



Using planetscope imagery to evaluate herbicide efficacy in maize (*Zea mays*) through post-application weed detection

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Abstract

Background Optimizing herbicide efficacy is increasingly critical due to the absence of new herbicide modes of action (MOA) and their widespread overuse. This study developed a satellite-based approach to map herbicide control failures for evaluating efficacy, based on the hypothesis that effective control reduces crop-weeds co-existence and thus spectral-spatial heterogeneity over time, whereas low efficacy increases it.

Methods In controlled experimental maize plots (2022–2023), analysis of Unmanned Aerial Vehicle (UAV) multispectral imagery characterized weed-suppression dynamics following application of two herbicides with different MOA. Satellite imagery was processed to select gray-level co-occurrence matrix (GLCM) texture features sensitive to herbicide-induced pixel differences. Features selected were used to compare two satellite-based approaches for mapping herbicide control failures cover (%) across seven commercial maize fields: (i) a rule-based framework and (ii) UAV to satellite upscaling using a Random Forest model.

Results Results showed that by 10 days after spraying (DAS), herbicide effects were uniformly expressed in both MOA, enabling separation between damaged and healthy weeds in UAV images. At the satellite scale, Near-Infrared (NIR)-based GLCM variance and mean were the most sensitive indicators of weed suppression. Using these features and Normalized Difference Vegetation Index (NDVI) from 10 and 14 DAS, a rule-based framework showed better performance compared to UAV to satellite upscaling, achieving within field precision and recall of 0.71 both, and between fields agreement with a coefficient of determination (R^2) of 0.97 and root mean square error (RMSE) of 1.86 (%).

Conclusions These results demonstrate that rule-based GLCM framework provide an effective tool for evaluating herbicide control efficacy using PlanetScope satellite image.

Keywords Maize · Rule-based classification · Spectral · Spatial · Temporal · Gray-Level Co-Occurrence Matrix (GLCM) · UAV-Satellite upscaling

Introduction

Herbicides are the most widely used method of weed control in modern agriculture, supporting high crop yields at relatively low cost. However, overreliance on herbicides is associated with declining field performance due to increased risk of herbicide-resistant weed populations and raising concerns about the long-term sustainability of herbicide-based weed control systems (Hicks et al., 2018; Kniss, 2017; Sun et al., 2024). Thus, to ensure the long-term efficacy of available herbicides, the development of rapid methods to evaluate herbicide efficacy against target weed species is of great interest (Li et al., 2014). Remote sensing has been proposed as a potential approach for detecting weed responses to herbicide application, enabling indirect assessment of herbicide efficacy through plant physiological signals (Mink et al., 2020). Nonetheless, a limited body of studies directly addressed this agronomic aspect. Among these few, Nehurai et al., (2023) used ground-based hyperspectral imaging and machine learning for early detection of glyphosate and glufosinate impact on *Solanum nigrum*. These authors detect weed response to these herbicides as early as 24 h after application. More recently, Ali et al., (2026) demonstrated that hyperspectral imaging analysis enables real-time detection of herbicide-induced physiological damage in maize and weeds, revealing rapid pigment degradation and stress signals within four days after application. However, both studies were conducted at plant or small-plot scales, highlighting the difficulty of translating herbicide damage detection into operational, field-scale monitoring of herbicide efficacy.

Because direct assessment of herbicide efficacy by detecting physiological damage under real-world, field-scale conditions is challenging, weed control efficacy is most reasonably inferred from changes in weed presence or spatial distribution following application. Consequently, weed detection and mapping by remote sensing before and after herbicide treatment provide a practical basis for field-scale evaluation. Unmanned Aerial Vehicle (UAV) remote sensing has increasingly been applied to weed mapping in crops under field conditions (e.g., de Villiers et al., 2023; Pei et al., 2022; Yue & Zhao, 2025). However, high operational costs and limited spatial coverage limit their adoption by farmers, particularly for weed mapping (Istiak et al., 2023).

In contrast, satellite imagery has become increasingly accessible for precision agriculture due to its broad spatial coverage, frequent revisits, and relatively low cost, supporting wider adoption (Erickson et al., 2025). Satellite spectral data enable repeated, large-area monitoring of vegetation dynamics and allowing indirect assessment of herbicide effectiveness through changes in canopy reflectance and vegetation indices. Pause et al., (2019) demonstrated that Sentinel-2 Normalized Difference Vegetation Index (NDVI) time series can detect glyphosate-induced vegetation decline in fields without crops, i.e. containing only weeds, within a few days after application, confirming the sensitivity of satellite imagery to short-term herbicide effects. Furthermore, extending beyond weed-only conditions, Bautista et al., (2024) showed that Sentinel-2 spectral bands and NDVI can distinguish herbicide-treated from untreated rice plots with coexisting crops and weeds, demonstrating that satellite imagery can detect herbicide response also under mixed vegetation conditions, rather than weeds-only scenarios. However, both studies quantify aggregate vegetation response rather than explicitly resolving the spatial distribution of weed patches, and therefore do not constitute direct weed mapping at the pixel level. For weed detection, the lower spatial resolution of satellite imagery remains a major constraint, limiting identification of

weed patches at the pixel level, a limitation widely recognized in satellite-based agricultural applications (Alibabaei et al., 2022; de Villiers et al., 2023).

A recent solution in remote sensing for this challenge is to upscale high-resolution UAV observations to satellite imagery using machine learning models (Chen et al., 2024; Habibi et al., 2021; Salgado et al., 2025; Schiefer et al., 2023). Bergamo et al., (2023) demonstrated the practical application of upscaling UAV-derived RGB imagery with PlanetScope multi-spectral satellite imagery to estimate the fractional cover of the invasive weed *Rosa rugosa* across seven coastal sites along the Estonian Baltic coastline. The study focused on ecological monitoring of invasion in heterogeneous coastal habitats with varying invasion density. Their model was trained on data from all sites and then applied to predict each site individually using a random forest framework, enabling evaluation of cross-site transferability and upscaling performance. Prediction accuracy varied considerably among the seven sites ($R^2=0.03\text{--}0.74$), indicating limited model transferability across heterogeneous environments and contrasting weed infestation levels. These findings highlight a key challenge of UAV-to-satellite upscaling: site-specific accuracy does not readily generalize without extensive, diverse, and well-labeled datasets. Generating these datasets is labor-intensive and time-consuming, requiring extensive UAV campaigns and repeated field measurements. As an alternative, recent studies have explored rule-based methods for robust satellite classification tasks (Li et al., 2026; Zang et al., 2023). Rule-based classification uses expert knowledge encoded as decision rules rather than learned statistical patterns (Berhane et al., 2018; Cohen & Shoshany, 2002; Sader et al., 1995). For example, Yang et al., 2023 developed a rule-based framework to automatically classify winter wheat fields over China using multi-temporal satellite spectral and Synthetic Aperture Radar (SAR) data. First, winter crops were identified using phenological knowledge of wheat development, characterized by seasonal rises and declines in NDVI during early and late growth stages. Winter wheat was then separated from winter rapeseed using VH (cross-polarized) radar backscatter, as differences in flowering-stage canopy structure produced distinct radar scattering responses that served as a reliable decision rule.

Following a similar rule-based logic, this study developed a framework to map herbicide control failures using satellite data. The underlying hypothesis was that such failures can be detected in satellite imagery through increased spectral–spatial heterogeneity within crop fields. Specifically, high herbicide efficacy is expected to reduce crop–weed coexistence, resulting in more spatially uniform spectral patterns, whereas low efficacy maintains heterogeneous mixtures that increase local variability. From an operational perspective, this approach enables post-application weed detection using widely available satellite imagery, offering a scalable alternative for monitoring herbicide efficacy under real-world farming conditions. This spectral–spatial heterogeneity can be quantified using Gray-Level Co-occurrence Matrix (GLCM) texture features, which capture local pixel variability within a defined neighborhood (Haralick et al., 1973). By translating within-field heterogeneity into measurable satellite-derived metrics, GLCM features provide a structured and interpretable means to map weed persistence at the field scale without direct measurement of herbicide action. Such features have proven effective for integrating spatial information in agricultural remote sensing applications (Chetty et al., 2021; de Freitas et al., 2024; Dos Reis et al., 2020; Romano et al., 2021).

