International Journal of Plant & Soil Science

Volume 38, Issue 9, Page 66-81, 2026; Article no.IJPSS.164132
ISSN: 2320-7035

Next-generation Site-specific Weed Management: A Critical Synthesis of Sensing, Artificial Intelligence and Precision Actuation

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Authors' contributions

This work was carried out in collaboration between both authors. Both authors read and approved the final manuscript.

Article Information

DOI: https://doi.org/10.9734/ijpss/2026/v38i96267

Open Peer Review History:
This journal follows the Advanced Open Peer Review policy. Identity of the Reviewers, Editor(s) and additional Reviewers, peer review comments, different versions of the manuscript, comments of the editors, etc are available here: https://pr.sdiarticle5.com/review-history/164132

Review Article

Received: 14/06/2026
Accepted: 12/08/2026
Published: 18/08/2026

Abstract

Weed management is entering a transition from uniform field-wide treatment to spatially selective intervention at patch, row and individual-plant scales. This critical narrative review evaluates the technological and agronomic evidence underpinning site-specific weed management, with emphasis on the coupling of sensing, artificial intelligence, positioning, decision logic and precision actuation. The review focuses on peer-reviewed literature from 2000 to 9 June 2026, supplemented by foundational work within that interval that established practical sensor-based systems. Evidence was appraised for methodological quality, field realism, generalisability and the degree to which technical performance translated into weed-control efficacy, crop safety, input reduction and operational viability. The literature shows that sensing and computer vision have advanced rapidly, especially through high-resolution unmanned aerial vehicle imagery and deep-learning-based crop–weed discrimination. Yet benchmark classification accuracy remains an incomplete predictor of field performance because domain shift, occlusion, weed growth stage, illumination, georeferencing error, latency and actuator footprint can propagate through the control chain. Targeted spraying currently has the strongest field evidence for preserving agronomic efficacy while reducing herbicide use when weeds are spatially heterogeneous, although savings are highly context-dependent. Camera-guided hoeing and robotic intra-row

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Cite as: *Jayasree, P., & Thomas, U. C. (2026). Next-generation Site-specific Weed Management: A Critical Synthesis of Sensing, Artificial Intelligence and Precision Actuation. International Journal of Plant & Soil Science, 38(9), 66–81. https://doi.org/10.9734/ijpss/2026/v38i96267*

cultivation can reduce hand labour and herbicide dependence, but crop safety, soil conditions and work rate remain decisive constraints. Laser and electrical methods demonstrate credible biological mechanisms and increasingly realistic prototypes, but their large-scale energy, throughput, safety and economic performance remains less established. The central conclusion is that next-generation weed management should be judged as a closed-loop agronomic system rather than as an isolated detection algorithm or actuator. Research priorities therefore include multi-environment validation, uncertainty-aware decision thresholds, standardised field metrics, interoperable sensing–actuation architectures, resistance-aware treatment rules and transparent whole-system economic and environmental assessment.

Keywords: Precision weed control; machine vision; agricultural robotics; targeted spraying; unmanned aerial vehicles; deep learning; mechanical weeding; integrated weed management.

1. Introduction

Weeds remain a persistent constraint on crop productivity because their spatial and temporal occurrence is heterogeneous, their competitive effects are strongly stage-dependent, and effective control often requires intervention during a narrow window. Conventional broadcast treatment simplifies this biological variability into a uniform management decision: the same herbicide dose or mechanical operation is applied across a field regardless of local weed presence. Site-specific weed management (SSWM) instead treats spatial heterogeneity as usable information. The core proposition is not simply to detect weeds, but to link detection to a management decision and then to an actuator whose spatial footprint is sufficiently precise to change the treatment at the required scale. Early sensor-based work demonstrated that real-time machine vision, global positioning and independently controlled nozzles could be integrated into precision herbicide systems, while field studies subsequently showed substantial herbicide savings without necessarily sacrificing weed control (Gerhards & Oebel, 2006; Tian, 2002).

The technological trajectory since those early systems has moved from patch-level discrimination towards plant-level intervention. Mapping approaches use remote or proximal sensing to create treatment maps that are executed later, whereas real-time systems perceive and act during a single field pass. Both architectures remain relevant. Mapping can decouple image acquisition from application and permits human or algorithmic review of treatment maps, but it is vulnerable to changes in weed size or position between sensing and control. Real-time systems reduce this temporal mismatch, yet impose stringent constraints on image processing latency, positioning accuracy, computational reliability and actuator timing. Reviews of SSWM have consistently identified weed detection, robust classification and equipment integration as central challenges even as sensor and computing capability have improved (Gerhards et al., 2022; López-Granados, 2011; Slaughter et al., 2008).

The recent acceleration of deep learning has altered the perception layer more than any other component. Convolutional neural networks can learn discriminative image features directly from examples and have achieved high accuracy in curated plant datasets and increasingly complex field scenes (Dyrmann et al., 2016; Hasan et al., 2021; Olsen et al., 2019). Nevertheless, the agronomic significance of an image-classification score is conditional. A model may classify cropped images accurately while still missing small weeds under residue, confusing overlapping crop and weed canopies, or failing when illumination, soil colour, camera height or growth stage differs from the training domain. Moreover, the consequence of a false negative is not equivalent to that of a false positive: a missed competitive or resistant weed can escape treatment, whereas a false-positive spray may merely reduce the expected input saving. These asymmetric errors mean that classifier optimisation cannot be separated from decision thresholds and actuator risk (Lottes et al., 2020; Peteinatos et al., 2020; Wu et al., 2021).

Recent field-oriented evaluations further show that weed-detection performance is sensitive to environmental background and deployment constraints, reinforcing the need to assess generalisability and real-time feasibility under conditions that approximate intended field use (Allmendinger et al., 2025; Matsuhashi et al., 2025).

Actuation has diversified in parallel. Camera-controlled boom sprayers, robotic spot sprayers and map-based systems can restrict herbicide to detected weeds or infested patches. Camera-guided hoes and intra-row tools mechanically remove or bury weeds while protecting crop plants. Directed-energy concepts, including lasers, target plant meristems without physical soil disturbance, and electrical systems exploit current flow through plant tissue. Field evidence is strongest for targeted chemical and mechanical systems, which now include full-width commercial-scale or near-commercial machinery. Laser and electrical methods are progressing from biological proof of concept toward integrated field systems, but their comparative work rate, energy demand, safety envelope and robustness are not yet as well characterised (Andreasen et al., 2022; Gerhards et al., 2024; Gerhards et al., 2026; Lehnhoff et al., 2026; Spaeth et al., 2024).

Recent syntheses likewise frame remote sensing and intelligent mechanical weeding as integrated decision-and-control problems in which sensing quality must be considered alongside treatment timing, targeting requirements and actuator constraints (Das et al., 2025; Huang et al., 2025).

The central challenge is therefore systems integration rather than component novelty. A technically impressive sensor may have limited practical value if its output cannot be georeferenced at actuator resolution, if the decision rule treats biologically irrelevant seedlings, or if the machine operates too slowly for the available field window. Conversely, a modest classifier may provide excellent agronomic performance when crop geometry is predictable, the treatment footprint is forgiving and conservative decision thresholds are used. This distinction is increasingly important because the literature is fragmented across agronomy, computer vision, remote sensing, robotics and machinery engineering. Studies in these domains often report different endpoints, from precision and recall to weed control efficacy, crop stand loss, herbicide savings or field capacity, making direct comparison difficult (Fennimore et al., 2016; Upadhyay et al., 2024).

