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Short title: Targeted Sprayer Efficiency

Commercial Sprayer Efficiency for Application Success on Targeted Weeds

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Abstract

Commercializing targeted sprayer systems allows producers to reduce herbicide inputs but risks the possibility of not treating emerging weeds. Currently, targeted applications with the John Deere system allow for five spray sensitivity settings, and no published literature discusses the impact of these settings on detecting and spraying weeds of varying species, sizes, and positions in crops. Research was conducted in AR, IL, IN, MS, and NC in corn, cotton, and soybean to determine how various factors might influence the ability of targeted applications to treat weeds. These data included 21 weed species aggregated to six classes with height, width, and densities, ranging from 25 to 0.25 cm, 25 to 0.25 cm, and 14.3 to 0.04 plants m^{-2}, respectively. Crop and weed density did not influence the likelihood of treating the weeds. As expected, the sensitivity setting alters the ability to treat weeds. Targeted applications (across sensitivity settings, median weed height and width, and density of 2.4 plants m^{-2}) resulted in a treatment success of 99.6% to 84.4%, 99.1% to 68.8%, 98.9% to 62.9%, 99.1% to 70.3%, 98.0% to 48.3%, and 98.5% to 55.8% for *Convolvulaceae*, decumbent broadleaf weeds, *Malvaceae*, *Poaceae*, *Amaranthaceae*, and yellow nutsedge, respectively. Reducing the sensitivity setting reduced the ability to treat weeds. Size of weeds aided targeted application success, with larger weeds being more readily treated through easier detection. Based on these findings, various conditions could impact the outcome of targeted multi-nozzle applications. Additionally, the analyses highlight some of the parameters to consider when using these technologies.

Nomenclature: *Amaranthaceae*; *Convolvulaceae*; *Malvaceae*; *Poaceae*; yellow nutsedge, *Cyperus esculentus* L.; corn, *Zea mays* L.; cotton, *Gossypium hirsutum* L.; soybean, *Glycine max* (L.) Merr.

Keywords: Palmer amaranth, waterhemp, targeted spray, machine vision, John Deere, nominal logistic regression, See & Spray

Introduction

Weeds often emerge in clumps or patches throughout a field, creating an opportunity for site-specific management in these localized regions, reducing overall inputs in specific production systems (Cardina et al. 1997; El Jgham et al. 2023; Metcalfe et al. 2019; Rew and Cousens 2001; Sapkota et al. 2020; Stafford and Miller 1993; Wiles et al. 1992). Spray systems to detect emerged weeds on bare soil (i.e. green-on-brown) have been used for several decades in fallow systems (Felton & McCloy 1992; Haggar et al. 1983). However, recent technological advancements have enabled the development of foliar application systems to discern between the crop plant and emerged weeds (i.e. green-on-green). Despite several years of research developing targeted sprayers, limited processing capability, intermingling and occlusion of weeds and crops, and plasticity of weeds across environments create a challenging situation for highly accurate and efficient machine vision technology (Fernandez-Quintanilla et al. 2018; Franz et al. 1991; Munier-Jolain et al. 2014). However, technologies such as Greeneye™ (Greeneye Technology, Lincoln, NE, USA) and See & Spray™ (Deere & Company, Moline, IL, USA) are becoming more common, offering machine vision technologies that target-apply herbicides through simultaneous detection and action (Khait et al. 2023; Padwick et al. 2023; Walter and Houis 2024). The recent commercial development of targeted sprayer technologies provides an opportunity to reduce herbicide inputs through targeted applications, specifically to weeds, rather than broadcasting over the entire field.

Weed control is vital in almost all cropping systems to sustain the increasing food and fiber demand across the globe. Herbicides are practical and economical for controlling weeds and have been utilized extensively since the 1960s (Gianessi and Reigner 2007). However, the overreliance on herbicides and lack of integrated tactics have driven widespread herbicide resistance (Heap 2024; Norsworthy et al. 2012). If machine vision technologies are not optimized for maximum efficacy, these systems may accelerate herbicide resistance evolution by missing weeds at susceptible growth stages, resulting in larger-than-recommended sizes at later applications or low-dose exposure from partial coverage (Hearn 2009; Norsworthy et al. 2012; Villette et al. 2021).

Field research is needed to evaluate commercial machine vision technologies in corn, cotton, and soybean to improve system efficiency and avoid unintended impacts of targeted sprays. Existing research has reported comparable Palmer amaranth control from targeted and broadcast applications in corn and soybean with the Greeneye and John Deere systems (Leise et al. 2025), with broadcast and targeted applications providing similar Palmer amaranth control between 94% and 99%. Other research has demonstrated that targeted applications performed similarly to a broadcast for Palmer amaranth, morningglory (*Ipomoea* spp.), purslane (*Portulaca* spp.), and broadleaf signalgrass [*Urochloa platyphylla* (Munro ex C. Wright) R.D. Webster] control within a program approach (Avent et al. 2024). However, both sources noted that a range of sensitivity settings are available for targeted applications with John Deere sprayers and could influence the results observed.

John Deere utilizes computer vision and deep learning to perform simultaneous detection and action (Fu et al. 2022; Padwick et al. 2023). The detection algorithm classifies individual pixels in images as either weeds, crops, or neither. Technically, the algorithm predicts the probability of being one of these classes using several observed variables, called *predictors*. Such probabilities are then turned into an actual predicted class using decision thresholds (James et al. 2021). With machine vision, the threshold to classify a weed could be adjusted and ultimately affect performance, which is mentioned in patents held by Blue River Technology (Fu et al. 2022; Padwick et al. 2023; Redden 2023; Venkataraju et al. 2023). Once a weed is detected, the processors determine where the weed is and activate any nozzle body where droplets from the nozzle tip can contribute to the area deemed a weed based on the specific nozzle tips and position in three-dimensional space at the time of activation.

John Deere targeted sprayers provide a setting called “spray sensitivity,” which consists of five levels: lowest, low, medium, high, and highest. Spray sensitivity adjusts the decision threshold for detecting a weed (Lazaro et al. 2024; Patzoldt et al. 2022), which could also be subject to change with software updates. Plant reflectance and architecture are considered predictors, providing a predicted probability (Fu et al. 2022; Padwick et al. 2023), which must then exceed the decision threshold to be classified as a weed (Redden 2023). Therefore, different colors, species, sizes, and positions of weeds in crops could be more difficult to detect than others. Targeted applications are currently supported in fallow, soybean, corn, and cotton, with different algorithms (i.e., models) for detecting weeds. The objective of these experiments was to

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determine to what extent selected factors (spray sensitivity, weed size, weed position, weed species, and crop) influence the likelihood of treating weeds with targeted applications.

Materials and Methods

The experiment was conducted using a randomized complete block design with two factors and four replications. Factor A consisted of application timing: 14, 21, or 28 days after planting (DAP). Factor B included the application method: broadcast and three detection sensitivity settings: highest, medium, and lowest corresponding to internal algorithm threshold levels of 0.4, 0.7, and 0.9, respectively. Nontreated, preemergence (PRE)-only, and hand-weeded controls were added for comparisons but are not included in this analysis. Each experiment was conducted in corn, cotton, and soybean across various sites in 2022 (Table 1). Corn experiments were conducted in Champaign, IL; West Lafayette, IN; and Greenville, MS. Cotton experiments were performed in Kinston, NC; Keiser, AR; and Greenville, MS. Lastly, soybean experiments were established in Champaign, IL; West Lafayette, IN; Greenville, MS; Keiser, AR; and Kinston, NC.