To operationalize the study objective under real-world conditions, maize, a widely cultivated field crop, was used as a model system. To test the research hypothesis, The study

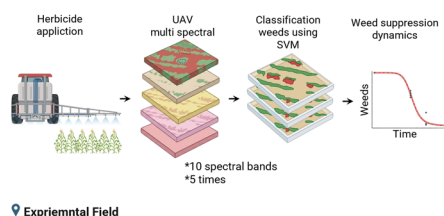
aimed to: (1) characterize weed-suppression dynamics using time-series UAV multispectral data; (2) identify satellite-derived GLCM features that discriminate between suppressed and unsuppressed weeds (indicating herbicide control failures) under experimental field conditions; and (3) evaluate satellite-based mapping of herbicide control failures under operational commercial conditions using spectral, spatial, and spatio-temporal GLCM features within a rule-based framework, and compare performance with a UAV-to-satellite upscaling approach.

Materials and methods

Overview of the analytical workflow

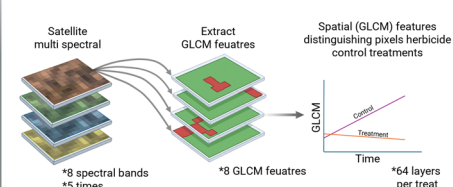
Based on the study aims, this research followed a four-stage workflow to evaluate herbicide efficacy using satellite remote sensing (Fig. 1). Stages 1—2 were conducted in controlled experimental plots, whereas stages 3—4 transferred and applied the experimental findings to commercial maize systems. Stage 1 addressed aim 1 by characterizing weed-suppression dynamics in experimental maize plots using a time series of high-resolution UAV multispectral imagery, thereby identifying the optimal DAS for clear spectral separation between suppressed weeds and unsuppressed weeds indicating herbicide control failures. Stage 2 addressed aim 2 by using satellite multispectral imagery to extract and select features, integrating spectral, spatial, and temporal (SST) information to distinguish herbicide-treated from control pixels, indicating suppressed and unsuppressed weeds, respectively. GLCM

Stage 1: UAV-based weeds suppression characterization



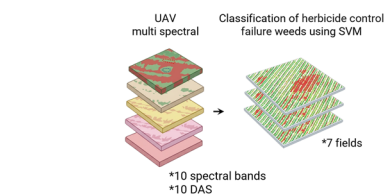
Experimental Field

Stage 2: Satellite feature selection to distinguish herbicide-treated and control pixels



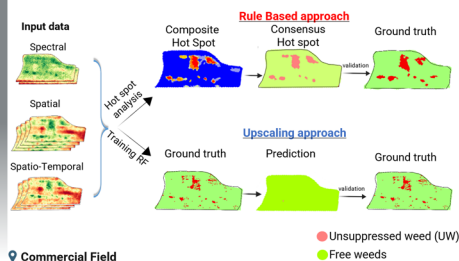
Experimental Field

Stage 3: UAV mapping of weeds exhibiting herbicide control failure in commercial fields



Commercial Field

Stage 4: Satellite-based mapping of herbicide control failures: rule-based vs. upscaling



Commercial Field

Fig. 1 Conceptual workflow for mapping herbicide control failure in maize fields, integrating UAV-derived data with satellite spectral, spatial, and spatio-temporal analysis across experimental and commercial fields. Created with BioRender.com

texture features were generated from individual spectral layers to describe spatial differences at the pixel level between herbicide and control treatments (described in Sect. "Study sites and experimental design"), while the temporal component was incorporated by quantifying changes in textural features over the course of the experiment.

Stages 3 and 4 addressed aim 3 by evaluating satellite-based mapping of herbicide control failures, defined as the presence of unsuppressed weeds, across seven commercial maize fields. UAV multispectral imagery was used to generate field-scale ground-truth maps for validation of satellite predictions (Stage 3). In Stage 4, two satellite-based prediction strategies were compared using spectral, spatial, and temporal data: (i) a rule-based framework integrating multi-layer hotspot analyses derived from SST features, and (ii) a UAV-to-satellite upscaling approach based on a generalized machine-learning Random Forest model.

Stage 1- UAV-based weeds suppression characterization

Study sites and experimental design

Two experiments were conducted in 2022 and 2023 to describe differences in weed control scenarios. Both experiments were conducted at the Newe Ya'ar Research Station, the northern campus of the Israel Agricultural Research Organization (ARO). Two hectares of silage maize were divided into four treatments using a randomized block design with five replicates (Fig. 2). Each replicate was 20 m by 25 m with an area of ~0.05 ha. Maize seeds were sown at a density of nine seeds per 5-m row. Weed infestation was based on the natural seed bank. Control treatments were classified into positive and negative controls. The positive control consisted of a weed-free treatment, achieved by applying preemergence herbicides: Metolachlor-S (1195 g a.i. ha⁻¹) and Atrazine (400 g a.i. ha⁻¹) immediately after maize sowing to prevent weed emergence. The negative control represented a condition in which maize and weeds were allowed to establish without weed management, simulating a herbicide control failure scenario. Postemergence herbicide treatments included two dis-

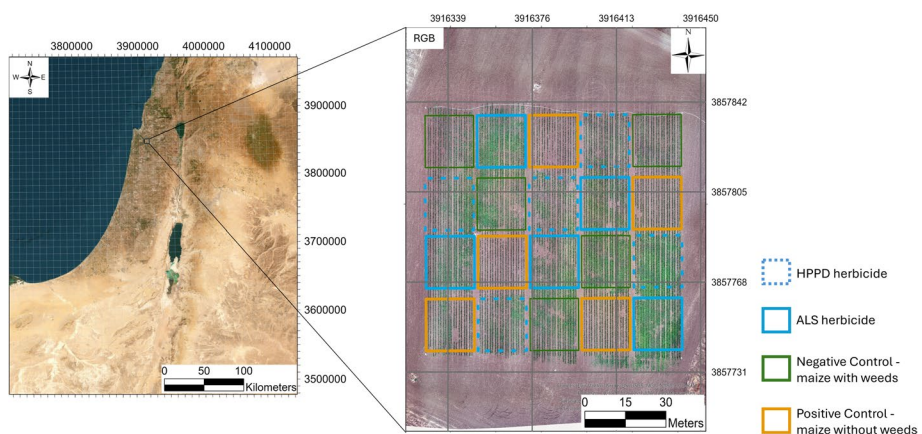


Fig. 2 Field experiment design overlaid on UAV image in DAS 0 (2023) (4 treatments $\times$ 5 replicates). The left panel shows an RGB basemap from ArcGIS Pro, and the right panel shows a UAV RGB image. Coordinates are presented in the WGS 1984 Web Mercator coordinate system, with units in kilometers (left panel) and meters (right panel)

tinct modes of action (MOA). The first targeted the acetolactate synthase (ALS) enzyme, with foramsulfuron applied at a rate of 45 g a.i. ha⁻¹. The second mode of action involved the inhibition of 4-hydroxyphenylpyruvate dioxygenase (HPPD), an enzyme essential for carotenoid biosynthesis, using tembotrione at a rate of 94.5 g a.i. ha⁻¹. All postemergence herbicides were applied at the V2–V4 maize growth stage using a tractor-mounted commercial sprayer. The maize variety used in the study was resistant to both herbicides. The sowing maize directions and the size of the replicates were designed to fit the orientation of the PlanetScope satellite image.

UAV data collection from the experimental plots

In both experimental plots (2022 and 2023), six UAV multispectral image acquisitions were conducted at defined days after spraying (DAS: 0, 3, 7, 10, 14, and 21; Table 1) following herbicide application to characterize weed suppression dynamics. Data were collected using a MicaSense RedEdge-MX Dual sensor (MicaSense, Seattle, WA, USA), providing 10 narrow spectral bands spanning the visible, red-edge, and near-infrared regions. Detailed sensor characteristics and band specifications are provided in Supplementary Table S1. UAV flights were conducted using a Matrice 300 RTK platform (DJI, Shenzhen, China) at an altitude of 30 m with 80% forward and side image overlap, producing multispectral imagery with a ground sampling distance (GSD) of 0.015 m. Images of a calibrated grayscale reflectance panel (MicaSense) were acquired immediately prior to each UAV imaging mission and used for radiometric calibration. Multispectral imagery was collected in TIFF format for each spectral band, with embedded metadata including geographic coordinates and sensor calibration parameters. Radiometric calibration and image processing were performed in Pix4Dmapper (Pix4D SA; Lausanne, Switzerland), resulting in georeferenced surface reflectance orthomosaics for each spectral band and acquisition date.

