasheed Lone F. Towards leveraging the role of machine learning and artificial intelligence in precision agriculture and smart farming. *Computers and Electronics in Agriculture*, 2022, **198**: 107119
11. Rai N, Zhang Y, Ram B G, Schumacher L, Yellavajjala R K, Bajwa S, Sun X. Applications of deep learning in precision weed management: a review. *Computers and Electronics in Agriculture*, 2023, **206**: 107698
12. Balaska V, Adamidou Z, Vryzas Z, Gasteratos A. Sustainable crop protection via robotics and artificial intelligence solutions. *Machines*, 2023, **11**(8): 774
13. Albahri G, Alyamani A A, Badran A, Hijazi A, Nasser M, Maresca M, Baydoun E. Enhancing essential grains yield for sustainable food security and bio-safe agriculture through latest innovative approaches. *Agronomy*, 2023, **13**(7): 1709

14. Pandey P C, Pandey M. Highlighting the role of agriculture and geospatial technology in food security and sustainable development goals. *Sustainable Development*, 2023, **31**(5): 3175–3195
15. Tataridas A, Jabran K, Kanatas P, Oliveira R S, Freitas H, Travlos I. Early detection, herbicide resistance screening, and integrated management of invasive plant species: a review. *Pest Management Science*, 2022, **78**(10): 3957–3972
16. Peerzada A M, Bukhari S A H, Dawood M, Nawaz A, Ahmad S, Adkins S. Weed Management for Healthy Crop Production. In: Hasanuzzaman, M, ed. Agronomic Crops. Singapore: *Springer*, 2019, 225–256
17. Cordeau S, Baudron A, Busset H, Farcy P, Vieren E, Smith R G, Munier-Jolain N, Adeux G. Legacy effects of contrasting long-term integrated weed management systems. *Frontiers in Agronomy*, 2022, **3**: 769992
18. Salem N M, Abumuslem M, Turina M, Samarah N, Sulaiman A, Abu-Irmaileh B, Ata Y. New weed hosts for tomato brown rugose fruit virus in wild Mediterranean vegetation. *Plants*, 2022, **11**(17): 2287
19. Siyar S, Majeed A, Muhammad Z, Ali H, Inayat N. Allelopathic effect of aqueous extracts of three weed species on the growth and leaf chlorophyll content of bread wheat. *Acta Ecologica Sinica*, 2019, **39**(1): 63–68
20. N'cho S A, Mourits M, Rodenburg J, Oude Lansink A. Inefficiency of manual weeding in rainfed rice systems affected by parasitic weeds. *Agricultural Economics*, 2019, **50**(2): 151–163
21. Ojija F, Arnold S E J, Treydte A C. Plant competition as an ecosystem-based management tool for suppressing *Parthenium hysterophorus* in rangelands. *Rangelands*, 2021, **43**(2): 57–64
22. Ghirardelli A, Otto S, Masin R, Bano C, Altissimo L, Russo S, Zanin G. Thirty-year monitoring of s-triazine herbicide contamination in the aquifer north of Vicenza (north-east Italy). *Science of the Total Environment*, 2021, **752**: 141647
23. Mehdizadeh M, Mushtaq W, Anusha Siddiqui S, Ayadi S, Kaur P, Yeboah S, Mazraedoost S, AL-Taey D K A, Tampubolon K. Herbicide residues in agroecosystems: fate, detection, and effect on non-target plants. *Reviews in Agricultural Science*, 2021, **9**(0): 157–167
24. Marcelino A F, Wachtel C C, Ghisi N D C. Are our farm workers in danger? Genetic damage in farmers exposed to pesticides. *International Journal of Environmental Research and Public Health*, 2019, **16**(3): 358
25. Restuccia A, Scavo A. Sustainable weed management. *Plants*, 2023, **12**(8): 1673
26. Scavo A, Mauromicale G. Integrated weed management in herbaceous field crops. *Agronomy*, 2020, **10**(4): 466
27. Tahat M M, Alananbeh K M, Othman Y A, Leskovar D I. Soil health and sustainable agriculture. *Sustainability*, 2020, **12**(12): 4859
28. Wang W, Straffelini E, Pijl A, Tarolli P. Sustainable water resource management in steep-slope agriculture. *Geography and Sustainability*, 2022, **3**(3): 214–219
29. Li Y, Al-Sarayreh M, Irie K, Hackell D, Bourdot G, Reis M M, Ghamkhar K. Identification of weeds based on hyperspectral imaging and machine learning. *Frontiers in Plant Science*, 2021, **11**: 611622
