Enhancing Precision Agriculture through Dual Weed Mapping: Delineating Inter and Intra-row Weed Populations for Optimized Crop Protection

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Abstract.

In the field of precision agriculture, effective management of weed populations is essential for optimizing crop yield and health. This paper presents an innovative approach to weed management by employing dual weed mapping techniques that differentiate between inter-row and intra-row weed populations. Utilizing advanced imaging and data analysis of CropEye images collected by the Robotti robot from AgroIntelli (AgroIntelli A/S, Aarhus, Denmark), we have developed methods to generate distinct crop and weed population maps, with a focus on the unique characteristics of different field areas.

The research involves the detailed analysis of two separate zones in crop fields: inter-row bands (spaces between crop rows) and intra-row bands (spaces within crop rows). Our methodology enables a precise understanding of weed distribution patterns by leveraging data from high-resolution images and deep learning algorithms. This differentiation is key for implementing adaptive targeted weed control strategies that are both efficient and environmentally sustainable.

Our findings show a significant reduction in weed density within mechanically weeded inter-row bands compared to the untreated intra-row regions. This difference highlights the potential for more nuanced and effective weed control practices that can adapt to varying weed densities and locations. The paper also examines the implications of such dual weed mapping for integrated weed management (IWM) plans, suggesting a transition towards more localized and specific weed control measures.

In conclusion, our study emphasizes the importance of spatial specificity in weed management within precision agriculture. By recognizing the nuances of inter and intra-row weed populations, we propose a pathway toward more targeted, effective, and sustainable crop protection management.

Keywords.
Inter-row and Intra-row weed populations, Automated Weed Detection, Spatial Variability, Integrated Weed Management (IWM), Machine Learning, Sustainable Crop Management

Introduction

The emergence of precision agriculture has fundamentally transformed agronomic management practices, with a notable impact on weed control strategies. Traditionally, the management of weed populations has largely relied on experiential knowledge of crop rotation and limited field-level sparse weed population monitoring. The advent of sophisticated agricultural machinery enabled variable application of herbicides and precision row guidance, marking a significant shift in plant protection paradigms. However, this shift has introduced complexities in achieving targeted weed control due to the challenges in timing management tasks plus optimizing herbicide mixtures and dosages for specific weed populations.

Several publications confirm significant herbicide savings are possible by implementing Integrated Weed Management (IWM) principles. In row crops, the simplest obtainable herbicide savings are achieved by doing mechanical interrow weed control and only band spraying the narrow crop bands saving between 50% to 80% depending on the row distance and bandwidth (Vasileiadis et al. 2015; Loddo et al. 2019; Wiltshire, Tillett, and Hague 2003; Gerhards, Weber, and Kunz 2020). Secondly, a significant reduction of herbicides can also be obtained by the use of scouting and the predictive model optimized weed control, allowing for reductions in herbicide inputs or replacing herbicides with mechanical weeding (Vasileiadis et al. 2015; Somerville et al. 2019; Per Rydahl 2004).

The RoboWeedSupport (P. Rydahl et al. 2017) and RoboWeedMaps (Teimouri, Jørgensen, and Green 2022) projects in Denmark exemplify the progress in computer-assisted weed population mapping and spatial distribution analysis, facilitating more precise herbicide mixtures and dose applications (Per Rydahl et al. 2022; Jørgensen et al. 2021). Despite these technological advances, there persists a notable challenge in accurately distinguishing between micro-environments within crop fields, specifically the inter-row (spaces between crop rows) and intra-row (spaces within crop rows) areas. These zones exhibit distinct weed populations because of different treatment regimes e.g. performing mechanical interrow weeding and crop band spraying, necessitating a nuanced approach to weed management. Gerhards *et al.* (2020) manually assessed weed population separately between the rows and within the row in a 10 cm wide strip using a frame of 0.5 m² but only for evaluating uniform intrarow/interrow treatments.

This paper presents an innovative dual weed mapping technique that leverages the advanced imaging capabilities of the CropEye camera system, mounted on the AgroIntelli Robotti robotic platform. By analyzing high-resolution images, we generate detailed maps that delineate weed populations across these distinct field zones, thus providing the necessary agricultural intelligence for refining Integrated Weed Management (IWM) practices. Our approach segments the field into inter-row (between crop rows) and intra-row (within crop row) zones, utilizing deep learning algorithms to accurately map weed distribution patterns, which is critical for implementing adaptive weed control strategies that are both effective and environmentally sustainable.

Significantly, the inclusion of the CropEye camera system in Robotti's array of equipment in 2023 has enhanced its functionality beyond mere seeding and mechanical weeding tasks. This integration allows for the detailed inspection of crops and weeds, enabling remote field monitoring and reducing the need for physical field visits, as detailed in the initial findings from the field trials conducted with Robotti (Besana and Trénel 2022).

By comparing the field-level weed density counts with the counts within the specified inter-row and intra-row bands, we aim to highlight the significant reduction in weed density achieved through mechanical weeding in the inter-row areas compared to untreated intra-row regions. This differential underscores the need for a shift towards localized and specific weed control measures that are grounded in the spatial specificity provided by dual weed mapping. Through this study, we advocate for a more intelligent, targeted, and sustainable approach to crop protection in the realm of precision agriculture.

Methods

This study was conducted on a maize crop during the growth season of 2023 in Denmark, focusing on two adjacent fields: field 85-0 (west) covering 4.97 hectares and field 84-0 (east) spanning 8.22 hectares. Both fields had been sown with winter rye in the previous growth season, providing a consistent baseline for the assessment of weed populations and the effectiveness of weed management strategies employed in the current season.

Field Setup and Data Collection

The fields were chosen for their proximity and similar agronomic histories, allowing for a controlled comparison of weed populations. Two 3m wide (wheel center) Robotti 150D autonomous robots, equipped with the CropEye imaging system from AgroIntelli, were deployed across these fields to collect high-resolution images while seeding and nursing the crop. This advanced camera system, positioned behind the robot's front bumper and slightly to the left of its centerline, facilitated the detailed inspection of crops and weeds. The 5-megapixel imagery covered approximately 1.1 m in width and 0.92 m in height equal to 1 m2 images and a ground sampling distance of 0.45 mm per pixel. The setting of the CropEye camera sampling density was set to 10 % sampling coverage of the total area the 1.1 m wide band a single CropEye camera traverses when Robotti is in work mode ideally imaging ~3.5% of the field area or 350 images per hectare. The CropEye camera was fixed behind the front bumper with a left offset of ~0.44 m. This location ensured the bottom of the imaged area where at the Robotti navigation line the navigation controller used to estimate the deviation from the centerline also addressed as Cross Track Error (XTE). XTE refers to the deviation of the robot's actual path from its intended path and will deviate to some extent when navigating the preplanned path. The collected images were uploaded to the AgroIntelli AWS cloud service in real-time during a nursing operation if having sufficient bandwidth beyond crucial safety and navigational data. In cases of insufficient bandwidth to keep up the CropEye image filling the biggest gap in the sampling was prioritized from the buffer.