Classification weeds using SVM in an experimental field

RGB composites were generated from the 10 reflectance orthomosaics to facilitate manual delineation of training polygons for supervised classification. 200 Polygons representing maize, soil, and healthy weeds in untreated control plots, as well as damaged weeds in

Table 1 Unmanned Aerial Vehicle (UAV) and satellite image acquisition dates and corresponding days after spraying (DAS) in the experimental plots

Year	UAV imagery date	UAV DAS	Satellite imagery date	Satellite DAS
2022	28—07—2022	0	29—07—2022	1
	31—08—2022	3	30—07—2022	2
	04—08—2022	7	02—08—2022	5
	07—08—2022	10	07—08—2022	10
	11—08—2022	14	12—08—2022	15
	18—08—2022	21	17—08—2022	20
2023	22—08—2023	0	21—08—2023	-1
	25—08—2023	3	24—08—2023	2
	29—08—2023	7	27—08—2023	5
	01—09—2023	10	30—08—2023	8
	05—09—2023	14	04—09—2023	13
	12—09—2023	21	14—09—2023	23

herbicide-treated plots, were manually delineated for each day after spraying (DAS) using ArcGIS Pro (Esri; Redlands, CA, USA). Spectral reflectance values were first extracted by overlaying the training polygons onto all 10 multispectral reflectance-band orthomosaics and calculating the mean reflectance per band within each polygon using polygon-based zonal statistics implemented in the *terra* package in RStudio (Hijmans et al., 2022). These polygon-level spectral data were then used to train a supervised support vector machine (SVM) classifier implemented in the *e1071* package in RStudio (Dimitriadou et al., 2006). The trained SVM model was subsequently applied to the full multispectral imagery of the experimental fields to predict pixel-level class labels for each DAS (0, 3, 7, 10 and 14). To reduce pixel-scale noise and isolated misclassifications (the “salt-and-pepper” effect), GIS-based-post-classification spatial filtering was applied. Contiguous pixel within each class were first identified using the Region Group tool with 4-neighbor connectivity. Small regions comprising fewer than 20 connected pixels ($\sim 7 \text{ cm}^2$) were then removed using the Set Null tool, and the resulting gaps were reassigned to the nearest neighboring class using the Nibble tool. All post-classification filtering steps were performed in ArcGIS Pro (Esri; Redlands, CA, USA). Validation was evaluated exclusively at two DAS: the day of herbicide application (DAS 0) and 14 days after spraying (DAS 14). These times were selected because they represent periods with clear weed status, enabling reliable reference labeling. At DAS 0, all weeds were physiologically healthy, whereas at DAS 14, weeds in herbicide-treated plots were expected to be uniformly damaged, based on label information provided by the herbicide manufacturer. In contrast, at intermediate DAS (3, 7 and 10 DAS), individual weeds frequently exhibited mixed physiological responses, with portions of the same replicate appearing healthy while others showed herbicide-induced damage. This spatial heterogeneity prevented the creation of reliable “true” reference polygons for healthy and damaged weed classes at these time points. For each evaluated DAS, 200 random points per class were generated, fully separated from the training polygons. The comparison points were manually labeled by an independent operator using an RGB composite, with no prior knowledge of the classification outputs. All point generation and labeling procedures were performed in ArcGIS Pro.

Model performance was evaluated using confusion matrices constructed from validation results, in which predictions for each class were categorized as true positive (TP), true negative (TN), false positive (FP), or false negative (FN). Classification performance was summarized using class-specific precision and recall metrics. Precision was defined as $TP/(TP+FP)$ and represents the proportion of pixels assigned to a given class that were correctly classified. Recall was defined as $TP/(TP+FN)$ and represents the proportion of true pixels belonging to a class that were correctly detected by the classifier. All models' performance computations were performed using *terra* package in RStudio (Hijmans et al., 2022).

Weed suppression dynamics characterization

Characterization of weed-suppression dynamics was based on data from the 2023 experimental plot, as weed infestation levels in 2022 were very low ($\sim 2\%$ at the time of spraying). In contrast, the 2023 experiment exhibited higher initial weed pressure ($\sim 20\%$), enabling reliable classification and temporal quantification of weed condition (Supplementary, Fig. S1). Weed suppression dynamics were quantified as the temporal change in the ratio of healthy-to-damaged weed pixels for each treatment. Weed pixels in both control and her-

bicide-treated plots were classified based on spectral similarity, where pixels resembling the control condition were defined as healthy weeds, and pixels resembling the herbicide-treated condition were defined as damaged weeds. Temporal changes in this ratio reflected a shift from healthy to damaged weed status following herbicide application. These dynamics during the first 14 days after application were modeled using a four-parameter log-logistic function implemented in the *drc* package in R Studio (Ritz et al., 2016).

Stage 2 – Satellite feature selection to distinguish herbicide treatments to control

Satellite data imagery in an experimental field

Satellite images were obtained from the PlanetScope satellite constellation (<https://www.planet.com/explorer/>). PlanetScope is a satellite constellation of over 200 CubeSats (“Doves”) flying in near-polar orbit at an altitude of ~475 km, providing daily coverage of the Earth’s land surface. The imagery used in this study was acquired by the SuperDove (Dove-R) satellites, which provide eight spectral layers, described in supplementary (Supplementary, Table S1). PlanetScope imagery has a spatial resolution of ~3 m at nadir (Planet team, 2024), with an equatorial overpass time between 08:30 and 09:30 a.m. (Israel solar time). All scenes were obtained as the “Analytic Ortho Scene” surface-reflectance product, pre-processed by Planet Labs. These products include radiometric calibration, geometric correction (orthorectification), and atmospheric correction to derive surface reflectance (SR) using 6SV2.1 radiative transfer code (Planet Surface Reflectance Version, 2025). Finally, these analysis-ready products are harmonized to ensure radiometric and spatial consistency across the satellite constellation and are provided as normalized surface reflectance. Cloud-free scenes were selected to match the field campaign dates as closely as possible at 0, 3, 7, 14 and 21 DAS (Table 1). Based on these layers, we created four vegetation indices: NDVI, GNDVI, SAVI, and MSAVI (equations provided in Supplementary Table S2).

Spatial features extraction using GLCM

All eight satellite image bands and vegetation indices from all DAS were processed to compute spatial features using GLCM. GLCM evaluates the spatial relationships between pixel intensity values by computing the frequency of specific gray-level pairs within a defined window (batch pixels, e.g., 3×3 , 5×5), the distance between them, and the angle between them. The resulting metrics quantify spectral-spatial patterns, providing insights into the texture and composition of the imagery. Pixel adjacency was defined using an offset angle of 45° . The moving window size was empirically set to 3×3 pixels. Eight GLCM texture indices were calculated using the equations provided in Supplementary Table S3 and are summarized in Table 2. These indices were derived from all eight spectral reflectance bands and four vegetation index layers mentioned above (Table 2). Following GLCM computation, all features were normalized using min–max scaling, rescaling values to 0–1 based on the local minimum and maximum values of each GLCM feature. This normalization was performed after defining the experimental area, excluding field edges and non-informative regions dominated by bare soil. All GLCM computations were performed using *glcm* package in R Studio (Zvoleff, 2015).