30. Gao J, Nuyttens D, Lootens P, He Y, Pieters J G. Recognising weeds in a maize crop using a random forest machine-learning algorithm and near-infrared snapshot mosaic hyperspectral imagery. *Biosystems Engineering*, 2018, **170**: 39–50
31. Ip R H L, Ang L M, Seng K P, Broster J C, Pratley J E. Big data and machine learning for crop protection. *Computers and Electronics in Agriculture*, 2018, **151**: 376–383
32. Seol J, Kim J, Son H I. Field evaluations of a deep learning-based intelligent spraying robot with flow control for pear orchards. *Precision Agriculture*, 2022, **23**(2): 712–732
33. Gathala M K, Laing A M, Tiwari T P, Timsina J, Rola-Rubzen F, Islam S, Maharjan S, Brown P R, Das K K, Pradhan K, Chowdhury A K, Kumar R, Datt R, Anwar M, Hossain S, Kumar U, Adhikari S, Magar D B T, Sapkota B K, Shrestha H K, Islam R, Rashid M, Hossain I, Hossain A, Brown B, Gerard B. Improving smallholder farmers' gross margins and labor-use efficiency across a range of cropping systems in the Eastern Gangetic Plains. *World Development*, 2021, **138**: 105266
34. Benos L, Tagarakis A C, Dolias G, Berruto R, Kateris D, Bochtis D. Machine learning in agriculture: a comprehensive updated review. *Sensors*, 2021, **21**(11): 3758
35. Rao A N, Singh R G, Mahajan G, Wani S P. Weed research issues, challenges, and opportunities in India. *Crop Protection*, 2020, **134**: 104451
36. Raschka S, Patterson J, Nolet C. Machine learning in python: main developments and technology trends in data science, machine learning, and artificial intelligence. *Information*, 2020, **11**(4): 193
37. Ghatrehsamani S, Jha G, Dutta W, Molaei F, Nazrul F, Fortin M, Bansal S, Debangshi U, Neupane J. Artificial intelligence tools and techniques to combat herbicide resistant weeds-a review. *Sustainability*, 2023, **15**(3): 1843
38. Wang P, Tang Y, Luo F, Wang L, Li C, Niu Q, Li H. Weed25: a deep learning dataset for weed identification. *Frontiers in Plant Science*, 2022, **13**: 1053329
39. Javaid M, Haleem A, Khan I H, Suman R. Understanding the potential applications of artificial intelligence in agriculture sector. *Advanced Agrochem*, 2023, **2**(1): 15–30
40. van Evert F K, Fountas S, Jakovetic D, Crnojevic V, Travlos I, Kempenaar C. Big data for weed control and crop protection. *Weed Research*, 2017, **57**(4): 218–233
41. Juwono F H, Wong W K, Verma S, Shekhawat N, Lease B A, Apriono C. Machine learning for weed-plant discrimination in agriculture 5.0: an in-depth review. *Artificial Intelligence in Agriculture*, 2023, **10**: 13–25
42. Hasan A S M, Diepeveen D, Laga H, Jones M G K, Sohel F. Object-level benchmark for deep learning-based detection

and classification of weed species. *Crop Protection*, 2024, **177**: 106561

43. Gardezi M, Joshi B, Rizzo D M, Ryan M, Prutzer E, Brugler S, Dadkhah A. Artificial intelligence in farming: challenges and opportunities for building trust. *Agronomy Journal*, 2023: agj2.21353
44. Elbasi E, Zaki C, Topcu A E, Abdelbaki W, Zreikat A I, Cina E, Shdefat A, Saker L. Crop prediction model using machine learning algorithms. *Applied Sciences*, 2023, **13**(16): 9288
45. Mesías-Ruiz G A, Pérez-Ortiz M, Dorado J, de Castro A I, Peña J M. Boosting precision crop protection towards agriculture 5.0 via machine learning and emerging technologies: a contextual review. *Frontiers in Plant Science*, 2023, **14**: 1143326
46. Venkataraju A, Arumugam D, Stepan C, Kiran R, Peters T. A review of machine learning techniques for identifying weeds in corn. *Smart Agricultural Technology*, 2023, **3**: 100102
47. Partel V, Charan Kakarla S, Ampatzidis Y. Development and evaluation of a low-cost and smart technology for precision weed management utilizing artificial intelligence. *Computers and Electronics in Agriculture*, 2019, **157**: 339–350
48. Varanasi A, Prasad P V V, Jugulam M. Impact of climate change factors on weeds and herbicide efficacy. *Advances in Agronomy*, 2016, **135**: 107–146
49. Hashemi-Beni L, Gebrehiwot A, Karimoddini A, Shahbazi A, Dorbu F. Deep convolutional neural networks for weeds and crops discrimination from UAS imagery. *Frontiers in Remote Sensing*, 2022, **3**: 755939