Table 1. Robotti's & implements used to seed, mechanical interrow weeding, and interrow band spraying.

Seeding Robotti PR00021 (field 85-0)	Mechanical weeding Robotti PR00021	Band spraying Robotti PR00030
		
Gaspartdo, 4-rows SP540 precision seeder	Kongskilde Poland, Mechanical interrow weeder	Danfoil, Band-sprayer
The base version of the SP seed drill was used: the front clod deflector facilitates the action of the coulter boot. With the right seeding disc, this version is ideal for many crop types including maize on well-worked soil	The mechanical interrow cleaner was a custom-built cleaning featuring a design where each parallelogram situated between crop rows (with a row spacing of 0.75 meters) was equipped with 5 VCO-tines which included duckfoot blades.	Danfoil is one of Denmark's leading manufacturers of field sprayers. With Danfoil field sprayers, the driving force is not liquid, but air pressure. SpitFire is a ROBOTTI-customized band sprayer with 21 nozzles separated by 12.5 cm. Each nozzle has a manual valve enabling band spraying setup.

Note: Seeding of field 84-0 was done with Robotti PR00030 equipped with a Monosem NG+4 seeder in parallel with PR00021 seeding field 85-0

Table 1 states the different Robotti's and implements used to seed the maize on April 27-28, 1st mechanical weeding on May 17-18, and the 2nd on May 27-28, and doing band spraying on June 2-3.

Image Pre-processing within the AgroIntelli AWS cloud

Upon upload of the recorded CropEye images to the AgroIntelli AWS cloud, the images undergo a pre-processing workflow designed to extract meaningful agricultural data. This section outlines the sequential steps taken from the moment images are uploaded to their storage as processed JPEG images with accompanying metadata such as GPS position (Edwards 2022).

Cloud-based Image Processing Workflow

1. **Rosbag Uploads and Processing:** Images may be captured directly onto an SD harddrive in areas with too narrow internet bandwidth. These are initially stored in rosbag format, a common robotics data format that bundles images with other sensory data. These rosbags are uploaded to an S3 bucket on AWS, triggering a Lambda function upon insertion. For images already in the cloud, an ECS instance extracts the image data from the rosbags, converting them into PNG format for further processing.
    a. **Real-time upload:** The latter ECS instance task extracting the image data from the rosbags, converting them into PNG format for further processing is performed directly within the Robotti vision computer before direct uploads using the remnant bandwidth. This is the approach used in this project.
2. **Image Conversion and Pre-processing:** Upon conversion to PNG format, another Lambda function is triggered to further process these images. This includes adjustments such as color balancing and contrast enhancements to make the images more suitable for machine reading. This pre-processing step is critical for ensuring the subsequent image analysis algorithms can effectively differentiate between crops, weeds, and soil.
3. **Metadata Annotation and Storage:** The processed images are then converted to JPEG format and stored in a separate S3 bucket, alongside metadata that includes precise GPS coordinates. This metadata is crucial for mapping the spatial distribution of weeds and crops across the field, enabling precise agricultural interventions.

Detection and classification of crop and weed objects using deep learning

The pre-processed images stored in the S3 bucket could be analyzed for crop and weed objects directly within the AWS AgroIntelli cloud and further processed into crop and weed maps enabling patch weed management as described by G. Edwards (2022). However, these maps will not split the maps according to the intrarow and interrow band maps which is the scope of this work. Hence, the following additional steps were added enabling statistical analysis and map generation using RStudio, a comprehensive platform for statistical computing and graphics. Specifically, we employed RStudio version 2023.06.1 Build 524, the 'Mountain Hydrangea', operating on a Windows environment. This software, developed by Posit Software, PBC, supports extensive data manipulation, calculation, and graphical display functionalities, essential for the rigorous examination of our study's findings.

Export of processed CropEye images to external quality assessment service

To perform model-based crop and weed detection and classification, quality assessment, and export to further analysis the images needed to be parsed onto the RoboWeedMaps service provided by I-GIS Denmark (https://i-gis.dk/roboweedmaps/). This was done by use of Athena SQL locating the images from the field within the S3 bucket, and listing them in a csv file, which was then used to invoke an export instance transferring them to the RoboWeedMaps server.

Deep learning CropWeed model for inference, quality assessment, and model retraining

The model used in this work via the RoboWeedMaps service used a vision foundation model in form of a YOLOv5m model pre-trained on the COCO dataset. The COCO dataset includes approximately 1.5 million objects of 80 categories marked out in images (Teimouri, Jørgensen, and Green 2022). The CropWeed model version 117 (M117) is a specialized, finetuned, and further trained YOLOv5m model. The finetuning dataset consists of in total, around 53,000 training images from ~900 fields in mainly Denmark and less in Germany, England, and Netherlands, across 9 growth seasons. The main contributors to this dataset are Aarhus University, I-GIS Denmark, and AgroIntelli ApS partly co-funded by the GUDP project RoboWeedSupport and the Innovation Fund Denmark project RoboWeedMaPs. The CropWeed model received an additional 236 training images from the Robotti weed nursing tasks collected in this project refining the model performance further. Figure 1 illustrates the CropWeed model performance pooling the classes to Maize crop (ZEAMX), Plant Stem Emergence Zone (PSEZ), Monocot grass weed (PPPMM), Dicot weeds (PPPDD), and Creeping thistle weed (CIRAR).