Table 2 Gray-Level Co-Occurrence Matrix (GLCM) texture features used for satellite-based analysis

Feature	Description	Spatial interpretation
Contrast	Measures the intensity contrast between a pixel and its neighbor over the entire image	Heterogeneity
Correlation	Evaluates the correlation between pixel pairs in the image	Homogeneity
Entropy	Quantifies the randomness in the image texture, with higher values indicating higher randomness	Heterogeneity
Homogeneity	Assesses the similarity of pixel values, with higher values for more homogeneous images	Homogeneity
Variance	Measures the dispersion of pixel intensities around the mean value	Heterogeneity
Mean	Measures the average of gray level values in an image	Heterogeneity
Dissimilarity	Measures the variation in pixel pairs, representing the average difference between pixel pairs	Heterogeneity
Second moment	Evaluates the strength of the linear relationship between pixel pairs	Homogeneity

Spatial feature selection distinguishing pixels of herbicide treatment

Based on the study's hypothesis, effective herbicide control was expected to produce more consistent, lower spatial variability in satellite-derived texture, characterized by a gradual reduction in within-field heterogeneity over time. This temporal pattern enables discrimination between successful weed control and herbicide control failure. To identify satellite-derived GLCM features sensitive to herbicide-induced changes, we focused on the temporal behavior of each feature. Accordingly, linear models were fitted to each GLCM feature extracted from multispectral satellite imagery, for each corresponding spectral band, and the temporal slope of each texture feature across multiple DAS (0–21) was used as the selection criterion. Slope values were compared between the untreated control (weed-infested maize) and the herbicide-treated conditions across all features, and the treatments were ranked by the slope differences. Although weed infestation in 2022 was low and thus excluded from the evaluation of weed suppression dynamics in Stage 1, it served as a low-infestation reference scenario in the satellite dataset spanning 2022 and 2023. To evaluate feature sensitivity to weed infestation pressure, a selected feature extracted from satellite imagery was regressed against UAV-derived weed cover at the grid-cell level across control (weed-infested maize) in both experimental years at 10 DAS.

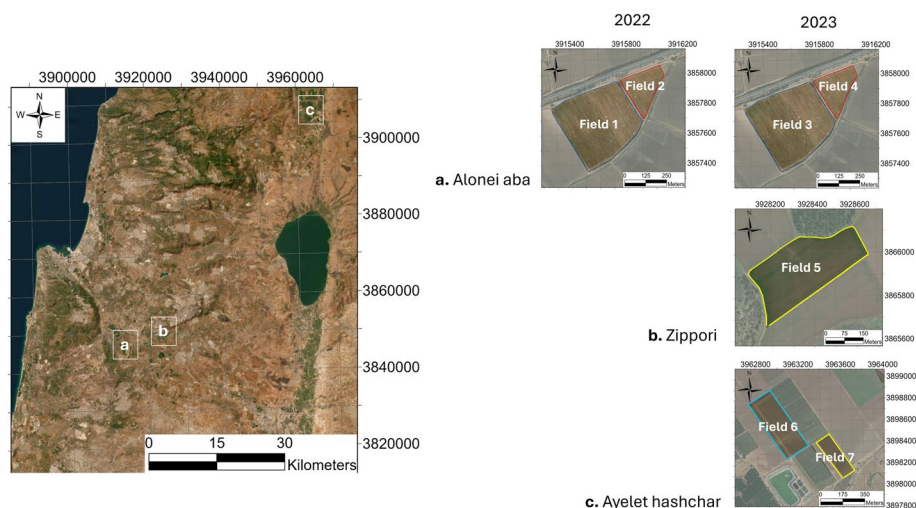


Fig. 3 Location of the seven commercial maize fields in northern Israel. Fields 1–2 were monitored in 2022 and Fields 4–7 in 2023. The left panel shows an RGB basemap from ArcGIS Pro, and the right panel shows a UAV RGB image. Coordinates are presented in the WGS 1984 Web Mercator coordinate system, with units in kilometers (left panel) and meters (right panels)

Table 3 Characteristics of commercial maize fields, including soil conditions, herbicide modes of action (MOA; HPPD and ALS), and timing of unmanned aerial vehicle (UAV) and satellite data acquisition (days after spraying, DAS)

Farm	Field ID	Year	Area (ha)	Maize type	Soil condition	Herbicide MOA	UAV imaging timing (DAS)	Satellite acquisition timing (DAS)
Alonei Aba	1	2022	15	Silage	Wheat residue	HPPD	0,7,10,14	3,6,10,14
Alonei Aba	2	2022	5	Silage	Wheat residue	ALS	0,7,10,14	3,6,10,14
Alonei Aba	3	2023	15	Silage	Wheat residue	HPPD	0,7,10,14	0,7,11,14
Alonei Aba	4	2023	5	Silage	Wheat residue	HPPD	0,7,10,14	0,7,11,14
Zippori	5	2023	15	Silage	Wheat residue	ALS	0,5,8,11	-1,6,10,16
Ayelet Hashachar	6	2023	15	Sweet	Bare soil	HPPD	0,7,14	0,7,11,14
Ayelet Hashachar	7	2023	4	Sweet	Bare soil	HPPD	0,7	0,7,11,14

Stage 3- UAV mapping of unsuppressed weeds exhibiting herbicide control failure in commercial fields

The last stages (3 and 4) were conducted across seven commercial maize fields during the 2022 and 2023 growing seasons located on three farms of northern Israel: a. Alonei Aba, b. Zippori, and c. Ayelet HaShahar (Fig. 3). Together, these fields encompassed a range of commercial management and environmental conditions, providing a representative evaluation of the proposed approach. Field details are provided in Table 3.

UAV data collection—field commercial

Herbicide control failure was mapped in all seven commercial fields using multispectral UAV imagery acquired approximately 10 DAS, which was identified as the post-treatment timing at which spectral differences between healthy and herbicide-damaged weeds were most clearly detectable (based on the results in Fig. 5). UAV data acquisition and preprocessing followed the procedures described in Sect. "[UAV data collection from the experimental plots](#)". Briefly, multispectral imagery was collected at a flight altitude of 50 m and processed to generate radiometrically and geometrically corrected orthomosaics for each spectral band.

Classification of herbicide control failure using SVM

For each field, 200 training polygons per class (maize, soil, and weeds) were manually delineated from RGB-composite UAV multispectral imagery in ArcGIS Pro. In this classification step, all weed-class pixels were labeled as herbicide control failures, reflecting weeds that survived herbicide application (~10 DAS). polygon-mean spectral values were extracted from each orthomosaic band and used as training data for SVM classification. The trained SVM model was applied to all the multispectral data. Then, classification across all fields was performed using the *e1071* package in RStudio (Dimitriadou et al., 2009). To reduce salt-and-pepper noise and improve spatial coherence, post-classification spatial filtering was applied in ArcGIS Pro (details in Sect. "[Classification weeds using SVM in an experimental field](#)"). Classification performance was assessed by using confusion matrices based on 200 independently labeled validation points per class, annotated by an independent operator with no prior knowledge of the classification maps, and summarized using class-specific precision and recall metrics computed as described in Sect. "[Classification weeds using SVM in an experimental field](#)" using the *terra* package in RStudio (Hijmans et al., 2022).

UAV-ground truth data align with satellite data

UAV-derived ground-truth maps were generated by isolating the herbicide control failure class from the SVM classification of maize, soil, and weeds. As defined above, the weed class represents herbicide control failures following application. To enable pixel-level comparison with satellite data, a spatial grid was generated across the boundaries of all seven classification maps and aligned with the PlanetScope pixel grid to ensure exact correspondence between UAV and satellite pixels. For each grid cell, the coverage of weeds was calculated as the ratio of UAV pixels classified as weeds to the total number of UAV pixels intersecting the cell. Area-weighted zonal extraction was applied to account for partial pixel overlap along grid boundaries, ensuring proper representation of fractional pixel contributions. The resulting grid-cell weed cover values were used as ground-truth reference data for comparison with satellite-derived features. All spatial analyses were performed using *terra*, *sf*, and *exactextractr* packages, respectively in R Studio (Baston et al., 2021; Hijmans et al., 2022; Pebesma & Bivand, 2023). Model performance was summarized using class-specific precision and recall metrics as described in Sect. "[Classification weeds using SVM in an experimental field](#)".

Satellite-based mapping of herbicide control failures: rule-based vs. upscaling UAV to satellite

Three types of PlanetScope satellite-based features were generated for each commercial field: spectral, spatial, and spatio-temporal. The first feature consisted of a spectral component, represented by the normalized difference vegetation index (NDVI) derived approximately at 10 and 14 DAS. Although NDVI showed limited pixel-level discrimination between treatments in the experimental plots (Stage 2), it was included because herbicide control failure zones in commercial fields are expected to increase vegetation density, which is reflected in higher NDVI values. The second feature consisted of spatial texture summaries derived from Near-Infrared (NIR)-based GLCM variance and mean, computed using the configuration described in Sect. "[Spatial features extraction using GLCM](#)" at approximately 10 and 14 days after spraying (DAS). The third feature captured spatio-temporal texture patterns based on NIR-based GLCM variance. GLCM variance layers from four acquisition dates (approximately 0, 3, 7, and 14 DAS) were stacked and summarized per-pixel using mean, median, and maximum values, representing average, robust central, and peak texture responses over time, respectively. Although temporal slopes were initially calculated using linear models, visual inspection indicated that slope-based features did not spatially correspond with failure control pixels and were therefore not retained for further analysis. All calculations are done in RStudio.

