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# A brief insight on precision weed management technologies

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**Abstract**
The increasing global population intensifies demand for food production, placing significant strain on agricultural systems. This challenge is compounded by threats from climate change, water scarcity, and the decline of arable land. Weeds exacerbate these pressures by competing with crops for natural resources, leading to reduced yield and quality. To address this issue sustainably, a balanced integration of cultural, mechanical, and chemical weed control methods is essential, as overreliance on intensive mechanization and herbicides risks ecosystem harm and has led to the widespread issue of herbicide-resistant weeds. Recent technological advancements offer a pathway toward more sustainable systems by enabling precision weed management (PWM). This approach synergizes integrated weed management practices with site-specific, economically viable sensing systems to enhance farm productivity, reduce input requirements, and minimize environmental impact. Consequently, future research should focus on developing and integrating these innovative strategies to advance sustainable agriculture.

**Keywords:** Precision Weed Management (PWM), herbicide resistance, site-specific sensing

## Introduction

Weeds have coexisted with cultivated crops since the dawn of agriculture and remain one of the most persistent and universal threats to food production systems. Their resilience and adaptability make them an ever-present challenge that continues to undermine global agricultural productivity (Buhler *et al*. 2000) [11]. As the global population is projected to reach nearly nine billion by 2050, up from around seven billion at present (Young, 2014) [68], the demand for food, fibre, and fuel will increase dramatically. Meeting this escalating demand amid shrinking arable land, water scarcity, and the intensifying impacts of climate change is one of humanity's most pressing challenges. Within this context, the management of weeds—often termed "the silent yield robbers" has become a defining factor in ensuring sustainable agricultural production systems worldwide (Ribas, 2009) [53].

Weeds interfere with crop growth by aggressively competing for essential resources such as water, nutrients, and sunlight, thereby causing significant yield losses. The Food and Agriculture Organization (FAO) estimates that global crop losses due to weeds range from 30-40%, depending on the crop and region. Traditionally, weed management has relied heavily on two primary approaches: mechanical (or cultural) control and chemical (herbicidal) control. While mechanical methods such as tillage, uprooting, or hoeing can suppress weed growth, they are labour intensive and may cause detrimental effects like soil erosion, loss of soil structure, and reduced microbial activity. On the other hand, chemical herbicides though initially considered revolutionary have brought severe ecological and health-related consequences, including contamination of soil, water, and food, and the emergence of herbicide-resistant weed biotypes (Gnanavel, 2015) [24]. Excessive dependence on herbicides has disrupted ecological equilibrium by altering weed population dynamics and promoting the selection of resistant species. Moreover, continuous herbicide application leads to biodiversity loss and degradation of soil and aquatic ecosystems (Mia *et al*. 2020) [39]. For instance, *Oenothera laciniata* (cutleaf evening primrose) has developed resistance to both paraquat and glyphosate (Lancaster, 2021) [35]. Although the advent of herbicide-resistant (HR) transgenic crops has provided short-term relief, their widespread adoption covering nearly 80% of the 190 million hectares under biotech crops by 2019 has sparked significant debate regarding biosafety and long-term sustainability (ISAAA, 2019; Beckie *et al.* 2019) [31 5]. The repercussions of conventional weed management methods, including soil biodiversity loss, nutrient imbalance, and pollution, have therefore intensified calls for more sustainable, site-specific, and intelligent weed management approaches.

Precision agriculture has emerged as a transformative concept in modern farming, utilizing information technology and geospatial tools to manage spatial and temporal variability within fields. It enables the application of precise inputs such as water, fertilizers, and herbicides at the right place, time, and quantity, optimizing both productivity and environmental sustainability (Bongiovanni *et al*. 2004) [8]. Often referred to as satellite or site-specific crop management (SSCM), precision agriculture integrates Global Navigation Satellite Systems (GNSS), sensors, robotics, high-resolution remote sensing, and data analytics to monitor crop and soil conditions in real time. These technologies enable the collection and analysis of field-level data on soil fertility, moisture, weed distribution, and microclimate variations (Christensen *et al*. 2009; Brown & Noble, 2005) [13, 10]. In recent decades, precision farming has evolved from a theoretical framework to a data-driven reality, thanks to advances in automation, artificial intelligence (AI), and machine learning (Monteiro and Santos, 2022; Balafoutis *et al*. 2020) [41, 4]. The broader paradigm, often referred to as *Agriculture 4.0*, represents the integration of Information and Communication Technologies (ICT), the Internet of Things (IoT), and robotics into traditional agricultural systems (Nukala *et al*. 2016) [43]. These innovations enable farmers to monitor soil health, plant growth, pest and weed infestations, and irrigation status with unprecedented accuracy, thereby reducing input costs, enhancing yields, and minimizing environmental impact (Perez-Ruíz *et al*. 2014; Lowenberg-DeBoer *et al*. 2020) [48, 37]. Smart farming technologies have also become instrumental in promoting sustainable weed management practices by employing data analytics and AI to selectively target weeds, minimizing herbicide usage and preventing off-target effects (Anonymous, 2017; Blucher, 2014) [2, 6].

Agrobiodiversity also plays a crucial role in this context, as it supports ecosystem services such as pollination, soil fertility enhancement, and biological pest control (Anonymous, 2017; MacLaren *et al*. 2020) [2, 38]. However, conventional weed eradication programs and agrochemical overuse have threatened this diversity, destabilizing agroecosystems. Sustainable weed management, therefore, emphasizes integrated approaches that combine ecological, cultural, mechanical, and technological methods—collectively referred to as Integrated Weed Management (Hartzler & Buhler, 2007) [27]. The aim of IWM is to balance effective weed suppression with minimal environmental harm while maintaining profitability and long-term soil health.

Despite the advantages of traditional methods, their limitations are increasingly apparent. Continuous tillage practices degrade soil structure, deplete organic matter, and enhance erosion, compromising long-term soil productivity (Peera *et al*. 2020) [47]. Conversely, reduced tillage systems, though conserving soil moisture and reducing erosion, may increase weed pressure and soil compaction, thereby necessitating greater herbicide use Hollick, 2014) [30]. Similarly, non-chemical strategies such as mulching, cover cropping, flaming, and grazing—present practical and economic constraints. For instance, organic mulches can introduce weed seeds or alter soil pH, while living mulches may compete with crops for nutrients and water (Dabney *et al.* 2001; Peera *et al*. 2020) [14, 47]. Flaming, though effective, demands high fuel consumption, and livestock grazing can damage soil structure or spread weed seeds through feces (Popay & Field, 1996) [49]. Such limitations underscore the urgent need for technologically advanced, precise, and ecologically sound weed management strategies. This is where *Precision Weed Management (PWM)*—a critical subset of precision agriculture—plays a transformative role. PWM employs sensors, cameras, robotics, and AI-based algorithms to detect, map, and control weeds with sub-meter accuracy (Gerhards & Oebel, 2006) [22]. By enabling site-specific application of herbicides or mechanical removal, PWM reduces chemical usage, operational costs, and environmental contamination, while preserving soil and water health (Gerhards *et al*, 2022; Rao, 2021) [23, 52].

Globally, the cost of weed control measures runs into billions of dollars annually (Chauhan, 2020) [12]. The traditional "one-size-fits-all" broadcast herbicide approach fails to account for the spatial heterogeneity of weed infestations, leading to inefficiencies and ecological damage (Rao, 2021) [52]. In contrast, PWM represents a paradigm shift towards sustainability and precision. Through real-time sensing, data-driven decision-making, and targeted actuation, PWM systems ensure that weed control measures are applied *only where and when* necessary, minimizing input waste and promoting environmental stewardship (Christensen *et al*. 2009) [13]. Recent advances in robotics, computer vision, and automation have catalysed the development of site-specific weed control systems capable of identifying weed species, mapping infestations, and implementing targeted mechanical or chemical control measures (Perez & Gonzalez, 2014 [48]; Osten & Cook, 2016) [45]. These intelligent technologies not only address herbicide resistance but also enhance biodiversity conservation and soil health, aligning weed management with the principles of circular and regenerative agriculture (European Commission, 2019 [19]; European Commission, 2020) [20]. In essence, precision weed management marks a new era in sustainable agriculture one that harmonizes productivity, environmental protection, and profitability. By leveraging the power of data, automation, and artificial intelligence, PWM embodies the vision of Agriculture 4.0: a future where every drop of herbicide, every joule of energy, and every byte of data contributes to smarter, cleaner, and more resilient food systems.