Existing reviews have provided valuable surveys of weed detection, robotic platforms, automation in specialty crops and SSWM technologies, but many organise the field by component category rather than by the propagation of uncertainty through the full sensing–decision–actuation chain (Fennimore et al., 2016; Gerhards et al., 2022; Hasan et al., 2021; Upadhyay et al., 2024; Wu et al., 2021). A cross-layer synthesis is needed because apparently contradictory results often become coherent when the spatial scale of treatment, weed density, crop geometry, sensing-to-treatment delay and outcome metric are considered together. The relevant question for next-generation weed management is therefore not whether artificial intelligence or robotics can recognise or kill weeds under selected conditions, but under which agronomic and operational conditions those technologies deliver reliable control with lower chemical, labour or environmental burdens.

1.1 Scope, Research Gap and Objectives

This review examines site-specific weed management in arable and vegetable cropping systems, with emphasis on technologies that vary weed-control action spatially at patch, row or individual-plant scales. The scope integrates proximal and aerial sensing, machine vision and deep learning, georeferencing and sensor fusion, decision rules, targeted spraying, camera-guided and robotic mechanical control, and emerging laser and electrical methods. Outcomes of interest include weed-control efficacy, crop safety, yield protection, herbicide or labour reduction, work rate, environmental performance and deployment feasibility. The principal research gap addressed is the weak integration between algorithm-centred evidence and agronomic field evidence: high detection performance is frequently reported without demonstrating reliable closed-loop control, while field studies often provide limited insight into how sensing error, decision thresholds and actuator geometry generated the observed outcome. The review therefore aims to establish a systems-level framework for evaluating next-generation SSWM, compare the maturity and limitations of major sensing and actuation pathways, identify reasons for inconsistent performance across environments, and prioritise research that can convert promising prototypes into robust, scalable components of integrated weed management. Purely non-agricultural weed detection, vendor-only performance claims and laboratory algorithm studies with no plausible link to field deployment are outside the primary scope.

2. Methods for Literature Selection

2.1 Review Design and Rationale

A critical narrative review design was selected because the evidence base spans heterogeneous technical and agronomic study types that cannot be meaningfully reduced to a single pooled effect estimate. The literature includes computer-vision benchmarks, remote-sensing studies, machinery prototypes, field experiments, on-farm demonstrations and technology reviews, with outcomes ranging from classification accuracy and geospatial precision to weed-control efficacy and herbicide saving. A narrative design permits comparison across these evidence forms while retaining attention to methodological differences and causal limitations. Transparency, structured searching and explicit critical appraisal were retained as quality requirements, consistent with guidance for rigorous narrative reviews and the principles represented by the Scale for the Assessment of Narrative Review Articles (Baethge et al., 2019; Ferrari, 2015).

2.2 Information Sources

Live web-assisted scholarly searching was used to locate peer-reviewed literature. Bibliographic identity and accessible content were cross-checked through PubMed/MEDLINE and PubMed Central where relevant, the Directory of Open Access Journals, OpenAIRE, ScienceOpen, institutional research repositories, and official journal or DOI landing pages. Backward citation searching from recent reviews and representative primary studies was combined with related-record and forward-citation exploration where accessible. Direct subscription searches of Scopus and Web of Science Core Collection were not conducted, and no claim of complete coverage of those databases is made.

2.3 Search Strategy and Search Period

The search period was 1 January 2000 to 9 June 2026. The starting date captures the period in which machine vision, positioning and variable-rate actuation began to be practically integrated for sensor-based weed control, while allowing early systems to be evaluated alongside modern artificial-intelligence-enabled platforms. Representative search concepts combined the weed-management problem with spatial selectivity, perception and actuation terms. A typical Boolean structure was: (weed* AND ("site-specific" OR "precision weed management" OR "spot spraying" OR "patch spraying" OR "plant-specific")) AND (camera OR "machine vision" OR sensor* OR UAV OR drone OR multispectral OR hyperspectral OR "deep learning" OR robot* OR autonomous) AND (spray* OR herbicide* OR hoe* OR cultivat* OR laser OR electric* OR mechanical) AND (efficacy OR "weed control" OR herbicide OR yield OR "crop injury" OR runoff OR adoption OR cost OR throughput). Searches were adapted to the terminology of individual platforms and actuation modes.

2.4 Eligibility Criteria

Eligible sources were English-language, peer-reviewed journal articles and high-quality reviews that directly addressed sensing, discrimination, decision support, actuation or agronomic performance in SSWM. Field studies were prioritised for claims about weed control, crop safety, input reduction and operational performance. Controlled-environment studies were retained when they established biological dose–response or mechanism necessary to interpret an emerging physical-control technology. Computer-vision papers were included when their datasets, methods or evaluation addressed realistic agricultural deployment. Studies were excluded when bibliographic identity or DOI could not be verified, when results were purely promotional, when the application was unrelated to crop weed management, or when an algorithmic exercise lacked a defensible pathway to field treatment.

2.5 Screening, Duplicate Handling and Study Selection

Records were screened iteratively by title, abstract and, where accessible, full text. Duplicate records were reconciled primarily by DOI, title and author-year matching. When multiple web records represented the same article, the verified version of record or an authoritative scholarly repository was used for metadata. Inaccessible records whose bibliographic details or relevant findings could not be verified were not used as evidence. Selection was purposive rather than exhaustive because the objective was a critical narrative synthesis rather than a systematic census; consequently, no PRISMA-style record counts or screening flow diagram are presented.

2.6 Critical Appraisal and Evidence Synthesis

Evidence was appraised according to study design, field realism, sample or trial scale, comparators, transparency of methods, relevance of performance metrics, replication across sites or seasons, crop and weed diversity, and external validity. For perception studies, attention was given to dataset provenance, environmental variability, spatial resolution, class imbalance and whether testing represented domain shift. For actuator studies, appraisal focused on weed-control efficacy, crop injury or stand loss, yield, treatment selectivity, throughput, environmental conditions and comparison with conventional management. The synthesis was organised around the closed-loop sequence of sensing, inference, decision and actuation. Apparent disagreements were interpreted in relation to weed density, spatial scale, crop geometry, timing, environmental context and treatment footprint rather than treated as simple contradictions. No formal numerical risk-of-bias score was assigned.

3. From Patch Management to Plant-Level Intervention: Architecture and Decision Scales

SSWM systems differ most fundamentally in the spatial and temporal scale at which they make decisions. Patch spraying treats contiguous areas judged to exceed a weed threshold; row-oriented systems exploit crop geometry to distinguish safe and unsafe treatment zones; plant-specific systems attempt to localise individual weeds and direct a chemical, mechanical or physical action to each target. The move towards finer spatial resolution is often presented as an unqualified technological advance, but resolution is only useful when sensing uncertainty and actuator footprint are commensurate. A centimetre-scale map cannot deliver centimetre-scale selectivity if georeferencing drift, boom motion or nozzle spray width is much larger. Likewise, individual-plant classification is unnecessary for some inter-row mechanical operations in which reliable crop-row detection is the main safety requirement (Gerhards et al., 2020; López-Granados, 2011).

