Weed Science

www.cambridge.org/wsc

Research Article

Cite this article: Barnhart IH, Proctor CA, Werle R, Miller KA, Lancaster SR, Roozeboom KL, Dille JA (2025). Evaluating ONE SMART SPRAY for weed control in midwestern U.S. corn and soybean crops. Weed Sci. **73**(e85), 1–10. doi: 10.1017/wsc.2025.10058

Received: 20 December 2024
Revised: 27 June 2025
Accepted: 2 September 2025

Associate Editor:
Debalin Sarangi, University of Minnesota

Keywords:
Artificial intelligence; detection thresholds; herbicide savings; site-specific weed management; targeted spraying

Corresponding author:
J. Anita Dille; Email: dieleman@ksu.edu

Evaluating ONE SMART SPRAY for weed control in midwestern U.S. corn and soybean crops

Isaac H. Barnhart[1], Christopher A. Proctor[2], Rodrigo Werle[3], Kalvin A. Miller[4], Sarah R. Lancaster[5], Kraig L. Roozeboom[6] and J. Anita Dille[6]

[1]Graduate Research Assistant, Department of Agronomy, Kansas State University, Manhattan, KS, USA; [2]Associate Extension Educator, Department of Agronomy and Horticulture, University of Nebraska–Lincoln, Lincoln, NE, USA; [3]Associate Professor, Department of Plant and Agroecosystem Sciences, University of Wisconsin–Madison, Madison, WI, USA; [4]Field Engineer, BASF Corporation, Seymour, IL, USA; [5]Assistant Professor, Department of Agronomy, Kansas State University, Manhattan, KS, USA and [6]Professor, Department of Agronomy, Kansas State University, Manhattan, KS, USA

Abstract

Targeted sprayers use artificial intelligence to enable on-the-go weed detection and herbicide application, reducing the need to spray entire fields with foliar herbicides. A targeted sprayer was evaluated for treating weeds in corn (*Zea mays* L.) and soybean [*Glycine max* (L.) Merr.] cropping systems in the midwestern United States. Using a ONE SMART SPRAY sprayer, our objectives were to (1) evaluate the efficacy of different herbicide application programs: two-passes, spot-spray (SS) only, or simultaneous broadcast residual and SS foliar herbicides; (2) determine whether weed detection thresholds influence weed control; and (3) determine the cost for each herbicide program compared with a traditional broadcast application. Field experiments were conducted in 2022 and 2023 near Manhattan, KS, and in 2023 in Seymour, IL. Both green-on-brown (GOB; burndown applications) and green-on-green (GOG; in-crop applications) were applied. Main plot treatments consisted of four herbicide programs, and the split-plot consisted of four weed detection thresholds: herbicide Efficacy, Balanced, Savings, and a Broadcast application. The percentage of area infested with weeds within each plot was estimated visually 42 d after the GOG application. An "as-applied map" was constructed using raw sprayer data to show when nozzles were turned on or off within a subplot and used to determine herbicide program costs based on the percentage of each plot area sprayed. Results indicated that herbicide programs with simultaneous broadcast and SS components in many cases resulted in a similar area infested with weeds compared with broadcast applications with the same herbicide products. As expected, herbicide costs were lower in SS applications than in broadcast applications. The ONE SMART SPRAY sprayer demonstrated potential to reduce herbicide input costs without compromising weed control.

Introduction

Weeds often grow in distinct patches rather than uniformly across an entire agricultural field (Maxwell and Luschei 2005). Despite this reality, herbicides are traditionally applied broadcast instead of only where the weeds occur (Huang et al. 2018). To address this, site-specific weed management (SSWM) has been proposed, which is defined as the process of adapting weed management strategies within a field to match the location of the weed infestations (Fernández-Quintanilla et al. 2018; Wiles 2009). Opportunities for farmers to reduce total herbicide applied, reduce input costs, and minimize environmental contamination while maintaining weed control are possible with SSWM (Barroso et al. 2004; Bongiovanni and Lowenberg-DeBoer 2004). In terms of chemical weed control, this would result in herbicides being sprayed only where they are needed (Rozenberg et al. 2021). However, a major challenge to SSWM is developing a reliable and accurate method of weed detection that is robust to a multitude of field conditions (Gao et al. 2020).

In the last decade, artificial intelligence (AI) has become a major part of modern-day life and is defined as the science behind producing and creating intelligent machines (McCarthy 2007). First described by Alan Turing in a 1950 paper entitled "Computing Machinery and Intelligence" (Turing 1950), AI has evolved from a simple series of "if-then" statements to complicated algorithms that make decisions as the human brain does (Kaul et al. 2020). A subset of AI known as deep learning is most often used for SSWM; more specifically, convolutional neural networks (CNNs) are used because they can analyze and extract features within imagery that cannot be seen with the human eye (Albawi et al. 2017; Sapkota et al. 2020). With advances in graphics processing units and computer processors, weed detection using CNNs has become more feasible. AI algorithms have been used to detect weeds in many crops, including corn (*Zea mays* L.), soybean [*Glycine max* (L.) Merr.] (Ahmad et al. 2021), rice (*Oryza sativa* L.) (Yang et al. 2021), bermudagrass [*Cynodon dactylon* (L.) Pers.] turf (Xie et al. 2021), sugar beet (*Beta vulgaris* L.) (Gao et al. 2020), lettuce (*Lactuca sativa* L.) (Osorio et al. 2020), and wheat (*Triticum aestivum* L.) (Jabir and Falih 2022).

Even though AI can be used to detect weeds, the challenge is to accomplish this in real time and simultaneously deliver effective weed control. Two common types of real-time weed detection platforms are self-propelled weeding robots and field sprayers (Gerhards et al. 2022). Machines such as the Tertill® weeding robot (Tertill®, North Billerica, MA, USA) can locate weeds and use either herbicides or a mechanical string trimmer to treat them. Research has shown that the Tertill® led to an 18% to 41% improvement in weed control when compared with standard cultivation (Sanchez and Gallandt 2020). Additionally, Ruigrok et al. (2020) trained the AI object detection algorithm You Only Look Once (YOLOv3) (Redmon and Farhadi 2018) to detect volunteer potatoes (*Solanum tuberosum* L.) in sugar beet crops and uploaded the trained model to an autonomous spraying robot. The authors reported that 96% of the volunteer potatoes were effectively controlled, while only 3% of the sugar beets were incorrectly sprayed.