## 1. Constraints of Traditional Approaches to Weed Control

Weeds represent one of the most persistent and formidable constraints to sustainable global food production. Growing in close association with cultivated crops, they compete vigorously for essential growth resources such as light, water, nutrients, and space, ultimately reducing both yield quantity and the quality of harvested produce. In agricultural systems, weeds are estimated to account for more than 45% of total yield losses in field crops surpassing losses caused by plant diseases (25%) and insect pests (20%). The extent of these losses is determined by multiple interrelated factors, including the timing of weed emergence, species composition, density, and the competitiveness of the crop. In severe infestations, unchecked weed proliferation can result in yield losses approaching 100%. Beyond direct yield impacts, weeds serve as alternate hosts for a range of insect pests and pathogenic organisms (fungi, bacteria, and viruses), further exacerbating crop health issues (Oerke, 2006) [44].

The deleterious effects of weeds are not confined to productivity alone. They also degrade land value particularly in cases involving perennial or parasitic species such as Striga and Cuscuta and disrupt efficient water management systems by increasing evapotranspiration losses and obstructing irrigation channels. Weed problems become particularly severe when three conditions coincide: the presence of susceptible crops, a large soil seed bank containing viable seeds or vegetative propagules, and environmental conditions favourable for weed germination and growth. While weed management efforts aim to mitigate these negative effects, total eradication remains an unrealistic goal due to the regenerative capacity of weed seeds and vegetative propagules. Nevertheless, it is worth noting that under low densities, certain weed populations may offer limited ecological or agronomic benefits such as enhancing biodiversity, supporting beneficial insects, and contributing to soil cover and erosion control (Swanton & Weise, 1991) [61].

Traditional weed management practices, long relied upon in conventional agriculture, can broadly be categorized into chemical, mechanical, physical, cultural, and biological approaches. Among these, chemical control through synthetic herbicides has become the dominant strategy owing to its rapid action, ease of application, and cost-effectiveness in large-scale farming systems. However, the widespread and often indiscriminate use of herbicides has raised significant ecological, agronomic, and socio-economic concerns (Chauhan, 2020) [12]. Persistent herbicide residues in the soil may impair the growth of subsequent crops and negatively affect soil microbial diversity and function. Herbicide drift during spraying can damage neighbouring crops and contaminate non-target ecosystems, while excessive chemical inputs contribute to surface and groundwater pollution. Furthermore, the overreliance on specific herbicides has accelerated the evolution of herbicide-resistant weed biotypes, posing a major threat to the long-term sustainability of chemical weed management. In addition, herbicide application requires technical expertise for correct dosage calibration and timing, and the cost of newer, proprietary formulations can be prohibitively high for smallholder farmers. Mechanical and physical weed control methods such as ploughing, hoeing, mowing, flaming, or thermal weeding are traditional and environmentally safer alternatives. These practices rely on physically removing or destroying weeds before they compete with the main crop. While effective in reducing weed biomass, they are labour-intensive, time-consuming, and often economically unsustainable in large-scale operations. Repeated tillage may also degrade soil structure, accelerate erosion, and disrupt beneficial soil biota. Non-chemical physical methods, including flame or steam weeding, provide chemical-free alternatives but suffer from limitations in precision, energy efficiency, and scalability. Biological control, which employs natural enemies such as insects, pathogens, or grazing animals to suppress weed populations, represents another ecologically sound strategy. Although successful examples existsuch as the use of *Cactoblastis cactorum* for prickly pear control or *Zygogramma bicolorata* for *Parthenium hysterophorus* biocontrol remains highly species-specific, slow-acting, and often influenced by environmental variability. Cultural methods, including crop rotation, intercropping, and the use of competitive cultivars, contribute to integrated weed suppression but may require long-term planning and site-specific adaptation (Heap, 2023) [29].

Given the numerous limitations associated with conventional weed management approaches, there is an urgent need for innovative and ecologically grounded strategies that integrate multiple control tactics in a holistic framework. Modern weed science increasingly advocates for a systems-based paradigm, wherein weed control decisions are guided by ecological principles, site-specific data, and sustainable resource use. The shift toward precision weed management and smart agricultural technologies thus represents not merely a technological advancement but a necessary evolution in achieving long-term weed suppression, environmental safety, and agricultural resilience.

## 2. Emergence of Precision Weed Management

Weeds have persistently posed a problem in agriculture since its inception. They impede crop growth by competing for water, nutrients, and sunlight, leading to substantial losses in crop production. Common weed control methods involve mechanical practices or the use of herbicides. However, extensive mechanization contributes to soil erosion, diminishing fertility, while herbicide use results in soil, water, food, and air contamination, causing health issues in humans and animals (Swanton & Weise, 1991) [61]. This has led to herbicide resistance and disrupted ecosystems. Biodiversity, particularly agrobiodiversity, plays a crucial role in providing ecosystem services in agricultural systems. Over the past century, there has been a rise in the diversity of weed species, despite the use of highly effective herbicides. This phenomenon is attributed to current crop/pest management systems that favour the presence of weed species well-adapted to specific cultural, chemical, and environmental conditions. For instance, heavy reliance on chemical methods for weed control can result in shifts in weed species composition and density over time. Additionally, the escalating costs of herbicides in the last decade have added to variable expenses in an agricultural landscape where profit margins are already narrow. Consequently, there is a renewed interest in adopting integrated weed management strategies (IWM) to both prevent the establishment of weed species highly adapted to specific management approaches and reduce control costs.

Sustainable weed management includes integrated weed management (IWM), which employs a variety of strategies to optimize crop production and increase profitability. This involves preventive measures, scientific knowledge, management skills, monitoring procedures, and efficient control practices. The field of sustainable weed management has witnessed the development and implementation of various technologies, contributing to economic and environmental sustainability. The challenge for IWM lies in utilizing conceptual and technological tools to devise and execute integrated strategies that avoid the evolution of weed species specifically adapted to particular control methods (Young *et. al.* 2014) [68]. Precision farming stands out as a significant platform for designing and implementing IWM strategies that enhance overall system efficiency. The extensive elimination of weeds and wild plants, coupled with the toxicity of agrochemical inputs, poses a threat to agrobiodiversity and associated services like pollination, soil structure improvement, and natural pest control. Weeds contribute significantly to soil quality and biodiversity support, sustaining agroecosystem productivity in the long term. In light of these challenges, a transition to sustainable weed control is imperative for environmental, social, and economic reasons associated with sustainable agriculture. Precision weed management (PWM) stands out by reducing inputs without compromising weed control effectiveness. Utilizing grid technology aids in planning the usage of pesticides and insecticides, preventing excessive application that could compromise the quality and nutrient levels of the produce (Balafoutis, 2020) [4].

## 3. Sensing and Detection Technologies

Weeds cause significant economic and yield losses by competing with crops for vital resources including nutrients, water, and light (Thorp & Tian, 2004) [63]. The global yield loss attributed to weed competition is estimated to exceed 30% in several major crops, with developing countries often facing even greater challenges due to limited access to advanced management tools. Conventional weed control strategies uniform herbicide applications and manual or mechanical weeding often result in high input costs, soil degradation, and environmental contamination (Gerhards *et al*. 2022) [23]. Excessive herbicide use not only escalates production costs but also contributes to the emergence of herbicide-resistant weed biotypes, soil microbial imbalance, and non-target toxicity to beneficial organisms.

Consequently, there is a growing demand for sustainable, targeted, and eco-efficient approaches to weed control. Precision Weed Management (PWM), also known as Site-Specific Weed Management (SSWM), integrates sensor-based detection, geospatial mapping, and variable-rate application to optimize weed control while minimizing chemical and energy inputs (Liu *et al*. 2021) [36]. Through spatial and temporal precision, PWM allows real-time discrimination between crops and weeds, facilitating site-specific herbicide spraying or mechanical interventions. This system thus contributes to sustainable intensification by applying interventions only where needed, reducing costs, improving resource use efficiency, and minimizing environmental footprints. Advances in sensors, data fusion techniques, and intelligent image-processing algorithms have revolutionized PWM by enabling accurate and real-time weed detection even under complex field conditions.