Table 1. Decision scales and system architectures in site-specific weed management

Decision scale / architecture	Typical sensing and decision logic	Principal strengths	Critical limitations	Supporting references
Patch or management-zone, usually map-based	Aerial or proximal imagery converted to georeferenced weed patches or density classes; treatment executed later	Large-area coverage; auditable maps; compatible with conventional machinery	Sensing-to-treatment delay; georegistration and map-transfer error; savings depend on patchiness and threshold	Gerhards & Oebel (2006); López-Granados (2011); Peña et al. (2013); Allmendinger et al. (2024)
Real-time selective boom spraying	On-machine cameras detect vegetation or weeds and trigger section or nozzle control during the same pass	High field capacity; minimal temporal mismatch; compatible with broad-acre practice	Latency, boom dynamics, lighting and nozzle footprint constrain spatial precision	Tian (2002); Spaeth et al. (2024); Gerhards et al. (2026)
Row-specific mechanical control	Camera or positioning detects crop rows and steers hoes or side-shift frames	Does not require species-level weed recognition between rows; reduces herbicide reliance	Intra-row weeds remain difficult; crop injury and soil conditions constrain operation	Gerhards et al. (2020); Naruhn et al. (2023); Gerhards et al. (2025)
Individual-plant robotic control	Plant detection/classification plus localised chemical, mechanical or directed-energy actuation	Maximum theoretical selectivity; can individualise treatment modality	High decision density; actuator throughput; crop–weed confusion; capital and integration complexity	Lottes et al. (2020); Wu et al. (2020); Upadhyay et al. (2024); Zhu et al. (2022)

Note. SSWM = site-specific weed management; GNSS = global navigation satellite system.

Map-based architecture separates perception from treatment. Its main advantage is temporal and computational flexibility: high-resolution aerial or proximal imagery can be processed offline, management zones can be inspected, and application files can be generated before the sprayer enters the field. This architecture was central to early patch management and remains relevant because remote sensing can cover large areas quickly. The principal weakness is change between acquisition and application. Weeds may emerge, grow, be obscured or be altered by weather and field operations, while geospatial errors accumulate across image orthorectification, map generation and machine navigation. On-farm UAV-based spot spraying demonstrates that these errors can be controlled sufficiently for agronomic use, but the result depends on image timing and the spatial resolution of the final treatment rather than on image accuracy alone (Allmendinger et al., 2024; Peña et al., 2013).

Real-time architecture compresses perception, decision and action into one pass. Early machine-vision sprayers established the feasibility of this approach, and modern systems extend it through edge computing and individually controlled nozzles (Partel et al., 2019; Spaeth et al., 2024; Tian, 2002). The practical benefit is that the observed weed and the treated weed are nearly contemporaneous, reducing temporal mismatch. The cost is a much tighter engineering budget. The system must acquire images, classify or segment plants, calculate a treatment decision, compensate for vehicle motion, and trigger the actuator before the target passes the nozzle or tool. Errors therefore become coupled: a small timing bias can convert an accurate detection into a misplaced treatment. This coupling is why field-scale evaluation of the complete machine is more informative than isolated model accuracy.

Plant-specific robotic systems offer the smallest action footprint and potentially the greatest flexibility in treatment modality. They can, in principle, spray, cut, disturb, irradiate or electrically treat different plants according to species, size or risk. Yet finer control increases the number of decisions per hectare and magnifies the importance of work rate. A field containing many weeds may convert an efficient plant-specific machine into an actuator-limited system because each target consumes processing and treatment time. Reviews of robotic weed control therefore identify scalability, navigation, robustness and cost as continuing limitations even when individual components perform well (Slaughter et al., 2008; Upadhyay et al., 2024).

The evidence supports a hierarchical interpretation of SSWM rather than a single end-state. Patch, row and plant scales should be selected according to the biological decision required, the spatial distribution of weeds, the selectivity of the control tool and the cost of error. Table 1 summarises these architectures and shows that increasing spatial granularity shifts the limiting factor from map resolution towards closed-loop latency, target localisation and actuator throughput.

4. Weed Sensing and Spatial Intelligence

4.1 Proximal Sensing

Proximal sensing places the camera or other sensor close to the crop canopy, which increases spatial resolution and reduces some atmospheric and platform effects associated with remote imagery. The trade-off is a smaller field of view and stronger exposure to vibration, dust, shadows, crop motion and rapidly changing viewing geometry. Early systems relied on vegetation indices, colour segmentation and hand-crafted shape or texture features. Their performance could be adequate when crop rows were clear or weeds were visually distinct, but fixed features were brittle across soil backgrounds and phenological stages. The progression towards learned features and deep convolutional models was therefore not merely a change in algorithmic fashion; it addressed the need to represent plant appearance across more complex field conditions (Dyrmann et al., 2016; Hasan et al., 2021; Wu et al., 2021).

Proximal sensing is particularly attractive for real-time actuation because the sensing geometry can be mechanically fixed relative to the tool. This permits calibration between image coordinates and nozzle, hoe or laser coordinates. Yet apparent spatial precision can be misleading. The plant part that should be targeted may differ from the object used for classification, and the crop–weed boundary can be ambiguous under overlapping leaves. Stem localisation and sequence-based inference are therefore important for plant-specific control. Lottes et al. (2020) showed how temporal image sequences and joint stem detection can improve robustness for treatment localisation, illustrating a broader point: perception should be designed for the actuator's target, not only for class labels.

4.2 UAV and Map-based Sensing

Unmanned aerial vehicle (UAV) imagery changed the practical scale at which high-resolution weed maps could be created. Early work demonstrated that low-altitude platforms with visible and multispectral cameras could resolve vegetation at early crop stages and support object-based weed mapping in crops such as maize and sunflower (Peña et al., 2013; Torres-Sánchez et al., 2013). Multi-temporal work in wheat further showed that visible imagery could provide high-accuracy vegetation mapping when crop geometry and acquisition timing were favourable (Torres-Sánchez et al., 2014). These studies were important because they established that remote weed detection need not wait for coarse satellite revisit cycles or late-season canopy differentiation.

The agronomic value of UAV maps depends on more than classification. A map must be acquired early enough to support effective control, processed quickly enough to remain biologically current, and converted into a treatment layer whose spatial error is smaller than the intended application zone. Sapkota et al. (2023) demonstrated a complete UAS imagery and computer-vision workflow linked to chemical-use reduction, while Allmendinger et al. (2024) evaluated map-based spot spraying in on-farm maize fields and reported substantial herbicide savings with weed control broadly comparable to broadcast treatment. These field integrations are more informative than standalone image studies because they expose the cumulative effects of mapping, threshold selection and spray execution.

UAV sensing also introduces a distinctive scale mismatch. Images can be extremely fine, yet herbicide application may still occur through nozzles or sections that treat areas much larger than individual weeds. In such cases, increasing image resolution beyond the actuator's effective footprint may improve confidence without proportionally increasing chemical savings. Conversely, if the map is coarser than the patch structure, untreated or overtreated margins increase. The optimal sensing resolution is therefore an engineering–agronomic quantity determined by weed aggregation, map error, machine guidance and treatment footprint, not by image quality in isolation (López-Granados, 2011; Peña et al., 2013).

4.3 Positioning, Sensor Fusion and Timing

Geospatial positioning underpins any system that separates sensing from actuation or that uses seed/crop position as prior information. Global navigation satellite system (GNSS) guidance can stabilise rows, align treatment maps and reduce reliance on crop appearance, but positioning error interacts with vehicle dynamics and tool geometry. Camera-guided mechanical systems illustrate a complementary approach in which visual row detection continuously corrects lateral tool position; this can be especially useful where centimetre-scale clearance is required (Gerhards et al., 2020). Hybrid systems are likely to be more robust because GNSS, row geometry and vision fail under different conditions.

Timing is equally important. The most visually separable weed stage may not be the most agronomically desirable treatment stage, and machine-learning models trained on later, larger plants can overstate usefulness for early control. Site-specific management therefore confronts a temporal paradox: early intervention offers biological advantages and often lower energy or dose requirements, but seedlings provide less morphological information and are more easily obscured. This problem is evident across remote sensing, mechanical control and laser studies, and it favours systems that integrate spatial priors, temporal sequences and crop geometry rather than relying on a single image frame (Lottes et al., 2020; Marx et al., 2012; Torres-Sánchez et al., 2013).