A major drawback of current robotic weed control technology is that several robots working together are required to cover large-acreage fields in a reasonable time frame (Gerhards et al. 2022). For this reason, many have turned to AI-powered field sprayers to increase efficiency and speed of weed control applications. Hussain et al. (2020) designed a sprayer to detect common lambsquarters (*Chenopodium album* L.) for herbicide applications and detect diseased potato plants for fungicide applications. The authors reported that chemical savings were 42% for herbicide and 43% for fungicide applications. Jin et al. (2023) constructed an intelligent sprayer to control weeds in bermudagrass turf and reported no differences in control of broadleaf weed species between plots receiving conventional broadcast and plots receiving precision spot-spray (SS) applications. In addition to these prototype sprayers developed by academic research groups, commercial intelligent sprayers are becoming available on the market. Examples of such sprayer systems, both available and soon to be available in the United States, include the John Deere® See & Spray™ Ultimate (John Deere, Moline, IL, USA), Greeneye Technology™ (Greeneye Technology, Tel Aviv-Yafo, Israel), and ONE SMART SPRAY (Bosch BASF Smart Farming, Cologne, Germany).

Intelligent sprayers are equipped with AI weed detection algorithms that allow for different settings known as confidence levels or thresholds when detecting objects within imagery (Barnhart et al., 2022). When objects are correctly detected, they are known as true positives, whereas incorrectly detected objects or a misplaced detection are known as false positives (Ralašić 2021). Thresholds regulate the number of false positives in the final detection pass (Wenkel et al. 2021) and are expressed as confidence levels between 0 and 1. Based on how the algorithm was trained, object detection algorithms assign a series of confidence levels to objects within each image/video frame when deployed. When a detection threshold is specified by users, algorithms will detect all objects with confidence levels equal to and greater than the specified threshold. Lower thresholds result in more false positives, ensuring that almost all weeds are detected. Conversely, higher thresholds would result in fewer false positives, so that some weeds are not being detected, as the object has a confidence level less than the specified detection threshold (Barnhart et al. 2022). In terms of targeted spraying, these confidence levels can be set to achieve greater efficacy (more herbicide applied; lower detection threshold) or achieve more savings (less herbicide applied; higher detection threshold).

Many of these AI-enabled commercial sprayers are equipped with a dual tank and multiple nozzles or dual boom spray systems and are able to simultaneously broadcast soil-residual herbicides and also SS foliar herbicides whenever weeds are detected (Greeneye Technology 2023; John Deere 2023). Additionally, different sprayer systems trigger single or multiple nozzles on the SS boom upon weed detection. Such technologies open new opportunities to determine how they can be used to optimize control of weeds in agronomic cropping systems. Therefore, the objectives of this study were to (1) evaluate the weed control efficacy of different herbicide application programs adapted for the ONE SMART SPRAY system: two passes, SS-only treatments, and simultaneous broadcast residual and SS foliar herbicides compared with traditional broadcast applications; (2) determine whether weed detection threshold settings influence weed control; and (3) determine the cost for each herbicide application program as compared with a traditional broadcast application.

Materials and Methods

Description of Field Sites

Field experiments were established in 2022 and 2023 in Kansas and in 2023 in Illinois. The Kansas experiments were in rainfed corn/soybean no-till production fields at the Kansas State University, Department of Agronomy Research Farm near Manhattan, KS. In 2022, two locations were initiated and will be referred to as MAN 1 (39.125°N, 96.648°W) and MAN 2 (39.130°N, 96.644°W). MAN 1 and MAN 2 were planted with corn and soybean in 2022, respectively, and were rotated to the subsequent crop in 2023. In 2023, additional corn and soybean field experiments were established south of the BASF Midwest Research Farm near Seymour, IL (40.039°N, 88.403°W) (SEY Corn and SEY Soy for corn and soybean experiments, respectively). Locations in IL were conventionally tilled and rainfed. For all locations, crops were planted in rows spaced 76 cm apart (Table 1).

Both MAN 1 and MAN 2 were located on a Smolan silty clay loam (fine, smectic, mesic Pachic Arguistolls) with 3% to 7% slope (USDA-NRCS 2023). The SEY Corn and SEY Soy experiments were established in a field with Drummer silty clay loam (fine-silty, mixed, superactive, mesic, Typic Endoaquolls) with 0% to 2% slope (USDA-NRCS 2023). Due to drought early in the season, weed infestations in Illinois were much less than in the Kansas fields (data not shown).

Field Sprayer

A ONE SMART SPRAY research sprayer was used for this study. The sprayer was equipped with the same external hardware as a commercial ONE SMART SPRAY sprayer but was custom-built for small-plot research. The spray apparatus consisted of an aluminum frame mounted to the front of a John Deere® 6125R™ tractor. The sprayer was equipped with two booms: the front boom was reserved for SS with nozzles spaced 25.4 cm apart, while the rear boom was used for broadcast applications with nozzles spaced 50.8 cm apart. Applied spray swath was 3.05-m wide for both booms. Spray pressure was provided with CO_2-pressurized tanks mounted at the rear of the spray apparatus, and pressure was manually adjusted before spraying. Within each meter of boom, a camera was mounted between two light-emitting diode (LED) lights to provide consistent lighting across diverse field conditions

https://doi.org/10.1017/wsc.2025.10058

Table 1. Planting information for corn and soybean experiments evaluating ONE SMART SPRAY herbicide programs and weed detection thresholds.

Year	Location	Planting information	Corn	Soybean
2022	Manhattan KS	Field	MAN 1	MAN 2
		Date	May 16	May 17
		Seeding rate (no. ha^{-1})	59,300	331,000
		Hybrid or variety[b]	Pioneer P1089AM	Pioneer P39T61SE
2023	Manhattan KS	Field	MAN 2	MAN 1
		Date	May 19	May 19
		Seeding rate (no. ha^{-1})	59,300	331,000
		Hybrid or variety[b]	Pioneer P0995AM	Pioneer P42A84E
2023	Seymour IL[a]	Field	SEY Corn	SEY Soy
		Date	July 3	July 3
		Seeding rate (no. ha^{-1})	88,900	346,000
		Hybrid or variety	Wyffles[c] 7878RIB	Xitavio[d] 3651E

[a]Illinois trials were planted later than usual due to drought conditions and limited space at the research farm.
[b]Pioneer Hi-Bred, Corteva Agriscience, 974 Center Road, Wilmington, DE, USA.
[c]Wyffles Hybrids, 13344 US Highway 6, Geneseo, IL, USA.
[d]Xitavio Soybean Seed, BASF Corporation, 2 TW Alexander Drive, Durham, NC, USA.

