Scientific Papers. Series E. Land Reclamation, Earth Observation & Surveying, Environmental Engineering. Vol. XV, 2026
Print ISSN 2285-6064, CD-ROM ISSN 2285-6072, Online ISSN 2393-5138, ISSN-L 2285-6064

UAV-DERIVED VEGETATION INDICES FOR SPATIAL ASSESSMENT OF WEED INFESTATION IN ARABLE CROPS

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Abstract

Early identification of weed infestation is essential for improving the efficiency and sustainability of crop protection practices. This paper presents a spatial assessment of weed infestation in arable crops based on vegetation indices derived from unmanned aerial vehicle (UAV) multispectral imagery. UAV flights were conducted during early crop development stages, and the acquired data were processed to generate NDVI-based spatial maps. Spatial variability analysis was applied to differentiate crop-dominated areas from zones affected by weeds and to identify infestation hotspots within the field. The results indicate that UAV-derived vegetation indices provide valuable information for early weed detection and support site-specific management decisions. The proposed approach contributes to reducing unnecessary agrochemical inputs and promotes more environmentally responsible weed control strategies. This work highlights the potential of UAV-based monitoring as a practical tool for supporting precision agriculture and integrated weed management in arable farming systems.

Key words*: NDVI, precision farming, spatial analysis, UAV, weed infestation.*

INTRODUCTION

Weed infestation remains a major constraint on crop productivity, input-use efficiency, and the sustainability of arable farming systems. Because weeds are rarely distributed uniformly within a field and instead tend to occur in patches, uniform herbicide application often leads to unnecessary chemical use, higher production costs, and greater environmental pressure. Site-specific weed management addresses this limitation by targeting interventions only where weed pressure justifies treatment, provided that reliable spatial information is available at the appropriate stage of crop development (López-Granados, 2011; Peña et al., 2013).

In this context, unmanned aerial vehicles (UAVs) provide an effective remote-sensing platform for early weed assessment in arable crops. Their flexibility in acquisition timing, low flight altitude, and centimetre-level spatial resolution make them especially useful during early growth stages, when crop and weed plants are still small and spatially distinguishable. When equipped with multispectral sensors, UAVs can capture reflectance in the visible, red-edge, and near-infrared regions, enabling the calculation of vegetation indices such as NDVI, NDRE, GNDVI, and chlorophyll-related metrics that support vegetation discrimination, crop vigor assessment, and the detection of anomalous zones associated with weed infestation (Clevers & Gitelson, 2013; Schlemmer et al., 2013; Stroppiana et al., 2018). Even so, spectral information alone is rarely sufficient for reliable weed discrimination, because crops and weeds may show similar reflectance patterns at early developmental stages. For this reason, vegetation indices are most useful when interpreted together with spatial variability analysis, crop-row structure, field observations, and management-zone delineation. This integrated approach strengthens weed mapping, hotspot identification, and the practical implementation of targeted herbicide application or other

integrated weed management strategies. Weed mapping is therefore one of the most promising UAV applications in precision agriculture, although its wider use still depends on robust classification under variable field conditions (López-Granados, 2011).

Despite the increasing number of studies addressing UAV-based weed mapping, several methodological limitations remain insufficiently resolved. First, many approaches rely on vegetation indices as direct indicators of weed presence, although crop and weed plants may exhibit similar spectral responses during early growth stages. Second, the transition from spectral variability maps to agronomically meaningful weed-management zones is not always clearly described, particularly in relation to crop-row structure, vegetation masking, and hotspot delineation. Third, the operational feasibility of these workflows remains uneven, as some studies emphasize classification accuracy while providing limited discussion on radiometric calibration, field-side processing, and practical decision-support outputs. These gaps indicate the need for an integrated methodological framework that links UAV-derived vegetation indices with spatial analysis, crop geometry, validation requirements, and site-specific weed management decisions.