### 3.1. Optical RGB Imaging

Optical RGB cameras, which capture visible light in red, green, and blue wavelengths, are among the most commonly used sensors in PWM due to their affordability, portability, and ease of integration with agricultural equipment such as tractors, drones, and robotic systems (Wu *et al.* 2021) [66]. RGB imagery offers high spatial resolution and fast data acquisition, making it ideal for detecting weeds during early crop growth stages when canopy closure is minimal. This imaging technique performs effectively in “green-on-brown” scenarios where vegetation contrasts sharply with the soil background allowing accurate segmentation and classification of weed patches (Allmendinger *et al*. 2022) [1]. RGB-based systems often employ colour indices such as Excess Green (ExG), Normalized Green-Red Difference Index (NGRDI), and Vegetation Index (VI) to enhance vegetation detection and reduce background noise. These indices have been widely used to distinguish living plants from soil and residue. Additionally, texture-based parameters (e.g., Gabor filters or Gray Level Co-occurrence Matrices) have been incorporated to improve differentiation between crops and weeds based on leaf shape and surface structure. Despite its advantages, RGB imaging faces several challenges in **“**green-on-green**”** conditions when crop and weed species share similar spectral signatures or in fields with uneven illumination, shadows, or occlusions caused by overlapping canopies (Gerhards *et al*. 2022) [23]. For example, in dense maize or sugar beet crops, RGB cameras struggle to distinguish weed leaves beneath the crop canopy, resulting in misclassification or underestimation of weed density. Moreover, variations in sunlight intensity, soil moisture, and residue reflectance can significantly affect RGB data quality.

Nevertheless, RGB imaging remains foundational in PWM and continues to evolve through integration with machine learning and deep learning frameworks that enhance its robustness and adaptability. Advanced neural networks such as Convolutional Neural Networks (CNNs) and Vision Transformers (ViTs) are increasingly being trained on RGB datasets to automatically extract discriminative spatial features, enabling accurate weed identification even under challenging illumination and background conditions. Thus, while RGB sensors are relatively simple, their integration with sophisticated computational models makes them indispensable in low-cost and scalable PWM systems.

### 3.2. Multispectral, Hyperspectral, and Near-Infrared (NIR) Sensors

Multispectral and hyperspectral sensors extend beyond the visible spectrum by acquiring reflectance data across multiple narrow spectral bands, including near-infrared and shortwave infrared regions. These sensors enable precise differentiation of vegetation types based on biochemical and physiological properties such as chlorophyll content, water status, and cell structure (Allmendinger *et al*. 2022) [1]. By capturing subtle differences in reflectance, they facilitate discrimination between crop and weed species even when visual color cues are similar. Multispectral sensors typically measure reflectance in a limited number of discrete bands (e.g., blue, green, red, red-edge, and NIR), whereas hyperspectral sensors capture hundreds of contiguous bands, allowing the generation of unique spectral fingerprints for each species. This spectral richness enables accurate classification using vegetation indices such as the Normalized Difference Vegetation Index (NDVI), Normalized Difference Red Edge Index (NDRE), and Green Chlorophyll Index (GCI), which quantify the differences in canopy reflectance linked to plant health and morphology (Seiche *et al*. 2023) [56].

One of the most important advantages of hyperspectral imaging lies in its ability to detect physiological stress or pigment variations—such as anthocyanin or carotenoid levels that distinguish weeds from crops even before visible differences appear. This early detection capability allows timely intervention, reducing competition at the initial growth stages. Studies have demonstrated that NIR-based sensing can effectively detect weeds like *Amaranthus retroflexus* or *Chenopodium album* in wheat and maize fields by leveraging spectral contrast in the 700-900 nm range (Gerhards *et al.* 2022) [23]. However, despite their superior accuracy, multispectral and hyperspectral systems have limitations. They generate large data volumes, demanding high computational power and storage for real-time analysis. Moreover, sensor calibration, atmospheric correction, and cost considerations remain significant barriers to their widespread field application. Nevertheless, the declining cost of sensors and the advent of cloud-based data processing platforms have made these technologies increasingly feasible for commercial PWM. When deployed on UAVs or autonomous robots, hyperspectral systems allow for high-throughput weed mapping over large areas with centimeter-level accuracy (Gomes *et al*. 2024) [25]. Combined with artificial intelligence algorithms, these sensors provide an indispensable component for precise, automated, and sustainable weed detection frameworks.

### 3.3. LiDAR, Thermal, and Multi-Sensor Fusion

LiDAR (Light Detection and Ranging) systems use laser pulses to measure distances and generate three-dimensional point clouds of the crop canopy and ground surface. This structural data enables the characterization of plant height, canopy geometry, and leaf orientation—attributes useful for distinguishing weeds growing beneath or between crop rows (Gerhards *et al.* 2022) [23]. For example, LiDAR can identify low-lying weed clusters under cereal canopies that are otherwise obscured in optical imagery. The integration of LiDAR with RGB data also enhances the ability to detect weeds in shaded or occluded areas by adding a depth dimension to traditional imaging. Thermal sensors, on the other hand, detect infrared radiation emitted by plants to measure canopy temperature differences. Since weeds often exhibit different transpiration rates and stomatal conductance compared to crops, thermal imagery can highlight these variations as temperature anomalies (Allmendinger *et al*. 2022) [1]. Such thermal contrast is especially useful for identifying water-stressed weeds or distinguishing them from crops with different evapotranspiration dynamics. Recent advancements have emphasized multi-sensor fusion, integrating RGB, multispectral, hyperspectral, LiDAR, and thermal data to improve detection reliability and accuracy (Seiche *et al.* 2023) [56]. This approach leverages the complementary strengths of different sensors spectral, structural, and thermal to overcome individual limitations. For instance, while RGB offers spatial resolution, hyperspectral sensors provide spectral sensitivity, and LiDAR adds 3D context. Together, these create a comprehensive dataset for robust weed classification.

Multi-sensor fusion models often employ data-level, feature-level, or decision-level fusion strategies. Data-level fusion combines raw data streams before processing, while feature-level fusion merges extracted features from multiple sensors. Decision-level fusion combines outputs from independent classifiers to enhance overall confidence in weed detection. This layered approach reduces false positives and improves classification accuracy under diverse environmental conditions. Although multi-sensor systems involve higher costs, energy consumption, and complex calibration, they represent the frontier of precision weed detection. Future research focuses on miniaturizing sensors, improving synchronization between data streams, and developing on-board fusion algorithms capable of real-time decision-making for autonomous field operations.

## 4. Algorithmic Approaches: From Rule-Based to Deep Learning

The evolution of algorithmic approaches in Precision Weed Management (PWM) has been transformative, progressing from simplistic image thresholding to sophisticated deep learning systems capable of autonomous decision-making. The central challenge in weed detection lies not only in differentiating weeds from crops but also in handling the enormous variability introduced by field heterogeneity, lighting conditions, weed species diversity, growth stages, soil textures, and canopy structures. Each stage of algorithmic evolution rule-based, classical machine learning, and deep learning has contributed unique advantages and limitations toward achieving accurate, real-time weed identification and control (Allmendinger *et al*. 2022) [1].