Table 2. Main treatment herbicide application programs, products, and rates for corn field experiments in Kansas and Illinois.[a]

	GOB		GOG	
Program	Broadcast	Spot-spray	Broadcast	Spot-spray
	g ai or ae ha^{-1}			
Residual-at-plant	Dimethenamid-P[b]: 841 Atrazine[c]: 2,244	Glyphosate[d]: 840 Topramezone[e]: 12.3	—	Glyphosate[d]: 840 Topramezone[e]: 12.3
Overlapping-residual	Dimethenamid-P[b]: 841 Atrazine [c]: 1,122	Glyphosate[d]: 840 Topramezone[e]: 12.3	Dimethenamid-P[b]: 420 Atrazine [c]: 1,122	Glyphosate[d]: 840 Topramezone[e]: 12.3
Spike	Glyphosate[d]: 578 Topramezone[e]: 12.3	Glyphosate[d]: 578	Glyphosate[d]: 578 Topramezone[e]: 12.3	Glyphosate[d]: 578
Spot-spray-only	—	Glyphosate[d]: 840 Topramezone[e]: 12.3	—	Glyphosate[d]: 840 Topramezone[e]: 12.3

[a]Green-on-brown (GOB) applications were sprayed preemergence immediately after crop planting, and green-on-green (GOG) applications were sprayed postemergence at 21 to 28 d after planting.
[b]Outlook™, BASF Corporation, 26 Davis Drive, Research Triangle Park, NC, USA.
[c]Atrazine 4L™, Makhteshim Agan of North America (ADAMA), 3120 Highwoods Boulevard, Suite 100, Raleigh, NC, USA. Treatments containing atrazine were applied with 10 ml of crop oil concentrate L^{-1} solution.
[d]Roundup PowerMax 3™, Bayer Crop Science, 800 N Lindbergh Boulevard, St Louis, MO, USA. Treatments containing glyphosate were applied with 120 g of dry ammonium sulfate L^{-1} solution.
[e]Armezon™, BASF Corporation, 26 Davis Drive, Research Triangle Park, NC, USA. Treatments containing topramezone were applied with 2.5 ml of crop oil concentrate L^{-1} solution.

(Spaeth et al. 2024). The camera uses an RGB imager equipped with a red/near-infrared filter, allowing the sprayer to distinguish between plants and other objects. Both the cameras and LED lights were mounted at a 25° forward angle relative to the ground, and the system detected weeds as small as 36 mm^2 in area.

The ONE SMART SPRAY system was capable of two types of applications: green-on-brown (GOB) and green-on-green (GOG) (Quigley 2023). GOB refers to burndown/preemergence applications where no crops are present; the system does not use AI for these applications, because green vegetation can be easily detected with IR and NIR light (Nguyen et al. 2012). The GOG applications are made in-crop and therefore use AI to recognize crop row bands and spray green vegetation detected between the crop rows (Spaeth et al. 2024). The SS boom will turn on a minimum of one nozzle up to full boom depending on the amount of green area detected.

Field Experiments

At each location, experiments were set up in a split-plot arrangement of treatments in a randomized complete block design with five replications. The main plot factor was four herbicide application program treatments (Table 2), and the split-plot factor was four weed detection thresholds. For the MAN 1, SEY Corn, and SEY Soy locations, subplot dimensions were 3-m (4 crop rows) wide by 30.5-m long, whereas subplot dimensions for the MAN 2 location were 3-m wide by 35.1-m long as the field area available was larger.

The four main plot treatments were herbicide application programs where GOB applications were preemergence at crop planting, while GOG applications were postemergence and approximately 21 to 28 d after planting. Program 1 was as a two-pass "Residual-at-plant" approach with a GOB application including simultaneous broadcast soil-residual and SS foliar herbicides followed by a GOG application with SS foliar herbicides only. Program 2 was a two-pass "Overlapping-residual" approach with a split application of soil-residual herbicides for both GOB and GOG together with SS foliar herbicides at each timing. Program 3 introduced a novel concept known as a "Spike" approach in which a base recommended rate of foliar herbicide was broadcast at both GOB and at GOG with the goal to control small, undetected weeds, and superimposed with an SS spike application to increase the rate of the same herbicides when weeds were detected and to increase likelihood of control. Finally, Program 4 was a two-pass "Spot-spray-only" approach that consisted of SS GOB and SS GOG applications of foliar herbicides, with no broadcast soil-residual herbicides applied.

The split-plot treatments were four weed detection thresholds including one traditional broadcast application and three SS

https://doi.org/10.1017/wsc.2025.10058

Table 3. Main treatment herbicide application programs, products, and rates for soybean field experiments in Kansas and Illinois.[a]

Program	GOB Broadcast	GOB Spot-spray	GOG Broadcast	GOG Spot-spray
	g ai or ae ha^{-1}			
Residual-at-plant	Pyroxasulfone[b]: 109	2,4-D[c]: 1,067 Glyphosate[d]: 840	—	2,4-D[c]: 1,067 Glyphosate[d]: 840
Overlapping-residual	Pyroxasulfone[b]: 55	2,4-D[c]: 1,067 Glyphosate[d]: 840	Pyroxasulfone[b]: 55	2,4-D[c]: 1,067 Glyphosate[d]: 840
Spike	2,4-D[c]: 799 Glyphosate[d]: 578	2,4-D[c]: 266 Glyphosate[d]: 578	2,4-D[c]: 799 Glyphosate[d]: 578	2,4-D[c]: 266 Glyphosate[d]: 578
Spot-spray-only	—	2,4-D[c]: 1,067 Glyphosate[d]: 840	—	2,4-D[c]: 1,067 Glyphosate[d]: 840

[a]Green-on-brown (GOB) applications were sprayed preemergence immediately after crop planting, and green-on-green (GOG) applications were sprayed postemergence at 21 to 28 d after planting.
[b]Zidua SC™, BASF Corporation, 26 Davis Drive, Research Triangle Park, NC, USA.
[c]Enlist One™, Corteva Agriscience LLC, 9330 Zionsville Road, Indianapolis, IN, USA.
[d]Roundup PowerMax 3™, Bayer Crop Science, 800 N Lindbergh Boulevard, St Louis, MO, USA. Treatments containing glyphosate were applied with 120 g of dry ammonium sulfate L^{-1} solution.

Table 4. Dates for green-on-brown (GOB) and green-on-green (GOG) applications and crop stage for GOG at each location, field and year.