Each soybean and cotton experiment was planted to a glyphosate- and glufosinate-resistant cultivar at regionally recommended seeding rates in fields containing a natural population of weeds (Table 1). Corn hybrids were at least glyphosate-resistant and planted into natural weed populations at regionally recommended seeding rates. The corn experiments utilized labeled rates of *S*-metolachlor + atrazine + paraquat PRE followed by (fb) atrazine + mesotrione + glyphosate + *S*-metolachlor postemergence (POST) (Table 2). The soybean herbicide program included *S*-metolachlor + metribuzin + paraquat PRE fb glufosinate + *S*-metolachlor early POST (EPOST) fb glufosinate + acetochlor mid-POST (MPOST). The cotton herbicide program was the same as the soybean program, with the exception being the herbicide program used fluometuron rather than metribuzin PRE. Corn experiments did not have sequential POST applications, but soybean and cotton received MPOST applications 14 days after EPOST applications. All POST treatments also included NIS (Preference, Winfield United, Arden Hills, MN, USA) at 0.25% (v/v). To indicate whether weeds were treated or not, POST-active herbicides included blue dye (Super Signal Blue, Precision Labs LLC, Kenosha, WI, USA) at 0.25% (v/v). Cultural practices and soil information, including planting dates, soil series

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and textures, and row widths can be found in Table 1. All plots were 3.8 m wide and 29.5 m to 32.8 m long.

The sprayer utilized in the studies was previously described by Avent et al. (2024) as a dual-boom targeted sprayer engineered by Blue River Technology and was mounted to the front-end loader of a tractor. Ten nozzle bodies were spaced 38.1 cm apart. All treatments were made utilizing the dual boom system capable of applying both broadcast and targeted applications in the same pass. At the PRE application timing, broadcast treatments used PSLDMQ2003 (Deere & Company, Moline, IL, USA) nozzle tips calibrated to deliver 140 L ha^{-1} of water. Preemergence targeted applications were made using SF4003 nozzles (Greenleaf Technologies, Covington, LA, USA) calibrated to deliver 140 L ha^{-1} of water and placed in a prototype cap that inclined the nozzle tip rearward at 30-degrees.

Postemergence treatments included the soil residual herbicides *S*-metolachlor or acetochlor applied through the broadcast boom with AIXR11002 (TeeJet Technologies, Glendale Heights, IL) nozzles calibrated to deliver 97 L ha^{-1} of water. In contrast, the foliar-active herbicides, glufosinate and mesotrione + atrazine + glyphosate, were sprayed through the targeted application boom. Glufosinate in cotton and soybean experiments was applied with PS3DQ0004 nozzles (Deere & Company, Moline, IL, USA) all orientated toward the rearward position and calibrated to deliver 140 L ha^{-1} of water. Corn experiments with applications of mesotrione + atrazine + glyphosate utilized PSLDMQ2003R4 nozzles (Deere & Company, Moline, IL, USA) all orientated to the rearward position and calibrated to deliver 140 L ha^{-1} of water.

Nozzles were selected based on droplet spectrum and characterization requirements for targeted applications (Gizotti de Moraes et al. 2024). Broadcast treatments contained foliar-active and residual herbicides in the same tank and were applied using the same nozzles as the targeted herbicide applications, but in the standard configuration for broadcast applications (Supplementary Figure 1). For example, the PS3DQ0004 nozzles were alternated on the boom to create a twin-fan pattern and the PSLDMQ2003 nozzles tips were orientated straight down. While the different nozzle orientations could impact spray particle coverage, the different orientations should not impact the ability to hit a weed (Ferguson et al. 2016).

Individual plant data

Before each POST application, weeds were marked with numbered wooden stakes in 3.3 m increments, traversing with the rows. Stakes were placed perpendicular to the direction of travel and at an angle to avoid blocking the camera view of each weed. Additionally, stake color (natural wood, orange, and red) was tested before application to ensure the stake did not trigger applications, and varying sites used different colors. The goal was to mark at least ten plants in the area; if ten weeds did not occur within the first 3.3 m, an additional 3.3 m was marked. Areas of interest were only within the center furrow to avoid wheel tracks and could be as long as the entire plot (29.5 m to 32.8 m). Each weed was recorded for species, height, width, and position relative to the crop (in-row or between rows). The position of the weed was classified as "in-row" if the weed was within or beneath the crop canopy. Otherwise, it was denoted as "between rows." The success of treating a weed was determined immediately after application by the presence or absence of blue dye on the plant: "yes" or "no," respectively.

Data preprocessing

A data column was created for each plot, dividing the number of weeds by the length of the area of interest to estimate weed density since some weeds could have been treated due to the presence of neighboring, larger weeds from multi-nozzle activation. Other predictors included crop (corn, cotton, or soybean), application timing, and sensitivity setting. In the results, the detection algorithm decision threshold will be referenced back to the 2022 sensitivity settings for clarity and consistency. A decision threshold set at 0 was tested and confirmed that targeted applications would broadcast the entire area, so broadcast applications were 0 for the decision threshold predictor. Lowest, medium, and highest sensitivity settings were set to the corresponding decision thresholds (0.9, 0.7, and 0.4, respectively). Continuous predictors included weed height, weed width, weed density, and decision threshold, while application timing, crop, weed aggregate class, and weed position relative to the crop were considered categorical predictors.

Across all sites and crops, 7,971 weeds were marked and recorded as treated or missed, but some species had too few observations to characterize the relationship or were never missed. The weeds with too few observations included common cocklebur (*Xanthium strumarium* L.), honeyvine swallowwort [*Cynanchum laeve* (Michx.) Pers.], Carolina horsenettle (*Solanum*

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carolinense L.), and sicklepod [*Senna obtusifolia* (L.) H.S. Irwin & Barneby]. All weeds > 25.4 cm (height and width) were never missed or killed, so these observations were excluded. Weeds were aggregated into specific groups to preserve as many observations as possible (Table 3). All grasses were grouped into *Poaceae*. Three morningglory species were combined into *Convolvulaceae*. Palmer amaranth and waterhemp [*Amaranthus tuberculatus* (Moq.) J.D. Sauer] became *Amaranthaceae*. Yellow nutsedge (*Cyperus esculentus* L.) remained individually. Prickly sida (*Sida spinosa* L.) and velvetleaf (*Abutilon theophrasti* Medik) were combined to *Malvaceae*. Lastly, decumbent broadleaves included carpetweed (*Mollugo verticillata* L.), curly dock (*Rumex crispus* L.), dandelion (*Taraxacum officinale* L.), horse purslane (*Tranthema portulacastrum* L.), and wild radish (*Raphanus raphanistrum* L.). A total of 21 different weeds were classified into six distinct groups. All other weeds were excluded from the analysis due to not occurring in two or more experimental sites or having never been missed. A total of 7,164 observations remained in the dataset (Table 4).