### 4.1. Rule-Based Image Processing

Early PWM systems were primarily based on heuristic or rule-based image processing, relying on manually defined thresholds and handcrafted features to differentiate vegetation from soil or crop plants (Liu *et al*. 2021) [36]. These methods typically utilized color-space transformations such as RGB to HSV or CIELab to improve vegetation-background contrast. Indices like the Excess Green Index (ExG), Normalized Difference Vegetation Index (NDVI), or Green-Red Vegetation Index (GRVI) were employed to isolate vegetation pixels from non-vegetative regions. Texture-based segmentation techniques, such as Gray Level Co-occurrence Matrix (GLCM) and Local Binary Patterns (LBP), were later integrated to capture surface characteristics, helping to differentiate weed leaves from crop foliage based on edge, smoothness, or repetitive pattern features. Similarly, morphological operations (erosion, dilation, opening, and closing) were applied to refine segmentation results and remove noise. Although computationally lightweight and easy to implement, these systems were highly sensitive to environmental variability. Variations in illumination intensity, soil colour, moisture, and shadowing often led to inconsistent results. In “green-on-green” conditions where crops and weeds exhibit similar colour and texture, their accuracy declined sharply. Consequently, rule-based algorithms were primarily confined to controlled experimental setups or early-stage weed detection under uniform backgrounds. Despite their limitations, these early systems laid the groundwork for subsequent automation by defining basic image-processing pipelines still used as pre-processing steps in modern frameworks (Thorp & Tian, 2004) [63].

### 4.2. Emergence of Classical Machine Learning

The introduction of supervised machine learning (ML) approaches marked the second phase of algorithmic advancement in PWM. Instead of manually coding rules, ML algorithms could learn relationships between input features and class labels (crop vs. weed) from annotated datasets (Wu *et al*. 2021) [66]. Common algorithms included Support Vector Machines (SVM), k-Nearest Neighbours (k-NN), Decision Trees, and Random Forests. In these systems, vegetation features were extracted manually from colour indices, shape descriptors, or texture matrices and used to train classifiers. For example, Random Forests leveraged ensembles of decision trees to improve generalization and robustness against noise, while SVMs optimized decision boundaries for high-dimensional feature spaces (Osten & Cook, 2016) [45]. These techniques achieved higher accuracy than heuristic methods and handled moderate variability in field conditions. Moreover, Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) were often applied for dimensionality reduction, minimizing computational load while retaining discriminatory information. ML-based classifiers could also be trained to identify specific weed species (e.g., Amaranthus, Chenopodium, Convolvulus) based on geometric and spectral characteristics. However, a major limitation of classical ML was the reliance on manually engineered features (Thorp & Tian, 2004) [63]. The performance of these models was strongly dependent on the quality of feature selection, which required expert domain knowledge. In dynamic field environments, features designed for one crop or location often failed when transferred to new regions or lighting conditions. Hence, these methods lacked scalability for diverse, real-world agricultural systems.

### 4.3. Transition to Deep Learning Frameworks

The advent of deep learning (DL) revolutionized weed detection by enabling automatic feature extraction from raw images, eliminating the need for handcrafted descriptors (Wu *et al*. 2021) [66]. Deep learning models, particularly Convolutional

Neural Networks (CNNs), learn hierarchical representations from low-level pixel features (edges, colours) to high-level semantic features (leaf patterns, plant morphology). This capacity allows CNNs to distinguish between visually similar crop and weed species with unprecedented accuracy. Modern PWM applications commonly employ CNN architectures such as VGGNet, ResNet, Inception, and MobileNet, tailored for field images captured under variable conditions. In addition, object detection frameworks like YOLO (You Only Look Once) and Faster R-CNN (Region-Based Convolutional Neural Network) enable real-time identification and localization of individual weeds within complex scenes (Zhang *et al*. 2022) [70]. These networks generate bounding boxes around detected weeds, allowing variable-rate sprayers or robotic actuators to target specific locations with millimeter-level precision. Furthermore, semantic segmentation models such as U-Net, SegNet, and DeepLab have been employed to perform pixel-level classification of crop versus weed, providing spatially detailed maps that guide selective spraying. Such models achieve segmentation accuracies exceeding 90% in controlled trials, greatly outperforming traditional machine learning systems (Osten & Cook, 2016) [45]. Deep learning has also fostered transfer learning, where pre-trained models (on datasets like ImageNet or PlantVillage) are fine-tuned using smaller agricultural datasets, significantly reducing data requirements. Additionally, data augmentation techniques such as rotation, flipping, and lighting adjustment help simulate diverse field conditions, improving model robustness (Gomes *et al*. 2024) [25].

However, several challenges remain. Deep learning models are data-hungry, requiring large, well-annotated datasets that are often unavailable in agriculture. Moreover, their generalization ability is limited: models trained on one crop or geographic region frequently perform poorly when transferred to new settings with different weed flora, soil backgrounds, or illumination (Slaven *et al*. 2023) [60]. Computational constraints further restrict the deployment of high-complexity models on embedded devices or edge computing platforms typically mounted on field machinery. Despite these limitations, deep learning represents the current frontier of PWM research, enabling automated, real-time, and adaptive weed detection at high precision and scalability (De Melo et. al., 2024) [16]. Integration with cloud computing, Internet of Things (IoT) devices, and edge-based AI processors is gradually transforming weed management into a data-driven, fully autonomous agricultural process.

### 4.4. Hybrid and Next-Generation Algorithmic Trends

Building upon deep learning's success, the latest research is exploring hybrid architectures that combine multiple algorithms to improve performance and adaptability. For instance, integrating CNNs with Random Forest classifiers or deep features with SVMs has been shown to enhance accuracy under limited data availability. Attention mechanisms and Vision Transformers (ViTs), inspired by natural language processing, are emerging as powerful alternatives capable of capturing long-range dependencies in weed crop images, thus improving performance in complex canopy structures (Zhang *et al*. 2022) [70]. Additionally, unsupervised and semi-supervised learning methods are being investigated to overcome the scarcity of labelled datasets by learning feature representations from unlabelled images. Few-shot learning and meta-learning further aim to enable model training with minimal data, a crucial development for region-specific weeds or new crop varieties (Murad *et al*. 2023) [42].

Edge-AI integration is another significant trend, allowing lightweight CNN architectures (e.g., MobileNet, EfficientNet) to be deployed on compact embedded devices mounted on drones, tractors, or robotic weeders. This decentralizes computation, enabling real-time weed recognition and control without reliance on cloud connectivity. Ultimately, as algorithmic capabilities mature, the integration of deep learning with decision-support systems, sensor fusion, and real-time actuation will define the next era of precision weed management. These algorithmic advances will allow not only detection and classification but also adaptive decision-making such as determining the optimal control method or herbicide dosage based on weed species, density, and crop growth stage (Rabade *et al*. 2025) [50].

## 5. Actuators and Control Mechanisms

Actuators represent the execution arm of Precision Weed Management (PWM) systems, translating digital detection and mapping information into targeted physical actions on the field. These mechanisms apply localized weed-control interventions chemical, mechanical, thermal, or optical based on sensor feedback and decision algorithms. Their primary objective is to reduce overall herbicide use, minimize off-target impacts, and optimize operational efficiency. In modern precision agriculture, actuators are integrated with advanced control systems that enable real-time responsiveness, spatial accuracy, and automation, transforming traditional weed control into an intelligent, site-specific management process. The evolution of actuation systems has progressed from simple nozzle control units to sophisticated autonomous sprayers and robotic platforms capable of selective herbicide application, mechanical uprooting, or even laser ablation. Each actuation strategy comes with specific advantages, constraints, and suitability for different cropping systems and farm scales (Islam *et al.* 2024) [32].

### 5.1. Spot and Patch Sprayers

Spot and patch sprayers are the most widely adopted actuation mechanisms in PWM due to their compatibility with existing farm equipment and their proven ability to reduce herbicide usage. These systems function based on selective activation of spray nozzles, which deliver herbicide only when a weed is detected by onboard sensors or when the sprayer passes over pre-mapped infested zones (Patel *et al.* 2022) [46]. Spot sprayers operate in real time, often using optical sensors (such as RGB or multispectral cameras) and computer vision algorithms to detect weeds during operation. Once a weed is identified, individual solenoid valves or pulse-width modulation (PWM) systems trigger microbursts of herbicide directly onto the target plant. In contrast, patch sprayers rely on weed maps generated from prior field surveys typically via UAV or tractor-mounted sensors and adjust the spray rate spatially according to weed density and distribution. Field trials conducted by Allmendinger *et al.* (2022) [1] demonstrated herbicide savings between 23-89% in cereal and sugar beet systems without any negative impact on crop yield. These results highlight the potential of selective application to maintain productivity while achieving significant cost and chemical reductions. Similar outcomes were observed in Montana State University Northern Agricultural Research Center (2025) [40] experiments, where up to 90% reduction in herbicide use was recorded under favourable field conditions.