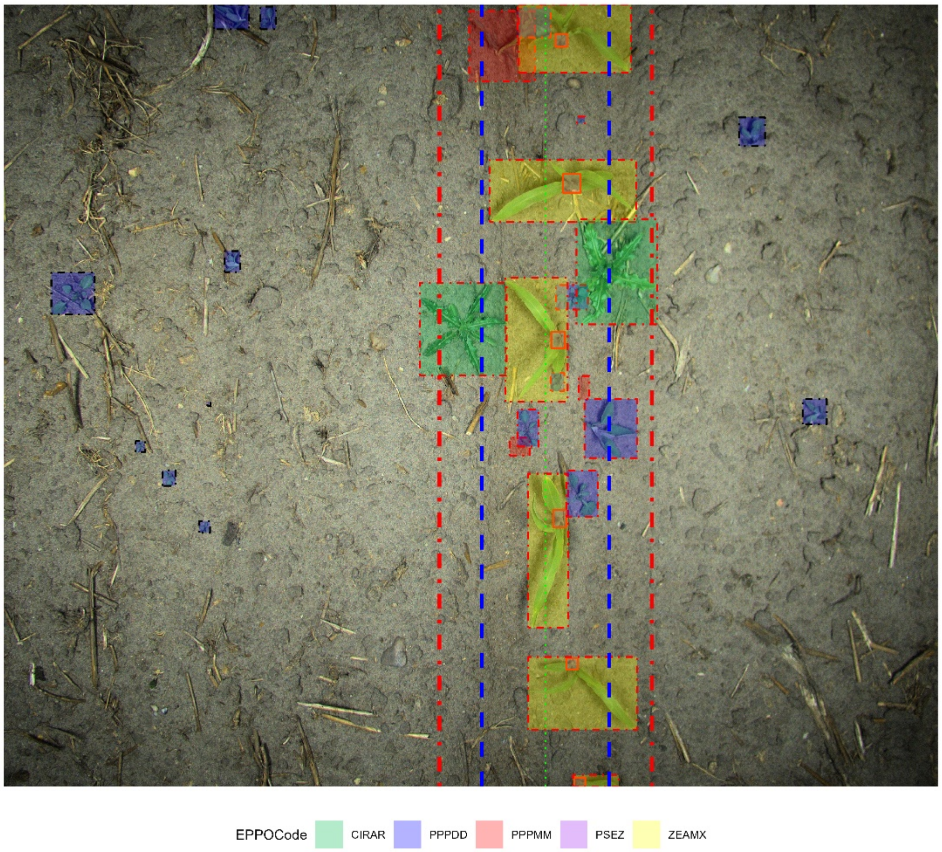

Fig 1. CropEye sample image with overlays. The vertical lines indicate the expected: crop row center line assuming XTE=0 (green dotted); 12.5 cm wide crop band (blue dashed); 25 cm wide (2 x 12.5 cm single spray nozzle width) crop band (red dotdashed). The bounding boxes (BBox) illustrate the objects detected by the CropWeed model. The BBox fill color illustrates the object classification Eppo Codes (dotdashed) except "PSEZ" (solid line) which is an abbreviation for the maize crop Plant Stem Emergence Zone. The color of BBox lines indicates whether the object is classified as within (red) the intrarow crop band or between the intrarow bands (black). Note XTE for this image is estimated to -3.6 cm shifted based on the 6 detected PSEZ's

During an iterative process, a weed expert annotated additional images for retraining. This process continues until the expert based on a qualitative assessment approves the model performance.

Datamining and mapping of crops and weeds in RStudio

When the crop and weed detection and classification model had been approved. Then a REST API interface to the RoboWeedMaps service was used within RStudio to retrieve all CropEye images together with the JSONs defining the detected and classified crop and weed objects. This data was used as the basis for deriving interrow and intrarow maps.

Assigning the detected objects to intrarow and interrow bands

The crop row distance was 75 cm placed in 2x2 rows symmetrically along the centerline (XTE=0) of the Robotti. The band sprayer nozzle width was 12.5 cm with one center nozzle above the latter center line. Hence, the crop rows will be between two nozzles. Therefore, two nozzles will be needed to spray a crop row resulting in 25 cm wide crop bands (see table 1).

Knowing the CropEye offset relative to the center line and the relative offset of the 4 crop rows, then it is possible to project the 25 cm wide crop bands onto the CropEye images assuming XTE is 0 and the rows are vertically orientated in the images. This is illustrated with the red dotdashed lines in figure 1.

The assignment of the detected objects or bounding boxes (bboxes) was based on whether their center point was within the projected crop band(s). If yes, then tagged with intrarow else tagged with interrow.

The above tagging procedure assumes the XTE or Robotti's deviation from the planned path when seeding and the subsequent weed controlling tasks in the form of two mechanical interrow weedings and one band spraying task can be neglected.

Validating if the Robotti deviation from the planned task can be neglected

Our approach focuses on analyzing bounding box data derived from Crop (ZEAMX) or Plant Stem Emergence Zone (PSEZ) annotations, reflecting the actual emergence points of crop plants, thus offering a precise reference for row center estimation.

The process begins with the extraction of bounding boxes for each image, representing detected crop regions. These bounding boxes are analyzed to determine their horizontal (X) and vertical (Y) extents within the image frame, to identify the densest aggregation of crop emergence points along the horizontal axis (the bounding boxes are illustrated in figure 1). This aggregation, represented by a density estimate of pixel distribution, allows for the approximation of the row center. The method assumes that the maximum of the probability density function, derived from the pixel counts across horizontal bands, accurately indicates the center of the crop row in pixel units.

Subsequently, the Cross-Track Error (XTE) is computed in centimeters, leveraging the known width of the image frame in pixels and the predefined row distance in meters, as specified in the configuration parameters. This calculation adjusts for the row's center not aligning with the frame's center, a condition noted for all analyzed images. Compared to using the crop bounding boxes, the precision of the PSEZ-based bounding boxes is emphasized for its potential to minimize parallax errors and enhance the accuracy of XTE estimations.

Figure 2 summarizes the density of the derived XTEs from the CropEye images while Robotti is navigating a crop nursing plan. The intrarow crop band equal to two spray nozzles in width shows the vast majority of the crop locations were within the 25 cm crop band. The density maxima is higher for the body which only consists of straight rows compared to the headland rows following the curvy shapes of the two fields forcing the Robotti to deviate from the path. However, for the first mechanical interrow weeding even for the body XTE extremum seems shifted ~4 cm. The operator confirms this because of missed Robotti self-configuration after a major system update over the air.

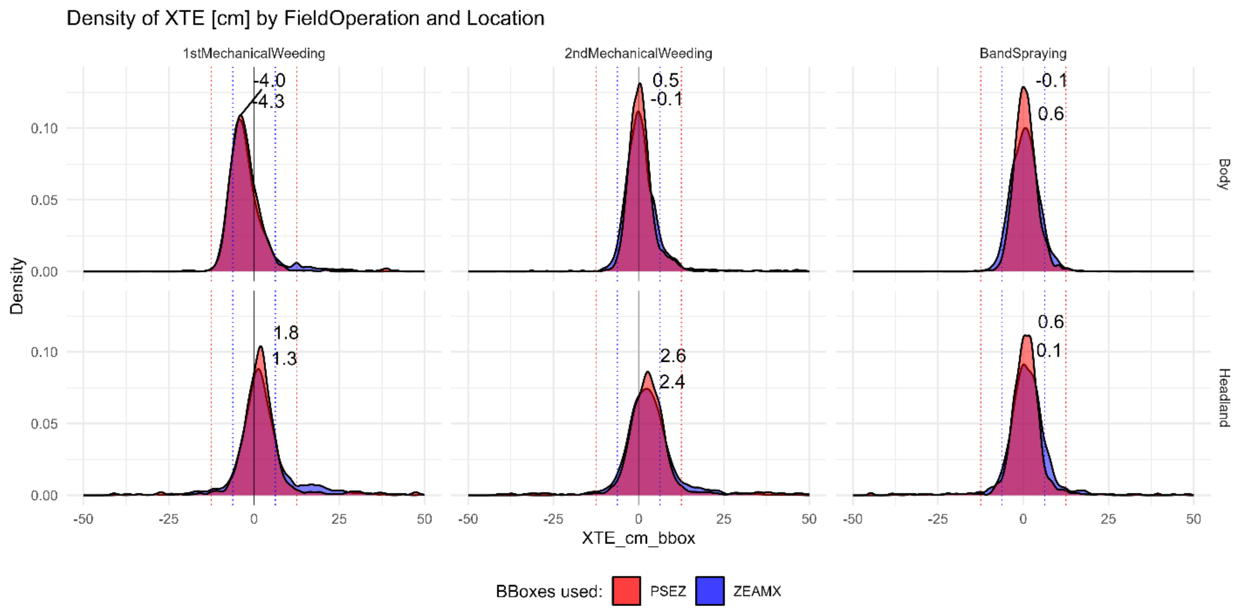

Fig 2. Density plots of XTE estimated for all CropEye images based on either the bounding boxes (BBox) from the crops (ZEAMX ~ blue) or crop Plant Stem Emergence Zone (PSEZ ~ red). The vertical lines indicate ½ a crop intrarow band width (blue dotted) or full width (red dotted) which is 2x12.5 cm. The columns separate according to the task performed by Robotti and the rows splits the XTE estimates into the body or headland areas of field 84-0 and 85-0. The numbers state the XTE for the density extremum which ideally should be 0.