Table 2 shows that sensing platforms should be compared by their role in a control system rather than by nominal resolution. Proximal cameras offer low-latency target localisation, while UAVs provide scalable spatial context and treatment planning. Their limitations are complementary and motivate hybrid approaches.

Table 2. Sensing pathways, operational roles and principal uncertainty sources

Sensing pathway	Representative evidence	Operational advantage	Main failure modes or uncertainty	Supporting references
Proximal RGB / machine vision	Real-time plant or row detection on sprayers and robots	Low latency; direct calibration to actuator; high spatial detail	Variable illumination, shadows, residue, occlusion, vibration, growth-stage domain shift	Tian (2002); Lottes et al. (2017); Peteinatos et al. (2020); Spaeth et al. (2024)
Deep-learning crop–weed vision	Species or crop–weed classification using learned features	Reduces dependence on hand-crafted colour/shape rules; adaptable to multiple tasks	Dataset bias; class imbalance; confidence poorly calibrated outside training conditions	Dyrmann et al. (2016); Hasan et al. (2021); Olsen et al. (2019); Wu et al. (2021)
UAV visible / multispectral mapping	Early-season vegetation and weed maps from low-altitude imagery	Rapid coverage; georeferenced field context; supports offline treatment planning	Processing delay; orthomosaic/georegistration error; canopy overlap; regulation/weather constraints	Torres-Sánchez et al. (2013); Peña et al. (2013); Torres-Sánchez et al. (2014); Sapkota et al. (2023)
Vision plus positioning / crop geometry	Camera row guidance or sequence-based plant localisation combined with spatial priors	Redundant cues can improve target localisation and crop safety	Calibration drift; error propagation between coordinate frames; dependence on planting accuracy	Gerhards et al. (2020); Lottes et al. (2020); Allmendinger et al. (2024)

Note. RGB = red-green-blue; UAV = unmanned aerial vehicle

5. Artificial Intelligence for Crop–Weed Discrimination and Decision Making

5.1 From Engineered Features to Deep Representations

Traditional crop–weed discrimination used explicit colour, shape, texture and row-location features. These approaches are interpretable and can be computationally light, but their assumptions tend to fail as scenes become more variable. Deep learning reduces the need to pre-specify discriminative features and has therefore become dominant in image-based weed research. Dyrmann et al. (2016) demonstrated multi-species seedling classification across diverse image sources, while later field systems used convolutional architectures for detection, segmentation and crop–weed separation in operational contexts (Peteinatos et al., 2020; Wu et al., 2020). Reviews of the field confirm strong gains in representational capability, but also show that the dominant evidence remains supervised and dependent on labelled datasets (Hasan et al., 2021; Wu et al., 2021).

High within-dataset accuracy does not establish field generalisability. The DeepWeeds dataset, for example, provided a valuable large collection of in situ images and demonstrated high classification performance for eight weed species, but its ecological context is Australian rangeland rather than crop-row management (Olsen et al., 2019). Its value to SSWM lies in demonstrating how realistic backgrounds, varied lighting and field acquisition can be incorporated into dataset design, not in implying direct transfer to every cropping system. Similarly, strong seedling classification in a finite species set is useful evidence of algorithmic capability but does not remove the need to validate across farms, seasons, cultivars, camera systems and weed communities (Dyrmann et al., 2016).

5.2 Domain Shift and the Benchmark-to-Field Gap

Domain shift is the central unresolved problem in agricultural vision. A model trained under one combination of soil texture, illumination, crop stage and weed flora may encounter a different combination at deployment. Lottes et al. (2020) explicitly addressed robustness using image sequences and data from different farms, illustrating a move from random image splits towards more realistic cross-domain evaluation. Peteinatos et al. (2020) tested convolutional neural networks across maize, sunflower and potato scenes, further demonstrating that crop context materially affects discrimination. These studies support a methodological principle: test sets should represent new environments, not merely new images from the same acquisition campaign.

The benchmark-to-field gap is also a metric problem. Classification accuracy averages errors over classes, whereas weed management requires spatially and biologically weighted errors. Missing one large, competitive weed or a species with known resistance can matter more than correctly classifying many inconsequential seedlings. Conversely, false-positive treatment of crop plants can be catastrophic for a mechanical blade or high-energy laser but may only cause a small input penalty for a herbicide that is selective to the crop. Therefore precision, recall and intersection-over-union should be interpreted alongside actuator-specific cost functions and agronomic consequences. The literature rarely reports these consequences in a unified way, which limits comparison between perception studies and field machinery trials (Hasan et al., 2021; Upadhyay et al., 2024).

5.3 Real-time Deployment, Latency and Uncertainty

Deployment shifts the optimisation objective from maximum offline accuracy to a feasible trade-off among accuracy, latency, memory use, power consumption and robustness. The low-cost precision sprayer of Partel et al. (2019) is important because it evaluated artificial-intelligence-based target discrimination as part of a complete spraying platform rather than as an isolated model. Wu et al. (2020) similarly integrated automated crop–weed classification with robotic control. These studies show that edge inference and actuation are technically feasible, but they also illustrate why nominal model accuracy should not be interpreted without information about operating speed and control delay.

Uncertainty-aware decision making remains underdeveloped. Most systems convert model output into a binary weed/no-weed action, often through a confidence threshold. Yet the appropriate threshold depends on treatment risk and weed economics. A targeted herbicide system may rationally favour high recall to avoid escapes, accepting some overspray. A crop-destructive actuator should favour extremely high crop-safety confidence near stems and may abstain under ambiguity. This is not merely a software detail; it is a mechanism for converting statistical uncertainty into agronomic risk. Future systems should therefore report calibration, abstention behaviour and performance under deliberately shifted conditions, not only average detection metrics.

Species-level recognition also has strategic value beyond target localisation. If a system can identify weed species or functional groups, it can potentially choose herbicide mode of action, dose, mechanical intensity or treatment priority according to biology. Current commercial and field systems often use simpler vegetation or crop/weed separation because it is more robust and computationally efficient. The evidence therefore suggests a staged hierarchy: reliable crop protection and weed localisation are prerequisites, while species-level treatment decisions add value only when classification confidence and treatment options justify the complexity (Gerhards et al., 2026; Peteinatos et al., 2020).

Table 3. Representative artificial-intelligence evidence and implications for field deployment

Study / AI role	Evidence contribution	Why it matters for SSWM	Deployment caveat	Supporting references
Multi-species seedling CNN classification	Demonstrated learned features across 22 plant species and varied image sources	Established feasibility of deep representations for early plant identification	Finite species set and image-level classification do not by themselves prove closed-loop field control	Dyrmann et al. (2016)
Field crop–weed classification and localisation	Vision models tested in sugar beet and multi-crop field scenes	Moves evaluation towards crop-context recognition and target localisation	Performance remains sensitive to crop stage, overlap and environmental domain	Lottes et al. (2017); Peteinatos et al. (2020)
Image-sequence stem detection	Uses temporal information for joint crop–weed classification and stem localisation	Aligns perception output with plant-specific actuation target	Requires stable motion, calibration and sufficient frame overlap	Lottes et al. (2020)
Large in-situ weed dataset	17,509 images of eight weed species with natural backgrounds	Shows value of realistic acquisition and public benchmark data	Ecological domain differs from crop-row SSWM; high benchmark accuracy may not transfer directly	Olsen et al. (2019)
Integrated AI sprayer / robot	Real-time classification coupled to selective chemical or robotic control	Demonstrates that edge inference can drive actuators in operational systems	Latency, field speed and false decisions become whole-system rather than model-only errors	Partel et al. (2019); Wu et al. (2020)

Note. CNN = convolutional neural network; SSWM = site-specific weed management

Table 3 summarises representative artificial-intelligence evidence and the deployment lesson from each study. The consistent pattern is that model sophistication increases capability, but field reliability depends more strongly on dataset diversity, spatial target definition and integration with the control system than on architecture alone.