50. Jiang T, Gradus J L, Rosellini A J. Supervised machine learning: a brief primer. *Behavior Therapy*, 2020, **51**(5): 675–687
51. Shorewala S, Ashfaque A, Sidharth R, Verma U. Weed density and distribution estimation for precision agriculture using semi-supervised learning. *IEEE Access: Practical Innovations, Open Solutions*, 2021, **9**: 27971–27986
52. Hasan A S M M, Sohel F, Diepeveen D, Laga H, Jones M G K. A survey of deep learning techniques for weed detection from images. *Computers and Electronics in Agriculture*, 2021, **184**: 106067
53. Bansal M, Goyal A, Choudhary A. A comparative analysis of K-nearest neighbor, genetic, support vector machine, decision tree, and long short term memory algorithms in machine learning. *Decision Analytics Journal*, 2022, **3**: 100071
54. Rasti P, Ahmad A, Samiei S, Belin E, Rousseau D. Supervised image classification by scattering transform with application to weed detection in culture crops of high density. *Remote Sensing)*, 2019, **11**(3): 249
55. Amram O, Suarez C M. Tag N' Train: a technique to train improved classifiers on unlabeled data. *Journal of High Energy Physics*, 2021, **2021**(1): 153
56. Pérez-Ortiz M, Peña J M, Gutiérrez P A, Torres-Sánchez J, Hervás-Martínez C, López-Granados F. A semi-supervised system for weed mapping in sunflower crops using unmanned aerial vehicles and a crop row detection method. *Applied Soft Computing*, 2015, **37**: 533–544
57. Oršolić D, Pehar V, Šmuc T, Stepanić V. Comprehensive machine learning based study of the chemical space of herbicides. *Scientific Reports*, 2021, **11**(1): 11479
58. Sinaga K P, Yang M S. Unsupervised K-means clustering algorithm. *IEEE Access: Practical Innovations, Open Solutions*, 2020, **8**: 80716–80727
59. Gupta S, Singal G, Garg D. Deep Reinforcement Learning Techniques in Diversified Domains: A Survey. *Archives of Computational Methods in Engineering*, 2021, **28**(7): 4715–4754
60. Xia K, Sacco C, Kirkpatrick M, Saidy C, Nguyen L, Kircaliali A, Harik R. A digital twin to train deep reinforcement learning agent for smart manufacturing plants: Environment, interfaces and intelligence. *Journal of Manufacturing Systems*, 2021, **58**: 210–230
61. Gautron R, Maillard O A, Preux P, Corbeels M, Sabbadin R. Reinforcement learning for crop management support: review, prospects and challenges. *Computers and Electronics in Agriculture*, 2022, **200**: 107182
62. Vaishnnave M P, Manivannan R. An empirical study of crop yield prediction using reinforcement learning. In: Kanthavel R, Ananthajothi K, Balamurugan S, Ganesh R K, eds. Artificial Intelligent Techniques for Wireless Communication and Networking. Beverly: *Scrivener Publishing LLC*, 2022, 47–58
63. Li C, Li X, Chen M, Sun X. Deep Learning and Image Recognition. In: Proceedings of the 2023 IEEE 6th International Conference on Electronic Information and Communication Technology (ICEICT). Qingdao, China: *IEEE*, 2023, 557–562
64. Janiesch C, Zschech P, Heinrich K. Machine learning and deep learning. *Electronic Markets*, 2021, **31**(3): 685–695
65. Shah T M, Nasika D P B, Otterpohl R. Plant and weed identifier robot as an agroecological tool using artificial neural networks for image identification. *Agriculture*, 2021, **11**(3): 222
66. Luo T, Zhao J, Gu Y, Zhang S, Qiao X, Tian W, Han Y. Classification of weed seeds based on visual images and deep learning. *Information Processing in Agriculture*, 2023, **10**(1): 40–51
67. Jin X, Bagavathiannan M, Maity A, Chen Y, Yu J. Deep learning for detecting herbicide weed control spectrum in turfgrass. *Plant Methods*, 2022, **18**(1): 94
68. Alirezazadeh P, Schirrmann M, Stolzenburg F A. Comparative analysis of deep learning methods for weed classification of high-resolution UAV images. *Journal of Plant Diseases and Protection*, 2024, **131**(1): 227–236
69. G C S, Zhang Y, Koparan C, Ahmed M R, Howatt K, Sun X. Weed and crop species classification using computer vision and deep learning technologies in greenhouse conditions. *Journal of Agriculture and Food Research*, 2022, **9**: 100325