The practical relevance of UAV multispectral imagery in arable systems lies in its narrow spectral bands, typically including blue, green, red, red-edge, and near-infrared wavelengths, as used by platforms such as the MicaSense RedEdge family and DJI agricultural multispectral systems (MicaSense, 2024a). These bands support both conventional vigor indices and chlorophyll-sensitive or soil-adjusted metrics that become increasingly informative as canopy conditions vary. Therefore, the aim of this study was to evaluate how UAV-derived vegetation indices can be integrated with spatial analysis for the early assessment of weed infestation in arable crops. The specific objectives were: (i) to develop a structured image-processing workflow for generating radiometrically corrected vegetation-index maps; (ii) to assess the complementary role of NDVI, red-edge, chlorophyll-sensitive, and soil-adjusted indices in identifying vegetation variability; (iii) to translate index-based outputs into probable weed hotspots and management-oriented spatial layers; and (iv) to discuss the operational relevance, limitations, and scientific contribution of UAV-based weed assessment for site-specific weed management. The working hypothesis was that vegetation indices alone are insufficient for reliable weed discrimination, but their integration with crop-row structure, spatial aggregation, and field validation can improve the interpretation of weed infestation patterns and support more targeted crop-protection decisions.

Among lightweight multispectral solutions used in agricultural UAV applications, the Parrot Sequoia and Sequoia+ sensors are notable for integrating four narrow spectral bands - green, red, red-edge, and near-infrared - with an RGB camera and a sunshine sensor for radiometric correction. This configuration supports the generation of vegetation indices under changing illumination conditions and makes the system suitable for crop monitoring, vigor assessment, and weed-mapping workflows in precision agriculture (Parrot, 2025).

MATERIALS AND METHODS

Study design and data acquisition

Multispectral data acquisition was designed for photogrammetric reconstruction rather than routine RGB inspection. Flight plans followed grid missions with about 75% frontlap and 75% sidelap, extended beyond the field boundary, and, where crop rows were clearly visible, were oriented perpendicular to the rows to improve both row detection and image alignment. Illumination conditions were controlled by scheduling flights close to local solar noon and avoiding rapidly changing cloud cover. Reflectance-panel images were collected immediately before and after each mission, and these observations were complemented, when available, by downwelling light sensor measurements. Ground observations recorded during the flights were used to label crops, weed, mixed-vegetation, and bare-soil samples and to provide independent validation for the final maps (MicaSense, 2024b).

Orthomosaic generation and analytical workflow

After image acquisition, the dataset was processed into a radiometrically corrected orthomosaic and, where useful, a digital surface

model, since UAV-derived 3-D information can support the structural interpretation of vegetation patterns and crop canopy variability (Torres-Sánchez et al., 2015). The workflow comprised reflectance calibration, image alignment, camera optimization, dense reconstruction, orthomosaic generation, and the derivation of vegetation-index layers for subsequent analysis. This sequence is consistent across the main software environments used for multispectral UAV processing, including Pix4D, Agisoft Metashape, OpenDroneMap/WebODM, and ArcGIS Drone2Map, even though implementation details differ among platforms (Agisoft, 2026).

For weed assessment, the analytical workflow moved from calibrated imagery to management-oriented outputs. Vegetation masks were created first, followed by crop-row or crop-object detection, and vegetation occurring outside expected crop positions was classified as probable weed cover. Where crop and weed signatures overlapped, additional multispectral, textural, or structural features were used to improve discrimination. The final weed layers were then aggregated into management cells to identify hotspots and support prescription mapping, in line with established UAV weed-mapping approaches in row and narrow-row crops (Torres-Sánchez et al., 2014).

Image processing and vegetation index formulas

Radiometric and geometric preprocessing

Radiometric and geometric preprocessing was treated as a prerequisite for any meaningful vegetation-index analysis. Raw multispectral values were first normalized and then corrected for sensor-specific effects such as black level, exposure, gain, and vignette distortion before conversion to radiance and reflectance. Panel-based calibration was used to scale imagery to certified reflectance values, while incident-light measurements provided an additional correction pathway for platforms equipped with light sensors. Band co-registration was then applied to ensure spatial correspondence among spectral channels before index calculation (DJI, 2020; DJI, 2023; MicaSense, 2026; MicaSense, n.d.).

$$p_n = \frac{DN}{2^N}$$

where DN is the raw pixel value and N is the sensor bit depth. This normalization step follows standard radiometric calibration workflows for multispectral sensors (MicaSense, 2026).

A practical panel-based reflectance conversion can then be expressed as:

$$k_\lambda = \frac{\rho_{\text{panel},\lambda}}{\bar{L}_{\text{panel},\lambda}}$$

$$R_\lambda(x,y) = k_\lambda\, L_\lambda(x,y)$$

where: ρpanel,λ is the certified reflectance of the calibration panel at wavelength λ, L̄panel,λ is the mean radiance measured over the panel region, and Rλ(x,y) is the reflectance image for that band. This panel-scaling approach is consistent with published multispectral image-processing workflows (MicaSense, n.d.).