In conclusion, it can be assumed Robotti's deviations while navigating can be neglected assuming a fixed location of the intrarow crop band and the interrow crop bands.

Estimating density counts and bbox coverage within interrow and intrarow bands and data structuring

Our methodology advances the precision agriculture field by introducing a refined analysis of weed and crop densities within specified crop bands, contrasting with traditional field-level assessments. This approach leverages high-resolution CropEye imagery to quantify densities with enhanced spatial specificity, focusing on the unique distribution within 25 cm crop bands, centered around the crop rows, under the assumption of zero Cross-Track Error (XTE).

Density Calculation Framework:

1. Field-Level Density: Represents the average density across the entire 1 m² CropEye image area, serving as a baseline for comparison.
2. Intra Crop Band Density: Calculated within a narrow band of 0.92 m x 0.25 m (0.23 m²), reflecting the focused area surrounding the crop rows.
3. Inter Crop Band Density: Assessed across the remaining area of 0.92 m x 0.85 m (0.782 m²), encompassing the spaces between crop rows.

Special Consideration for Crop (ZEAMX) and PSEZ:

For PSEZ and ZEAMX maize, density calculations account for the 75 cm row spacing by scaling the counts to reflect a single row's presence within the 0.92 m height of the image area. This results in an adjusted scaling factor of 1.45, acknowledging the spatial distribution peculiarities of these crops compared to dispersed weed populations.

Data Structuring and Analysis Steps:

1. Counting Occurrences: Enumerate each EPPO code within the images, categorizing counts by field characteristics (FieldName, FieldOperation, Location) and whether they fall within the intra-row or inter-row areas.
2. Absent Data Handling: In instances where an EPPO code is absent, counts are recorded as zero to accurately reflect the distribution across the dataset.
3. Bounding Box Area Calculations: For each EPPO code occurrence, the bounding box

area is calculated in pixels, alongside the percentage of the total intra-row or inter-row area it occupies, offering insights into spatial distribution.

4. Comprehensive Data Combination: Ensures a full dataset representation by combining all grouping variables, including EPPOCode, with their respective counts and areas, even for combinations absent in the raw data.
5. Merging Data for Complete Analysis: Combines the counted and calculated data with the full set of combinations, assigning zero where appropriate, to ensure a thorough representation for analysis.

Map generation based on density counts for visual exploration by use of Inverse Distance Weighting (IDW)

To enhance the visual interpretation and exploration of crop and weed densities across the field, we employed Inverse Distance Weighting (IDW) interpolation for map generation. This spatial analysis technique facilitates a clearer understanding of distribution patterns by interpolating the density counts from discrete point observations across a continuous surface.

Interpolation Parameters:

- Grid Resolution: Adopting a 3 m grid resolution aligns with the tracking width of the Robotti, ensuring that the interpolated maps accurately reflect the scale of the agricultural operations.
- IDW Interpolation: Utilizes inverse distance weighting to interpolate values, with a focus on nmax set to 15, optimizing the influence of neighboring points based on their proximity.
- Color Scaling: A logarithmic-like color scale is implemented to differentiate density levels effectively. This scale is particularly adept at illustrating variations in weed counts that are relevant for weed management decisions, transitioning from minimal (0 - 1) to extremely dense (1000 - Inf) weed occurrences.

Visualization by Field Operation:

For each field operation, maps are generated to exhibit density distributions across different assessments: field level, intra-row, and inter-row. This comparison is crucial for visually assessing the impact of agricultural practices on weed and crop distributions, providing insights into the efficacy of targeted interventions.

Faceted Grid Presentation:

The final visualization comprises faceted grid plots, organized to display density levels for various weed types (Creeping Thistles (CIGR), Dicot weeds (PPPDD), Monocot weeds (PPPMM)) and crop-related measures (PSEZ and maize (ZEAMX)). This organization facilitates a direct comparison between field-level assessments and more granular intra-row and inter-row analyses, highlighting the distinct advantages of spatially specific density evaluation.

Due to page limitations on the faceted grid maps from the last nursing operation will be presented.

Map generation based on bounding box coverage for visual exploration

Expanding on our density count mapping technique, we also generate maps based on bounding box coverage to further elucidate crop and weed distributions. This method allows us to visualize spatial competition dynamics beyond mere presence, acknowledging that plant size and coverage area significantly influence crop-weed interactions.

Selective Mapping and Rationale:

- Focus on Intrarow and Interrow Assessments: We concentrate on mapping intrarow and interrow coverage, sidestepping field-level maps to more accurately depict weed management outcomes.
- Faceted Grids for Temporal Analysis: Maps are organized into faceted grids distinguishing between dicot weeds (PPPDD) and monocot grass weeds (PPPMM).

Each grid represents weed coverage across three field operations—highlighting the progression of weed control efforts.

Advanced Visualization for Comparative Insights:

An additional faceted grid contrasts the percentage-point differences in weed coverage between intrarow and interrow areas for each field operation. This direct comparison visualizes the spatial effectiveness of weed control strategies over time.

Bounding box coverage mapping complements density-based visualization, offering nuanced insights into the spatial dynamics of crop and weed competition. This method enhances our understanding of agricultural ecosystems, supporting more targeted and effective weed management strategies.

Environmental Considerations and Weed Control Strategies

Acknowledging the importance of sustainable agriculture, this study also evaluated the environmental impact of different weed control strategies. By comparing mechanically weeded inter-row bands with untreated intra-row regions, we assessed the efficacy of targeted interventions. This approach not only aimed to decrease weed density effectively but also sought to reduce the overall usage of herbicides, aligning with Integrated Weed Management (IWM) principles.

Results

It's important to note that the density counts and bbox coverages for a field operation reflect the impact of the previous operation, as the CropEye cameras are positioned ahead of the implement.

There are numerous ways of evaluating the effect on e.g. the dicot weed density counts. Figure 3 illustrates this by using violin density plots. This confirms that mechanical weeding has a reducing effect on the interrow dicot weed densities but no clear effect for the intrarow bands. At the first mechanical weeding the interrow dicot density counts appear significantly higher in the intrarow bands. Hence, the sowing operation compacting the soil may have a stimulation effect on the dicot weed emergence. In general, the dicot weed density is higher within the headlands of the fields compared to the body areas.