70. Zou K, Chen X, Zhang F, Zhou H, Zhang C. A field weed density evaluation method based on UAV imaging and

modified U-net. *Remote Sensing*, 2021, **13**(2): 310

71. Fraccaro P, Butt J, Edwards B, Freckleton R P, Childs D Z, Reusch K, Comont D. A deep learning application to map weed spatial extent from unmanned aerial vehicles imagery. *Remote Sensing*, 2022, **14**(17): 4197
72. Haug S, Ostermann J A. Crop/Weed Field Image Dataset for the Evaluation of Computer Vision Based Precision Agriculture Tasks. In: Agapito L, Bronstein M, Rother C, eds. Computer Vision—ECCV 2014 Workshops. ECCV 2014. Cham: *Springer*, 2015, 105–116
73. De Rainville F M, Durand A, Fortin F A, Tanguy K, Maldague X, Panneton B, Simard M J. Bayesian classification and unsupervised learning for isolating weeds in row crops. *Pattern Analysis & Applications*, 2014, **17**(2): 401–414
74. Pathak H, Igathinathane C, Howatt K, Zhang Z. Machine learning and handcrafted image processing methods for classifying common weeds in corn field. *Smart Agricultural Technology*, 2023, **5**: 100249
75. Ajayi O G, Ashi J. Effect of varying training epochs of a faster region-based convolutional neural network on the accuracy of an automatic weed classification scheme. *Smart Agricultural Technology*, 2023, **3**: 100128
76. Saqib M A, Aqib M, Tahir M N, Hafeez Y. Towards deep learning based smart farming for intelligent weeds management in crops. *Frontiers in Plant Science*, 2023, **14**: 1211235
77. Subeesh A, Bhole S, Singh K, Chandel N S, Rajwade Y A, Rao K V R, Kumar S P, Jat D. Deep convolutional neural network models for weed detection in polyhouse grown bell peppers. *Artificial Intelligence in Agriculture*, 2022, **6**: 47–54
78. Haq S I U, Tahir M N, Lan Y. Weed detection in wheat crops using image analysis and artificial intelligence (AI). *Applied Sciences*, 2023, **13**(15): 8840
79. Sa I, Popović M, Khanna R, Chen Z, Lottes P, Liebisch F, Nieto J, Stachniss C, Walter A, Siegwart R. WeedMap: a large-scale semantic weed mapping framework using aerial multispectral imaging and deep neural network for precision farming. *Remote Sensing*, 2018, **10**(9): 1423
80. de Castro A I, Torres-Sánchez J, Peña J M, Jiménez-Brenes F M, Csillik O, López-Granados F. An automatic random forest-OBIA algorithm for early weed mapping between and within crop rows using UAV imagery. *Remote Sensing*, 2018, **10**(3): 285
81. Zhang T, Huang Y, Reddy K N, Yang P, Zhao X, Zhang J. Using machine learning and hyperspectral images to assess damages to corn plant caused by glyphosate and to evaluate recoverability. *Agronomy*, 2021, **11**(3): 583
82. Utstumo T, Urdal F, Brevik A, Dørum J, Netland J, Overskeid O, Berge T W, Gravdahl J T. Robotic in-row weed control in vegetables. *Computers and Electronics in Agriculture*, 2018, **154**: 36–45
83. Ghanizadeh H, Anderson C B, Franzmayr B K, Cook M, Buddenhagen C E, Ngow Z, James T K, Griffiths A G. Evaluation of high-resolution melting and RT-qPCR probe assays for high-throughput detection of target-site mutations conferring glyphosate resistance in *Lolium perenne*. *New Zealand Journal of Agricultural Research*, 2024, **67**(1): 54–65
84. Wu Z, Chen Y, Zhao B, Kang X, Ding Y. Review of weed detection methods based on computer vision. *Sensors*, 2021, **21**(11): 3647
85. Yang L, Xu S, Yu X, Long H, Zhang H, Zhu Y. A new model based on improved VGG16 for corn weed identification. *Frontiers in Plant Science*, 2023, **14**: 1205151
86. Saleem M H, Velayudhan K K, Potgieter J, Arif K M. Weed identification by single-stage and two-stage neural networks: a study on the impact of image resizers and weights optimization algorithms. *Frontiers in Plant Science*, 2022, **13**: 850666
87. Razfar N, True J, Bassiouny R, Venkatesh V, Kashef R. Weed detection in soybean crops using custom lightweight deep learning models. *Journal of Agriculture and Food Research*, 2022, **8**: 100308