Year	Location	Field	Crop	GOB	GOG	Crop stage at GOG
2022	Manhattan KS	MAN 1	Corn	May 19	June 17	V5
		MAN 2	Soybean	May 20	June 17	V2
2023	Manhattan KS	MAN 2	Corn	May 23	June 13	V5
		MAN 1	Soybean	May 23	June 20	V4
2023	Seymour IL	SEY Corn	Corn	July 5	July 27	V5
		SEY Soy	Soybean	July 7	July 31	V2

thresholds randomized within each main plot treatment. Exact settings for the confidence levels of each weed detection threshold are proprietary and based on manufacturer recommendations. In general, the most-sensitive (low-value) threshold was labeled "Efficacy" and corresponds to an AI algorithm that ensures all detected plants are sprayed, potentially including crop plants classified as weeds, known as false-positive detections. In the end, it would be expected that more herbicide would be applied but few if any weeds would be missed. Naming this as an Efficacy threshold was based on the goal that all weeds were detected and sprayed, not to be confused with "efficacy" used to describe the effectiveness of a given herbicide. The least-sensitive (higher-value) threshold tested was labeled as "Savings" and would correctly detect most weeds but miss some, known as false-negative detections. As a result, it would be expected that less herbicide would be sprayed and most of the weeds would be treated. An intermediate level of sensitivity was included, labeled as "Balanced," and a fourth treatment level was a traditional broadcast application, used to compare performance relative to the other SS weed detection thresholds. In 2022, different threshold capabilities were available at the GOB versus GOG application timings, such that only the Efficacy detection threshold was available for GOB applications, but all were available for GOG. By 2023, all threshold settings were available for both GOB and GOG applications. However, to be consistent between years, only the Efficacy threshold was used for GOB in 2023.

In general, for each herbicide application program, a standard broadcast application was used as a control to compare to all other main and subplot treatments. Herbicides, adjuvants, and application rates were unique for corn (Table 2) and soybean programs (Table 3). For all locations, broadcast applications were sprayed at a carrier volume of 93.5 L ha^{-1} and SS applications were sprayed at a carrier volume of 140.3 L ha^{-1}. Sprayer speed was 8 km h^{-1} in 2022, and due to software upgrades, speed was increased to 9.7 km h^{-1} in 2023. In 2022, broadcast applications were made with TTI 11002 flat-spray nozzles and SS applications with TP6502E even flat-spray nozzles (TeeJet® Spraying Systems, Wheaton, IL, USA), pressurized at 195 and 117 kPa, respectively. With the software upgrades and speed changes made in 2023, the same nozzles were used, but broadcast and SS boom pressures were increased to 276 and 159 kPa, respectively. All application dates and crop stages for GOG applications are in Table 4.

Data Collection

The percentage of area infested with weeds was determined visually for the area between the middle two crop rows of each plot, ignoring the first and last 1.5 m, using a scale of 0% to 100%, with 0 indicating no weeds and 100 indicating the entire plot area was infested with weeds. Visual estimates were made at 42 d after the GOG application (DAGT) in 2022 and 2023. Overall weed infestation across all species was collected rather than by individual species, because the ONE SMART SPRAY system was not yet able to differentiate among weed species.

End-of-season weed biomass and final grain yields were determined at harvest at the MAN 1 and MAN 2 locations in both 2022 and 2023, but not for SEY locations. In Kansas, end-of-season weed biomass combined across weed species was sampled just before crop harvest from two randomly placed 0.5 m by 1 m quadrats within each plot. Samples were oven-dried at 58 C until constant mass was achieved. Grain was harvested from the middle two rows of each plot with a small-plot combine at physiological maturity, and grain yield was determined at 15.5% moisture for corn and 13% for soybean. The MAN 1 location was not harvested in 2023 due to combine mechanical issues. Drought and availability of field space delayed planting of crops at SEY Corn and SEY Soy, and therefore the crops did not mature for harvest. No end-of-season weed biomass or grain was harvested at Seymour IL in 2023.

As-Applied Map Generation

An "as-applied map" was developed to show when nozzles were turned on and off for a given subplot to determine the percentage of each subplot that was actually sprayed. Maps were generated by converting spray nozzle point data into continuous as-applied maps. The ONE SMART SPRAY system collected geospatial data points for each nozzle on the SS boom and automatically labeled each point as "TRUE" when a nozzle was spraying or "FALSE" when not spraying. These data points were collected at a density of approximately 10 points m^{-2} and geotagged with GPS coordinates and stored as a CSV file within the machine. After each application, raw data files were imported into Jupyter Lab (Kluvyer et al. 2016), and as-applied spray maps were generated using the Python 3.9 (Python 2023) packages Geopandas (Jordahl et al. 2020), Shapely (Gillies et al. 2023), and SciPy (Virtanen et al. 2020). A grid of 0.2 m by 0.2 m cells was overlaid across each experimental location to ensure high resolution within the resulting map. A nearest-neighbor interpolation method (SciPy docs 2023) was used to generate the as-applied map. A nearest-neighbor interpolation assigns the value nearest to a corresponding grid cell to be the estimated value (Varella et al. 2015), with the goal of producing a binary map of 0 and 1 indicating when each nozzle was not spraying or spraying, respectively. With the high density of data points collected by the machine, a nearest-neighbor interpolation method required considerably less computational power than alternative methods such as kriging (van Stein et al. 2020). Maps were exported to QGIS 3.22.7 (QGIS 2023), where the percentage of sprayed area within each subplot was computed. To calculate the herbicide savings ($US ha^{-1}) of each treatment (herbicide application program and detection threshold level), the percentage of area actually sprayed within each subplot was multiplied by the cost of a broadcast application for each herbicide tank mixture; different herbicides and rates were accounted for in these calculations depending on the overall herbicide program. Product costs were taken from the 2023 Kansas State University Chemical Weed Control Guide (Lancaster et al. 2023).

Statistical Analysis

All statistical analyses were done using R v. 4.3.1 (R Core Team 2023). Corn and soybean experiments were analyzed separately by year. Linear mixed-effects models were used to analyze all data. The studies were analyzed as a split-plot design to analyze herbicide application program and detection threshold levels. The response variables were percentage of area that was weedy at 42 DAGT, end-of-season weed biomass measurements, and grain yields. The fixed effects were location, herbicide program, thresholds, and their interactions, while the random effects were replication, replication by herbicide program, and replication by threshold. Data were analyzed using a beta distribution with the GLMMTMB (Brooks et al. 2017) package in R. Data were logit transformed and automatically back-transformed by the package for ease of interpretation. Model residuals were checked for normality and homogeneity of variance using the DHARMA (Hartig 2022) package. The ANOVA models were conducted with type III Wald chi-square tests (Miranda et al. 2022), which was the test used by the GLMMTMB package. For significant models, Tukey's honest significant difference post hoc test was used to determine differences among main effect means, and a confidence level of $\alpha < 0.05$ was used. Post hoc tests were conducted with the EMMEANS (Lenth 2023) package.

Each location had different levels of weed infestation and was analyzed separately. Full-season herbicide costs (based on the percentage of each subplot sprayed) were limited to 2023 data, because the 2022 GOB application data were lost due to a machine data decoder error. Fixed and random effects for the herbicide cost data were the same as previously described for program and threshold analyses. We did not consider the operating costs of the sprayer or any subscription costs, as these were not yet described, but only input costs for herbicides and adjuvants.