If the sensor platform uses an incident light sensor, the reflectance formulation can be written in ratio form:

$$R_\lambda \propto \frac{X_{\text{camera},\lambda}}{X_{\text{incident},\lambda}}$$

Incident-light formulations estimate band reflectance as the ratio between reflected and incoming radiation, with band-specific calibration parameters used for sensor harmonization in DJI multispectral systems (DJI, 2023).

A generic vignette correction can be modeled with a radial polynomial:

$$I_c(x,y) = I(x,y)(k_6 r^6 + k_5 r^5 + \cdots + k_1 r + 1)$$

where is the distance from the optical center and is the corrected image. Radial-polynomial vignette correction and band co-registration through homography-based alignment are standard steps in DJI multispectral image processing (DJI, 2020).

$$\begin{bmatrix} x' \\ y' \\ w' \end{bmatrix} = H \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}, \qquad (x_r, y_r) = \left(\frac{x'}{w'}, \frac{y'}{w'}\right),$$

where is the alignment matrix estimated between bands, consistent with DJI multispectral preprocessing workflows (DJI, 2020).

Vegetation indices appropriate for weeds and crop vigor

NDVI was retained as the principal indicator because it is well suited to early crop development and sparse to moderate canopy cover, which matches the objective of early weed detection. To reduce the known limitations of NDVI under dense canopies or strong soil background, the analysis also included red-edge, chlorophyll-sensitive, and soil-adjusted indices.

Together, these indices provide a more stable description of vegetation status, chlorophyll-related variability, and partial soil exposure than NDVI alone (MicaSense, 2024c).

$$NDVI = \frac{NIR - Red}{NIR + Red}$$

$$NDRE = \frac{NIR - RedEdge}{NIR + RedEdge}$$

$$GNDVI = \frac{NIR - Green}{NIR + Green}$$

$$SAVI = \left(\frac{NIR - Red}{NIR + Red + L}\right)(1 + L)$$

$$MSAVI2 = \frac{1}{2}\left[2(NIR + 1) - \sqrt{(2NIR + 1)^2 - 8(NIR - Red)}\right]$$

$$VARI = \frac{Green - Red}{Green + Red - Blue}$$

$$CI_{green} = \frac{NIR}{Green} - 1$$

$$CI_{red-edge} = \frac{NIR}{RedEdge} - 1$$

$$MTCI = \frac{B6 - B5}{B5 - B4}$$

These formulas correspond to index definitions described in sensor documentation, GIS platforms, and remote-sensing literature. NDVI and NDRE are detailed by MicaSense and Esri, while GNDVI, SAVI, MSAVI2, VARI, CI_{green}, $CI_{red\text{-}edge}$, and related indices are available in common geospatial processing environments used for vegetation analysis (MicaSense, 2024a; Esri, 2026).

In interpretive terms, NDVI was used to characterize vegetation presence and overall crop vigor, whereas NDRE, GNDVI, and chlorophyll indices were used to capture chlorophyll-related variation when foliage became denser and NDVI sensitivity declined. SAVI and MSAVI2 improved performance in areas with partial soil exposure, and VARI remained a useful visible-band alternative when only RGB data were available. The combined use of these layers provided a more robust basis for weed discrimination under varying crop and soil conditions (Clevers & Gitelson, 2013; Schlemmer et al., 2013; MicaSense, 2024a; 2024c; Esri, 2026).

Software ecosystems and real-time workflows

Photogrammetry and geospatial processing software

The software ecosystem was organized by analytical function rather than by brand name. Photogrammetric reconstruction and orthomosaic generation were supported by platforms such as PIX4Dfields, Agisoft Metashape, DJI Terra, ArcGIS Drone2Map, and OpenDroneMap/WebODM, all of which provide multispectral processing, radiometric correction, and export of index layers. GIS and raster analysis were then used for thresholding, map algebra, and spatial aggregation, while Python- and AI-based tools supported more advanced feature extraction and weed classification when row geometry alone was insufficient. This functional workflow reflects current practice in multispectral crop analysis and allows both standard mapping and more advanced computer-vision pipelines to be integrated within the same methodological framework (DJI, 2024; Agisoft, 2026; QGIS Project, 2026; Pix4D, n.d.).