Data analysis

The analysis did not include the experimental site as a predictor to infer how targeted multi-nozzle applications performed across all locations. Additionally, application timing was not considered since this factor was implemented in the experimental design for whole plot comparisons and ultimately generated varying weed sizes and densities. Some weeds survived the EPOST application and were present at MPOST. These weeds were staked again for the sequential application, but injured weeds were not readily missed (visual observation). All other predictors were included in the analysis as one-way effects in the interest of parsimony. The response was a proportion of the weeds hit and is represented by p^h, which ranges between 0 and 1. To link the proportion of treated weeds to the predictors, a logistic regression model (Eq. 1) was used,

$$\ln\left(\frac{p_i^h}{1-p_i^h}\right)=\beta_0+\beta_1 X_{i1}+\beta_2 X_{i2}+\beta_3 X_{i3}+\beta_4 X_{i4}+\beta_5 Z_i^p+\beta_6 Z_{i1}^c+\beta_7 Z_{i2}^c+\beta_8 Z_{i1}^s+\beta_9 Z_{i2}^s+\beta_{10} Z_{i3}^s+\beta_{11} Z_{i4}^s+\beta_{12} Z_{i5}^s \qquad [1]$$

where X_{i1}, X_{i2}, X_{i3}, and X_{i4} is the *i*th observation of decision threshold, weed width, weed height, and weed density, respectively, with $i = 1, \ldots, 7164$. The variables Z_i^p, Z_{ij}^c, and Z_{ij}^s are binary dummy variables corresponding to the categorical predictors: weed position, crop, and aggregated weed species, respectively. The variables are explained as follows:

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- $Z_i^p = 1$ if the weed position is in-row and 0 otherwise.
- $Z_{i1}^c = 1$ if the crop is corn and 0 otherwise.
- $Z_{i2}^c = 1$ if the crop is cotton and 0 otherwise.
- $Z_{i1}^s = 1$ if the aggregated weed species is decumbent broadleaf and 0 otherwise.
- $Z_{i2}^s = 1$ if the aggregated weed species is Malvaceae and 0 otherwise.
- $Z_{i3}^s = 1$ if the aggregated weed species is Poaceae and 0 otherwise.
- $Z_{i4}^s = 1$ if the aggregated weed species is Amaranthaceae and 0 otherwise.
- $Z_{i5}^s = 1$ if the aggregated weed species is yellow nutsedge and 0 otherwise.

In Equation 1, β_j is the coefficient of the jth predictor or dummy variable, which captures the average change in the log-odds to treat a weed (left hand side of Equation 1) when the value of a predictor changes (James et al. 2021; Medard 2002). The estimation of the coefficients was done using the standard maximum likelihood estimation method.

Likelihood ratio tests were used to measure the *overall* significance of the predictors (James et al. 2021). A variable was deemed significant at $\alpha \leq 0.05$. Odds ratios with Wald tests were utilized for pairwise comparisons within the categorical predictors. Odds ratios are uncommon in weed science research (Menard 2002). In layman's terms, the odds of treating one scenario are compared to the odds of another scenario, while holding all other predictors constant, and if the ratio has 95% confidence interval including 1, then the two scenarios are similar. A value less < 1 indicates a reduction in the odds to treat a weed while a value > 1 indicates an increase. For continuous predictors, 95% confidence intervals were generated to visualize the estimated effects. The data analysis was performed using the 'fit model' platform of JMP Pro version 18.0 (SAS Institute, Cary, NC) with a generalized regression personality.

Interpreting the model

There are a range of responses depending upon the different predictors, and context is needed when stating a specific response in multivariate analyses. For clarity, predicted responses to aid in discussion will include specific scenarios considering the other predictors and the median height and width of each species (Table 3). Equation 1 can be used in combination with the parameter estimates to calculate the likelihood of treating a weed (Supplementary Table 1). Figures were generated for each aggregate weed class using the median height and width of the

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specific weed class except in cases where the figures use height or width as the independent variable. Additionally, the figures use the intercept for the categorical predictors, which are specific to between soybean rows.

Results and Discussion

Initial observations

If weeds were always treated, there is no variance in the response, and the data do not provide a contribution to the analysis. Additionally, if there are too few observations, the parameter estimate is biased and may not accurately portray the relationship (Menard 2002). To that end, some weed species had to be excluded from the analysis, despite occurring in multiple experimental sites, because the effects that impacted the ability to treat weeds with sufficient observations could not be accurately determined. Common cocklebur was never missed, with 52 observations. The other species that did not have enough data to determine the likelihood of treatment included: honeyvine swallowwort, with three misses in 65 observations, Carolina horsenettle, with one miss in 41 observations, and sicklepod, with two misses in 27 observations. Unfortunately, there were insufficient observations for these species, resulting in biased parameter estimates and the need to be excluded.

Based on the likelihood ratio tests, the most significant predictor for treating a weed was the decision threshold (Table 5), with a likelihood ratio $\chi 2 = 750.5$. In order of importance, other significant predictors included aggregate weed species, weed width, weed position (in-row or between rows), and weed height. Weed density and the crop were not significant according to the likelihood ratio tests, and did not influence the likelihood of treating a weed. Decision threshold (sensitivity setting) is the most important predictor, which is unsurprising because this setting dictates that weeds are classified as such. The weed width also appears to drive the predictions more than height, which is likely due to the orientation of the cameras being angled downwards and collinearity between weed height and width ($r = 0.727$). The decision to leave height and width in the model despite collinearity is due to the width being more relevant for the detection algorithm. However, height is more practical for applicators who measure height, not width, before herbicide applications.

Differences among aggregate species, weed position, and crop to treat weeds

Targeted applications (across sensitivity settings, median weed height and width, and density of 2.4 plants m^{-2}) resulted in a treatment success of 99.6% to 84.4%, 99.1% to 68.8%, 98.9% to 62.9%, 99.1% to 70.3%, 98.0% to 48.3%, and 98.5% to 55.8% for *Convolvulaceae*, decumbent broadleaf weeds, *Malvaceae*, *Poaceae*, *Amaranthaceae*, and yellow nutsedge, respectively (data not shown). On average, *Convolvulaceae* and decumbent broadleaf weeds were among the easiest to target (Table 6). These two aggregate classes would have a high groundcover percentage (Bryson and DeFelice 2009), lending to assumed easier detection with downward-oriented cameras (Lazaro et al. 2024). Yellow nutsedge was more difficult to control than all other aggregate species when using comparable sensitivity settings, which is unsurprising due to thin leaves and upright architecture (Bryson and DeFelice 2009), which suggests different machine settings would be required to increase the probability of treating this species. Alternatively, applicators could consider broadcasting an effective foliar-active herbicide along with targeted applications to improve control of specific species, such as yellow nutsedge.

Some species may require special attention when considering settings to target-apply herbicides, such as those from the *Amaranthus* genus. Palmer amaranth and waterhemp have many reported herbicide resistance cases (Carvalho-Moore et al. 2022; Evans et al. 2019; Foster and Steckel 2022; Heap 2024; Randell-Singleton et al. 2024). Other research has also demonstrated that young waterhemp and Palmer amaranth can grow up to 16.8 and 29 cm per week, respectively (Heneghan and Johnson 2017; Spaunhorst et al. 2018). Applicators utilizing targeted applications cannot afford to miss small *Amaranthus* species, which could be uncontrollable within a week after application.

Regarding weed position, odds ratios indicated that weeds were more easily treated between rows (96.1%) versus within the crop rows (94.9%), averaged over all other predictors (Table 6). The higher success rate for weeds between rows was expected since weed occlusion by intermingling plant parts has already been reported for weed detection by Franz et al. (1991) and herbicide coverage by Creech et al. (2018). However, targeted applications in this research were performed while the machine traversed with the rows, rather than at an angle against the rows. The results could be more severe if performing applications at an angle, which could more readily occlude weeds. Additionally, the lack of differences between the three crops evaluated indicates that the different detection algorithms performed similarly.

Differences in treating weeds among sensitivity settings, weed size, and weed density

To reiterate, the continuous decision thresholds of 0.4, 0.7, and 0.9 corresponded to the highest, medium, and lowest spray sensitivities in 2022, respectively. Broadcast applications were set at a 0 decision threshold, and applications at this setting confirmed uniform deposition across the area (100% area sprayed). Figure 1 utilizes the median height and width of each aggregate weed class for visualization of the decision threshold and is not intended to compare the different weed classes. On average, the range odds ratio (probability of a hit at 0 versus the probability of a hit at 0.9) is 0.0192 for the range of decision thresholds, indicating a decrease in the odds to treat a weed with decreasing sensitivity levels. Interestingly, the standard error for the likelihood to treat a weed also increased with the decision threshold from 0 to 0.9. The increase in the standard error demonstrates the uncertainty associated with changes in the sensitivity setting.