88. Fu L, Lv X, Wu Q, Pei C. Field weed recognition based on an improved VGG with inception module. *International Journal of Agricultural and Environmental Information Systems*, 2020, **11**(2): 1–13
89. Espejo-Garcia B, Mylonas N, Athanasakos L, Fountas S. Improving weeds identification with a repository of agricultural pre-trained deep neural networks. *Computers and Electronics in Agriculture*, 2020, **175**: 105593
90. Tao T, Wei X. A hybrid CNN-SVM classifier for weed recognition in winter rape field. *Plant Methods*, 2022, **18**(1): 29
91. Wu Y, He Y, Wang Y. Multi-class weed recognition using hybrid CNN-SVM classifier. *Sensors*, 2023, **23**(16): 7153
92. Liu T, Jin X, Zhang L, Wang J, Chen Y, Hu C, Yu J. Semi-supervised learning and attention mechanism for weed detection in wheat. *Crop Protection*, 2023, **174**: 106389
93. Somerville G J, Sønderskov M, Mathiassen S K, Metcalfe H. Spatial modelling of within-field weed populations: a review. *Agronomy*, 2020, **10**(7): 1044
94. Zhang S, Guo J, Wang Z. Combing K-means clustering and local weighted maximum discriminant projections for weed species recognition. *Frontiers of Computer Science*, 2019, **1**: 4
95. Andujar D, Martinez-Guanter J. An overview of precision weed mapping and management based on remote sensing. *Remote Sensing*, 2022, **14**(15): 3621
96. Nyamekye C, Ofosu S A, Arthur R, Osei G, Appiah L B, Kwofie S, Ghansah B, Bryniok D. Evaluating the spatial and temporal variations of aquatic weeds (Biomass) on Lower Volta River using multi-sensor Landsat images and machine learning. *Heliyon*, 2021, **7**(5): e07080
97. Corceiro A, Alibabaei K, Assunção E, Gaspar P D, Pereira N. Methods for detecting and classifying weeds, diseases and fruits using AI to improve the sustainability of agricultural crops: a review. *Processes*, 2023, **11**(4): 1263
98. López-Tirado J, Gonzalez-Andújar J L. Spatial weed distribution models under climate change: a short review.

PeerJ, 2023, **11**: e15220

99. Froese J G, Pearse A R, Hamilton G. Rapid spatial risk modelling for management of early weed invasions: balancing ecological complexity and operational needs. *Methods in Ecology and Evolution*, 2019, **10**(12): 2105–2117
100. Reinhardt Piskackova T, Reberg-Horton C, Richardson R J, Austin R, Jennings K M, Leon R G. Creating predictive weed emergence models using repeat photography and image analysis. *Plants*, 2020, **9**(5): 635
101. Sarker I H. Machine learning: algorithms, real-world applications and research directions. *SN Computer Science*, 2021, **2**(3): 160
102. Sabat-Tomala A, Raczko E, Zagajewski B. Comparison of support vector machine and random forest algorithms for invasive and expansive species classification using airborne hyperspectral data. *Remote Sensing*, 2020, **12**(3): 516
103. Ryo M. Explainable artificial intelligence and interpretable machine learning for agricultural data analysis. *Artificial Intelligence in Agriculture*, 2022, **6**: 257–265
104. Shendryk Y, Rossiter-Rachor N A, Setterfield S A, Levick S R. Leveraging high-resolution satellite imagery and gradient boosting for invasive weed mapping. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 2020, **13**: 4443–4450
105. Zhang H, Wang Z, Guo Y, Ma Y, Cao W, Chen D, Yang S, Gao R. Weed detection in peanut fields based on machine vision. *Agriculture*, 2022, **12**(10): 1541
106. Fan X, Chai X, Zhou J, Sun T. Deep learning based weed detection and target spraying robot system at seedling stage of cotton field. *Computers and Electronics in Agriculture*, 2023, **214**: 108317
107. Zhang W, Miao Z, Li N, He C, Sun T. Review of current robotic approaches for precision weed management. *Current Robotic Reports*, 2022, **3**(3): 139–151
108. Hickman D T, Comont D, Rasmussen A, Birkett M A. Novel and holistic approaches are required to realize allelopathic potential for weed management. *Ecology and Evolution*, 2023, **13**(4): e10018