Such systems also contribute to environmental sustainability, as they minimize chemical runoff, reduce the exposure of non-target organisms, and lower greenhouse gas emissions associated with chemical manufacturing and application. Furthermore, precision spraying technologies mitigate herbicide resistance by reducing continuous selection pressure on weed populations, thereby preserving herbicide efficacy for longer periods. Technologically, most modern selective sprayers employ high-speed optical sensors and control valves capable of responding within milliseconds. Manufacturers such as John Deere® ("See & Spray") and WEED-IT® have integrated real-time detection systems that allow sprayer speeds up to 25 km/h with sub-meter accuracy. However, these systems require frequent calibration, consistent lighting conditions, and precise boom height control to maintain detection accuracy. Additionally, economic feasibility remains a challenge for smallholder farmers due to the initial investment and maintenance costs (Sarma *et al*. 2024) [55]. Nonetheless, continuous improvements in sensor affordability, embedded computing, and AI algorithms are making these systems increasingly accessible.

### 5.2. Mechanical and Electromechanical Weeders
Mechanical weeders represent one of the oldest yet most sustainable methods of weed management, now revitalized through automation and robotics. These devices physically disrupt or uproot weeds using rotary blades, tines, hoes, or finger weeders, offering an entirely chemical-free solution that is particularly suitable for organic and low-input farming systems (Szulc *et al*. 2023) [62]. Mechanical weeders can be classified into intra-row and inter-row systems. Inter-row weeders, such as rotary hoes or spring tines, operate between crop rows, whereas intra-row systems such as finger weeders work closer to the crop, requiring precise navigation to prevent crop injury. With advancements in sensing and robotics, modern mechanical systems now incorporate machine vision and GPS guidance, allowing centimeter-level positioning to maintain safety margins between crop plants and weeding tools. Recent innovations in electromechanical weeders combine physical disturbance with electrical or vibrational mechanisms for more effective root destruction. Robotic weeders equipped with vision-guided manipulators can selectively remove individual weeds by mechanical grippers or micro-cultivators (Sarma *et al*. 2024) [55]. These systems are being successfully deployed in horticultural crops, vineyards, and vegetable production, where selective weeding is critical for maintaining soil structure and crop spacing.
The advantages of mechanical and electromechanical weeding systems are manifold, as they fundamentally eliminate dependency on herbicides, making them an ideal cornerstone for organic certification and residue-free crop production, while simultaneously addressing the growing threat of herbicide-resistant weeds by preventing their evolution through diverse control mechanisms. Furthermore, the physical action of these systems, often involving shallow cultivation, provides the secondary benefits of enhancing soil aeration and stimulating beneficial microbial activity, thereby contributing to improved overall soil health and structure (Zawada *et al*. 2023) [69].
However, these systems also have operational constraints, including slower field throughput, higher energy consumption, and potential crop injury if guidance precision is inadequate. The need for flat terrain, stable soil moisture conditions, and regular maintenance further limits their adoption in certain cropping systems. Moreover, the initial investment in autonomous robotic weeders remains substantial, which may restrict their use to high-value or specialty crops. Nonetheless, the continuous development of lightweight electric actuators, compact drive systems, and AI-enabled navigation is steadily overcoming these barriers, moving toward practical and scalable deployment.

### 5.3. Thermal, Electrical, and Laser Methods
In recent years, non-chemical physical weed control technologies have gained significant attention as sustainable alternatives to herbicides. These include thermal, electrical, and laser-based methods, all designed to destroy weeds by targeting their physiological structures without affecting surrounding crops or soil health. Thermal weeding involves applying heat energy through direct flame, hot water, steam, or infrared radiation to denature proteins and disrupt cell membranes in weed tissues. The thermal shock leads to rapid desiccation and plant death. Flame weeding, in particular, has shown promise in pre-emergence and inter-row applications in crops like maize and soybean, especially for organic systems. However, thermal methods may require multiple passes to achieve long-lasting control, and their fuel consumption can be relatively high. Electrical weeding employs high-voltage current delivered through electrodes to the plant stem, causing cellular disruption and root-system damage via resistance heating (Yaseen *et al*. 2024) [67].
This technique is particularly effective for perennial weeds with deep root systems that may survive mechanical disturbance. Electromechanical systems also integrate safety features to prevent accidental discharge and optimize current distribution, thereby improving selectivity and efficiency. Among these, laser-based precision weeding represents one of the most cutting-edge technologies. Brash *et al*. (2022) [9] demonstrated that a laser-guided variable-rate system used in orchard environments achieved a 58% reduction in pesticide volume while maintaining full control efficacy. Lasers enable pinpoint targeting of weeds, delivering concentrated energy pulses that rupture plant cells without disturbing nearby soil or crops. The system operates autonomously, using computer vision and AI algorithms to identify weed morphology and guide beam placement. Furthermore, AI-driven spot spraying technologies an emerging hybrid of sensor-based detection and robotic control have demonstrated remarkable potential for reducing environmental footprints and chemical dependency (Sarma *et al*. 2024) [55]. Such systems integrate deep-learning-based weed detection with high-precision actuation, ensuring that each droplet or energy pulse is applied exclusively to weed tissue.
Despite their promise, these technologies face challenges related to capital investment, energy consumption, and operational safety. For instance, laser and electrical weeders require robust energy sources and advanced cooling systems, which may increase operational costs. Safety mechanisms must also be integrated to prevent accidental exposure to laser radiation or electrical discharge. Moreover, field conditions such as rain, dense canopy cover, or reflective surfaces can interfere with beam accuracy or energy delivery. Nevertheless, continued research in power efficiency, optical control, and automation is rapidly improving the feasibility of these advanced systems. The integration of renewable energy sources (such as solar-charged batteries), precision targeting algorithms, and autonomous navigation systems is expected to make thermal, electrical, and laser methods a key component of next-generation, eco-friendly weed management strategies (Slaven *et al*. 2023) [60].

## 6. Robotic and Aerial Platforms
The integration of robotic and aerial platforms marks a transformative phase in Precision Weed Management (PWM), where detection, decision-making, and actuation are increasingly automated. These platforms combine sensing, computation, and

mechanical execution to perform precise, site-specific interventions with minimal human involvement. By functioning autonomously or semi-autonomously, they address critical agricultural challenges such as labour shortages, time constraints, and the need for ultra-targeted weed control. Robotic and UAV-based systems represent the embodiment of digital agriculture, uniting artificial intelligence, robotics, and remote sensing into cohesive field operations that are both data-driven and environmentally sustainable. While ground robots provide high spatial resolution and targeted intervention at the plant level, Unmanned Aerial Vehicles (UAVs) offer unmatched speed and spatial coverage for weed mapping and surveillance over large areas (Shahi *et al.* 2023) [57]. Both systems contribute uniquely to precision farming ecosystems, complementing each other within integrated weed management frameworks.

### 6.1. Ground Robots

Autonomous ground robots represent the cutting edge of site-specific, plant-scale weed control. These systems combine multiple modules sensor arrays, navigation units, perception algorithms, and actuatorsto identify, localize, and remove weeds autonomously in the field (Gerhards *et al*. 2022) [23]. Equipped with advanced vision systems (RGB, multispectral, LiDAR) and deep-learning models, they can distinguish crop plants from weeds in real time and initiate targeted interventions through mechanical, chemical, or optical actuators. Ground robots function through a closed-loop control system, wherein sensors continuously capture environmental data, onboard processors interpret weed presence and location, and actuators execute the appropriate control response spraying, uprooting, or laser ablation. Navigation is typically achieved using Real-Time Kinematic Global Navigation Satellite Systems (RTK-GNSS) for centimeter-level accuracy, often complemented by LiDAR and stereo vision to ensure obstacle avoidance and safe manoeuvring (Zhang *et al*. 2022) [70].