According to figure 3, the interrow median dicot weed density counts were approximately 25, 5, and 1 per m2 for the 1st & 2nd mechanical interrow weeding, and the band spraying, respectively. Whereas the median density counts for the intrarow crop band stayed constant at 5 plants per m2. Representative CropEye images for the latter can be seen in figure 4, which also illustrates the crop growth.

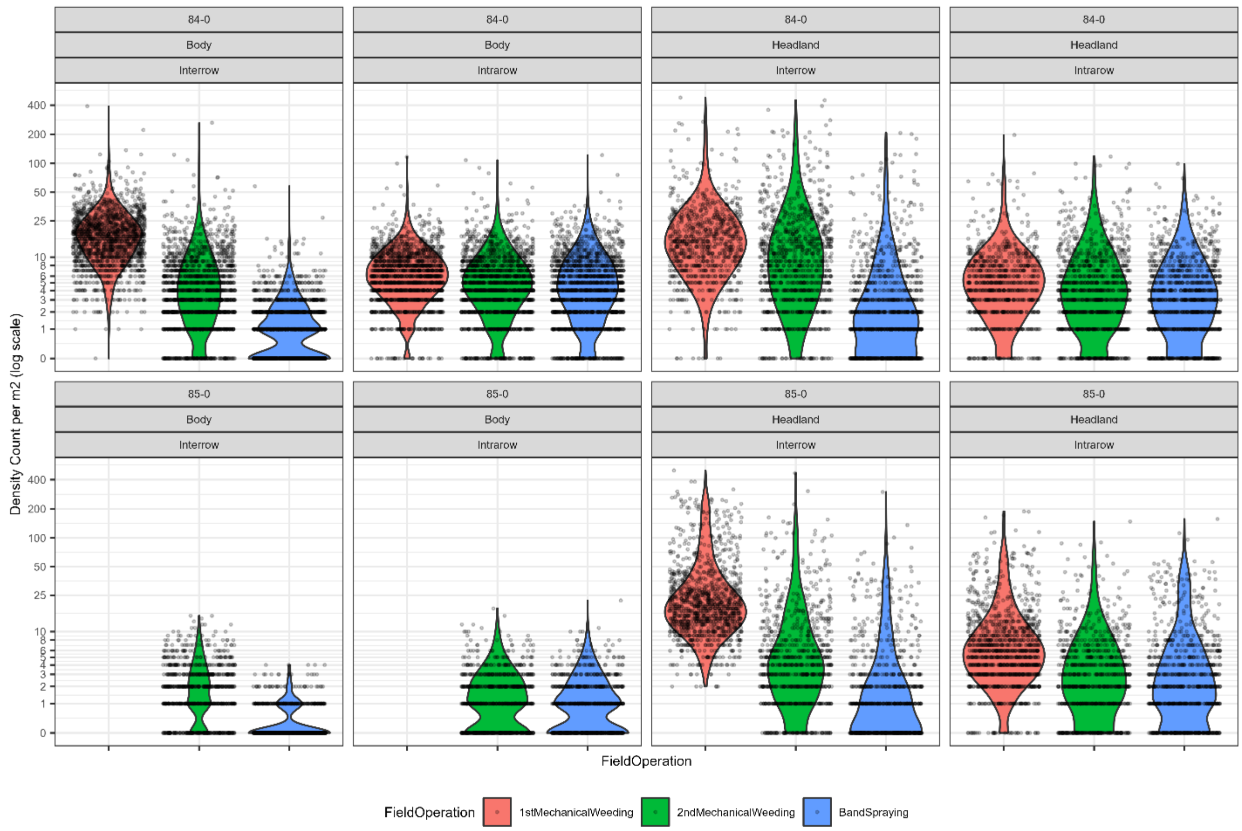

Fig 3. Density count distributions for dicot weeds (PPPDD) for each of the crop nursing operations separated by field name (84-0 or 85-0), the main area of the field (headland or body area), and whether it is the 25 cm wide crops bands (Intrarow) or between crop row bands (Interrow). The points indicate a single CropEye image registration nudged around the field operation.

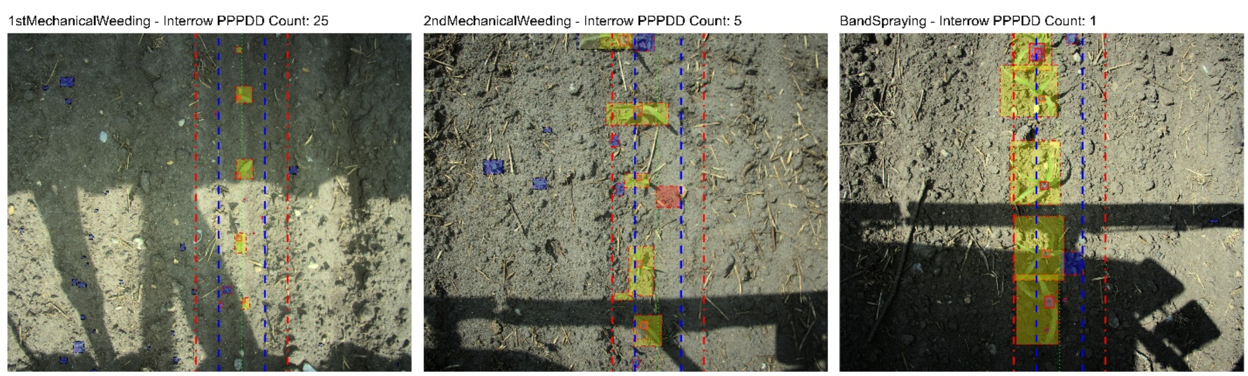

Fig 4. Interrow dicot weed (PPPDD) density counts per m2 of 25, 5, and 1 for 1st (left) & 2nd (center) mechanical interrow weeding, and band spraying (right) operation, respectively. The maize crop bounding box (yellow) coverages were 3%, 13%, and 44% of the 25 cm wide intrarow crop band. See Figure 1 for further details.

Map generation based on density counts for visual exploration

Figure 5 illustrates the effectiveness of mechanical interrow weeding compared to intrarow band spraying on controlling monocot (PPPMM) and dicot (PPPDD) weed populations. The mechanical weeding within inter-row spaces significantly reduced weed densities, showing a stark contrast to the higher densities within the untreated intrarow areas. This distinction is depicted in the maps, highlighting the variance across both fields.

Intrarow densities, particularly of maize, are concentrated within the crop bands. A notable exception is observed in the transition or border areas of the field where intermingling crop rows complicate the efficacy of mechanical interrow weeding.

The analysis suggests potential biases in field-level weed assessments when used as a decision-making basis for choosing between mechanical weeding and chemical band spraying. Specifically, creeping thistle (CIRAR) densities are effectively managed in the inter-row sections of the main field body but remain problematic in the headlands. This discrepancy indicates the need for diversified strategies tailored to different field sections.

Overall, the maps underscore the necessity of distinct assessments for intrarow and interrow weeds to optimize both mechanical and chemical control strategies. Such differentiation is crucial for implementing Integrated Weed Management (IWM) by providing clear visual representations of treated versus untreated areas, thereby facilitating more precise and effective weed control interventions.