109. Espig M, Henwood R J T. The social foundations for re-solving herbicide resistance in Canterbury, New Zealand. *PLoS One*, 2023, **18**(6): e0286515
110. Ruuskanen S, Fuchs B, Nissinen R, Puigbò P, Rainio M, Saikkonen K, Helander M. Ecosystem consequences of herbicides: the role of microbiome. *Trends in Ecology & Evolution*, 2023, **38**(1): 35–43
111. Ozaslan C, Gürsoy S, DiTommaso A. Band herbicide application combined with inter-row cultivation as a sustainable weed management strategy for reducing herbicide use: a meta-analysis. *Crop Protection*, 2024, **175**: 106474
112. Saberi Riseh R. Advancing agriculture through bioresource technology: the role of cellulose-based biodegradable mulches. *International Journal of Biological Macromolecules*, 2024, **255**: 128006
113. Alptekin H, Ozkan A, Gurbuz R, Kulak M. Management of weeds in maize by sequential or individual applications of pre- and post-emergence herbicides. *Agriculture*, 2023, **13**(2): 421
114. Barnes E R, Knezevic S Z, Lawrence N C, Irmak S, Rodriguez O, Jhala A J. Preemergence herbicide delays the critical time of weed removal in popcorn. *Weed Technology*, 2019, **33**(6): 785–793
115. Aekrathok P, Songsri P, Jongrungklang N, Gonkhamdee S. Efficacy of post-emergence herbicides against important weeds of sugarcane in North-East Thailand. *Agronomy*, 2021, **11**(3): 429
116. Gibson D J, Shupert L A, Liu X. Do no harm: efficacy of a single herbicide application to control an invasive shrub while minimizing collateral damage to native species. *Plants*, 2019, **8**(10): 426
117. MacLaren C, Storkey J, Menegat A, Metcalfe H, Dehnen-Schmutz K. An ecological future for weed science to sustain crop production and the environment. A review. *Agronomy for Sustainable Development*, 2020, **40**(4): 24–29
118. Gawande V, Saikanth D R K, Sumithra B S, Aravind S A, Swamy G N, Chowdhury M, Singh B V. Potential of precision farming technologies for eco-friendly agriculture. *International Journal of Plant and Soil Science*, 2023, **35**(19): 101–112
119. Gerhards R, Andujar Sanchez D, Hamouz P, Peteinatos G G, Christensen S, Fernandez-Quintanilla C. Advances in site-specific weed management in agriculture—A review. *Weed Research*, 2022, **62**(2): 123–133
120. Saleem S R, Zaman Q U, Schumann A W, Abbas Naqvi S M Z. Variable rate technologies: development, adaptation, and opportunities in agriculture. *Precision Agriculture*, 2023: 103–122
121. Tataridas A, Kanatas P, Chatzigeorgiou A, Zannopoulos S, Travlos I. Sustainable crop and weed management in the era of the EU Green Deal: a survival guide. *Agronomy*, 2022, **12**(3): 589
122. Silburn D M, Fillols E, Rojas-Ponce S, Lewis S, McHugh A D. Direct comparison of runoff of residual and knockdown herbicides in sugarcane using a rainfall simulator finds large difference in runoff losses and toxicity relative to diuron. *Science of the Total Environment*, 2023, **863**: 160976
123. Mehdizadeh M, Mushtaq W. Biological control of weeds by allelopathic compounds from different plants: a BioHerbicide approach. In: Egbuna C, Sawicka B, eds. Natural Remedies for Pest, Disease and Weed Control. Cambridge: *Academic Press*, 2020, 107–117
124. Sharma R, Kamble S S, Gunasekaran A, Kumar V, Kumar A. A systematic literature review on machine learning applications for sustainable agriculture supply chain performance. *Computers & Operations Research*, 2020, **119**: 104926
125. Talaviya T, Shah D, Patel N, Yagnik H, Shah M. Implementation of artificial intelligence in agriculture for optimisation of irrigation and application of pesticides and

herbicides. *Artificial Intelligence in Agriculture*, 2020, **4**: 58–73

126. Maraveas C. Incorporating artificial intelligence technology in smart greenhouses: current state of the art. *Applied Sciences*, 2022, **13**(1): 14
127. Niu Z, Rehman T, Young J, Johnson W G, Yokoo T, Young B, Jin J. Hyperspectral analysis for discriminating herbicide site of action: a novel approach for accelerating herbicide research. *Sensors*, 2023, **23**(23): 9300