Real-time and near-real-time processing options

Real-time implementation was considered as a spectrum of processing speeds rather than a single technical mode. The most operationally mature approach remains near-real-time fieldside processing, in which imagery is transferred to a laptop immediately after landing and processed into orthomosaics and index maps using software such as PIX4Dfields, DJI Terra, or ArcGIS Drone2Map. Fully onboard edge inference is increasingly feasible with embedded GPU platforms such as NVIDIA Jetson devices, particularly for lightweight detection or segmentation models, while cluster or server reconstruction remains useful when multispectral datasets are too large for rapid single-machine processing. In practical terms, near-real-time fieldside mapping currently offers the best balance between speed, robustness, and field usability for multispectral weed monitoring (DJI, 2024; Pix4D, 2024; NVIDIA, n.d.).

Chlorophyll and weed quantification

Chlorophyll calculations

Chlorophyll estimation from UAV multispectral imagery was approached as a calibrated remote-sensing problem rather than as a fixed biochemical conversion. The most defensible indicators for arable crops were chlorophyll-sensitive and red-edge indices such as CI_{green},

$CI_{red\text{-}edge}$, MTCI, and NDRE, which have been shown to respond well to canopy chlorophyll and nitrogen variation. Because the relationship between index values and chlorophyll content depends on crop type, growth stage, canopy architecture, illumination, and soil background, empirical calibration against field or laboratory measurements remained necessary for quantitative interpretation (Clevers & Gitelson, 2013; Schlemmer et al., 2013; Tian et al., 2025).

$$CI_{green} = \frac{NIR}{Green} - 1$$

$$CI_{red-edge} = \frac{NIR}{RedEdge} - 1$$

$$MTCI = \frac{B6 - B5}{B5 - B4}$$

$$NDRE = \frac{NIR - RedEdge}{NIR + RedEdge}$$

$$\widehat{Chl} = \beta_0 + \beta_1 CI_{red-edge} + \varepsilon$$

$$\widehat{Chl} = f(NDRE,\ CI_{green},\ MTCI,\ texture,\ height)$$

$$C_a = 12.25A_{663.2} - 2.79A_{646.8}$$

$$C_b = 21.50A_{646.8} - 5.10A_{663.2}$$

$$C_{x+c} = \frac{1000A_{470} - 1.82C_a - 85.02C_b}{198}$$

These spectrophotometric equations provide a laboratory reference for chlorophyll a, chlorophyll b, and total carotenoid determination and may be used to validate UAV-derived chlorophyll-sensitive indices when destructive pigment analysis is available (Lichtenthaler & Buschmann, 2001).

Weed calculations

Weed quantification translated spectral outputs into agronomically meaningful metrics. A binary vegetation mask was first generated from an index threshold, after which crop-row geometry was used to separate probable weeds from crop vegetation. Weed cover, weed pressure, and weed density were then calculated within grid cells or management zones to support hotspot detection and variable-rate treatment decisions. Where needed, a combined stress layer integrating weed presence with crop physiological status was used as a decision-support indicator. Validation focused on weed-specific accuracy measures such as overall accuracy, omission error, and commission error, which provide a more useful assessment of management performance than visual interpretation alone (Torres-Sánchez et al., 2014; Stroppiana et al., 2018; Esri, 2026).

$$M_v(i) = \begin{cases} 1, & VI(i) \geq T_v \\ 0, & VI(i) < T_v \end{cases}$$

$$M_w = M_v \wedge \neg M_c$$

$$WC_j = \frac{A_{\text{weed},j}}{A_{\text{cell},j}} \times 100$$

$$WP_j = \frac{A_{\text{weed},j}}{A_{\text{weed},j} + A_{\text{crop},j}} \times 100$$

$$WD_j = \frac{n_{\text{weed},j}}{A_{\text{cell},j}}$$

$$H_j = z(WC_j) - z(CI_{red-edge,j})$$

$$OA = \frac{TP + TN}{TP + TN + FP + FN}$$

$$OE = \frac{FN}{TP + FN}$$

$$CE = \frac{FP}{TP + FP}$$

RESULTS AND DISCUSSIONS

The proposed workflow illustrates how UAV-derived vegetation indices can provide a consistent basis for the early spatial assessment of weed infestation in arable crops. As shown in Figure 1, NDVI provided a useful first screening of vegetated areas and highlighted within-field variability that would not be captured by uniform field inspection. When interpreted alone, however, NDVI could not fully separate crop and weed signals, particularly where crop cover was already developing or where soil background remained visible.