Rule-based approach

A rule-based framework was applied to generate a binary classification map distinguishing satellite pixels representing herbicide control failure (1) from weed-free areas (0) using spectral, spatial, and spatio-temporal features for each commercial field separately. For each field and each satellite layer (Sect. "[Stage 3- UAV mapping of unsuppressed weeds exhibiting herbicide control failure in commercial fields](#)"), pixel values were extracted directly into aligned grid cells, as the grid boundaries exactly matched the PlanetScope pixel grid. The binary classification was derived through hotspot analysis conducted for NDVI (Fig. [4a–b](#)) and selected GLCM texture features (Fig. [4c–e](#)). Spatial clustering was quantified using the Getis–Ord G_i^* statistic with k -nearest-neighbor spatial weights ($k=4$) based on grid-cell centroids, including self-neighbors. Grid cells with G_i^* z -scores ≥ 1.96 were classified as hotspots (value=1), representing failure control pixels, whereas remaining cells were classified as non-hotspots (value=0), representing weed-free pixels. To reduce noise and enhance spatial coherence, hotspot layers were filtered using connected-component analysis with 8-neighbor connectivity, excluding clusters smaller than four contiguous grid cells.

All hotspot layers were combined into a composite hotspot stack (Fig. [4f](#)). A consensus hotspot map was then derived by identifying grid cells classified as hotspots in at least five of the nine individual layers. In the final consensus map, cells assigned value 1 were interpreted as having a high likelihood of herbicide control failure, whereas cells assigned value 0 were interpreted as weed-free (Fig. [4g](#)).

The same grid-based hotspot workflow was applied to UAV-derived herbicide-control-failure maps (Sect. "[UAV-ground truth data align with satellite data](#)"), in which each grid cell contained UAV-estimated weed cover. This enabled direct hotspot-to-hotspot comparison between UAV reference maps and satellite rule-based maps. All analyses were con-

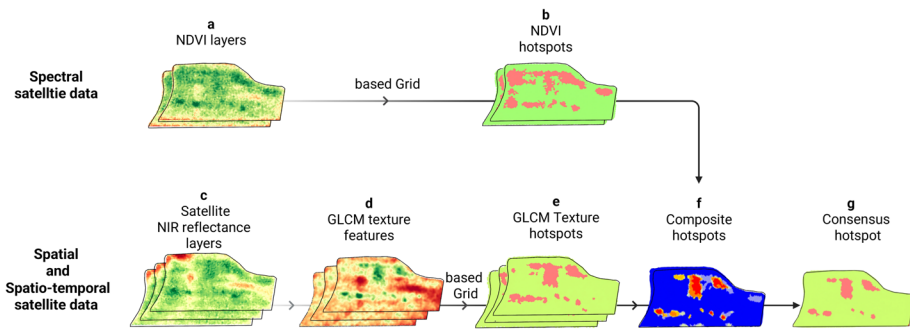


Fig. 4 Rule-based workflow for mapping herbicide failure control from satellite imagery. The workflow includes: (a) NDVI layers and (b) corresponding hotspot maps, (c) NIR reflectance layers acquired, (d) GLCM texture features (variance and mean) computed from the NIR band, (e) hotspot maps derived from GLCM spatial and spatio-temporal features, (f) a composite hot spots map obtained by merging hotspots across all feature layers (spectral, spatial and spatio-temporal), resulting in the (g) consesue hot spot classification

ducted separately for each field using the *terra*, *sf*, and *spdep* packages in RStudio (Hijmans et al., 2022; Pebesma et al., 2023; Bivand et al., 2005). Herbicide control failure cover was quantified for each commercial field as the proportion of grid cells classified as herbicide control failure relative to the total field area, providing a field-scale assessment of herbicide efficacy. Model performance was summarized using class-specific precision and recall metrics as described in Sect. "Classification weeds using SVM in an experimental field".

UAV-to-satellite upscaling approach

An upscaling UAV-to-satellite approach was applied to map herbicide control failure using satellite-derived spectral, spatial, and spatio-temporal features for each commercial field separately. As in the rule-based approach (Sect. "Rule-based approach"), satellite pixel values were extracted to grid cells aligned with the PlanetScope pixel grid to ensure pixel-level correspondence between UAV- and satellite-derived data. UAV-derived reference maps of herbicide control failure, generated as described in Sect. "Classification weeds using SVM in an experimental field", were used for model training and validation. For each grid cell, cells in which UAV-derived weeds cover exceeded 20% were labeled as containing herbicide control failure (value=1), whereas cells with lower cover were labeled as weed-free (value=0). These grid-cell labels served as the response variable for satellite-based classification. Random Forest (RF) models were trained using satellite-derived spectral, spatial, and spatio-temporal features aggregated at the grid-cell level (Sect. "Satellite-based mapping of herbicide control failures: rule-based vs. upscaling UAV to satellite"). Models were implemented with 500 trees, and class imbalance was addressed by applying class weighting to improve discrimination of the less frequent herbicide control failure class.

To test out-of-sample/new field performance, the assessment was performed using a leave-one-field-out (LOFO) cross-validation strategy, whereby each commercial field was iteratively excluded from model training and used as an independent test set. For each iteration, predictions were generated for all grid cells in the withheld field, producing binary maps of herbicide control failure presence. Herbicide control failure cover was quantified

for each commercial field as the proportion of grid cells classified as herbicide control failure relative to the total field area, providing a field-scale assessment of herbicide efficacy. Model performance was summarized using class-specific precision and recall metrics as described in Sect. "Classification weeds using SVM in an experimental field". To enable a direct and unbiased comparison with the rule-based approach, Hotspot analysis identical to that described in Sect. "UAV data collection - field commercial" was applied to the RF prediction maps for each field. This ensured that differences between approaches were attributable to the classification strategy rather than the spatial aggregation method. All upscaling analyses were conducted by *scikit-learn* library in Python (Pedregosa et al., 2011). Model performance was summarized using class-specific precision and recall metrics as described in Sect. "Classification weeds using SVM in an experimental field".

Results

Stage 1- UAV-Based weeds suppression characterization

As described in Sect. "Weed suppression dynamics characterization", characterization of weed-suppression dynamics was performed using the 2023 experimental field. In this analysis, suppression weeds resulting from both ALS- and HPPD-inhibiting herbicide treatments were grouped into a single "damaged weeds" class.

UAV-based weed classification using SVM – model performance

The UAV multispectral SVM model reliably discriminated between healthy and herbicide-damaged weeds and served as the basis for analyzing weed suppression dynamics (Table 4). At 0 DAS, classification accuracy was high (>0.93) across three classes (Table 4). At this stage, damaged weeds were absent, as herbicide effects were not yet apparent.

By 14 DAS, classification performance reflected the emergence of herbicide-induced weed damage. Healthy weeds in the control treatment, representing herbicide control failure, were detected with relatively high performance (recall=0.81, precision=0.901), while damaged weeds in herbicide-treated plots were classified with slightly lower performance (recall=0.72, precision=0.83). Maize maintained high classification performance (recall=0.83, precision=0.93). In contrast, soil exhibited high recall (0.94) but reduced precision (0.78), indicating that many herbicide-damaged weeds were misclassified as soil. This pattern suggests a temporary shift toward soil-like spectral characteristics associated with reduced vegetation vitality, whereas healthy weeds remained consistently well classified.