6. Precision Actuation: Chemical, Mechanical and Physical Control

6.1 Targeted Chemical Application

Targeted spraying is the most mature SSWM actuation pathway because it preserves the established biological efficacy of herbicides while changing where they are applied. Early patch systems already showed that spatially selective treatment could reduce herbicide use substantially in heterogeneous weed populations without consistently reducing weed control (Gerhards & Oebel, 2006). Modern camera-controlled sprayers increase spatial granularity through single-nozzle or small-section control and faster image processing. The agronomic question is no longer whether selective application is possible, but how much chemical reduction can be achieved without creating economically or biologically consequential escapes.

Field evidence demonstrates that savings are strongly context-dependent. Spaeth et al. (2024) evaluated a smart sprayer across plot and on-farm settings, supporting the practical feasibility of camera-based site-specific herbicide application. In ten maize experiments, a camera-controlled 36 m boom sprayer operated at 10 km h−1 and achieved weed-control efficacy comparable with broadcast treatment while saving, on average, approximately one quarter of the herbicide; the authors emphasised that weed density and treatment geometry constrained savings (Gerhards et al., 2026). This is an important corrective to claims that finer targeting automatically produces very large reductions. When weed presence is widespread or a nozzle treats a relatively broad footprint around each detected weed, many apparently weed-free pixels still fall inside activated spray zones.

Map-based spraying can achieve larger savings where weed patches are sparse and well resolved. Allmendinger et al. (2024) reported early post-emergence herbicide savings approaching one half in on-farm maize while maintaining effective control. Sapkota et al. (2023) similarly demonstrated the potential for imagery-derived treatment maps to reduce sprayed area. These findings are not directly interchangeable with real-time single-nozzle systems because treatment thresholds, mapping resolution, weed pressure and crop stage differ. The proper synthesis is that herbicide saving is an emergent property of weed spatial distribution multiplied by detection and actuator footprints, not an intrinsic specification of the sprayer.

Environmental benefit also requires more than a reduction in litres or treated area. A particularly informative field study in sugarcane compared robotic spot spraying with broadcast application over 25 ha and evaluated weed control, herbicide use and irrigation-runoff water quality. Spot spraying retained approximately 97% of broadcast weed-control efficacy while reducing herbicide use by about 35%; mean herbicide concentration and load in runoff were also lower (Rahimi Azghadi et al., 2025). This study is methodologically important because it links precision application to an environmental exposure pathway rather than assuming that chemical saving necessarily translates into environmental improvement.

The main agronomic risk of targeted spraying is untreated weeds resulting from sensing, threshold or actuation error. Where the cost of an escape is high, a zero-weed-tolerance rule can preserve efficacy but reduce chemical savings, as illustrated by modern boom-sprayer studies (Gerhards et al., 2026). Conversely, more aggressive thresholds can increase savings while accepting some escapes. Economic thresholds, weed species, resistance status and seed-return risk should therefore be embedded in decision logic. The next advance in chemical SSWM is likely to come as much from better decision rules and narrower treatment footprints as from further gains in image classification.

6.2 Mechanical and Robotic Control

Mechanical SSWM replaces chemical selectivity with spatial selectivity. Between crop rows, the problem is comparatively tractable because crop geometry creates a protected zone. Camera-guided side-shift systems have enabled hoeing at narrower row spacing and higher precision, including winter cereals where conventional hoeing was previously difficult (Gerhards et al., 2020). Intra-row control is harder because weeds and crop plants share the same line. Intelligent cultivators therefore rely on accurate crop localisation, controlled tool trajectories or finger-weeding principles that disturb weeds while tolerating crop contact.

The commercial Robovator evaluation in broccoli and transplanted lettuce illustrates the practical value and limitations of intelligent intra-row cultivation. Compared with a standard cultivator, the system removed more weeds at moderate to high weed densities and reduced subsequent hand-weeding time without reducing crop stand or marketable yield (Lati et al., 2016). This evidence is stronger than a laboratory demonstration because it measures a labour-relevant endpoint within an integrated weed-management system. Yet its advantage was smaller at low weed density, showing that the economic value of automation can depend on the amount of work available for the machine to replace.

Mechanical efficacy can be increased through system-level changes to crop establishment. Naruhn et al. (2023) used square-pattern maize sowing to permit hoeing both along and across crop rows, raising mean weed-control efficacy relative to one-direction hoeing but also increasing crop losses. This is a crucial example of co-design: rather than forcing a robot to solve every perception problem, the cropping system can be modified to make selective control easier. Such approaches may offer more robust gains than adding increasingly complex perception alone, but they require changes in planting equipment and agronomic practice.

Finger weeders offer a lower-complexity intra-row option whose selectivity depends on crop anchorage, weed size, soil condition and tool settings. Multi-crop field trials found useful weed control across processing tomato, sweet corn, sunflower, cotton and beetroot, but efficacy and crop response varied with context (Asaf et al., 2023). This heterogeneity reinforces the need to treat mechanical weeding as an interaction between machine, plant biomechanics and soil rather than as a fixed actuator performance. Sensor guidance can reduce lateral error, but it cannot remove the biological dependence on plant size and anchorage.

Comparative field testing of multiple robotic systems in sugar beet and rapeseed suggests that several distinct technologies can attain weed-control efficacy comparable with reference herbicide strategies, yet work rate, crop loss and treatment cost differ among machines (Gerhards et al., 2024). A 2025 study comparing camera-guided inter-row hoeing, finger weeding, automated intra-row hoeing and band spraying similarly showed that combined systems can approach broadcast-herbicide efficacy while reducing herbicide use, but a mis-set classification algorithm caused crop loss in one maize treatment (Gerhards et al., 2025). That failure is analytically valuable: it demonstrates that digital configuration is an agronomic safety variable.

6.3 Laser and Electrical Control

Laser weed control is attractive because it is non-contact, potentially highly localised and does not require soil disturbance. Controlled studies established a strong dependence of plant damage on energy density, growth stage, target position and species. Mathiassen et al. (2006) showed that directing laser energy at apical meristems could suppress or kill young weeds, while Marx et al. (2012) modelled dose–response relationships and demonstrated that inaccurate beam placement sharply reduces lethality. These findings explain why laser systems demand a more precise perception-to-actuator chain than selective herbicide spraying: a few centimetres of error may mean no biological effect or damage to the crop.

Integrated field prototypes are now narrowing the gap between mechanism and operation. Zhu et al. (2022) combined deep-learning-based detection, robotic aiming and a blue laser in maize; at a low travel speed the prototype achieved high weed damage with measurable crop injury. The study confirms field feasibility but also exposes the throughput constraint. A laser must dwell on each target long enough to deliver a lethal dose, so increasing weed density or plant size can reduce field capacity unless multiple beams, faster aiming or higher-power systems are used. Reviews of laser and optical weed control identify energy delivery, safety, target localisation and economic scalability as continuing constraints (Andreasen et al., 2022; Zhang et al., 2024).

Recent field comparisons provide stronger agronomic evidence. Sosnoskie et al. (2025) evaluated a deep-learning-based commercial laser weeder against conventional herbicide programmes in beet, spinach and pea production systems. The results showed that laser treatment can function as a practical weed-management tactic in vegetable crops, but performance varied across systems and does not yet justify a general claim that directed energy is universally equivalent to chemical control. Such comparisons are valuable because they include crop response and real weed communities rather than only target plants under controlled conditions.