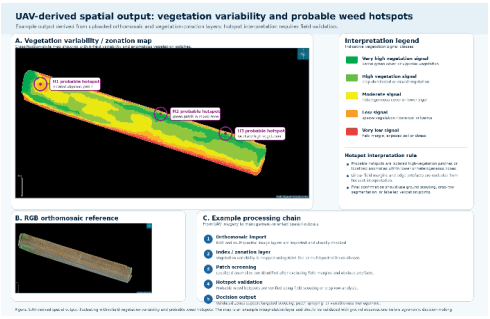


Figure 1. Example of a UAV-derived spatial output highlighting vegetation variability and probable weed hotspots within an arable field

The most informative interpretation was obtained when index maps were combined with crop-row structure and field observations, allowing anomalous vegetation outside expected crop positions to be interpreted more confidently as probable weed patches.

A second important result concerns the complementarity of the vegetation indices. As summarized in Table 1, NDVI remained useful for broad vegetation detection, but red-edge and chlorophyll-sensitive indices such as NDRE, GNDVI, CI_{green}, and $CI_{red-edge}$ added interpretive value where canopy density reduced NDVI sensitivity.

Table 1. Comparative relevance of selected vegetation indices for weed assessment in arable crops

Ind	Veg.	Soi.	Den.	Ch	Wee	Prac
NDVI	High	Modera te	Moderate	Low	High	Initial screening
NDRE / red-edge	High	Modera te	High	High	High	Dense-canopy use
SAVI / MSAVI2	Moderate	High	Moderate	Low–mod.	Modera te	Soil correction

Soil-adjusted indices, including SAVI and MSAVI2, were particularly relevant during early growth stages or in sparsely covered areas, where bare soil influenced reflectance patterns. Taken together, these layers produced a more stable representation of crop vigor and weed-related spatial anomalies than any single index alone, improving the agronomic relevance of the resulting weed maps.

From an operational perspective, the main value of the approach lies in its ability to transform multispectral imagery into management-oriented outputs. Once vegetation masks and crop-row information were integrated, the analysis could delineate localized weed hotspots and aggregate them into treatment zones suitable for targeted intervention. This is directly aligned with site-specific weed management, where the objective is not only to detect weeds but also to support variable-rate herbicide application and reduce unnecessary chemical use. In this sense, the results reinforce the practical role of UAV monitoring as a decision-support tool for precision agriculture rather than as a purely descriptive remote-sensing exercise.

The hotspot labels indicate probable areas requiring field verification rather than confirmed weed infestation classes.

The results demonstrate that UAV-derived vegetation indices should be interpreted not only as descriptive indicators of vegetation vigor, but also as spatial decision-support layers for weed assessment. In scientific terms, the main significance of the workflow lies in its capacity to convert multispectral reflectance variability into agronomically interpretable patterns. NDVI provided an initial map of vegetation presence and within-field heterogeneity, while red-edge, chlorophyll-sensitive, and soil-adjusted indices helped refine the interpretation under variable canopy density and soil-background conditions. This supports the view that weed assessment cannot rely on a single spectral index, but requires a multi-layer interpretation that combines spectral, spatial, and agronomic information.

The internal validation of the proposed approach can be assessed against the study objectives and working hypothesis. The methodological workflow generated the expected sequence of outputs: calibrated imagery, vegetation-index layers, vegetation masks, probable weed hotspots, and management-oriented spatial units. At the same time, the analysis supported the working hypothesis that vegetation indices alone are not sufficient for robust weed discrimination. Their value increases when they are combined with crop-row geometry, spatial aggregation, and field observations. This confirms that the scientific contribution of the study is not the isolated use of NDVI, but the integration of vegetation-index mapping into a structured weed-assessment workflow.

The findings are consistent with previous UAV weed-mapping studies carried out in different crop systems. Peña et al. (2013) demonstrated the importance of object-based UAV image analysis for early-season weed mapping in maize, while Torres-Sánchez et al. (2014) showed that multitemporal UAV imagery can support early site-specific weed control in narrow-row crops such as wheat. Similarly, Stroppiana et al. (2018) highlighted the relevance of multispectral UAV data for early-season weed mapping in rice crops. Compared with these studies, the present approach emphasizes the methodological link between vegetation-index selection, crop-row interpretation, chlorophyll-sensitive indicators, and management-zone delineation. This comparison suggests that UAV-based weed assessment is transferable across crop systems, but its reliability depends on adapting the workflow to crop architecture, canopy closure, weed distribution, and the timing of image acquisition.