Table 4 Classification accuracy of the SVM model derived from UAV multispectral imagery acquired at 0 and 14 days DAS based on 2023 experimental field

DAS	Class	Recall	Precision
0 (22-8-23)	Healthy weeds (control)	0.98	0.94
	Damaged weeds (Treatment)	-	-
	Soil	1.00	0.99
	Maize	0.93	0.99
14 (5-9-23)	Healthy weeds (control)	0.81	0.90
	Damages weeds (Treatment)	0.72	0.83
	Soil	0.94	0.78
	Maize	0.83	0.93

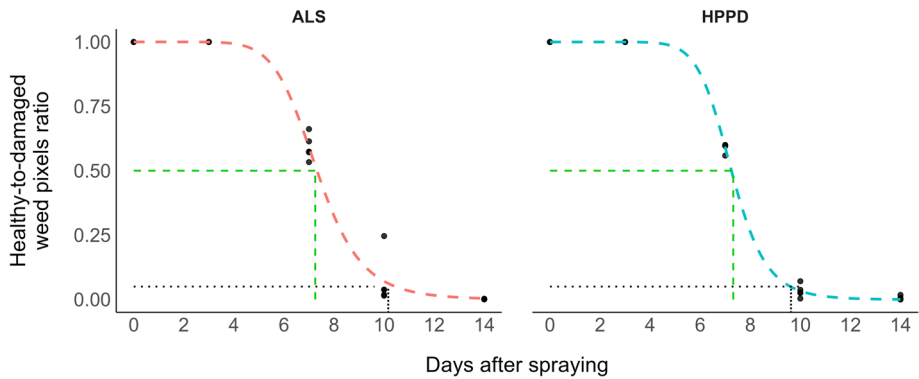


Fig. 5 Temporal change of healthy-to-damaged weed pixels ratio following ALS- and HPPD-inhibiting herbicide application based on 2023 experimental field. The green dashed lines indicate the estimated ED_{50} , and the black dashed lines indicate the estimated ED_{90}

Table 5 Temporal linear model slopes of satellite-based GLCM texture features and spectral data over 0–21 DAS for control and treated plots based on field experiments (2022–2023). Selected spectral bands and GLCM features are ranked by slope differences between treatments and the control. Asterisks (*, **, ***) indicate model significance at $p < 0.05$, 0.01, and 0.001, respectively

2022						2023				
Herbicide mode of action	Band/ spectral index	GLCM feature	Slope of Control Treatment	Slope of Herbicide Treatment	Differences slope	Band/ spectral index	GLCM feature	Slope of Control Treatment	Slope of Herbicide Treatment	Differences slope
ALS	NIR	Variance	0.171***	0.077**	0.093	NIR	Variance	0.102***	-0.005	0.107
	NIR	Mean	0.162***	0.076**	0.085	NIR	Mean	0.099***	-0.003	0.102
	NIR	Homogeneity	-0.047*	0.019	0.066	SAVI	Variance	0.086***	0.034***	0.052
	NIR	Dissimilarity	0.037	-0.013	0.051	NDVI	Variance	0.086***	0.034***	0.052
	Red edge	Homogeneity	0.037	-0.002	0.039	Green	Correlation	0.035***	-0.016***	0.051
HPPD	NIR	Variance	0.171***	0.110***	0.060	NIR	Variance	0.102***	-0.014***	0.117
	NIR	Mean	0.162***	0.114***	0.047	NIR	Mean	0.099***	-0.008***	0.107
	GNDVI	Variance	0.051*	0.091***	0.040	SAVI	Variance	0.086***	0.016***	0.070
	NDVI	Variance	0.039*	0.072***	0.033	NDVI	Variance	0.086***	0.016***	0.070
	SAVI	Variance	0.039*	0.072***	0.033	GNDVI	Variance	0.084***	0.016***	0.067

Weed suppression dynamics

For both herbicide treatments, the weed suppression dynamic exhibited a similar temporal pattern following herbicide application (Fig. 5). The healthy-to-damaged weed pixels ratio remained high shortly after application (0–3 DAS) and declined between 7 and 10 days, reaching low values after 10 DAS. According to the fitted response curves, both treatments were similar in shape and timing. ED_{50} occurred at 7.23 DAS for both ALS- and HPPD-inhibiting herbicides (green dashed line, Fig. 5). ED_{90} was reached at 9.5 DAS for HPPD

treatments and at 10.5 DAS for ALS treatments (black dashed line, Fig. 5). Overall, 10 DAS is the optimal timing for evaluating herbicide efficacy using UAV multispectral sensing, when damaged weeds are clearly expressed spectrally (90%).

Stage 2—Satellite feature selection to distinguish herbicide treatments from control

Among all spectral and GLCM features compared, NIR-based GLCM variance and mean features showed the greatest differences in linear model slopes between herbicide-treated and control plots in both 2022 and 2023, and across ALS and HPPD treatments (Table 5). In 2022, control plots showed positive temporal linear model slopes for NIR-based GLCM variance (0.171) and GLCM mean (0.162), indicating increasing spatial heterogeneity over time. In contrast, herbicide-treated plots exhibited substantially lower linear model slopes under both ALS (variance: 0.077; mean: 0.076) and HPPD (variance: 0.110; mean: 0.114) treatments, resulting in clear slope separation between treated and control plots.

A similar but more pronounced pattern was observed in 2023. Control plots again exhibited positive temporal linear model slopes for NIR-based GLCM variance (0.102) and GLCM mean (0.099), whereas herbicide-treated plots showed near-zero or negative temporal slopes linear model under both ALS (variance: -0.005 ; mean: -0.003) and HPPD (variance: -0.014 ; mean: -0.008) treatments.

The differences between 2022 and 2023 aligned with contrasting weed pressure at the time of herbicide application. Weed infestation at the time of spraying was low in 2022 ($\sim 2\%$) and substantially higher in 2023 ($\sim 20\%$). Spectral indices and reflectance bands alone did not show comparable slope separation between herbicide-treated and control plots (Supplementary Table S4—7). These results support the study hypothesis that herbicide efficacy alters within-field crop-weed composition and directly affects spectral-spatial heterogeneity over time in satellite pixels.

Sensitivity of NIR-based GLCM variance to weed infestation pressure

Building on the 2022–2023 differences in NIR-based GLCM variance driven by weed infestation levels, the sensitivity of this feature to weed infestation at 10 DAS is illustrated in Fig. 6. NIR-based GLCM variance, from 2022 and 2023 experiments, exhibited a strong positive relationship with UAV-predicted weed cover in control plots, with higher variance values corresponding to increasing weed infestation ($R^2=0.85$, $RMSE=0.095$ (GLCM variance on a normalized 0–1 scale). Overall, these findings demonstrate that NIR-based GLCM variability reliably reflects both the presence and intensity of herbicide control failure.

Stage 3 – UAV-based mapping of herbicide control failure using SVM

Table 6 summarizes the performance of the UAV-based SVM classification for mapping herbicide control failure across seven commercial fields. Table 2 provides details on image acquisition dates. For the weed class (representing herbicide control failure), precision was consistently high, ranging from 0.96 to 1.00 (mean = 0.99), while recall ranged from 0.75 to 0.95 (mean = 0.85). This trend was observed across all seven commercial fields, indicating that pixels classified as weeds were almost exclusively true weed pixels, although some

Fig. 6 Relationship between satellite-based NIR-GLCM variance (y) and UAV-based weed cover prediction (x) for control (untreated) replicates 10 DAS in the experimental field in 2022–2023

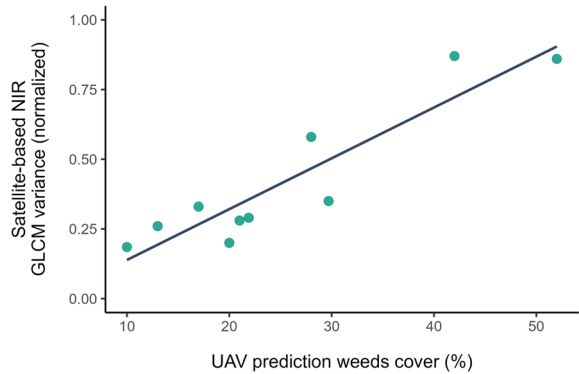


Table 6 Classification performance of UAV-based SVM mapping of herbicide control failure in commercial maize fields

Site	Maize		Soil		Weed	
	Precision	Recall	Precision	Recall	Precision	Recall
Filed 1	0.960	0.955	0.952	1	1	0.910
Field 2	0.835	0.905	0.873	0.901	0.982	0.835
Field 3	0.977	0.970	0.960	1	0.987	0.95
Field 4	0.940	1	0.948	0.995	0.994	0.906
Field 5	0.865	0.933	0.879	1	0.986	0.816
Field 6	0.821	0.976	0.941	1	1	0.754
Field 7	0.957	0.891	0.886	0.990	0.955	0.792
Average	0.908	0.947	0.920	0.983	0.986	0.851

Table 7 Classification performance of rule-based and upscaling approaches for satellite prediction of herbicide control failure cover in commercial fields

Site	Upscaling UAV to satellite		Rule-based framework	
	Precision	Recall	Precision	Recall
Field 1	0.514	0.995	0.933	0.815
Field 2	0.269	0.722	0.734	0.847
Field 3	0.304	1.000	0.87	0.673
Field 4	0.076	0.923	0.818	0.769
Field 5	0.003	1.000	0.72	0.781
Field 6	0.000	0.000	0.595	0.936
Field 7	0.017	0.012	0.424	0.223
Average	0.11	0.6	0.71	0.71

weed pixels remained undetected. For maize and soil, performance was high, with mean precision and recall exceeding 0.90. The resulting UAV-based herbicide control failure maps served as spatially explicit, field-scale reference layers for subsequent satellite-based validation analyses.