Results and Discussion

GOG Weed Infestations

By 42 DAGT, herbicide programs resulted in significantly different amounts of weedy area in both soybean and corn experiments. For soybean in Manhattan 2022, the interaction between herbicide program and detection threshold for percentage of area infested with weeds was significant ($P = 0.02$) (Table 5). Weed infestations in soybean were least in the Spike program for Efficacy and Savings thresholds, but not different from any of the herbicide programs treated with the traditional Broadcast application. The greatest weed infestation was observed with the Residual-at-plant program for the Savings threshold but was not different from Spot-spray-only or Overlapping-residual programs also applied with the Savings threshold. Overall, the Broadcast threshold within each program consistently had 4.30% to 14.25% area infested with weeds across the four herbicide programs, Efficacy ranged from 1.14% to 22.57%, and Balanced from 8.12% to 23.33%. For soybean in Manhattan 2023, there was no interaction between herbicide program and detection threshold for percentage weed infestation ($P = 0.99$) but main effects were significant ($P < 0.0001$ and $P = 0.0009$ for herbicide program and threshold, respectively) (Figure 1A and 1B). The Spot-spray-only program consistently was the weediest, and this was not surprising, because this was the only program that did not have a broadcast component to it. The main effect of detection threshold resulted in weed infestations in soybean that were not different between the Broadcast (1.75% ± 0.48) and Efficacy (3.36% ± 0.77) thresholds but had slightly less weed infestations than the Balanced (5.47% ± 1.08) and Savings (4.43% ± 0.92) thresholds. In general, this field (MAN 1) had less weed occurrence (data not shown). No interaction or main effect differences were observed for the soybean in Seymour 2023. In general, percentage area infested with weeds was more at Seymour compared with Manhattan in 2023 (data not shown). Differences were likely due to rainfall patterns: in 2023, the Manhattan fields received rainfall early in the season (89 mm between planting and GOG application; Kansas Mesonet 2024), and weeds were present for the GOG application, while the SEY Soy field was very dry at planting time (35 mm between June 1 and planting; CoCoRaHS 2024) but did receive rain later in the season (111 mm between GOG application and August 31, 2023; CoCoRaHS 2024), allowing weeds to emerge and grow after the GOG applications, and thus later emerging weeds were not treated.

In corn, an interaction between herbicide program and detection threshold ($P = 0.04$) for percentage weed infestation at 42 DAGT was observed at Manhattan 2022 (Table 5). Compared with soybean, fewer differences were observed, but notably the Spot-spray-only treatment was the weediest, with the Savings

https://doi.org/10.1017/wsc.2025.10058

Table 5. Percent of area infested with weeds (±SE) for each herbicide application program and four detection threshold levels at 42 d after green-on-green (GOG) application for soybean and corn in Manhattan, KS, 2022[a]

Crop: Herbicide program	Detection threshold level: Broadcast	Efficacy	Balanced	Savings
	% area infested with weeds			
Soybean:				
Residual-at-plant	8.19 (3.37) a-e	13.17 (4.76) a-e	19.37 (6.15) cde	28.57 (7.70) e
Overlapping-residual	4.30 (2.28) abcd	17.46 (6.42) b-e	16.22 (6.09) b-e	20.80 (7.21) cde
Spike	2.93 (1.48) abc	1.14 (3.40) ab	8.12 (3.45) a-e	1.80 (0.94) a
Spot-spray-only	14.25 (4.87) b-e	22.57 (6.71) de	23.33 (7.23) de	25.80 (7.62) de
Corn:				
Residual-at-plant	4.07 (1.74) abc	4.50 (1.89) abc	7.89 (2.97) abc	3.91 (1.85) abc
Overlapping-residual	7.39 (2.72) abc	9.32 (3.22) abc	9.06 (3.15) abc	9.86 (3.36) abc
Spike	6.53 (2.49) abc	6.53 (2.49) abc	3.73 (1.66) ab	6.53 (2.49) abc
Spot-spray-only	3.64 (1.68) a	16.87 (4.57) bc	20.00 (5.52) bc	22.00 (5.31) c

[a]Means followed by different letters indicate results of Tukey's honest significant difference test at α = 0.05.

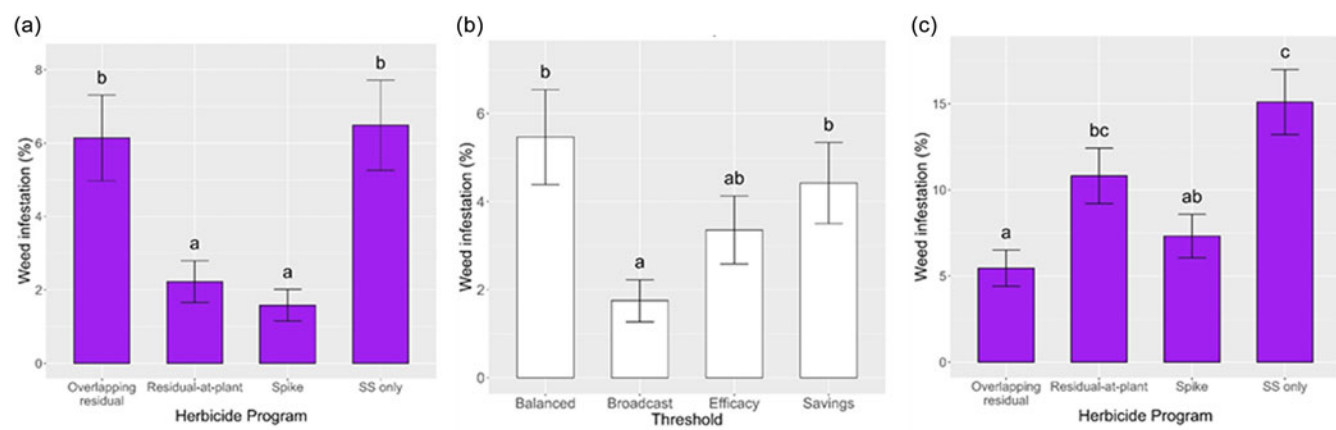

Figure 1. Percent area infested with weeds (% ±SE) at 42 d after the green-on-green application at Manhattan 2023 for (A) soybean herbicide application programs in MAN 1 field, (B) soybean weed detection thresholds in MAN 1 field, and (C) corn herbicide application programs in MAN 2 field. Herbicide application programs for corn and soybean are provided in Tables 2 and 3, respectively. Within a panel, different letters above each bar indicate significance at α = 0.05.

threshold at 22% ± 5.31% infestation. Additionally, Spot-spray-only had more variation than any of the other herbicide programs, with the least and greatest weed infestations ranging from 3.64% ± 1.68% to 22% ± 5.31%. For corn in Manhattan 2023, the main effect of herbicide program was significant ($P < 0.0001$) but not the detection threshold, while neither main effect of herbicide program or detection threshold was significant at Seymour 2023 (data not shown). In Manhattan 2023, the percentage weed infestation with the Overlapping-residual (5.45% ± 1.05%) and Spike (7.32% ± 1.26%) programs were not different and were less than the Spot-spray-only (15.1% ±1.61%) program (Figure 1C). The percentage weed infestation of the Residual-at-plant (10.81% ±1.61%) program was not different from the Spot-spray-only or Spike programs.