Table 4. Comparative evidence for major site-specific weed-control actuation pathways

Actuation pathway	Field evidence / maturity	Principal advantages	Key limitations and failure modes	Supporting references
Targeted herbicide spraying	Strong field and on-farm evidence, including conventional-width boom and robotic platforms	Preserves familiar herbicide efficacy; high work rate; direct chemical savings	Savings collapse at high weed density or broad nozzle footprint; misses may permit escapes; needs resistance-aware decision rules	Gerhards & Oebel (2006); Spaeth et al. (2024); Rahimi Azghadi et al. (2025); Gerhards et al. (2026)
Camera-guided inter-row hoeing	Mature field prototypes and commercial guidance systems	No herbicide required between rows; robust crop-row geometry can simplify perception	Intra-row weeds remain; crop clearance, soil condition and residue affect safety/efficacy	Gerhards et al. (2020); Naruhn et al. (2023)
Intelligent intra-row / robotic mechanical control	Field evaluations in vegetables and row crops; multiple commercial or near-commercial systems	Can reduce hand labour and chemical dependence; high spatial selectivity	Crop injury risk; plant anchorage and growth stage matter; work rate and tool setting are critical	Lati et al. (2016); Asaf et al. (2023); Gerhards et al. (2024); Gerhards et al. (2025)
Laser / optical directed energy	Mechanistic dose–response evidence plus integrated prototypes and recent crop-field comparisons	Non-contact; no chemical residue; potentially plant-specific without soil disturbance	Precise aiming and dose required; energy, safety and per-target dwell time constrain throughput	Mathiassen et al. (2006); Marx et al. (2012); Andreasen et al. (2022); Zhu et al. (2022); Sosnoskie et al. (2025); Zhang et al. (2024)
Electrical control	Emerging field evidence; diverse stationary and mobile concepts	Non-chemical mechanism and potential for targeted treatment	Power delivery, wet conditions, electrical safety and scalability remain uncertain	Lehnhoff et al. (2026)

Note. Evidence maturity reflects the body of field and mechanistic research considered in this review; it is not a formal grading score

Electrical control is less mature within plant-specific SSWM. Lehnhoff et al. (2026) tested a low-power solar electric 'mulch' for intra-row vineyard weed suppression and found season-long control at small treated scales, with efficacy declining as treated area increased. This is not directly analogous to mobile electrocution, but it provides a clear field demonstration of the scale–power constraint. The broader implication is that physical weed control cannot be evaluated on biological efficacy alone: energy distribution, electrical or optical safety, weather sensitivity, machine capacity and treatment density determine whether a mechanism can become a scalable agronomic tool.

Table 4 compares the actuation pathways. Targeted spraying currently offers the clearest route to broad-acre deployment; mechanical systems are especially relevant where herbicide options or labour are constrained; laser and electrical systems offer attractive non-chemical selectivity but remain more sensitive to throughput and energy constraints.

7. From Prototype Accuracy to Agronomic Performance

A recurrent weakness in the SSWM literature is the substitution of technical performance for agronomic performance. Image accuracy, localisation error and actuation precision are necessary intermediate outcomes, but the farmer's endpoint is a sufficiently weed-free crop with acceptable yield, crop safety, cost and timeliness. This distinction changes how evidence should be weighted. A computer-vision study can demonstrate that an algorithm is technically promising, whereas a replicated field trial with broadcast or standard-cultivation comparators can demonstrate agronomic equivalence or inferiority. The two forms of evidence are complementary but not interchangeable (Fennimore et al., 2016; Hasan et al., 2021).

The closed-loop error chain is multiplicative in practical terms. A weed must first be visible to the sensor, then correctly recognised or localised, then converted into an appropriate management decision, and finally treated at the correct position and dose or mechanical intensity. Failure at any stage can create an escape. Equally, a crop plant must be protected from false detection and actuator error. This means that an apparently small degradation at several stages can produce a meaningful reduction in field efficacy. Studies that integrate perception and actuation, such as robotised spraying, robotic classification, or laser control, are therefore especially valuable because they reveal compound errors that component benchmarks cannot capture (Gonzalez-de-Soto et al., 2016; Wu et al., 2020; Zhu et al., 2022).

Field performance is also shaped by the distribution of weeds. Targeted spraying saves little herbicide when weeds are nearly ubiquitous, regardless of detection quality. Conversely, sparse aggregated populations allow large savings even with modest spatial resolution. Gerhards and Oebel (2006) reported wide ranges of herbicide savings among crops and weed groups, and modern camera-controlled boom studies continue to show that weed density explains much of the variability in savings (Gerhards et al., 2026). This context dependence should be considered a core result rather than statistical noise. It argues against reporting a single percentage saving as a general property of a technology.

Treatment timing introduces another source of variance. Small weeds are generally easier to kill mechanically or with lower directed-energy dose, and early herbicide treatment can protect yield, but early plants are also more difficult to identify. Later treatment improves visible morphology but may increase competition, actuator energy or mechanical crop interference. The optimal timing is therefore a joint property of perception and biology. Laser dose–response studies show increasing difficulty with growth stage, while remote-sensing work shows that early-season discrimination can be constrained by small plant size and canopy geometry (Marx et al., 2012; Torres-Sánchez et al., 2013).

Crop safety is frequently underreported in perception-centred research. Mechanical and physical actuators can injure crops directly, and even targeted spraying can create harm if non-selective chemistry is used close to crop plants. Field trials of intelligent cultivation show that crop stand and yield may be preserved when localisation is reliable, but bi-directional hoeing and misconfigured automated intra-row systems demonstrate that increased weed removal can be accompanied by crop loss (Gerhards et al., 2025; Lati et al., 2016; Naruhn et al., 2023). The relevant performance surface therefore contains at least two competing outcomes: weed removal and crop protection.

Work rate is similarly decisive. Broad-acre spraying can operate at conventional field speeds, while individual-plant mechanical or laser tools may be limited by the time needed to align and treat each target. A machine with excellent efficacy but insufficient field capacity can miss the agronomic window during periods of rapid weed growth or wet weather. Upadhyay et al. (2024) identify scalability and operational efficiency as central barriers for ground robots. This concern is not solved simply by faster computing because many actuators have physical dwell-time or tool-motion constraints.

Comparative study design should therefore move beyond accuracy-first evaluation. At minimum, integrated SSWM trials should report weed density before treatment, weed-control efficacy by relevant spatial zone, crop injury or stand loss, yield where the crop reaches harvest, treatment area or input use, operating speed and effective field capacity, failure or intervention frequency, and environmental conditions. Where a perception model is central, field metrics should be paired with precision/recall or segmentation measures, but those metrics should not replace agronomic outcomes. This combined reporting would make the literature more comparable and reveal whether a performance gain arises from better sensing, more conservative thresholds, different weed pressure or actuator design.

8. Sustainability, Resistance Stewardship and System-Level Trade-offs

The sustainability case for SSWM is strongest when the technology reduces a clearly defined burden while preserving effective weed control. For targeted spraying, the most direct burden is herbicide use. Field evidence demonstrates that substantial reductions are possible, and the sugarcane study by Rahimi Azghadi et al. (2025) strengthens the environmental argument by showing lower herbicide concentration and load in irrigation runoff alongside chemical savings. Yet chemical-use reduction is not synonymous with risk reduction. Environmental outcome depends on active ingredient, dose, toxicity, transport pathways and the spatial location of treated weeds. Future studies should therefore measure exposure-relevant endpoints when environmental benefit is a principal claim.