Several commercial and prototype robotic systems exemplify these technologies:

- Ecorobotix ARA (Switzerland) uses AI-based cameras to detect individual weeds and apply micro-doses of herbicide, achieving up to 95% reduction in chemical usage.
- FarmDroid FD20 (Denmark) employs GNSS-based guidance for fully autonomous weeding and seeding, eliminating the need for herbicides in row crops.
- Naïo Oz and Dino (France) are electric field robots that perform mechanical inter-row weeding using sensor-guided tools.
- Blue River “See & Spray” (now owned by John Deere) combines deep-learning-driven vision systems with precision sprayers to apply herbicide exclusively on detected weeds at full field speed.

Field trials have reported herbicide reductions exceeding 50% without compromising weed control efficacy (Gerhards *et al.* 2022) [23]. These robotic systems not only lower input costs but also improve soil health and operator safety by minimizing exposure to agrochemicals. Furthermore, their ability to operate continuously day or night, under controlled navigation makes them highly efficient in large-scale or time-sensitive operations. However, several challenges hinder commercial scalability. Operational speed is typically lower than that of conventional tractor-based sprayers, limiting daily coverage. Field robots often struggle under adverse conditions such as mud, dense residue, or uneven terrain. Reliability in perception systems can be compromised by varying light conditions, crop density, and weed morphology (Upadhyay *et al*. 2024) [65]. Economic feasibility remains a barrier, as the initial cost, maintenance, and technical expertise required for operation can be prohibitive, especially for smallholder farmers.

In addition, energy consumption and battery life are limiting factors. While many robots are electric and eco-friendly, their runtime per charge often restricts field-scale operations. Despite these limitations, ongoing advances in AI, lightweight materials, power management, and modular robotics continue to improve their efficiency and cost-effectiveness. Looking forward, the integration of swarm robotics multiple robots coordinating tasks via wireless communication and machine-to-machine (M2M) connectivity will enable greater scalability and adaptability. Ground robots are poised to become integral to fully automated farms, where detection, decision, and action occur seamlessly without human intervention.

**6.2. Unmanned Aerial Vehicles (UAVs):** Unmanned Aerial Vehicles (UAVs), or drones, have revolutionized remote sensing and monitoring in precision agriculture, playing dual roles in PWM: (i) mapping and surveillance of weed infestations, and (ii) targeted aerial spraying for localized weed control (De Melo *et al*. 2024) [16]. Their versatility, agility, and scalability make them indispensable tools for real-time data acquisition and spatial decision-making in large and complex agricultural landscapes.

- **Weed Mapping and Prescription Generation:** The most widespread application of UAVs in PWM is high-resolution weed mapping. Equipped with RGB, multispectral, hyperspectral, or thermal sensors, drones capture imagery across large fields at centimeter-level spatial resolution. Using machine learning or deep learning models, weeds are automatically classified and mapped to generate prescription maps that guide ground-based variable-rate sprayers or robotic weeders (Islam *et al*. 2024) [32]. UAVs enable repeated data acquisition over time, allowing for temporal analysis of weed emergence, growth dynamics, and spread patterns. This temporal monitoring is essential for early intervention and adaptive weed management strategies. Studies have demonstrated that UAV-based mapping improves input efficiency by identifying precise weed hotspots, thereby reducing herbicide application areas by up to 70%, compared to uniform treatments (Shahi *et al.* 2023) [57].
- **Targeted Aerial Spraying:** Although UAVs are increasingly capable of direct spraying, most current systems are designed for small-scale, targeted applications rather than large-area blanket coverage. Multi-rotor UAVs equipped with precision nozzles and real-time feedback systems can apply herbicide microdroplets on specific weed patches or late-season escapes with high precision. Advanced drones use AI-assisted flight control and GPS waypoint navigation to ensure accurate spray positioning. However, payload capacity and flight duration remain significant constraints. Typical agricultural drones carry between 10-30 litres of liquid and can cover only 5-15 hectares per flight, depending on topography and spray density. In addition, strict aviation regulations governing UAV operations especially concerning altitude limits, chemical payloads, and operator licensing limit their widespread commercial adoption in many countries (Esposito *et al*. 2021) [18]. Nevertheless, UAVs are invaluable for rapid, large-scale reconnaissance and

integration with ground-based PWM systems. Data collected from drones can be seamlessly transferred to farm management software for creating variable-rate application maps, facilitating hybrid systems where UAVs handle detection and mapping while ground robots or tractor-mounted sprayers perform precise actuation.

- **Technological Advancements and Future Prospects:** Recent innovations are addressing traditional UAV limitations. Hybrid drones equipped with both fixed-wing and rotary capabilities now offer longer endurance and larger payloads. Emerging battery technologies and lightweight carbon-fibre frames are extending flight durations, while AI-driven flight planning algorithms are enhancing operational efficiency. Integration with cloud-based platforms allows real-time image analysis and automated prescription generation. The development of UAVrobot collaboration frameworks represents a key future direction. In such systems, UAVs perform scouting and generate weed distribution maps, which are transmitted to ground robots that execute localized mechanical or chemical interventions. This aerial-ground synergy optimizes both scale and precision UAVs provide macro-level monitoring, and robots handle micro-level interventions. Despite these advances, UAV adoption remains uneven due to regulatory restrictions, cost barriers, and technical complexity. However, as technologies mature and costs decline, drones are expected to become standard tools in integrated precision weed management systems, particularly for large farms, difficult terrains, and areas requiring minimal soil disturbance (Upadhyay *et al.* 2024 [65]; Shahi *et al.* 2023) [57].

## 7. Localization, Mapping, and Decision Support

Localization, mapping, and decision-support systems form the core intelligence layer of Precision Weed Management (PWM), transforming raw sensor data into actionable, spatially referenced prescriptions for field implementation. This process begins with high-accuracy localization, where technologies such as Real-Time Kinematic (RTK) GNSS provide centimetre-level precision to pinpoint individual weeds, a vast improvement over older metre-level system (Lahre & Satpathy 2024) [34]. Positional data are further enhanced through sensor-fusion, combining GNSS with Inertial Measurement Units (IMUs) and vision systems for reliable operation in challenging environments, while Simultaneous Localization and Mapping (SLAM) algorithms enable autonomous robots to navigate and operate in complex, unstructured fields (Shamshiri *et al.* 2024) [58]. Once localized, weed detections are integrated into comprehensive maps that visualise the distribution, density and dynamics of infestations, forming the basis for prescription files (Bohra *et al.* 2025) [7].

These maps, often formatted as shapefiles or ISO-XML, guide Variable-Rate Technology (VRT) on sprayers and other equipment to automatically apply herbicides or mechanical interventions only where needed based on economic thresholds and weed-pressure thereby minimising inputs and promoting sustainability (Sishodia *et al.* 2020) [58]. Standardised protocols (e.g., ISOBUS) facilitate interoperability across machinery from different manufacturers, and cloud-based platforms aggregate data from multiple sources for unified analysis. Furthermore, this information flow feeds into advanced Decision-Support Systems (DSS) that integrate spatial, temporal, and biological data (weed species, resistance profiles, real-time weather) to simulate scenarios, recommend cost-effective agronomic strategies, and even predict future weed-outbreaks using AI-driven analytics (Gao *et al.* 2025) [21]. Ultimately, the future of PWM hinges on full integration of these components into user-friendly, affordable systems that seamlessly connect data-driven insights with automated field actions though challenges in data governance, standardisation and cybersecurity must be addressed to realise its full potential.

## 8. Evidence of Efficacy, Herbicide Savings, and Environmental Benefits

The effectiveness of Precision Weed Management (PWM) systems has been extensively demonstrated through numerous empirical studies under a wide range of cropping conditions. The primary objective of PWM—to sustain or enhance weed-control efficiency while substantially reducing herbicide inputs—has been validated through multiple field-based experiments worldwide. For instance, Allmendinger *et al.* (2022) [1] reported herbicide savings ranging from 23% to 89% across cereal, maize, and sugar-beet cropping systems using selective-spraying technologies, with no statistically significant reduction in yield. These findings emphasize PWM's potential to maintain effective weed suppression even when chemical inputs are reduced by more than half. Such savings are achieved through the accurate detection of weed patches and site-specific herbicide delivery, ensuring that only infested zones are treated rather than entire fields. Further corroborating these findings, Timmermann *et al.*, (2022) [64] demonstrated herbicide reductions of 20-60% in fallow systems compared to uniform broadcast applications. Their work highlighted that precision spot-spraying maintained comparable weed control while significantly lowering total chemical usage. Similarly, Darbyshire *et al.* (2023) [15] found that camera-guided spot-spraying systems could effectively treat up to 93% of weeds while spraying only 30% of the field area, underscoring the spatial precision and efficiency of modern PWM tools.