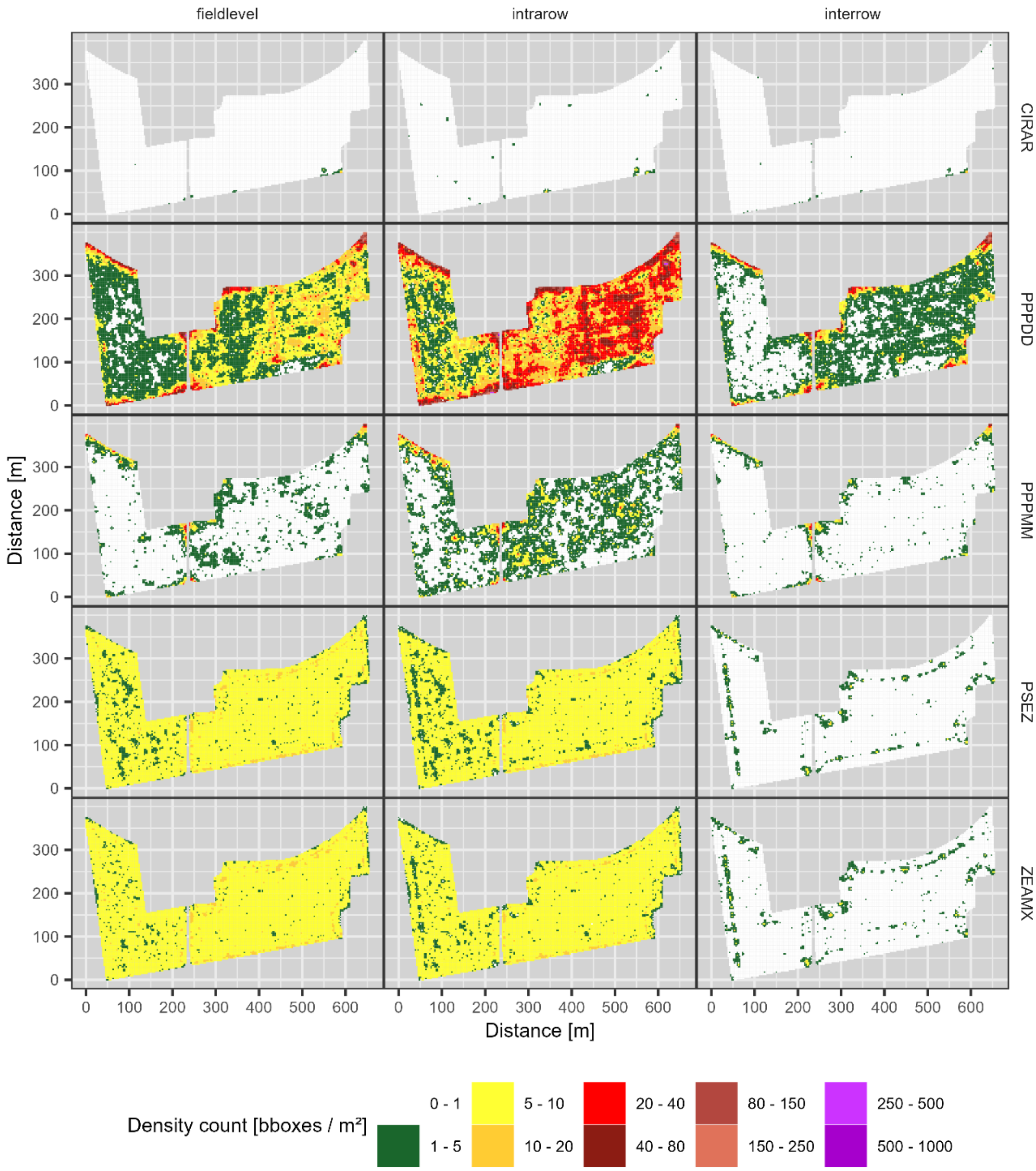

Fig 5. Inverse Distance Weighted (IDW) interpolated weed and crop density count maps based on CropEye images collected while performing band spraying. The left column does not distinguish between the 25 cm wide band sprayed intrarow crop bands (here the 1st application) and the mechanically weeded interrow bands. The rows are bounding box (bbox) density counts for Creeping Thistle (CIRAR), Dicot weeds (PPPDD), Monocot grasses (PPPMM), Crop Plant Stem Emergence Zone (PSEZ), and Maize crops (ZEAMX), respectively.

Map generation based on bounding box coverage

Our analysis leverages bounding box (bbox) coverage metrics to evaluate the impact of weed control strategies over time (figure 6). Specifically, the only observable weed control operation through the CropEye camera—which precedes the weed controlling implement—is mechanical interrow weeding. Consequently, we anticipate a decrease in weed bbox coverage within mechanically weeded inter-row bands, contrasting with an increase in intra-row or in-row crop band bbox coverage for both crop and weed classes.