If a farmer were interested in a complete Spot-spray-only program, with both GOB and GOG applications, our results indicate that this program would not provide acceptable weed control, such as better than 95% (and results in a much higher weed infestation) compared with other programs that include broadcast residual herbicide applications. The GOG targeted spray technology does not eliminate the importance and benefit of residual herbicides, because they continue to be an important part of SSWM (Owen et al. 2015). We recommend that soil-residual herbicides be included in application programs for intelligent sprayers.

The Spike program was used to test the effectiveness of broadcasting a base foliar herbicide rate and increasing the rate applied when weeds were detected using the SS boom. This could be a program used with a one-boom, one-tank system. For soybean, this approach resulted in the least area infested with weeds at all locations; in corn, this approach resulted in no differences from the program with the least area infested with weeds. It was likely that some weeds were not detected but were sprayed with at least the minimum labeled rate of herbicide that was broadcast applied. For more difficult to control weed species and those that were detected, applications with the maximum labeled rate of the herbicide (Spike amount) provided increased control and less weedy area. In most cases in this study, simultaneous broadcast applications of residual herbicides and SS applications of foliar herbicides provided better weed control (measured as less weedy area) compared with programs using no residual herbicides or Spot-spray-only components.

Overall, it was expected that the traditional Broadcast applications (both program and threshold) would result in the least weedy area. When differences were observed, however, the Efficacy threshold was not different (with the exception of the Manhattan 2022 corn study, Spot-spray-only program). Improvements and updates in the proprietary software that implemented the thresholds were installed between the 2022 and 2023 growing seasons, resulting in fewer differences observed in

https://doi.org/10.1017/wsc.2025.10058

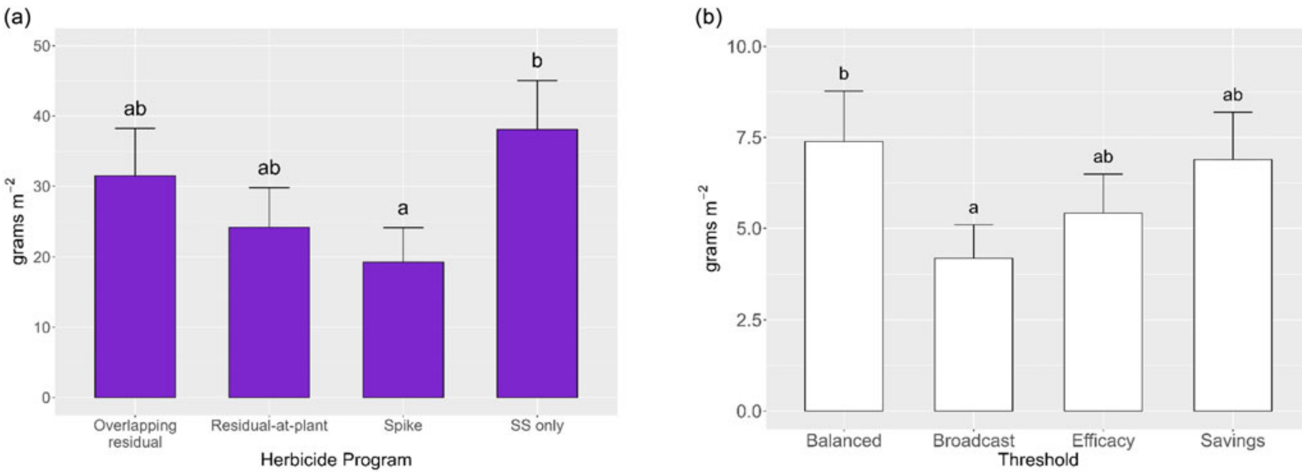

Figure 2. End-of-season weed biomass (g m^{-2} ±SE) in corn for (A) herbicide application programs in MAN 1 field in Manhattan 2022 and (B) weed detection thresholds in MAN 2 field in Manhattan 2023. Herbicide application programs for corn are provided in Table Table 2. For each panel, different letters above each bar indicate significance at $\alpha = 0.05$.

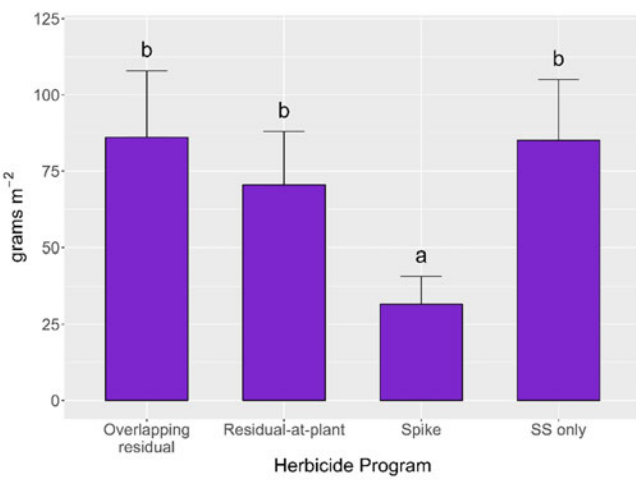

Figure 3. End-of-season weed biomass (g m^{-2} ±SE) in soybean for the herbicide application programs in MAN 2 field in Manhattan KS 2022. Herbicide programs for soybean are provided in Table 3. Different letters above each bar indicate significance at $\alpha = 0.05$.

2023 between Broadcast and Efficacy thresholds. These changes improved the ability to detect and spray with the SS foliar applications.

End-of-Season Weed Dry Biomass and Grain Yield

End-of-season weed biomass had different results depending on the crop. For corn studies in both Manhattan 2022 and 2023, no interaction between herbicide program and detection threshold was observed. However, main effect of herbicide program was significant for the Manhattan 2022 study ($P = 0.03$), and detection threshold was significant for the Manhattan 2023 study ($P = 0.04$) (Figure 2). In 2022, the Spot-spray-only program had the greatest weed biomass, while the Spike program had the least weed biomass. For the soybean study, only the herbicide program had a significant effect and only in Manhattan 2022 ($P = 0.004$) (Figure 3). Compared with the corn study on the MAN 1 field of that same year, overall weed biomass was greater in soybean, because the MAN 2 field had overall greater weed occurrence. However, the Spike program had less weed biomass than the Overlapping residual, Residual-at-plant, and Spot-spray-only programs. This also corresponds to the greater percentage of area infested with weeds observed for Spot-spray-only program as compared with the Spike program (Figure 1). The Spike program consistently resulted in the least weed biomass for both the Manhattan 2022 corn and soybean fields. No end-of-season weed biomass data were collected from the Seymour studies.