Mechanical control removes herbicide from the treated zone but can increase soil disturbance, fuel use and operational passes. Camera-guided systems can narrow the disturbed zone and reduce crop damage, but repeated inter-row cultivation may still alter soil structure or moisture relative to chemical treatment. The literature reviewed here provides stronger evidence for weed-control efficacy than for whole-system life-cycle impact. It is therefore premature to rank mechanical, chemical and directed-energy systems universally by sustainability. A defensible comparison requires a common functional unit such as hectare-season of adequate weed control, with energy, chemical use, labour, soil disturbance, crop yield and machinery embodied impacts considered together.

Resistance stewardship introduces a further complexity. Site-specific herbicide application can reduce the total area exposed to herbicide, which may reduce chemical loading, but the evolutionary outcome depends on whether weed escapes are allowed to reproduce. A high-recall selective sprayer using the same mode of action repeatedly could still exert intense selection on treated plants, whereas a mixed system that directs different tools according to species or location could diversify selection pressure. The technology therefore creates an opportunity for resistance-aware integrated weed management, but precision alone does not constitute resistance management. Decision algorithms should incorporate species identity, prior field history, threshold rules and seed-return risk where reliable data are available (Gerhards et al., 2022; Peteinatos et al., 2020).

Non-chemical plant-specific control could become especially valuable for resistant or herbicide-tolerant escapes. Mechanical, laser and electrical actuators are not governed by herbicide target-site mechanisms, so they can diversify control. Their efficacy nevertheless remains growth-stage and context dependent. Mechanical tools can fail when weeds are too large or soil conditions are unfavourable; laser dose increases with plant size and inaccurate aiming reduces damage; low-power electrical control can lose effectiveness as treated area or wetness changes (Lehnhoff et al., 2026; Marx et al., 2012; Naruhn et al., 2023). Integrated systems should therefore treat physical control as complementary rather than intrinsically fail-safe.

Biodiversity and non-target effects deserve more systematic evaluation. Targeted spraying can leave unsprayed field area chemically untreated, but whether this translates into higher within-field plant or arthropod diversity depends on which weeds are spared and when. Mechanical soil disturbance can affect non-target organisms differently from chemical application, and laser systems raise questions about optical safety, fire risk and incidental exposure. Reviews of laser weeding have highlighted these issues, but field evidence remains limited relative to efficacy studies (Andreasen et al., 2022; Zhang et al., 2024). Sustainability claims should therefore be calibrated to measured endpoints rather than inferred from the label 'precision' or 'non-chemical'.

The most promising sustainability pathway is likely hybrid treatment rather than universal replacement. A field could be mapped to identify dense patches for conventional treatment, sparse weeds for spot spraying, and herbicide-resistant escapes for mechanical or directed-energy removal. Such an architecture would allocate treatment intensity according to biological need and actuator strength. The information layer of SSWM makes this technically plausible, but evidence for multi-modal field decision systems remains sparse. Current research has largely optimised individual tools; the next step is to optimise portfolios of tools over seasons and crop rotations.

9. Deployment, Economics and Adoption Barriers

Technical feasibility does not guarantee adoption. SSWM changes the distribution of cost from consumable inputs and labour towards sensors, computing, precision actuation, software, calibration and maintenance. The economic balance therefore differs among farms and crops. Specialty crops with high hand-weeding costs can justify intelligent cultivation at smaller acreages than low-margin broad-acre crops, whereas broad-acre targeted spraying benefits from integration with conventional high-capacity machinery. This helps explain why automation pathways diverge by production system rather than converging on a single universal robot (Fennimore et al., 2016; Upadhyay et al., 2024).

Capital cost is only one component. Reliability during short agronomic windows, operator training, sensor cleaning, data transfer, calibration, access to parts and software support all affect effective cost. A robot that requires frequent intervention may shift labour from hoeing to technical supervision rather than eliminate it. Similarly, a mapping workflow that requires specialised image processing can impose transaction costs even if UAV acquisition is rapid. López-Granados (2011) identified training, cost and machinery compatibility as barriers more than a decade ago; many remain relevant because the technology stack has become more complex even as individual sensors have become cheaper.

Interoperability is a persistent structural barrier. Map-based systems require consistent geospatial formats and machine control interfaces. Real-time systems require stable communication among cameras, processors, vehicle control and actuators. Proprietary data formats or closed software can limit the ability to combine a sensor from one supplier with an actuator from another. From a research perspective, lack of common interfaces also makes replication difficult because performance may depend on undocumented calibration or software settings. Open data, explicit calibration procedures and standardised reporting would therefore support both scientific reproducibility and commercial interoperability.

Farm-level value also depends on weed pressure. A selective sprayer saves more chemical in sparse fields, but the same sparse field may have a low absolute herbicide cost to begin with. Conversely, high weed pressure increases the agronomic value of control while reducing percentage savings. Mechanical robots may show the opposite labour pattern: high weed densities can increase the value of automation but reduce work rate or increase tool load. Economic analysis should therefore avoid evaluating technologies at a single representative weed density. Scenario analysis across infestation levels is more appropriate.

Risk allocation influences adoption. Farmers bear yield and timing risk when a new tool fails, while many benefits such as reduced runoff or lower pesticide loading accrue partly to society. This creates a potential mismatch between private and public value. The sugarcane runoff evidence is an example of an environmental benefit that may not be fully monetised at farm level (Rahimi Azghadi et al., 2025). Policy incentives, service-provider models and shared machinery could therefore affect adoption, but these mechanisms require empirical study rather than assumption.

The strongest near-term adoption pathway is integration into familiar machinery and agronomy. Camera-controlled full-width boom sprayers retain conventional field capacity and workflow while adding spatial selectivity, which reduces behavioural and logistical disruption (Gerhards et al., 2026; Spaeth et al., 2024). Camera-guided hoeing similarly augments an established mechanical operation. Fully autonomous plant-specific robots may ultimately offer greater flexibility, but their value proposition must include navigation, supervision, safety and field logistics as well as weed control. Comparative economics should therefore evaluate complete operational systems rather than component purchase prices.

10. Future Directions

The immediate research priority is to close the benchmark-to-field gap through multi-environment, multi-season trials in which perception and actuation are evaluated together. Algorithms should be trained and tested across farms, soil backgrounds, cultivars, weed communities and acquisition hardware, with test environments separated from training environments. Agronomic outcomes should be collected in the same experiments. This would reveal whether a model's apparent robustness actually preserves weed control and crop safety when the domain changes (Hasan et al., 2021; Lottes et al., 2020).

A second priority is uncertainty-aware decision control. Detection confidence should be calibrated and linked explicitly to actuator risk. Systems should be able to abstain, enlarge the safety margin, switch to a lower-risk treatment or flag an area for later intervention when confidence is low. This is especially important for crop-destructive mechanical and laser tools. Research should compare decision policies under known error costs, not merely optimise a fixed image threshold. Field endpoints should include untreated weed escapes, crop injury, follow-up treatment requirement and seed-return potential.

Third, sensing and crop establishment should be co-designed. Precision seeding, known crop positions and row geometry can reduce the perception burden, as demonstrated by bi-directional hoeing and camera-guided systems (Gerhards et al., 2020; Naruhn et al., 2023). Experiments should test whether changing row spacing, seed placement accuracy or planting patterns yields greater whole-system benefit than adding more complex classifiers. Such research would reconnect robotics with agronomy and may produce simpler, more robust systems.