128. Hulme P E. Potential risks of future herbicide-resistant weeds in New Zealand revealed through machine learning. *New Zealand Journal of Agricultural Research*, 2024, **67**(1): 17–27
129. Zhang J, Huang Y, Reddy K N, Wang B. Assessing crop damage from dicamba on non-dicamba-tolerant soybean by hyperspectral imaging through machine learning. *Pest Management Science*, 2019, **75**(12): 3260–3272
130. Jiang W, Quan L, Wei G, Chang C, Geng T. A conceptual evaluation of a weed control method with post-damage application of herbicides: a composite intelligent intra-row weeding robot. *Soil & Tillage Research*, 2023, **234**: 105837
131. Nørremark M, Griepentrog H W, Nielsen J, Søgaard H T. Evaluation of an autonomous GPS-based system for intra-row weed control by assessing the tilled area. *Precision Agriculture*, 2012, **13**(2): 149–162
132. Sharma P, Kumar V, Jha P. Efficacy and economics of light-activated sensor-controlled sprayer for site-specific weed control. *Agronomy Journal*, 2023, **115**(5): 2590–2599
133. Travlos I, Tsekoura A, Antonopoulos N, Kanatas P, Gazoulis I. Novel sensor-based method (quick test) for the in-season rapid evaluation of herbicide efficacy under real field conditions in durum wheat. *Weed Science*, 2021, **69**(2): 147–160
134. Paul R A I, Arthanari P M, Pazhanivelan S, Kavitha R, Djanaguiraman M. Drone-based herbicide application for energy saving, higher weed control and economics in direct-seeded rice (*Oryza sativa*). *Indian Journal of Agricultural Sciences*, 2023, **93**(7): 704–709
135. Ercolini L, Grossi N, Silvestri N. A simple method to estimate weed control threshold by using RGB images from drones. *Applied Sciences*, 2022, **12**(23): 11935
136. Hiremath C, Khatri N, Jagtap M P. Comparative studies of knapsack, boom, and drone sprayers for weed management in soybean (*Glycine max* L.). *Environmental Research*, 2024, **240**: 117480
137. Dadashzadeh M, Abbaspour-Gilandeh Y, Mesri-Gundoshmian T, Sabzi S, Hernández-Hernández J L, Hernández-Hernández M, Arribas J I. Weed classification for site-specific weed management using an automated stereo computer-vision machine-learning system in rice fields. *Plants*, 2020, **9**(5): 559
138. Yu J, Schumann A W, Cao Z, Sharpe S M, Boyd N S. Weed detection in perennial ryegrass with deep learning convolutional neural network. *Frontiers in Plant Science*, 2019, **10**: 1422
139. Wang P, Peteinatos G, Li H, Gerhards R. Rapid in-season detection of herbicide resistant *Alopecurus myosuroides* using a mobile fluorescence imaging sensor. *Crop Protection*, 2016, **89**: 170–177
140. Longchamps L, Panneton B, Samson G, Leroux G D, Thériault R. Discrimination of corn, grasses and dicot weeds by their UV-induced fluorescence spectral signature. *Precision Agriculture*, 2010, **11**(2): 181–197
141. Elavarasan D, Vincent D R, Sharma V, Zomaya A Y, Srinivasan K. Forecasting yield by integrating agrarian factors and machine learning models: a survey. *Computers and Electronics in Agriculture*, 2018, **155**: 257–282
142. Chlingaryan A, Sukkarieh S, Whelan B. Machine learning approaches for crop yield prediction and nitrogen status estimation in precision agriculture: a review. *Computers and Electronics in Agriculture*, 2018, **151**: 61–69
143. Teimouri N, Dyrmann M, Nielsen P R, Mathiassen S K, Somerville G J, Jørgensen R N. Weed growth stage estimator using deep convolutional neural networks. *Sensors*, 2018, **18**(5): 1580
144. Freckleton R P, Stephens P A. Predictive models of weed population dynamics. *Weed Research*, 2009, **49**(3): 225–232
145. Wang A, Zhang W, Wei X. A review on weed detection using ground-based machine vision and image processing techniques. *Computers and Electronics in Agriculture*, 2019, **158**: 226–240
146. López-Granados F. Weed detection for site-specific weed management: mapping and real-time approaches. *Weed Research*, 2011, **51**(1): 1–11
147. Jin X, Che J, Chen Y. Weed identification using deep learning and image processing in vegetable plantation. *IEEE Access: Practical Innovations, Open Solutions*, 2021, **9**: 10940–10950