From a conceptual perspective, the study contributes to the advancement of site-specific weed management by framing UAV-derived vegetation indices as components of an integrated diagnostic system rather than as standalone classification tools. The proposed workflow connects remote-sensing outputs with practical weed-management decisions by moving from pixel-level vegetation variability to hotspot delineation and treatment-zone prioritization. This is important because the scientific and practical value of UAV monitoring depends not only on detecting spectral differences, but also on translating those differences into actionable agronomic decisions. In this sense, the study contributes a methodological bridge between UAV multispectral imaging, spatial weed ecology, and precision crop-protection planning.

Several limitations should nevertheless be acknowledged. First, the interpretation of probable weed hotspots remains dependent on field validation, because spectral similarity between crop and weed vegetation may lead to classification uncertainty. Second, the workflow is sensitive to illumination conditions, sensor calibration, flight altitude, crop growth stage, and the presence of exposed soil. Third, within-row weeds remain more difficult to detect than between-row weeds, especially in dense cereal crops or in fields with irregular crop emergence. Future research should therefore include larger multi-date datasets, ground-truth weed-density measurements, quantitative accuracy assessment, and comparison between index-based, object-based, and machine-learning classification approaches. Additional work is also needed to evaluate the feasibility of near-real-time processing under operational farm conditions and to connect UAV-derived weed maps with variable-rate herbicide application systems.

CONCLUSIONS

This study addressed the need for a more integrated interpretation of UAV-derived vegetation indices in weed assessment by linking multispectral image processing, vegetation-index analysis, crop-row structure, and management-zone delineation. The results support the working hypothesis that NDVI and related indices are valuable for early vegetation screening but are insufficient as standalone weed-detection tools. Their scientific and practical relevance increases when they are combined with red-edge and chlorophyll-sensitive indicators, soil-adjusted indices, spatial aggregation, and field validation. NDVI remains an effective primary screening layer because it captures general vegetation presence and within-field variability, but it should not be used in isolation. Red-edge and chlorophyll-sensitive indices, including NDRE, $CI_{red\text{-}edge}$, and MTCI, become more informative when canopy density increases or when the objective extends beyond simple vegetation detection to physiological differentiation. Soil-adjusted indices further strengthen early-season analysis under partial soil exposure (Clevers & Gitelson, 2013; Schlemmer et al., 2013; MicaSense, 2024c).

Methodologically, the analysis supports the interpretation that multispectral data alone are rarely sufficient for reliable weed discrimination in complex arable scenes. Classification becomes more robust when spectral information is combined with crop-row geometry, spatial aggregation, and field-based validation, especially where weeds and crops share similar reflectance during early growth. This also helps explain why UAV weed mapping is often more straightforward in wide-row crops than in dense cereal systems, where plant separation is inherently more difficult (López-Granados, 2011; Torres-Sánchez et al., 2014; Stroppiana et al., 2018).

From an operational perspective, near-real-time fieldside processing currently offers the most practical balance between speed, robustness, and agronomic usefulness, whereas fully onboard inference remains promising but more constrained by model complexity and hardware limitations. Overall, the most effective framework combines calibrated multispectral acquisition, NDVI-based screening, complementary red-edge and chlorophyll-sensitive indices, row-aware weed calculations, and management-zone aggregation. In this form, UAV-based monitoring can support more precise herbicide application, reduce unnecessary chemical inputs, and strengthen the implementation of site-specific weed management in arable farming systems (López-

Granados, 2011; DJI, 2024; Pix4D, 2024; Bohra et al., 2025; NVIDIA, n.d.).

ACKNOWLEDGEMENTS

This work was carried out with the institutional support of the National Institute of Research and Development for Food Bioresources – IBA Bucharest and the University of Agronomic Sciences and Veterinary Medicine of Bucharest. The study was developed in connection with research activities on integrated weed management and precision agriculture carried out within the ADER 2.1.4 project.

USE OF GENERATIVE ARTIFICIAL INTELLIGENCE (GENAI)

The authors declare the use of Generative Artificial Intelligence (GenAI) tools in the preparation of this manuscript. GenAI was used for language editing, text refinement, formatting support, and drafting assistance. All scientific content, data interpretation, methodological assumptions, references, and final conclusions were reviewed and verified by the authors.

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