The fact that lower sensitivity settings (increasing decision thresholds) reduces the ability to treat weeds is concerning since producers will be inclined to reduce the area sprayed for better herbicide savings or potential Environmental Protection Agency herbicide mitigation points (Anonymous 2024b). However, understanding these dynamics coupled with weed sizes can broaden the utility of targeted applications. If operators intend to mimic a broadcast treatment with targeted applications, the highest sensitivity setting (decision threshold 0.4) could maximize weed control success with targeted multi-nozzle applications. Alternatively, the low sensitivity setting (decision threshold 0.9) is not intended for typical applications. The low sensitivity setting makes the most sense when producers want to target only large weeds: 1) volunteer crops, 2) dual-boom applications with a standard rate in the broadcast tank and a spiking dose in the targeted tank, 3) application of multiple herbicides where one is broadcasted for small weeds and the targeted herbicides aid control of larger weeds (e.g., glufosinate broadcast and 2,4-D targeted, or atrazine broadcast and mesotrione targeted). Future research should evaluate the efficacy and economics of these scenarios to aid in the utility of targeted sprayers.

Both weed height and width positively influenced the ability to treat weeds with targeted applications (Figures 2 and 3). Averaged over all other predictors, both height and width had unit

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odds ratios (1 cm increments) of 1.07 and 1.15, respectively, meaning increases in either predictor result in increasing the odds to treat a weed. One of the primary limitations of a one-way analysis is not being able to ascertain the effects in combination with other main effects. However, when considering the *Amaranthaceae* aggregate class at an averaged medium spray sensitivity (decision threshold 0.7) and weed density of 2.4 plants m^{-2}, the probability of treating a 2.5 cm plant (height and width) was 0.69 to 0.84 based on 95% confidence intervals. Increasing the same weed size to 5 cm resulted in likelihoods to treat from 0.75 to 0.87 based on 95% confidence. Additionally, since width appears to drive the likelihood of treating weeds over height (Table 5), scouting practices prior to targeted herbicide applications should consider weed width when providing recommendations on the selection of sensitivity settings to achieve a desired result. However, this information would be in addition to plant height, which is the primary consideration for herbicide product labels.

When considering the combination of sensitivity setting, weed size, and weed species, the herbicide being applied also requires consideration. For example, field applications of glufosinate formulations require a minimum of 7, 10, and 5 days between sequential applications for corn, cotton, and soybean, respectively (Anonymous 2023). In addition to the reapplication restriction, if producers are applying a sequential POST, the general recommendation is to apply 14 d later (Barber et al. 2025). If weeds are missed while small, some could experience rapid growth between sequential applications, and weeds larger than 8 cm would likely be poorly controlled (Priess et al. 2022). Therefore, when treating small weeds, applicators should utilize a higher sensitivity setting (lower decision threshold) to maximize herbicide coverage and weed control, which provided 91.1% likelihood to treat *Amaranthaceae* weeds 2.5 cm tall and wide between soybean rows. The same scenario, but changed to a medium or lowest sensitivity setting, treated *Amaranthaceae* weeds 73.3% and 53.2% of the time, respectively.

Previous research has indicated that high weed densities could impact the ability of machine vision technologies to detect weeds in crops (Jgham et al. 2023; Franz et al. 1991). However, based on the results from this analysis, density did not appear to impact the likelihood of treating weeds (Table 5 and Figure 4). Even if some weeds were occluded, targeted multi-nozzle applications appeared to compensate by treating adjacent, detected weeds. However, this experiment did not directly evaluate detection performance or quantify spray coverage across the swath of activated nozzles. Other research simulating nozzle densities in turfgrass demonstrated that lower nozzle densities (wider nozzle spacings) generated higher false hits, meaning areas where weeds were undetected were sprayed (Petelewicz et al. 2024). In this research, targeted applications occurred through multi-nozzle activation with ≥100-degree nozzles (Gizotti de Moraes 2024), which likely inflated the likelihood to treat weeds through “false hits”. Weeds may have been present and adjacent to detectable weeds, but not actually detected by the machine vision algorithm. Narrower nozzle angles or single nozzle activating systems could increase the likelihood of missing weeds, and further research is needed to evaluate these concerns and quantify spray deposition at the edge of activated tapered nozzles.

Overall, if an operator treats a field of difficult-to-detect or small weeds, spray sensitivities should be higher to maximize detection and targeted application success. Currently, the user interface displays a scale from lowest to highest spray sensitivity and does not provide any metric on the likelihood or actual weed size or the decision threshold (Anonymous 2024a). An alternative solution could utilize data from these experiments and allow the operator to select a weed size (height or width), allowing the threshold to change to a setting that achieves > 0.90 probability of treating a specific weed class. However, one limitation of this analysis is the inability to look at specific crop and weed interactions. Future research should explore the effects of certain weed species within individual crops. Another consideration is that model updates are and will be continuous in the future, which means performance results may vary among model releases. Lastly, this research investigating targeted applications was conducted with a specific technology. Other systems that utilize individually activated, even-fan nozzles may perform differently than the technology evaluated here due to differing machine vision algorithms, sprayer speeds, nozzle orientations, etc.

Practical Implications

The research here highlights the ability of targeted applications to treat problematic weed species. Small weeds will always be difficult to detect and treat regardless of the detection system since successful targeted applications depend on both the ability to detect and apply herbicides. Even broadcast applications to small weeds can be difficult to provide adequate droplet coverage with some combinations of nozzle tips and carrier volumes. Regardless, continued advancements and improvements in targeted spray technology, such as camera resolution, boom stability, and detection algorithms should improve the ability to manage small weeds. The results also indicate that weed position (between or in crop row) and the subsequent occlusion of weeds did not influence the ability to spray weeds with targeted applications. These data highlight which aggregate species classes are problematic and allow targeted collection efforts to improve the training dataset used to develop the detection algorithm (Figure 5). Additionally, John Deere has made updates to the system since 2022 and these results may underestimate current system performance.

The analysis could optimize spray sensitivity selection so operators can select the appropriate spray sensitivity. Currently, producers or operators do not know the decision threshold corresponding to the spray sensitivity level options in the sprayer display. The corresponding decision thresholds are also subject to change based on performance or savings from internal testing within each year. More transparency is needed to allow applicators to make an informed decision when selecting the sensitivity level for a targeted herbicide application. Otherwise, failures could occur more frequently, or additional applications may be needed to control problematic weed species adequately. However, the observed data collected across all experimental sites could be utilized to optimize the applicator settings.

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Table 1. Site specific information of each crop and cultural practices in 2022.