148. Bloomer D J, Harrington K C, Ghanizadeh H, James T K. Robots and shocks: emerging non-herbicide weed control options for vegetable and arable cropping. *New Zealand Journal of Agricultural Research*, 2024, **67**(1): 81–103
149. Bangale R, Kumar M. Robot-based weed identification and control system. In: Khatri N, Kumar Vyas A, Iwendi C, Chatterjee P, eds. Precision Agriculture for Sustainability. *Apple Academic Press*, 2024, 169–194
150. Machleb J, Peteinatos G G, Kollenda B L, Andújar D, Gerhards R. Sensor-based mechanical weed control: present state and prospects. *Computers and Electronics in Agriculture*, 2020, **176**: 105638
151. Brugler S, Gardezi M, Dadkhah A, Rizzo D M, Zia A, Clay S A. Improving decision support systems with machine learning: identifying barriers to adoption. *Agronomy Journal*, 2023: agj2.21432
152. Colas F, Cordeau S, Granger S, Jeuffroy M H, Pointurier O, Queyrel W, Rodriguez A, Villerd J, Colbach N. Co-development of a decision support system for integrated weed management: contribution from future users. *European Journal of Agronomy*, 2020, **114**: 126010
153. Tonle F B, Niassy S, Ndadji M M, Tchendji M T, Nzeukou A, Mudereri B T, Senagi K, Tonnang H E. A road map for

developing novel decision support system (DSS) for disseminating integrated pest management (IPM) technologies. *Computers and Electronics in Agriculture*, 2024, **217**: 108526

154. Dainelli R, Toscano P, Di Gennaro S F, Matese A. Recent advances in Unmanned Aerial Vehicles forest remote sensing—A systematic review. Part II: research applications. *Forests*, 2021, **12**(4): 397
155. Quaglia G, Joris I, Broekx S, Desmet N, Koopmans K, Vandaele K, Seuntjens P. A spatial approach to identify priority areas for pesticide pollution mitigation. *Journal of Environmental Management*, 2019, **246**: 583–593
156. Kuppusamy P, Suresh J K, Shanmugananthan S. Machine Learning-Enabled Internet of Things Solution for Smart Agriculture Operations. In: Handbook of Research on Machine Learning-Enabled IoT for Smart Applications Across Industries (pp. 84–115). *IGI Global*, 2023. DOI: 10.4018/978-1-6684-8785-3.ch005
157. Araújo S O, Peres R S, Ramalho J C, Lidon F, Barata J. Machine learning applications in agriculture: current trends, challenges, and future perspectives. *Agronomy*, 2023, **13**(12): 2976
158. Etienne A, Saraswat D. Machine Learning Approaches to Automate Weed Detection By UAV Based Sensors. In: Proceedings of Autonomous Air and Ground Sensing Systems for Agricultural Optimization and Phenotyping IV. Baltimore, MD, United States: *SPIE*, 2019, 202–215
159. Araújo S O, Peres R S, Barata J, Lidon F, Ramalho J C. Characterising the agriculture 4.0 landscape-emerging trends, challenges and opportunities. *Agronomy*, 2021, **11**(4): 667
160. Islam N, Rashid M M, Wibowo S, Xu C Y, Morshed A, Wasimi S A, Moore S, Rahman S M. Early weed detection using image processing and machine learning techniques in an Australian Chilli farm. *Agriculture*, 2021, **11**(5): 387
161. Sharma A, Jain A, Gupta P, Chowdary V. Machine learning applications for precision agriculture: a comprehensive review. *IEEE Access: Practical Innovations, Open Solutions*, 2021, **9**: 4843–4873
162. Lee E K, Zhang W J, Zhang X, Adler P R, Lin S, Feingold B J, Khwaja H A, Romeiko X X. Projecting life-cycle environmental impacts of corn production in the US Midwest under future climate scenarios using a machine learning approach. *Science of the Total Environment*, 2020, **714**: 136697
163. Cravero A, Pardo S, Sepúlveda S, Muñoz L. Challenges to use machine learning in agricultural big data: a systematic literature review. *Agronomy*, 2022, **12**(3): 748
164. Lambert J P, Childs D Z, Freckleton R P. Testing the ability of unmanned aerial systems and machine learning to map weeds at subfield scales: a test with the weed *Alopecurus myosuroides* (Huds). *Pest Management Science*, 2019, **75**(8): 2283–2294