Stage 4 – Satellite-based mapping of herbicide control failure: rule-based vs. UAV-to-satellite upscaling

Satellite-based mapping of herbicide control failure was evaluated using two approaches: a rule-based framework and a UAV-to-satellite upscaling approach based on a Random Forest model. For both approaches, satellite-derived predictions were compared with UAV-derived herbicide control failure maps, which served as ground-truth data. Model performance was evaluated at two spatial scales, within-field (Table 6) and between-fields (Fig. 7). Within-field, the rule-based approach achieved moderate to high precision (0.42–0.93), whereas recall varied substantially between fields (0.22–0.94). Across all seven fields, mean recall and precision for the rule-based approach were both 0.71, indicating a comparable emphasis on detecting failure control and avoiding false detections (Table 6).

In contrast, the upscaling approach exhibited wider field-level variability, with precision ranging from 0.00 to 0.51 and recall ranging from 0.00 to 1.00. Across all seven fields, the upscaling approach yielded a mean precision and recall of 0.11 and 0.6, respectively (Table 6). To ensure that differences between approaches were not driven by the hotspot post-processing step, the same hotspot framework used in the rule-based approach was applied to the upscaled prediction maps. Comparing these hotspot-derived maps to UAV ground truth yielded only minor improvements (precision=0.71, recall=0.41; Supplementary, Table S8), which remained lower than those of the rule-based approach. This pattern indicates systematic under-prediction of herbicide control failure at the within-field scale. For both approaches, Field 7 showed the lowest performance and represented a clear exception to the overall pattern, with reduced recall and precision. In this field, UAV imagery was acquired at 7 DAS, a timing that may not fully represent the final weed suppression status, introducing additional uncertainty in the reference map. Excluding Field 7 increased mean precision and recall for the rule-based to 0.78 and 0.80, respectively, and increased mean precision and recall for the upscaling approach to 0.19 and 0.77, respectively. Between-field performance is illustrated in Fig. 7, which shows the relationship between herbi-

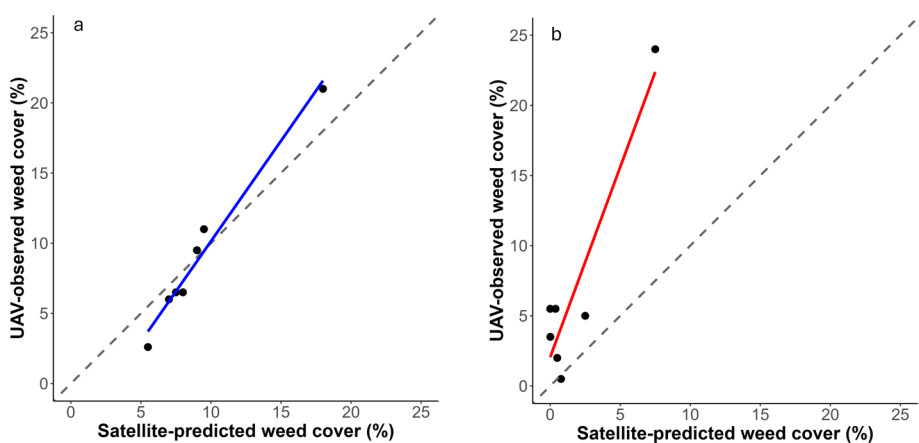


Fig. 7 Relationship between observed and predicted herbicide control failure cover in commercial fields using (a) the rule-based approach and (b) UAV-to-satellite upscaling. Points represent individual fields. The solid line shows the linear fit, with R^2 and RMSE reported for each model. The dashed grey line denotes the 1:1 reference line

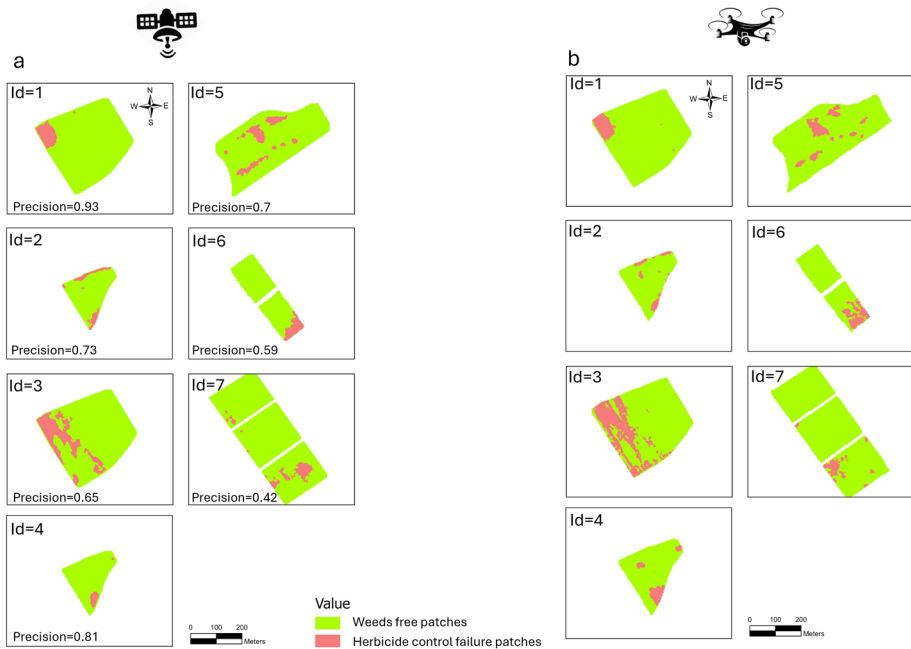


Fig. 8 Spatial distribution of herbicide control failure (red) and weeds-free (green) patches predicted by the rule-based approach across seven commercial maize fields (**a**). precision values indicate field-level agreement with UAV reference maps (**b**)

cide control failure cover predicted by satellite imagery and that mapped by UAV at the field scale. The rule-based model exhibited a strong linear relationship with UAV maps ($R^2=0.97$, $RMSE=1.86\%$), indicating that satellite-derived estimates closely tracked relative differences in weed cover among fields. In contrast, upscaling UAV to satellite predictions showed weaker correspondence with UAV-observed weed cover ($R^2=0.86$) and substantially higher error ($RMSE=7.07\%$), that correspond with systematic overestimation of weed cover at the field scale (Fig. 7b). In practice, the rule-based approach correctly distinguished fields with low herbicide control failure from those with high levels, although it did not capture all within-field failure patches (Fig. 8). Overall, these results show that the rule-based approach produced more consistent, field-specific maps of herbicide control failure, with relatively few missed areas compared to the UAV reference maps, whereas the upscaling approach tended to underpredict herbicide control failure by classifying many failure pixels as weed-free.

Discussion

Satellite imagery offers scalable coverage for agricultural monitoring, yet its spatial resolution limits weed detection at the field scale. Because herbicide efficacy was assessed in this study indirectly through weed persistence following application, we evaluated a texture-based, rule-driven approach using PlanetScope imagery to map weeds in maize after her-

bicide treatment. The decision to use a texture-based, rule-driven framework followed the hypothesis that herbicide control failure increases spectral-spatial heterogeneity within crop fields.

This study demonstrates that GLCM texture features derived from PlanetScope satellite imagery can effectively map weeds exhibiting herbicide control failure following herbicide application in maize.