Crop	Site	Planting date	Cultivar	Population	Row spacing	Soil series
				seeds ha^{-1}	cm	
Corn	Champaign, IL	Jun-09	G12S75-5122	84,000	76.2	Drummer silty clay loam
	West Lafayette, IN	Jun-01	DKC56-65	79,100	76.2	Drummer silty clay
	Greenville, MS	May-17	P2057VYHR	86,500	96.5	Commerce silt loam
Soybean	Champaign, IL	May-31	AG33XF2	345,900	76.2	Flanagan silt loam
	West Lafayette, IN	Jun-09	AG29XF1	345,900	76.2	Chalmers silty clay
	Keiser, AR	Jun-05	B4885XF	345,900	96.5	Steele loamy sand
	Greenville, MS	Jun-01	AG48XF2	358,300	96.5	Commerce silt loam
	Kinston, NC	Jun-27	AG48XF0	296,500	76.2	Johns sandy loam
Cotton	Keiser, AR	May-17	DP2020B3XF	108,700	96.5	Sharkey-Steele complex
	Greenville, MS	May-21	ST4990B3XF	111,200	96.5	Commerce silt loam
	Kinston, NC	Jun-12	DP2127B3XF	98,800	76.2	Johns sandy loam

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Table 2. Herbicide program for the experiments[ab]

	Corn		Soybean		Cotton	
Timing	Herbicide	Rate	Herbicide	Rate	Herbicide	Rate
		g ai/ae ha^{-1}		g ai/ae ha^{-1}		g ai/ae ha^{-1}
PRE	*S*-metolachlor	1,750	*S*-metolachlor	1,550	*S*-metolachlor	1,390
	atrazine	2,250	metribuzin	370	fluometuron	1,120
	paraquat	716	paraquat	716	paraquat	716
EPOST	*S*-metolachlor	1,400	*S*-metolachlor	1,390	*S*-metolachlor	1,390
	mesotrione	105	glufosinate	657	glufosinate	657
	atrazine	674				
	glyphosate	1,260				
MPOST			acetochlor	1,260	acetochlor	1,260
			glufosinate	657	glufosinate	657

[a] Abbreviations: EPOST, early-postemergence; MPOST, mid-postemergence; PRE, preemergence

[b] Herbicide sources: Acetochlor, Warrant, Bayer Crop Science, St. Louis, MO; Atrazine, Atrazine 4L, Drexel Chemical Company, Memphis, TN; fluometuron, Cotoran 4L, ADAMA, Raleigh, NC; glufosinate, Noventa, BASF corporation, Research Triangle Park, NC; glyphosate, Roudnup PowerMAX 3, Bayer Crop Science; mesotrione, Callisto, Syngenta Crop Protection, LLC, Greensboro, NC; metribuzin + *S*-metolachlor, Boundary 6.5 EC, Syngenta Crop Protection, LLC; *S*-metolachlor, Dual Magnum, Syngenta Crop Protection, LLC; paraquat, Gramoxone SL, Syngenta Crop Protection, LLC

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Table 3. List of aggregate weeds and number, median height and width, and common name within each class after preprocessing the dataset.[a]

Aggregate species	n	Height	Width	Common name
		------ cm ------		
Convolvulaceae	(2,446)	(3.8)	(5.1)	
	2,199	3.8	5.1	pitted morningglory
	200	1.9	2.5	ivyleaf morningglory
	47	5.1	10.2	tall morningglory
Amaranthaceae	(2,149)	(1.9)	(2.5)	
	1,985	1.5	2	Palmer amaranth
	164	3.8	4.1	waterhemp
yellow nutsedge	(956)	(7.6)	(8.3)	-
Poaceae	(614)	(3.2)	(5.1)	
	24	2.5	2.5	barnyardgrass
	9	1.9	11.4	bermudagrass
	216	2.5	3.2	broadleaf signalgrass
	14	5.1	5.1	fall panicum
	174	5.7	7.6	giant foxtail
	94	7.6	7.6	goosegrass
	81	1.3	1.3	large crabgrass
	2	11.4	7.0	yellow foxtail
Malvaceae	(504)	(1.3)	(1.5)	
	387	1.0	1.0	prickly sida
	117	3.2	6.4	velvetleaf
Decumbent broadleaf	(495)	(1.3)	(1.3)	
	366	1.3	1.3	carpetweed
	1	7	19	curly dock
	4	5.1	7.6	dandelion
	119	1.3	5.1	horse purslane
	5	5.1	10.2	wild radish

[a] Observations, heights and widths in parenthesis correspond to the aggregate species.

Table 4. Weeds evaluated and experimental sites.[a]

Common name	Genus	Species	Authority	Sites
barnyardgrass	*Echinochloa*	*crus-galli*	(L.) P. Beauv	AR, IN, MS
Bermudagrass	*Cynodon*	*dactylon*	(L.) Pers.	NC, SRD
broadleaf signalgrass	*Urochloa*	*platyphylla*	(Munro ex C. Wright) R.D. Webster	AR, NC, MS
carpetweed	*Mollugo*	*verticillata*	L.	IN, NC
curly dock	*Rumex*	*crispus*	L.	AR
dandelion	*Taraxacum*	*officinale*	F.H. Wigg.	IN
fall panicum	*Panicum*	*dichotomiflorum*	Michx.	NC
giant foxtail	*Setaria*	*faberi*	Herrm.	IL, IN
goosegrass	*Eleusine*	*indica*	(L.) Gaertn	NC
horse purslane	*Tranthema*	*portulacastrum*	L.	AR, NC, MS
ivyleaf morningglory	*Ipomoea*	*hederacea*	Jacq.	AR, NC, MS
large crabgrass	*Digitaria*	*sanguinalis*	(L.) Scop.	AR, NC, MS
Palmer amaranth	*Amaranthus*	*palmeri*	S. Watson	AR, IL, NC, MS
pitted morningglory	*Ipomoea*	*lacunosa*	L.	AR, IL, IN, NC, MS
prickly sida	*Sida*	*spinosa*	L.	AR, IL, NC, MS
tall morningglory	*Ipomoea*	*purpurea*	(L.) Roth	NC
velvetleaf	*Abutilon*	*theophrasti*	Medik	IL, IN, NC
waterhemp	*Amaranthus*	*tuberculatus*	(Moq.) J.D. Sauer	IL, IN
wild radish	*Raphanus*	*raphanistrum*	L.	NC
yellow foxtail	*Setaria*	*faberi*	Herm.	IN
yellow nutsedge	*Cyperus*	*esculentus*	L.	IN, MS

[a] Names and authorities are from the WSSA composite list of weeds since not all names are present in the USDA plants database (https://wssa.net/weed/composite-list-of-weeds/)

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Table 5. Likelihood ratio effect summary for the logistic regression of weeds treated.

Effect	DF	$\chi2$	P > $\chi2$
Decision threshold (sensitivity settings)	1	750.50	< 0.0001
Aggregate weed species	5	211.60	< 0.0001
Weed width	1	56.492	< 0.0001
Weed position (in-row or between-row)	1	9.8209	0.0017
Weed height	1	7.3847	0.0066
Crop	2	3.8941	0.1427
Weed density	1	0.4061	0.5240

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Table 6. Odds ratios of treating a weed given the categorical effects.[a]

Effects	Level comparison (likelihood of being treated %)			Odds ratio	P > χ2
Aggregate species	Convolvulaceae (98.0)	vs	Decumbent broadleaf (97.5)	1.233	0.3057
	Convolvulaceae (98.0)	vs	Malvaceae (96.7)	1.646	0.0079
	Convolvulaceae (98.0)	vs	Poaceae (95.7)	2.208	< 0.0001
	Convolvulaceae (98.0)	vs	Amaranthaceae (93.1)	3.582	< 0.0001
	Convolvulaceae (98.0)	vs	yellow nutsedge (85.1)	8.524	< 0.0001
	Decumbent broadleaf (97.5)	vs	Malvaceae (96.7)	1.335	0.2120
	Decumbent broadleaf (97.5)	vs	Poaceae (95.7)	1.790	0.0095
	Decumbent broadleaf (97.5)	vs	Amaranthaceae (93.1)	2.905	< 0.0001
	Decumbent broadleaf (97.5)	vs	yellow nutsedge (85.1)	6.913	< 0.0001
	Malvaceae (96.7)	vs	Poaceae (95.7)	1.341	0.1666
	Malvaceae (96.7)	vs	Amaranthaceae (93.1)	2.176	< 0.0001
	Malvaceae (96.7)	vs	yellow nutsedge (85.1)	5.179	< 0.0001
	Poaceae (95.7)	vs	Amaranthaceae (93.1)	1.622	0.0037
	Poaceae (95.7)	vs	yellow nutsedge (85.1)	3.861	< 0.0001
	Amaranthaceae (93.1)	vs	yellow nutsedge (85.1)	2.379	< 0.0001
Weed position	between-row (96.1)	vs	in-row (94.9)	1.339	0.0016
Crop	cotton (96.0)	vs	corn (95.6)	1.096	0.5608
	cotton (96.0)	vs	soybean (95.1)	1.236	0.0641
	corn (95.6)	vs	soybean (95.1)	1.128	0.3415

[a] Odds ratios are calculated from the ratio of the two levels: $\frac{\left(\frac{P_a}{1-P_a}\right)}{\left(\frac{P_b}{1-P_b}\right)}$ where P_a is the proportion of the treated weeds for one group and P_b is the proportion of treated weeds for the comparison group. As an example, if P_a = 0.9 and P_b = 0.8, the odds ratio would be $\frac{\left(\frac{0.9}{1-0.9}\right)}{\left(\frac{0.8}{1-0.8}\right)}=2.25$. Likelihoods parenthetically presented represent the likelihood averaged over all other predictors.