Yield data were collected from soybean in Manhattan 2022 and from corn in Manhattan 2022 and 2023, but no differences were detected in yield for interactions or main effects of herbicide program or detection threshold (data not shown). Averaged across all plots, the Manhattan 2022 soybean plots yielded more (2.934 Mg ha^{-1}) than the 2022 average soybean yield for Riley County, KS (2.370 Mg ha^{-1}; USDA-NASS 2023b). Corn grain yield did not differ across herbicide programs or detection thresholds for both Manhattan years. Overall, Manhattan 2023 had greater yield (7.020 ± 0.3 Mg ha^{-1}) than Manhattan 2022 (6.370 ± 0.3 Mg ha^{-1}), but was below the 2022 average corn yield for Riley County, KS (9.360 Mg ha^{-1}; USDA-NASS 2023a). The field conditions of the two locations differed in that MAN 1 was on a hilltop and more eroded, with less topsoil thickness, and rainfall would easily run off, while MAN 2 was situated at the bottom of a slope and would retain rainfall more easily. Overall, 2022 was a wetter year, with a total rainfall of 829 mm, compared with 2023, which had a total rainfall of only 624 mm (Kansas Mesonet 2024). Rainfall amounts in both years were less than the 30-yr average of 848 mm (Kansas State University 2024).

In general, based on results of weed infestation and biomass, the Efficacy threshold should be selected when using intelligent sprayers such as the ONE SMART SPRAY. This would decrease the likelihood that weeds are missed but could increase the likelihood of false-positive detections (i.e. detecting crop plants as weeds). However, in herbicide-tolerant cropping systems, this would not affect crop safety, provided all product labels are followed correctly (Barnhart et al. 2022). In addition, residual herbicides should be included with application programs for intelligent sprayers, as such products have clearly shown reduced weed densities for GOG applications (Bell et al. 2015; Nunes et al. 2018; Nurse et al. 2006).

Table 6. Herbicide program costs (US$ ha^{-1} ± SE) for soybean (Manhattan, KS, 2023 and Seymour, IL, 2023) and corn (Manhattan, KS, 2023)

Location–year–crop	Herbicide program cost[a]			
Herbicide program	Broadcast	Efficacy	Balanced	Savings
Manhattan, KS–2023–Soybean	US$ ha^{-1}			
Residual at-plant	217 (0) a	72 (7) d	68 (7) d	63 (6) d
Overlapping residual	217 (0) a	74 (8) d	76 (8) d	73 (7) d
Spike	211 (0) a	134 (7) bc	134 (7) bc	127 (7) c
Spot-spray-only	168 (0) b	44 (6) de	50 (6) de	32 (5) e
Seymour, IL–2023–Soybean				
Residual at-plant	217 (0) a	64 (7) cde	80 (8) c	71 (7) c
Overlapping residual	217 (0) a	72 (7) c	67 (7) cd	75 (7) c
Spike	209 (0) a	135 (9) b	145 (9) b	133 (9) b
Spot-spray-only	168 (0) b	35 (6) de	56 (8) cde	34 (5) e
Manhattan, KS–2023–Corn				
Residual at-plant	212 (0) a	172 (3) bc	157 (3) cd	157 (3) c
Overlapping residual	214 (0) a	170 (4) bcd	157 (4) c	157 (4) c
Spike	210 (0) a	176 (4) bc	181 (3) b	178 (4) b
Spot-spray-only	137 (0) e	107 (4) f	105 (4) f	93 (4) f

[a]Herbicide costs were computed using the as-applied map from the ONE SMART SPRAY system. Means within a location, year, and crop, followed by different letters, indicate results of Tukey's honest significant difference test at $\alpha = 0.05$.

Cost of Herbicide Programs and Detection Threshold

There is an opportunity for economic savings if less herbicide is applied across different herbicide program approaches and detection thresholds when using intelligent sprayers. Differences in total herbicide cost are presented for all four crop sites in 2023. Unfortunately, the 2022 data were lost to the ONE SMART SPRAY raw data decoder. Costs were determined solely based on as-applied herbicide geospatial data that were collected by the sprayer, and data were not validated by ground-truth measurements.

For both soybean and corn at Manhattan 2023, all detection thresholds resulted in lower costs than the corresponding Broadcast application across all herbicide programs. The Spot-spray-only program with all three SS detection thresholds cost less than the Residual-at-plant, Overlapping-residual (because of broadcast soil-residual herbicides), and Spike (because of broadcast foliar herbicides) programs. Soybean costs were similar for Seymour 2023 and for Manhattan, with all detection thresholds costing less than their respective Broadcast applications. The average savings across detection thresholds (i.e., difference between average detection threshold cost and Broadcast application cost) was US$123 ha^{-1} for soybean but only US$43 ha^{-1} for corn. The difference in savings between soybean and corn studies at Manhattan in 2023 can be attributed to level of weed occurrence and crop growth stage. First, greater weed occurrence in corn in the MAN 2 field compared with soybean in the MAN 1 field in 2023 resulted in more detections and required the sprayer to apply herbicide more often. Second, the GOG application occurred on taller corn plants that were at the V5 growth stage. As a result, corn leaves created a broader canopy, making less of the space between rows visible, and the ONE SMART SPRAY sprayer defaulted to a broadcast application (vs. detection thresholds) when interrow space could not be clearly observed. Total herbicide cost for corn at Seymour 2023 was different by main effect of weed detection thresholds, such that the cost of Broadcast (US$188 ha^{-1}) was greater than the cost of Efficacy (US$129 ha^{-1}), Balanced (US $158 ha^{-1}), and Savings (US$128 ha^{-1}) thresholds. Costs of the Overlapping-residual (US$181 ha^{-1}), Residual-at-plant (US $172 ha^{-1}), and Spike (US$161 ha^{-1}) herbicide programs were not different from one another, while the Spot-spray-only program cost less (US$90 ha^{-1}) than any of the other programs. Despite cost being less for Spot-spray-only programs, it was clear that the weed-free area was less than desired.

Herbicide cost reductions are possible using ONE SMART SPRAY sprayer with weed detection thresholds compared with traditional broadcast applications. The cost of the Efficacy threshold (could spray more due to false-positive detections) was never different from the cost of the Balanced or Savings thresholds (Table 6). An advantage of the ONE SMART SPRAY sprayer is the two-boom, two-tank system, in which simultaneously broadcasting a soil-residual herbicide and SS foliar herbicides can still result in herbicide cost savings. This supports our recommendation of using herbicide Efficacy thresholds for GOG SS applications along with foundational use of residual herbicides in intelligent sprayer applications.