By integrating GLCM variance and mean features with temporal change in a rule-based framework, the approach achieved 71% mean precision in detecting herbicide control failure across seven commercial maize fields. In both experimental and commercial settings, spatio-temporal texture features showed consistently greater sensitivity to weed-suppression dynamics than spectral features derived from the same imagery. Texture features enhance discrimination of vegetation structural patterns by capturing spatial heterogeneity beyond the spectral limits of the data, providing a valuable tool for precision agriculture (Cohen & Alchanatis, 2018; Cohen et al., 2013; Park & Guldman, 2020; Zhou et al., 2021). The utility of temporal change of texture information, i.e. spatio-temporal features, is supported by recent studies demonstrating improved vegetation characterization for mapping of forest tree species (Rösch et al., 2022), and crop yield prediction from satellite imagery (Cohen et al., 2025; de Freitas et al., 2024; Romano et al., 2021). Here, we demonstrate that this capability can also be applied to detect weeds exhibiting herbicide control failure after application, thereby supporting field-scale inference of herbicide efficacy.

Because herbicide effects unfold over a short period (approximately 0–14 days after application), the observation window is temporally constrained. The high revisit frequency of PlanetScope (most acquisitions < 36 h) is therefore particularly suited to capturing these short-term post-application dynamics. To evaluate this mechanism, temporal behavior was first characterized using high-resolution UAV multispectral data to describe the dynamics of weed suppression following herbicide application in experimental fields with herbicide treatments and a control without any control weeds. These analyses indicated that 10 DAS was the optimal time point for clear spectral separation between damaged and healthy (demonstrate control failure) weeds. On 3 and 7 DAS, herbicide effects were still developing, and treated pixels remained mixed with healthy vegetation, limiting reliable classification. This delayed response likely reflects species-specific differences in sensitivity to herbicide modes of action, which manifest as gradual spectral changes detectable at close range in remote sensing (Noh et al., 2025). Similar patterns were reported by Pause et al., (2019), who used Sentinel-2 imagery to evaluate NDVI responses following glyphosate application in bare fields. In their study, NDVI reductions were limited at 3–6 DAS, whereas a significant decline was observed only at approximately 10 DAS. Based on these findings, temporal dynamics were given primary emphasis in the present study.

Accordingly, temporal changes in GLCM texture features derived from PlanetScope imagery were evaluated to successfully distinguish between controlled and herbicide-control-failure pixels. Eight GLCM features were derived from each spectral reflectance layer across five observation dates, and linear models were fitted for each feature, with time as the explanatory variable and feature value as the response variable. Among all analyzed features, NIR-based GLCM variance and mean exhibited the highest sensitivity for distinguishing herbicide-suppressed pixels (herbicide treatments) from untreated weeds (control treatment), capturing spectral-spatial heterogeneity over time, consistent with the study hypothesis. Mean texture measures correspond to the average grey-level intensity of the

NIR spectral band within the moving window, which may contain information about weed presence after herbicide application, while variance quantifies the degree of variability in grey-level intensity within the same window, reflecting spatial heterogeneity that increases in areas where failure control persist.

Other features, textural and spectral, show no difference in slope. NDVI, for example, shows similar changes in pixel values between treats and control, even though in the untreated control treatment there was more vegetation due to the coexistence of maize and weeds, which highlights the contribution of each GLCM-derived texture layer. Similar findings were reported by Kelsey and Neff (2014), who demonstrated that the effectiveness of GLCM analysis depends on appropriate feature selection, with entropy, mean, and correlation contributing strongly to forest aboveground biomass estimation from Landsat imagery, whereas NDVI contributed relatively little. These findings, based on our experimental results and supported by previous studies, demonstrate that combining temporal and spatial data enables satellite texture analysis to serve as an operational monitoring tool for herbicide control failure under field conditions.

A common approach to use satellite data in field conditions is by integrating field and satellite data. The recent use of UAVs in agricultural fields enables their data to serve as a qualitative reference for upscaling UAV-to-satellite (Mao et al., 2022; Riihimäki et al., 2019; Salgado et al., 2025). However, using this upscaling data for weed detection remains limited due to challenges in getting availability and quality of datasets. Training models on limited datasets can lead to unstable performance, and even with transfer learning or data augmentation, robust model development typically requires sufficiently extensive and representative training data (Alibabaei et al., 2022). Under such constraints, rule-based or knowledge-driven approaches, such as the framework adopted in this study, offer a practical alternative for satellite-based weed detection when extensive training datasets are not available. Indeed, comparing the rule-based approach in this study with UAV-to-satellite upscaling based machine learning model to classify weed patches following herbicide application based on PlantScope multi-temporal images shows that the former performed considerably better. The precision of the rule-based and the upscaling were 0.42–0.93 and 0–0.51, respectively. These results reinforce the premise that limited reference data constrain the effective use of data-hungry machine-learning methods and highlight the value of knowledge-driven frameworks as an alternative that reduces reliance on large training datasets. Although rule-based methods are not new (Cohen & Shoshany, 2002), results from this study and recent work (Yang et al., 2023) suggest that they offer practical advantages under data-limited conditions, particularly where ML-based upscaling is constrained.

Moreover, the improved performance of the rule-based framework may be related to its integration of spatial information at two complementary levels. In addition to pixel-scale GLCM texture features, the framework introduces a hotspot-based aggregation step that groups pixels into spatially persistent clusters. While GLCM features capture local spectral-spatial heterogeneity associated with weeds, the hotspot layer emphasizes coherent infestation patterns and reduces isolated noise. This dual spatial structure may contribute to more stable detection of herbicide control failure. Despite these advantages, the hotspot-based aggregation may also lead to over-detection under low signal conditions, as spatial clustering can highlight relative patterns even when absolute differences are small (Ord & Getis, 1995). This effect may explain discrepancies observed in some fields (e.g., id=7; Fig. 8). On the other hand, the lower sensitivity and coarser spatial resolution of satellite imagery

compared to UAV data may lead to missed detection of small or sparse weed patches due to mixed-pixel effects and spectral mixing (e.g., $id=3$; Fig. 8). Further refinement of thresholds and the integration of spectral unmixing models in future work may improve prediction accuracy (Ronay et al., 2025).

Such improvements, with development of stage-specific knowledge-based rules adapted to early canopy conditions may also support the extension of this framework to pre-herbicide weed mapping and support precision spraying. In the present study, herbicide control failure were identified within a bounded post-application window (~ 10 DAS), when maize was at the V4–V6 phenological stage and vegetation signals were strongly expressed. Pre-application conditions occur earlier (maize growth stages V2–V4), when canopy development is reduced and vegetation contrast is weaker, narrowing the temporal window for reliable detection. Therefore, the current results do not guarantee similar performance at earlier stages and highlight the need to further refine knowledge-driven satellite frameworks to fully exploit their potential for early-season weed mapping.

Conclusion

This study demonstrates that spatio-temporal GLCM texture features derived from Planet-Scope satellite imagery can detect weeds exhibiting herbicide control failure under operational field conditions. By integrating temporal change with rule-based spatial aggregation, the framework achieved consistent precision across commercial maize fields and outperformed a UAV-to-satellite upscaling approach that relied on limited training data. The results confirm the study hypothesis that herbicide control failure manifests as increased spectral-spatial heterogeneity, which can be operationalized using knowledge-driven satellite texture analysis. These findings establish a methodological pathway for satellite-based inference of herbicide efficacy at the field scale, independent of extensive training datasets.

From a practical perspective, this approach offers farmers and researchers a scalable tool for monitoring herbicide efficacy. Detection of herbicide control failure at approximately 10 DAS may provide a window for site-specific follow-up interventions. Farmers can use satellite-derived maps to identify zones of herbicide control failure and implement targeted second-round applications, optimizing weed management while reducing unnecessary inputs. Moreover, historical satellite records further enable trend analysis to guide long-term herbicide decisions, allowing farmers to estimate weed pressure before the season and adjust management strategies accordingly. For researchers, the framework provides a new avenue to investigate agronomic drivers of herbicide efficacy, including crop rotation, herbicide programs, and tillage systems, supporting more sustainable weed management strategies. This study represents an initial operational demonstration. Future work should validate the framework across larger geographic regions, diverse cropping systems, and earlier phenological stages to refine knowledge-based rules and extend applicability to pre-herbicide weed mapping under commercial farming conditions.

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Data Availability No datasets were generated or analysed during the current study.

Declarations

Conflict of interest The authors declare no competing interests.

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