[b] P > χ2 are Wald based tests from the model estimates.

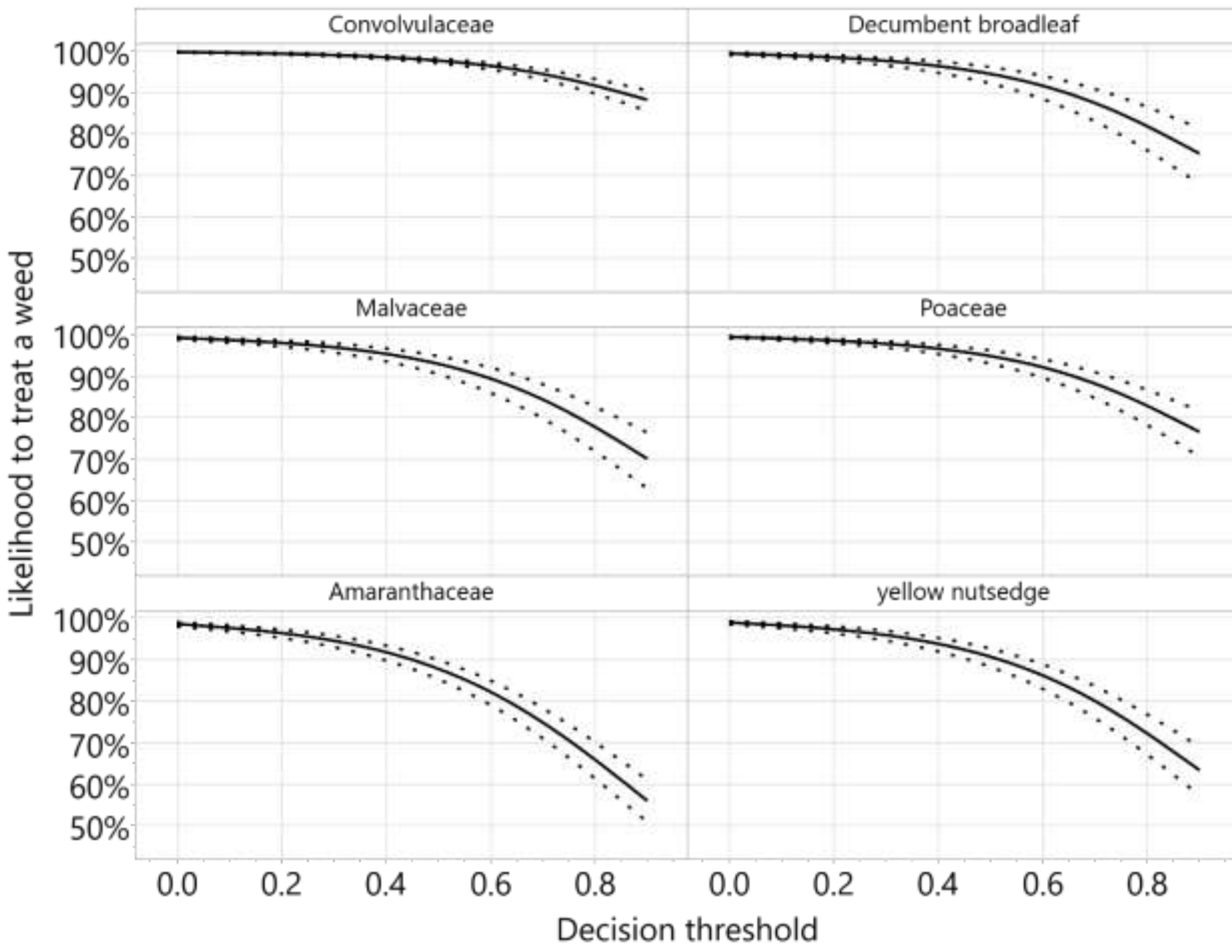

Figure 1. The effect of decision threshold on the likelihood of treating each weed class, averaged over the median height and width of each class, 2.4 plants m^{-2}, and the categorical combination of between soybean rows. This figure should not be used to compare differences between weed classes due to differences between median weed height and width: *Covolvulaceae*, 3.8 cm and 5.1 cm; decumbent broadleaf, 1.3 cm and 1.3 cm; *Malvaceae*, 1.3 cm and 1.5 cm; *Poaceae*, 3.2 cm and 5.1 cm; *Amaranthaceae*, 1.9 cm and 2.5 cm; yellow nutsedge, 7.6 cm and 8.3 cm; respectively. Decision thresholds of 0.4, 0.7, and 0.9 correspond to the highest, medium, and lowest sensitivity settings in 2022, respectively. Broadcast applications are represented by 0. Average range odds ratio for decision threshold = 0.0192 (from broadcast to the lowest sensitivity). The solid line represents the predicted likelihood to treat a weed, while the broken line represents the 95% confidence interval. Both lines were generated using the save columns function within the ‘fit report’ of JMP Pro version 18.0 (SAS Institute, Cary, NC), with a smooth spline curve λ = 0.05.