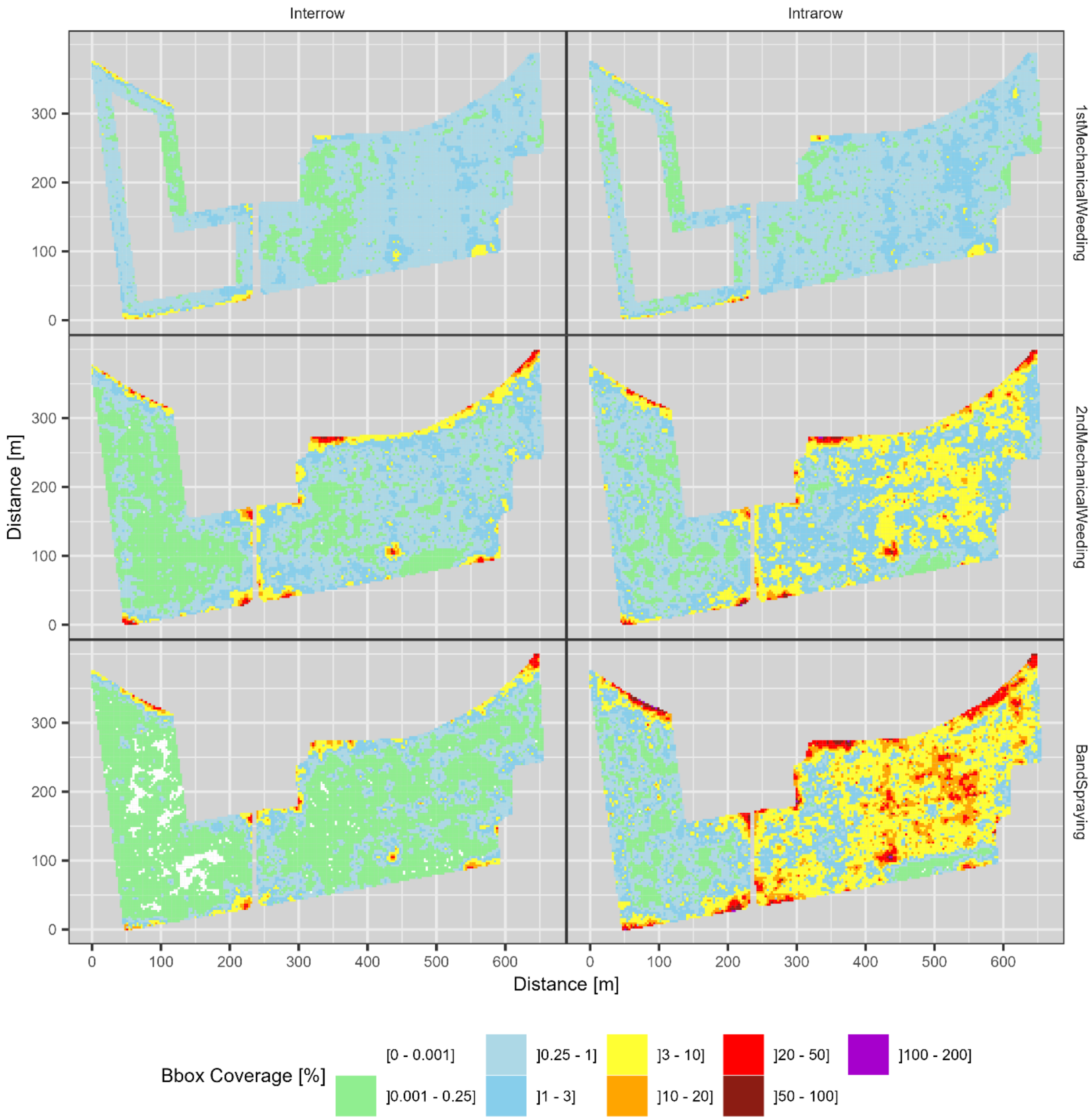

Fig 6. Inverse Distance Weighted (IDW) interpolated dicot weed (PPPDD) bounding box (bbox) coverage based on CropEye images collected while performing 1st & 2nd mechanical interrow weed and crop row intrarow band spraying, respectively.

In mechanically weeded interrow bands, dicot weed (PPPDD) bbox coverage generally declines over time. However, this trend is not consistent along the perimeter headland paths, where deviations lead to significant increases in both dicot weed density counts and bbox coverages. According to the Robotti operator, these inconsistencies are primarily due to the outermost wheelset riding on an elevated ridge created by the plow, which prevents the mechanical weeder from fully accessing these areas.

Conversely, within the intrarow crop bands, we observe a steady increase in dicot weeds bbox coverage, notably higher in field 84-0 (West) compared to field 85-0 (East). This pattern is replicated in the mechanically weeded inter-row bands, indicating spatial variability in weed pressures across different field areas.

A notable observation in field 84-0, particularly in the horizontal middle close to the transition between the south headland and the field body (approximately at coordinates 440 m, 110 m), is an outlier in dicot weed bbox coverage. This anomaly, significantly higher both in the mechanically weeded and the crop bands, suggests localized factors influencing weed proliferation, confirmed through a virtual field walk and analysis of random CropEye images from this area, as shown in Figure 7. The mechanical weeder seems to have had no effect, which often is caused by a local ridge and or firm soil resulting in the cultures being elevated above the ground according to the Robotti operator.

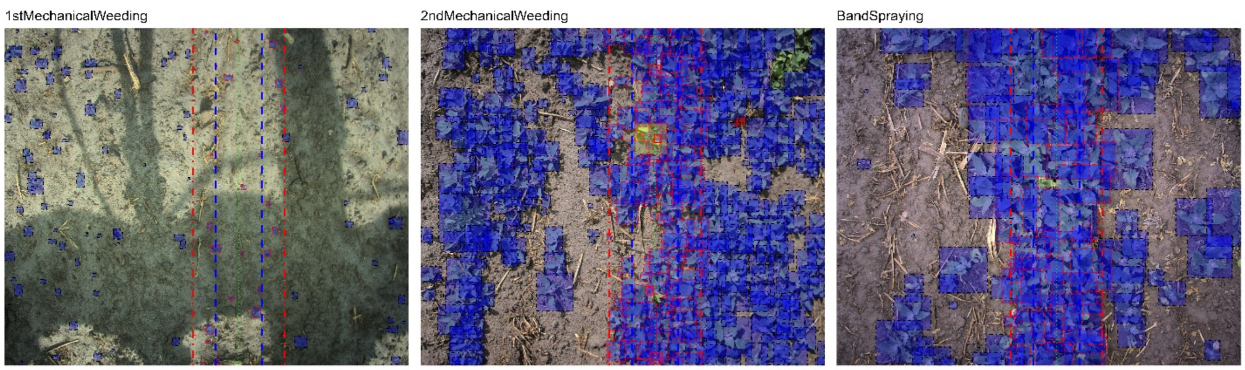

Fig 7. Visual inspection of interrow and intrarow dicot hotspot at ~440 m,110 m in figure 6 for 1st 2nd mechanical weed, and last band spraying. See Figure 1 for further details.

For monocot weeds (PPPMM), similar trends are observed, albeit with generally lower bbox coverages. Effective control is seen in the mechanically weeded inter-row bands across both fields, with the exception of the headland perimeters. Meanwhile, within the crop bands, sporadic high-coverage hotspots of monocot growth, particularly in field 84-0, highlight the challenges of uniform weed control. Still, it is reassuring there is correspondence between the maps generated and the CropEye subsample images visually inspected.

Crop row band spraying and herbicide savings compared to conventional field-level application

The herbicide band spraying was performed as planned a week after the 2nd mechanical weeding. However, after a physical field walk by the farmer and his consultant, they didn't find sufficient herbicide effect within field 84-0. Hence, they decided to spray the whole field a 2nd time with the farmer's conventional sprayer with the maximum dose possible. The collective result is given in Table 2.

Table 2. Herbicide mix and dosing at band spraying the field headland areas and the body of field 85-0 (east) and 84-0 (west). For field 84-0 the entire field was in addition uniform sprayed with a conventional sprayer. For each field, the weighted average Treatment Frequency Index per hectare (TFI ha^{-1}) and the environmental Pesticide Load per hectare (PI ha^{-1}) are calculated according to P. Kudsk *et al.* (2018) using the Danish Pesticide Database (SEGES Innovation 2024). TFI app and PI app state the TFI and PI at the directly sprayed areas like the crop bands.

Field name	Field part	Application	Field Area	Treated Area	Tocalis	Harmony SX	Maister	Mais Oil	Renol	TFI app	TFI ha^{-1}	PI app	PI ha^{-1}
84-0	Body	1st band spraying	4.53	1.51	120 g	5.6 g			0.5L	0.77	0.26	0.16	0.05
	Headland		3.69	1.23	120 g	5.6 g	60 g	0.8 L		1.17	0.39	0.20	0.07
	Entire Field	2nd spraying	8.22	8.22	120 g	5.6 g	60 g	0.8 L		1.17	1.17	0.20	0.20
Field overall average				10.96							**1.49**		**0.26**
85-0	Body rows	1st band spraying	2.70	0.9	120 g	5.6 g			0.5L	0.77	0.26	0.20	0.05
	Headland		2.27	0.76	120 g	5.6 g	60 g	0.8 L		1.17	0.39	0.20	0.07
	Entire Field	2nd spraying	0.00	0						0.00	0.00	0.00	0.00
Field overall average				1.66							**0.32**		**0.06**

Discussion

The adoption of dual weed mapping presents an important shift in Integrated Weed Management (IWM), advancing the precision with which we can manage weed populations. Our study demonstrates the benefit of distinguishing between interrow mechanical weeding and intrarow band spraying in mapping and following weed dynamics. By spatially and temporally segregating these two modes of control zones, our approach enables more nuanced weed management that adapts to the unique conditions within crop fields.