Large-scale demonstration projects, such as the GrowIWM Initiative (2025) [26], have reported average herbicide savings of 76%, with reductions ranging between 43.9% and 90.6% across over 400 acres of farmland using precision spray technologies. These systems maintained or improved weed-control efficacy relative to conventional broadcast spraying, validating PWM's potential to deliver environmental and economic benefits at a commercial scale. Furthermore, Azghadi *et al.*, (2024) [3] demonstrated in sugarcane systems that robotic spot-spraying achieved up to 65% reduction in herbicide use, while maintaining nearly 97% of the weed-control efficacy of conventional broadcast methods and simultaneously reducing herbicide loads in runoff by 54%, thereby mitigating downstream pollution risks. Complementing these observations, Bohra *et al.* (2025) [7] reviewed advances in site-specific weed management and found consistent herbicide savings of around 50%, depending on the heterogeneity of weed infestations and crop type. Collectively, these results confirm that PWM not only achieves substantial input savings but also maintains yield stability, protects the environment, and enhances farm profitability.

**8.1. Weed-Control Efficacy and Yield Stability:** One of the chief apprehensions regarding PWM adoption is whether reduced herbicide use compromises weed control or yield. However, multiple studies affirm that PWM sustains or even improves weed suppression compared to conventional broadcast applications. High-resolution imaging and precise nozzle control enable site-specific targeting, ensuring optimal herbicide distribution while avoiding over-application in weed-free areas.

Studies by Allmendinger *et al*., (2022) [1] and Darbyshire *et al*., (2023) [15] confirmed that PWM-treated crops exhibited no measurable yield loss, and in some instances, enhanced crop vigour due to reduced phytotoxic stress on non-target plants. Moreover, the integration of PWM with real-time weed detection facilitates adaptive spraying, allowing operators to address weed emergence dynamically throughout the growing season, thereby maintaining long-term weed suppression and yield stability.

**8.2. Herbicide Savings and Cost Efficiency:** Herbicide-use efficiency represents one of the most tangible advantages of PWM. Savings are realized by avoiding redundant spraying in weed-free zones, which often account for 40-70% of cultivated area. By deploying machine-vision algorithms and variable-rate spraying, PWM ensures precision droplet delivery, minimizing both volume and drift. The 23-89% savings reported by Allmendinger *et al*., (2022) [1], 20-60% by Timmermann *et al*., (2022) [64], and up to 76% by GrowIWM (2025) [26] demonstrate substantial input reductions with no yield penalty. These savings translate into direct financial gains, reducing expenditure on herbicides, labour, and equipment wear while boosting operational efficiency.

**8.3. Environmental Benefits and Sustainability Outcomes:** PWM's environmental contributions are profound. Traditional broadcast spraying contributes to soil and water contamination, biodiversity loss, and non-target toxicity. PWM mitigates these impacts through spatially targeted applications, thereby reducing chemical runoff and drift. Azghadi *et al*., (2024) [3] reported that robotic PWM systems significantly lowered herbicide residues in water bodies, aligning with ecological sustainability objectives. Additionally, PWM reduces selection pressure for herbicide-resistant weed biotypes a growing concern under intensive herbicide use (Rao, 2021) [52]. By minimizing total chemical exposure and promoting judicious herbicide deployment, PWM extends herbicide efficacy lifespan while simultaneously reducing greenhouse gas emissions linked to chemical production and transport. Thus, PWM aligns seamlessly with the principles of climate-smart agriculture and sustainable intensification.

**8.4. Broader Implications for Integrated Weed Management:** The demonstrated success of PWM extends beyond chemical efficiency it forms the technological backbone of Integrated Weed Management (IWM) frameworks. By combining precision-based chemical control with cultural, mechanical, and biological weed-suppression practices, farmers can achieve comprehensive, long-term management of weed populations. Data derived from PWM sensors and weed maps can guide crop rotations, cover-cropping, and mechanical weeding interventions (Bohra *et al*. 2025) [7]. These synergies make weed management proactive and site-specific rather than reactive and uniform, enhancing both sustainability and resilience. Ultimately, the widespread adoption of PWM technologies can revolutionize weed management, fostering an era of resource-efficient, environmentally conscious, and economically viable agriculture.

## 9. Challenges and Future Prospects in Precision Weed Management

The advancement of Precision Weed Management (PWM) technologies is accelerating rapidly, yet their widespread adoption continues to face a series of technical and infrastructural barriers that limit scalability and operational reliability. Despite the maturity of individual components such as sensors, cameras, GNSS modules, machine-learning algorithms, and actuators integrating them into a single, cohesive, and field-hardy system remains a formidable engineering challenge. Sensor limitations are a persistent issue, as performance is highly sensitive to environmental factors such as illumination variability, dust accumulation, humidity, and canopy density. Even state-of-the-art RGB and multispectral sensors struggle in "green-on-green" conditions, where crops and weeds share similar spectral characteristics (Gao *et al*. 2025) [21]. Frequent calibration and protection against field hazards like moisture, vibration, and impact further complicate sensor deployment in rugged agricultural environments. In addition, high-resolution imagery and multi-sensor data streams produce enormous volumes of data that demand powerful onboard processors or reliable cloud connectivity for real-time analysis. This creates a bottleneck for farms in developing regions, where poor internet infrastructure hinders cloud-based analytics (San *et al*. 2025) [54]. Consequently, the development of low-latency edge-computing solutions capable of autonomous, real-time inference without external connectivity has become a technological imperative.

Algorithmic generalization also presents a significant constraint: deep learning models trained on specific regions or weed species often fail to perform consistently across diverse environments due to variations in soil reflectance, crop morphology, and illumination. This limits transferability and necessitates costly, region-specific training datasets (Rai *et al*. 2023) [51]. Furthermore, hardware robustness and power autonomy continue to be problematic, especially for UAVs and electric field robots that operate under fluctuating temperatures, uneven terrain, and long working hours. Limited battery performance and degradation over time reduce operational efficiency, emphasising the need for lightweight, energy-efficient designs and the integration of renewable power sources such as solar charging. Finally, the lack of system standardisation and interoperability among devices, software, and data formats remains a major technical barrier. Although frameworks like ISOBUS have improved communication between machinery and sensors, proprietary hardware ecosystems still dominate, hindering seamless data exchange and system scalability (Gao *et al*. 2025) [21].

The economic and adoption-related challenges are equally critical, particularly in regions dominated by smallholder and medium-scale farmers. High capital costs associated with precision sprayers, robotic weeders, and multispectral sensors often deter adoption, as the initial investment can exceed the annual income of an average farmer. While cost recovery through input savings is achievable over multiple growing seasons, the long payback period and uncertain market incentives make it economically unattractive without subsidies or cooperative models (San *et al*., 2025) [54]. Furthermore, the operation of PWM technologies requires specialised technical skills for calibration, troubleshooting, and software maintenance — skills that are still scarce in many rural areas. This lack of technical capacity often leads to under-utilisation, system downtime, and maintenance challenges (Jeevan *et al*. 2024) [33]. Scale and field geometry also constrain adoption; most existing PWM systems are designed for large, uniform fields characteristic of industrial agriculture in developed nations. However, in Asia and Africa, where small, irregular and fragmented plots are common, autonomous navigation and consistent weed detection become more difficult. Market fragmentation further complicates diffusion: the absence of affordable, region-specific solutions tailored to local crops and weed ecotypes restricts accessibility (Szulc *et al*. 2023) [62]. Achieving economic scalability will depend on the creation of modular, cost-effective and customisable platforms adaptable to diverse agro-climatic zones and farming systems, ensuring equitable technological inclusion across scales.