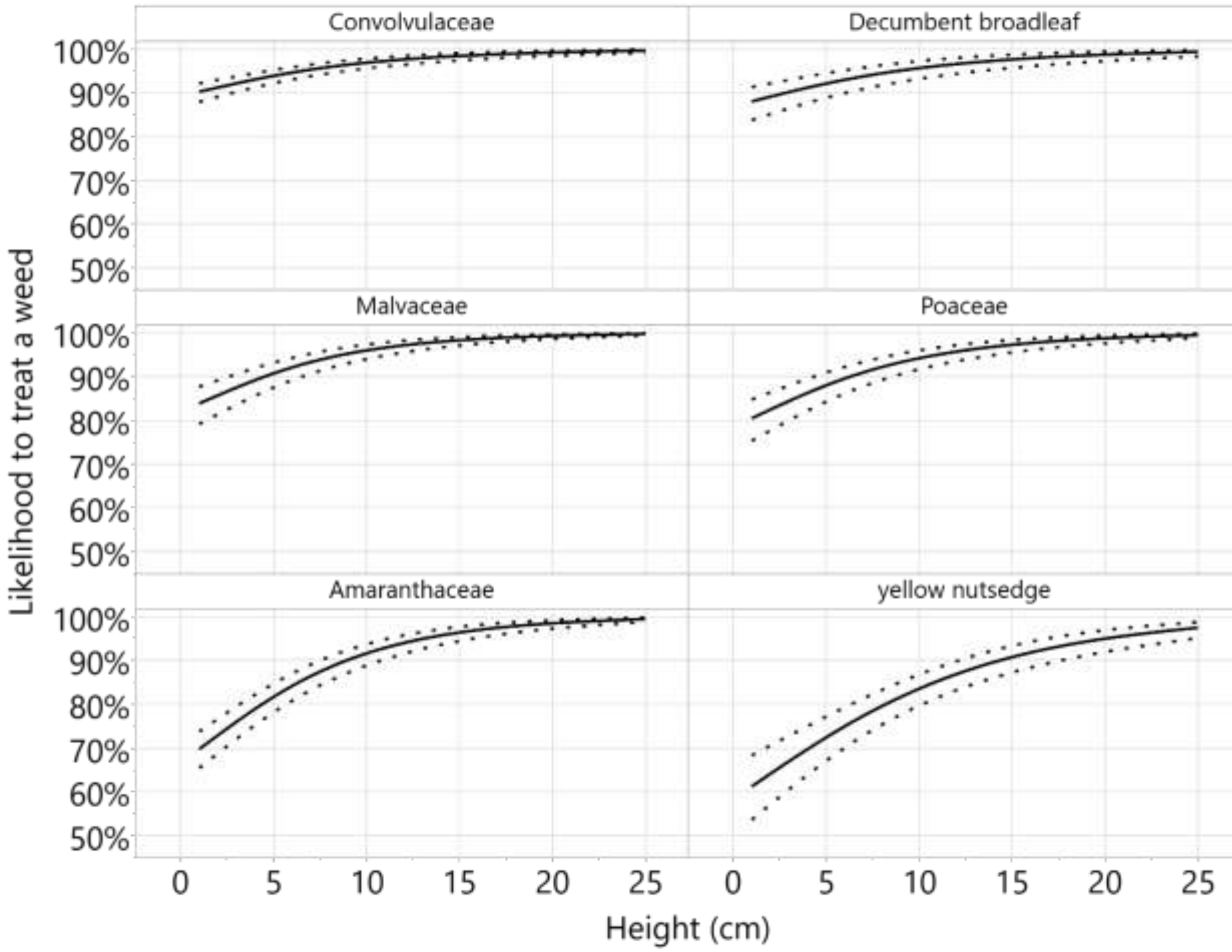

Figure 2. The effect of weed height (cm) on the likelihood of treating a weed with targeted applications, at a 0.7 decision threshold (medium sensitivity) and the categorical combination of between soybean rows. Average unit odds ratio for width = 1.065. The solid line represents the predicted likelihood to treat a weed, while the broken line represents the 95% confidence interval. Both lines were generated using the save columns function within the 'fit report' of JMP Pro version 18.0 (SAS Institute, Cary, NC), with a smooth spline curve λ = 0.05.

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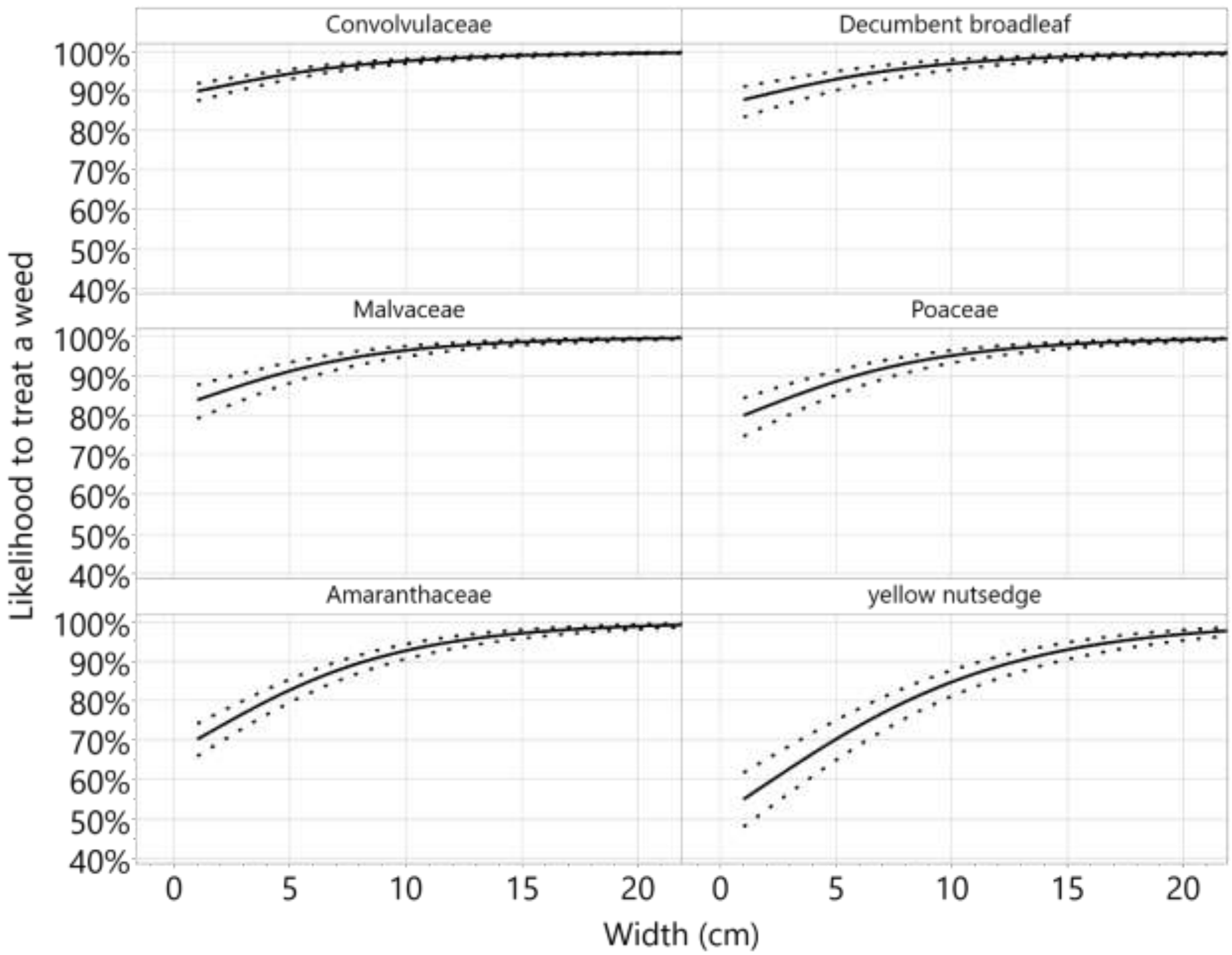

Figure 3. The effect of weed width (cm) on the likelihood of treating each weed class, at a medium sensitivity setting (decision threshold 0.7) and the categorical combination of between soybean rows. Unit odds ratio for width = 1.150. The solid line represents the predicted likelihood to treat a weed, while the broken line represents the 95% confidence interval. Both lines were generated using the save columns function within the 'fit report' of JMP Pro version 18.0 (SAS Institute, Cary, NC), with a smooth spline curve λ = 0.05.