The termination of Robotti's nursing operation and the subsequent return to conventional full-coverage herbicide spraying preclude a direct assessment of the band spraying's impact. This underscores a critical consideration in the deployment of CropEye cameras: positioning them post-intervention would allow for immediate evaluation of weed control measures, enhancing real-time operational decisions and potentially averting crop damage from mechanical faults. Current robotic operations lack this real-time adaptability across different brands, representing a significant area for future development.

This research also highlights the limitations of field-level weed assessments, which can lead to suboptimal management decisions when diverse weed control tools are applied. A case in point is the mechanical weeding’s variable performance in the headland areas, likely due to the physical landscape like ridges from plowing that obstructs the weeder's operation. Conversely, the intrarow weed densities suggest a persistent and growing competition with crops, despite the mechanical intervention in the inter-row zones. This reveals the need for weed management where different strategies are necessary for different field areas.

Furthermore, our findings reveal that crop and weed coverage, and not just density counts, is critical for evaluating competitiveness and growth. While weed density counts remain constant, uncontrolled growth leads to increased coverage, emphasizing the importance of monitoring both metrics for effective IWM.

Through the novel intra/inter-row density maps, we provide concrete examples of how this new agricultural intelligence can inform more precise and efficient IWM plans. For instance, if an organic farmer were to apply our dual mapping technique, even without the option of band spraying, it could significantly aid in optimizing future mechanical weeding operations by precisely targeting areas with high weed pressure.

Our maps also expose underperforming crop regions and planning issues caused by the Robotti’s pathing, specifically in overlapping passes which result in mixed crop distances (not addressed literately but visibly in the maps). These findings are critical for future corrections in automated field planning systems.

Conclusion

In synthesis, while the current limitations of in-field technology and data interpretation present challenges, the benefits of dual weed mapping for optimized weed management practices are unequivocal. Our research provides a framework for more targeted, effective, and environmentally sustainable crop protection, thereby reinforcing the essential role of spatial specificity in the realm of precision agriculture.

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References

Besana, Riccardo, and Philipp Trénel. 2022. “Brug Af Vision-Og Sprøjte-Teknologi Til Reduktion

Af Pesticidforbrug.” MST Id nr.: 3159804. The Danish Environmental Protection Agency, Denmark.

Edwards, Gareth. 2022. “Reducing the Environmental Impact of Agriculture with Robotics (ROB209).” presented at the Amazon re:MARS 2022, ARIA Resort & Casino, Las Vegas, Nevada, USA. https://www.youtube.com/watch?v=srNgmJAQtaA&t.

Gerhards, Roland, Jonas Felix Weber, and Christoph Kunz. 2020. “Evaluation of Weed Control Efficacy and Yield Response of Inter-Row and Intra-Row Hoeing Technologies in Maize, Sugar Beet and Soybean.” *Landtechnik* 75 (4): 247–60.

Jørgensen, Rasmus Nyholm, Per Rydahl, Morten S. Laursen, Nima Teimour, Ole M. Bøjer, Morten Back Nielsen, Laura-Carolota Pas, et al. 2021. “Analysis of Potential Herbicide Savings Using Experience and Data from the RoboWeedMaPS Project.” Project 2020-6879. The Danish Environmental Protection Agency. https://agrinavia.com/wp-content/uploads/2021/04/Analysis-potential-herbicide-savings.pdf.

Kudsk, Per, Lise Nistrup Jørgensen, and Jens Erik Ørum. 2018. “Pesticide Load—A New Danish Pesticide Risk Indicator with Multiple Applications.” *Land Use Policy* 70 (January): 384–93.

Loddo, Donato, Laura Scarabel, Maurizio Sattin, Antonio Pederzoli, Chiara Morsiani, Renato Canestrale, and Maria Grazia Tommasini. 2019. “Combination of Herbicide Band Application and Inter-Row Cultivation Provides Sustainable Weed Control in Maize.” *Agronomy* 10 (1): 20.

Rydahl, P., Niels-Peter Jensen, Mads Dyrmann, Poul-Henning Nielsen, and Rasmus Nyholm Jørgensen. 2017. “RoboWeedSupport - Presentation of a Cloud Based System Bridging the Gap between in-Field Weed Inspections and Decision Support Systems.” *Advances in Animal Biosciences* 8 (2): 860–64.

Rydahl, Per. 2004. “A Danish Decision Support System for Integrated Management of Weeds.” *Aspects of Applied Biology 72, Advances in Applied Biology: Providing New Opportunities for Consumers and Producers in the 21st Century* 72: 43–53.

Rydahl, Per, Ole M. Boje, Niels-Peter Jensen, Morten Back-Nielsen, Laura-Carlota Paz, Birger Hartmann, Per Andersen, Rasmus Jørgensen, and Martin Sørensen. 2022. “Economic Potential of RoboWeedMaps - Use of Machine Learning for Production of Weed Maps and Herbicide Application Maps.” In *Proceedings of the 15th International Conference on Precision Agriculture*, 11.

SEGES Innovation. 2024. “Middeldatabasen.” 2024. https://www.middeldatabasen.dk/.

Somerville, G. J., R. N. Jørgensen, O. M. Bojer, P. Rydahl, M. Dyrmann, P. Andersen, N-P Jensen, and O. Green. 2019. “Marrying Futuristic Weed Mapping with Current Herbicide Sprayer Capacities.” In *Precision Agriculture ’19*, 231–37. 28. Wageningen Academic Publishers.

Teimouri, Nima, Rasmus Nyholm Jørgensen, and Ole Green. 2022. “Novel Assessment of Region-Based CNNs for Detecting Monocot/Dicot Weeds in Dense Field Environments.” *Agronomy* 12 (5): 1167.

Vasileiadis, V. P., S. Otto, W. van Dijk, G. Urek, R. Leskovšek, A. Verschwele, L. Furlan, and M. Sattin. 2015. “On-Farm Evaluation of Integrated Weed Management Tools for Maize Production in Three Different Agro-Environments in Europe: Agronomic Efficacy, Herbicide Use Reduction, and Economic Sustainability.” *European Journal of Agronomy: The Journal of the European Society for Agronomy* 63 (February): 71–78.

Wiltshire, J. J. J., N. D. Tillett, and T. Hague. 2003. “Agronomic Evaluation of Precise Mechanical Hoeing and Chemical Weed Control in Sugar Beet.” *Weed Research* 43 (4): 236–44.