From an agronomic and ecological perspective, integrating PWM technologies into existing weed management frameworks remains a complex and evolving challenge. Weed populations are inherently dynamic, adapting to spatial and temporal variations influenced by seed dispersal, tillage, crop rotation, and environmental changes (Chauhan, 2020) [12]. As a result, mapping and treating weeds in one season do not guarantee long-term control, necessitating continuous monitoring and multi-year data accumulation to construct predictive weed population models. Although PWM significantly reduces herbicide usage, over-reliance on site-specific chemical control in the same zones can create localised selection pressure, inadvertently accelerating herbicide resistance evolution. Therefore, sustainable PWM deployment requires its integration with non-chemical control methods such as mechanical weeding, cover cropping, residue retention and crop diversification (Chauhan, 2020) [12]. Another agronomic challenge lies in minimizing crop injury during mechanical or robotic weeding operations. Delicate crops, narrow inter-row spacing, and variable planting geometry increase the risk of root or stem damage, especially when actuation is not synchronised with crop growth stages. Soil and microclimatic variability such as texture, moisture, or surface roughness further affect sensor accuracy, traction and actuation performance. Developing adaptive algorithms and resilient hardware systems capable of functioning under such heterogeneous field conditions remains a major scientific and engineering frontier (Hasan *et al.* 2021) [28]. Furthermore, PWM must be ecologically validated to ensure that reduced herbicide applications do not shift weed community composition toward more competitive or tolerant species, potentially creating new management challenges over time.

In addition to technological and agronomic hurdles, a range of institutional, regulatory and policy challenges limits the operational and economic scalability of PWM, particularly in developing nations. Many agricultural policies still prioritise fertiliser and pesticide subsidies over digital or precision technology investments, leaving PWM initiatives underfunded and poorly incentivised (Jeevan *et al.* 2024) [33]. Policy instruments that recognise precision weed control as a form of climate-smart and resource-efficient agriculture could significantly accelerate adoption through targeted subsidies, innovation grants, or tax incentives. Regulatory barriers also persist — especially for UAV-based spraying systems which face stringent airspace regulations and chemical application restrictions in many countries (Jeevan *et al*. 2024) [33]. Compliance requirements related to licensing, operator training and aerial pesticide use can delay or prevent large-scale implementation. Data governance is another emerging concern as precision agriculture becomes increasingly data-intensive. Issues surrounding data ownership, privacy and equitable access must be addressed through transparent frameworks that ensure farmers retain control over their data while enabling fair collaboration among technology providers, research institutions and policymakers (Timmermann *et al*. 2022) [64]. Moreover, widespread adoption of PWM demands a fundamental transformation of extension systems, which have traditionally focused on conventional agronomic training. Extension programmes must now incorporate digital literacy, data interpretation, and equipment maintenance training, empowering farmers to manage, troubleshoot and optimise precision systems independently (San *et al*. 2025) [54]. Without such institutional capacity building, even the most advanced technologies risk remaining confined to research projects and demonstration plots, unable to achieve real-world impact at scale.

### 9.1. Persistent Challenges to Widespread Adoption

a. **Technical and Algorithmic Constraints:** A primary technical barrier lies in the robustness of sensing and machine-learning systems. While sensors perform well in controlled conditions, their accuracy can diminish in complex field environments due to variable lighting (e.g., glare, overcast conditions), leaf occlusion, and the presence of crop residues (Gao *et al.* 2025) [21]. Furthermore, the “data-hungry” nature of deep-learning models necessitates vast, meticulously labelled datasets of weed and crop images. This requirement is a major bottleneck, as curating such datasets is labour-intensive and expensive. Consequently, models trained on data from one geographic location or specific crop stage often fail to generalise effectively to different regions, soil types, or growth conditions, a phenomenon known as poor domain adaptation (Rai *et al.* 2023) [51].
b. **System Integration and Compatibility Barriers:** PWM is not a single technology but a complex cyber-physical system requiring seamless integration of detection, decision-making and actuation components. A significant challenge is the lack of standardised communication protocols and interoperability between hardware and software from different manufacturers. For instance, a highly accurate weed-detection algorithm may not be compatible with the control system of a specific robotic sprayer or mechanical weeders (Gao *et al*. 2025) [21]. This inconsistency leads to fragmented solutions, increases system complexity and hinders the development of reliable, plug-and-play PWM platforms that farmers can easily adopt and maintain.
c. **Economic Viability and Accessibility:** The high capital investment for advanced PWM equipment including high-resolution cameras, computing hardware, and automated actuation systems poses a major barrier. Beyond the initial cost, ongoing expenses for maintenance, software updates and operator training further strain budgets. This economic model is particularly prohibitive for smallholder farmers and in developing countries where agricultural systems are characterised by smaller field sizes and limited capital (Wu *et al*. 2021) [66]. The return on investment for these farmers is often unclear or too long-term, effectively limiting PWM’s benefits to large-scale, capital-intensive agricultural enterprises.
d. **Regulatory, Infrastructural, and Social Hurdles:** The scalability of PWM is also constrained by external factors. The use of UAVs for scouting or spraying is heavily regulated, with restrictions on airspace, flight paths, and payloads that vary by country. Data privacy and ownership concerns arise from the high-resolution spatial data collected by these systems. Moreover, effective real-time operation often depends on robust internet connectivity for data transfer and cloud computing, which is frequently unavailable in rural and remote agricultural areas (San *et al.* 2025) [54]. Finally, a lack of technical literacy and farmer scepticism towards autonomous systems can act as

significant social barriers to adoption (Rai *et al*. 2023) [51].

### 9.2. Forging a Path Forward: Key Research and Development Priorities

a. **Advancing Core Technology:** Future work must prioritise the development of low-cost, robust and energy-efficient sensors that can withstand harsh agricultural environments. To address the data bottleneck, the creation of large, open-access, and curated multi-species weed datasets is crucial for benchmarking and advancing algorithm development (Gao *et al*. 2025) [21].
b. **Enhancing Algorithmic Intelligence:** Research should focus on leveraging transfer learning and domain adaptation techniques. These methods allow models pre-trained on large, generic datasets to be efficiently fine-tuned with smaller, local datasets, drastically improving generalisation across diverse farming conditions without the need for massive new data-collection each time (Rai *et al*. 2023) [51].
c. **Designing for Accessibility and Specificity:** There is a pressing need to develop small-scale, modular and economically viable robotic systems tailored for smallholder and diversified cropping systems, such as the complex and intercropped landscapes prevalent in India. These systems must be designed with affordability, ease of use, and repair in mind (Chauhan, 2020) [12].
d. **Integration into Holistic Frameworks:** Ultimately, PWM should not be seen as a standalone solution but as a powerful tool within broader Integrated Weed Management (IWM) frameworks. Combining PWM with cultural, biological and mechanical control strategies can manage weed seed banks, prevent herbicide resistance, and ensure long-term agricultural sustainability (Chauhan, 2020) [12]. This synergistic approach will provide a more resilient and economically stable path forward for farmers worldwide (De Melo *et al*. 2024) [16].

## Conclusion

the evolution from conventional, blanket-application weed control to Precision Weed Management (PWM) represents a paradigm shift essential for the future of sustainable agriculture. The limitations of traditional methods herbicide resistance, environmental contamination, and soil degradation are no longer tenable in the face of a growing global population and escalating ecological pressures. PWM, powered by a sophisticated integration of sensing technologies, artificial intelligence, robotic platforms, and data-driven decision-support systems, offers a viable pathway forward. It demonstrates a proven capacity to drastically reduce herbicide usage, in some cases by over 90%, while maintaining crop yields and promoting soil health through targeted mechanical and chemical interventions. However, the widespread adoption of this promising paradigm is not without significant challenges. Technical hurdles related to sensor robustness and algorithmic generalization, economic barriers of high initial costs, and systemic issues of data interoperability and digital infrastructure must be overcome. The future of PWM hinges on a concerted, collaborative effort to develop more affordable, user-friendly, and adaptable systems, particularly for smallholder farmers. By advancing core technologies, fostering open-data ecosystems, and integrating PWM within holistic Integrated Weed Management frameworks, we can transition these innovations from research prototypes to mainstream practice. Ultimately, the successful implementation of PWM is not merely a technological upgrade but a critical step towards realizing a resilient, productive, and ecologically balanced agricultural system for generations to come.

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