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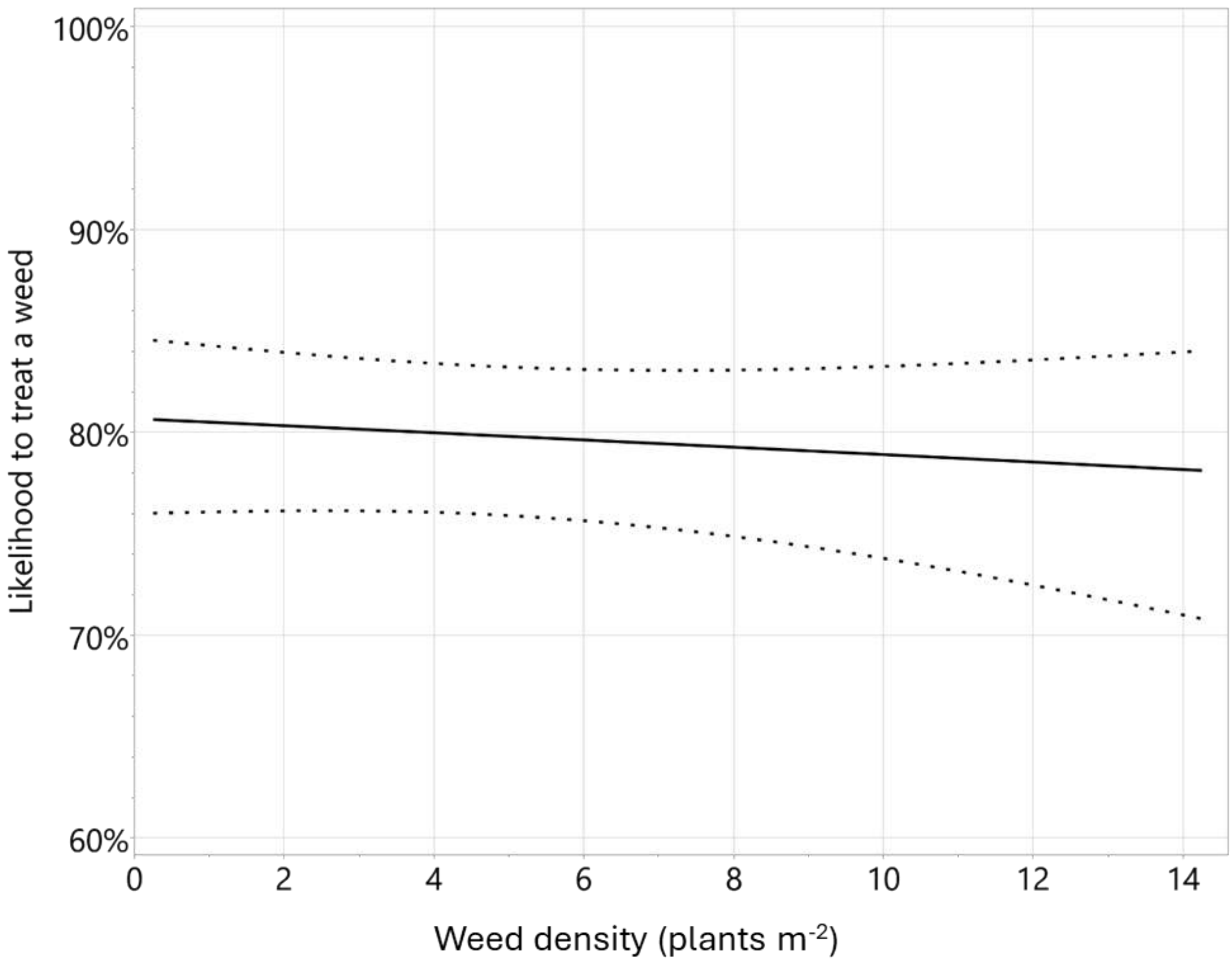

Figure 4. The effect of weed density (plants m^{-2}) on the likelihood of treating yellow nutsedge between soybean rows. The figure also uses the medium sensitivity setting (decision threshold 0.7) and the median yellow nutsedge height and width at 7.6 cm and 8.3 cm, respectively. Unit odds ratio for weed density = 0.989 and were insignificant. The solid lines represents the predicted likelihood to treat a weed, while the broken line represents the 95% confidence interval. Both lines were generated using the save columns function within the 'fit report' of JMP Pro version 18.0 (SAS Institute, Cary, NC) , with a smooth spline curve $\lambda = 0.05$.

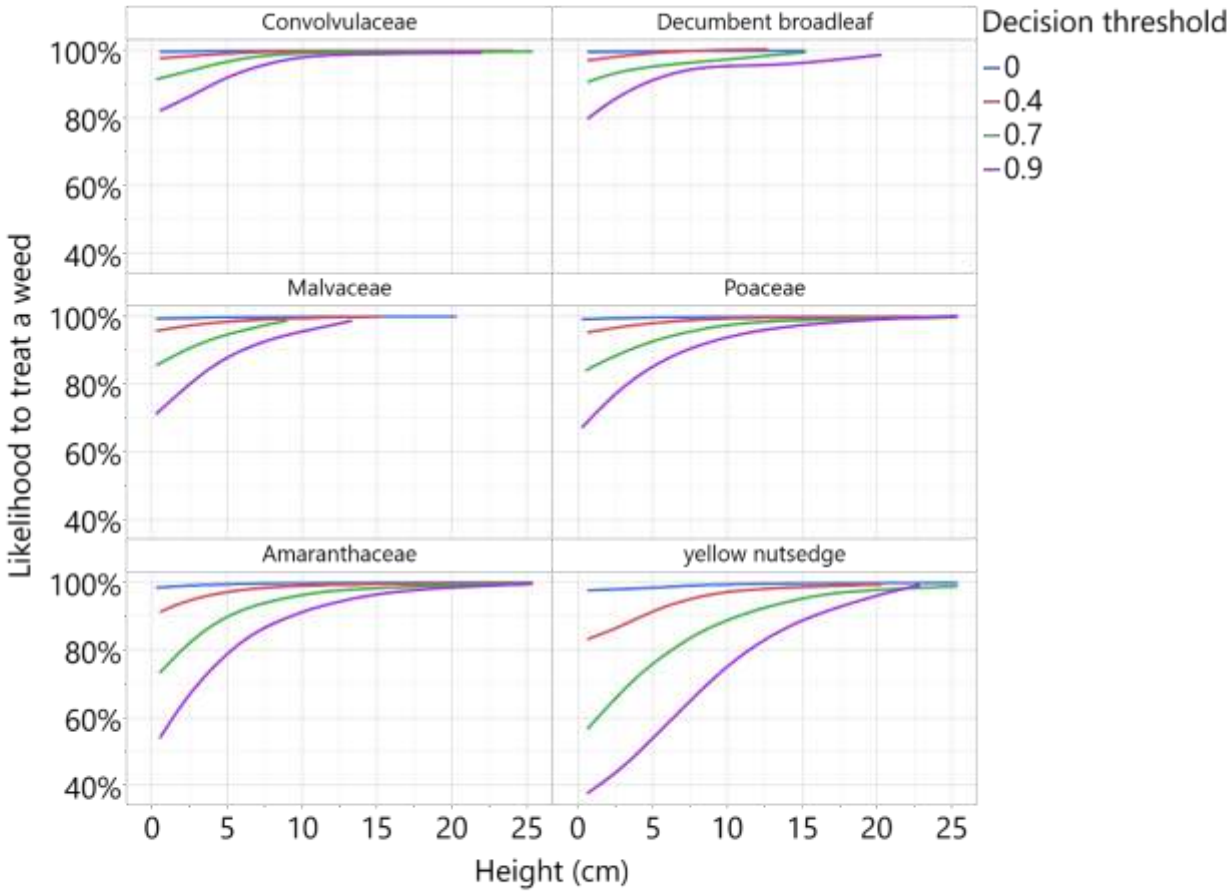

Figure 5. The observed likelihood of treating each aggregate group of weeds given the weed height (cm) and decision thresholds across observations. Decision thresholds of 0.4, 0.7, and 0.9 correspond to the highest, medium, and lowest spray sensitivities settings in 2022, respectively. Broadcast applications are represented by 0. Figure generated using the 'graph builder' platform of JMP Pro version 18.0 (SAS Institute, Cary, NC) with a smooth spline line with $\lambda = 8.5$.

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