Fourth, treatment decisions should move beyond binary weed presence. Species, growth stage, local density, resistance status, competitive risk and prior control history can support variable treatment intensity or modality. Targeted spraying could use narrower footprints or different herbicide choices, while resistant escapes could be assigned to mechanical or physical removal. The required research is longitudinal: field-scale experiments over rotations should compare weed population dynamics, seed return, herbicide use and resistance risk under adaptive SSWM against conventional programmes (Gerhards et al., 2022; Peteinatos et al., 2020).

Fifth, physical-control research needs rigorous energy and throughput accounting. Laser studies should report energy delivered per target, target size, treatment time, successful kill or suppression, crop injury and effective field capacity across weed densities. Electrical systems need comparable reporting of power, contact or treatment geometry, moisture sensitivity, safety controls and area scaling. The biological mechanism is sufficiently established to justify this shift from proof of concept to engineering and agronomic optimisation (Lehnhoff et al., 2026; Mathiassen et al., 2006; Marx et al., 2012; Sosnoskie et al., 2025).

Sixth, standardised reporting is needed across SSWM. A minimum field dataset should pair perception metrics with pre-treatment weed density, species composition, crop stage, treatment footprint, weed-control efficacy, crop safety, input use, speed, field capacity, weather/soil conditions and yield where appropriate. Environmental studies should add exposure-relevant endpoints rather than infer benefit from input reduction alone. Common reporting would make meta-analysis more plausible in the future and would prevent misleading comparisons between technologies tested under fundamentally different weed pressure.

Finally, implementation research should examine service models, interoperability, operator workload and lifecycle economics. The central question is not whether a machine can function, but whether it can deliver repeated, auditable value across seasons. On-farm trials should therefore include downtime, calibration burden, intervention frequency, data management and maintenance. Research consortia that combine weed science, agricultural engineering, computer vision, farm economics and environmental assessment are particularly well suited to this systems problem.

Table 5 translates these priorities into study designs and outcomes. The most urgent need is evidence that connects technical robustness to agronomic value under domain shift; longer-term priorities concern adaptive multi-modal management and whole-system sustainability.

Table 5. Prioritised research directions for next-generation site-specific weed management

Priority	Unresolved problem	Recommended study design	Key outcomes	Supporting references
Multi-environment closed-loop validation	High benchmark accuracy may not transfer across farms, seasons or hardware	Prospective multi-site, multi-season trials with held-out environments and complete sensing-to-actuation evaluation	Weed-control efficacy, crop injury, yield, precision/recall, latency, failure frequency	Hasan et al. (2021); Lottes et al. (2020); Upadhyay et al. (2024)
Uncertainty-aware treatment rules	Binary thresholds do not reflect unequal costs of misses and false treatments	Compare calibrated confidence, abstention and risk-weighted policies under common field conditions	Escapes, crop damage, input saving, follow-up treatments, seed-return risk	Peteinatos et al. (2020); Gerhards et al. (2026)
Agronomy–robot co-design	Perception complexity may compensate for avoidable crop-layout ambiguity	Factorial trials of planting geometry/positioning precision × guidance/actuation strategies	Control efficacy, crop loss, work rate, establishment cost, yield	Gerhards et al. (2020); Naruhn et al. (2023)
Resistance-aware multi-modal SSWM	Precision alone does not diversify selection pressure	Rotation-scale field experiments assigning chemical, mechanical or physical tools by species/risk	Herbicide use, weed seedbank/seed return, resistance indicators, yield, cost	Gerhards et al. (2022); Gerhards et al. (2025)
Energy and throughput benchmarking for physical control	Biological efficacy is not enough to establish scalability	Field trials across weed size/density with explicit energy and time accounting	Energy per treated target/area, field capacity, efficacy, crop injury, safety events	Mathiassen et al. (2006); Marx et al. (2012); Sosnoskie et al. (2025); Lehnhoff et al. (2026)
Whole-system environmental and economic assessment	Input savings may not equal net environmental or private economic benefit	On-farm comparative trials with exposure, labour, reliability and lifecycle cost measures	Runoff/load, fuel/electricity, labour, downtime, treatment cost, yield	Rahimi Azghadi et al. (2025); Spaeth et al. (2024)

Note. Outcomes should be interpreted jointly; no single technical metric is sufficient to establish agronomic value

11. Conclusions

Next-generation site-specific weed management is best understood as a closed-loop agronomic control problem. The strongest evidence no longer concerns the feasibility of detecting weeds or moving a robotic tool; it concerns whether sensing, inference, decision logic and actuation remain aligned under real field variability. Across the literature, the major gains have come from higher-resolution sensing, deep-learning-based perception, faster edge computing, precision positioning and actuators capable of switching at patch, row or plant scales. These advances have moved SSWM from isolated prototypes towards on-farm systems and, in some cases, integration with conventional-width machinery.

The evidence is strongest for targeted chemical application. Both map-based and real-time systems can preserve weed-control efficacy while reducing herbicide use when weeds are sufficiently heterogeneous, although the magnitude of saving is not a fixed property of the technology. It depends on weed density, spatial aggregation, decision thresholds and treatment footprint. Mechanical systems also have a credible field evidence base and can reduce herbicide or hand-labour dependence, especially when crop geometry and guidance support safe tool placement. Their limitations are primarily intra-row selectivity, soil and plant biomechanics, crop injury and work rate. Laser control has advanced from controlled dose–response studies to realistic field comparisons, but throughput, aiming precision, energy and safety remain more constraining than for selective spraying. Electrical control is promising but comparatively immature at scalable crop-field dimensions.

The most important methodological conclusion is that algorithmic accuracy and agronomic efficacy must not be conflated. High detection scores are useful only when they translate into correctly placed treatment, acceptable crop safety and reliable field capacity. Future systems should therefore be evaluated using linked technical and agronomic metrics under genuine domain shift. The highest-value innovations may come not from ever more complex classifiers, but from co-designing crop establishment, sensing, decision rules and actuators so that uncertainty is reduced at the system level. SSWM can become a practical foundation for integrated weed management when precision is used to allocate the right treatment to the right location at the right time, rather than treated as an end in itself.

12. Limitations

As a critical narrative review, this synthesis is intrinsically susceptible to selection and interpretive bias despite the use of a transparent search strategy, explicit eligibility criteria and structured appraisal. It was not designed as a systematic review and did not attempt exhaustive record capture or quantitative meta-analysis. Direct subscription searches of Scopus and Web of Science Core Collection were not available, so relevant articles indexed only in inaccessible sources may have been missed. English-language restriction may also have reduced coverage of region-specific machinery and field research.

The evidence base itself is heterogeneous. Computer-vision studies, engineering prototypes and agronomic field trials use different outcomes and scales, making direct quantitative comparison inappropriate. Many studies are conducted in a limited set of crops, locations or seasons, and rapidly evolving hardware and software can render older performance constraints less representative of current capability. Conversely, short-duration demonstrations of newer systems may overstate generalisability because long-term reliability, weed population dynamics and lifecycle economics are not yet established. Environmental evidence is particularly uneven: reductions in herbicide use are commonly reported, but direct measurements of runoff, biodiversity, soil effects or lifecycle energy are much less frequent. These limitations restrict the certainty with which technologies can be ranked across production systems and reinforce the need for standardised, multi-environment field evaluation.

Declaration of AI Use

This manuscript was prepared through the intellectual contributions of the author(s) to the study design, data analysis, interpretation of results, and scholarly content. Grammarly and ChatGPT were used solely to assist with grammatical refinement and reference formatting during manuscript revision. The author(s) accept full responsibility for the accuracy, integrity, and final content of the manuscript.

Competing Interests

Authors have declared that no competing interests exist.

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The peer review history for this paper can be accessed here:
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