This research demonstrated that significant herbicide use reductions are possible with intelligent sprayers compared with broadcast applications. Residual herbicides and multiple passes are still important when using this technology. Growers would benefit from the use of two-boom, two-tank intelligent sprayers for these simultaneous applications as they become available on the market. However, some of the herbicide programs evaluated would work well with a traditional one-boom, one-tank system, either with two passes across the field (residual at plant followed by SS, or with the Spike program. Incorporating integrated weed management principles with this technology, which includes crop rotations, use of residual herbicides, ensuring multiple effective sites of action for the dominant weed species, and two-pass programs, is still very important.

Acknowledgments. We thank Greg Kruger and Bruno Canella Vieira as coordinators of the ONE SMART SPRAY project with BASF Digital Farming. This is Contribution no. 25-126-J from the Kansas Agricultural Experiment Station.

Funding statement. We acknowledge support from BASF Corporation, the National Corn Growers Association (NCGA), and the North Central Soybean Research Program (NCSRP).

Competing interests. KAM was employed by BASF Corporation and conducted the research at Seymour, IL, in 2023. The other authors declare no competing interests.

References

Ahmad A, Saraswat D, Aggarwal V, Etienne A, Hancock B (2021) Performance of deep learning models for classifying and detecting common weeds in corn and soybean production systems. Comput Electron Agric 184:106081

Albawi S, Mohammed TA, Al-Zawi S (2017) Understanding of a convolutional neural network. Pages 1–6 *in* Proceedings of the 2017 International Conference on Engineering & Technology. Antalya, Turkey: Institute of Electrical and Electronics Engineers

Barnhart IH, Lancaster S, Goodin D, Spotanski J, Dille JA (2022) Use of open-source object detection algorithms to detect Palmer amaranth (*Amaranthus palmeri*) in soybean. Weed Sci 70:648–662

Barroso J, Fernandez-Quintanilla C, Maxwell BD, Rew LJ (2004) Simulating the effects of weed spatial pattern and resolution of mapping and spraying on economics of site-specific management. Weed Res 44:460–468

Bell HD, Norsworthy JK, Scott RC (2015) Effect of drill-seeded soybean density and residual herbicide on Palmer amaranth (*Amaranthus palmeri*) emergence. Weed Technol 29:697–706

Bongiovanni R, Lowenberg-DeBoer J (2004) Precision agriculture and sustainability. Precis Agric 5:359–387

Brooks ME, Kristensen K, van Benthem KJ, Magnusson A, Berg CW, Nielsen A, Skaug HJ, Maechler M, Bolker BM (2017) glmmTMB balances speed and flexibility among packages for zero-inflated generalized linear mixed modeling. R J 9:378–400

CoCoRaHS (2024) CoCoRaHS Historical Data for Station IL-CP-62: Champaign 2.5 S. https://dex.cocorahs.org/stations/IL-CP-62/precip-summary?from=2023-07-27&to=2023-08-31. Accessed: January 14, 2024

Fernández-Quintanilla C, Peña JM, Andújar D, Dorado J, Ribeiro A, López-Granados F (2018) Is the current state of the art of weed monitoring suitable for site-specific weed management in arable crops? Weed Res 58:259–272

Gao J, French AP, Pound MP, He Y, Pridmore TP, Pieters JG (2020) Deep convolutional neural networks for image-based *Convolvulus sepium* detection in sugar beet fields. Plant Methods 16:29

Gerhards R, Sanchez DA, Hamouz P, Peteinatos GG, Christensen S, Fernández-Quintanilla C (2022) Advances in site-specific weed management in agriculture—a review. Weed Res 62:123–133

Gillies S, van der Wel C, Van den Bossche J, Taves MW, Arnott J, Ward BC, *et al.* (2023) Shapely. https://doi.org/10.5281/zenodo.7583915. Accessed: October 2, 2023

Greeneye Technology (2023) Our Technology. https://greeneye.ag/technology/. Accessed: September 25, 2023

Hartig F (2022) DHARMa: Residual Diagnostics for Hierarchical (Multi-level/Mixed) Regression Models. R Package v. 0.4.6. https://CRAN.R-project.org/package=DHARMa. Accessed: October 2, 2023

Huang H, Deng J, Lan Y, Yang A, Deng X, Zhang L (2018) A fully convolutional network for weed mapping of unmanned aerial vehicle (UAV) imagery. PLoS ONE 13:e0196302

Hussain N, Farooque AA, Schumann AW, McKenzie-Gopsill A, Esau T, Abbas F, Acharya B, Zaman Q (2020) Design and development of a smart variable rate sprayer using deep learning. Remote Sens 12:4091

Jabir B, Falih N (2022) Deep learning-based decision support system for weeds detection in wheat fields. Int J Elec Comput Eng 12:816–825

Jin X, McCullough PE, Liu T, Yang D, Zhu W, Chen Y, Yu J (2023) A smart sprayer for weed control in bermudagrass turf based on the herbicide weed control spectrum. Crop Prot 170:106270

John Deere (2023) See & Spray Ultimate: Targeted, In-Crop Spraying. https://www.deere.com/en/sprayers/see-spray-ultimate/. Accessed: September 25, 2023

Jordahl K, van den Bossche J, Fleischmann M, Wasserman J, McBride J, Gerard J, Tratner J, Perry M, Badaracco AG, Farmer C, Hjelle GA, Snow AD, Cochran M, Gillies S, Culbertson L, *et al.* (2020) Geopandas/geopandas: v0.8.1. https://doi.org/10.5281/zenodo.3946761. Accessed: October 2, 2023

Kansas Mesonet (2024) Kansas Mesonet Historical Data. https://mesonet.k-state.edu/weather/historical/#. Accessed: January 14, 2024

Kansas State University (2024) Monthly Precipitation Maps. https://climate.k-state.edu/precip/county/. Accessed: March 3, 2024

Kaul V, Enslin S, Gross SA (2020) History of artificial intelligence in medicine. Gastrointest Endosc 92:807–812

Kluyver T, Ragan-Kelley B, Pèrez F, Granger B, Bussonnier M, Fredrick J, Kelley K, Hamrick J, Grout J, Corlay S, Ivanov P, Avila D, Abdalla S, Willing C, Jupyter Development Team (2016) Jupyter Notebooks—a publishing format for reproducible computational workflows. Pages 87–90 *in* Proceedings of the 20th International Conference on Electronic Publishing. Göttingen, Germany: Electronic Publishing

Lancaster SR, Fick WH, Currie RS, Kumar V (2023) 2023 Chemical Weed Control for Field Crops, Pastures, Rangeland, and Noncropland. https://bookstore.ksre.ksu.edu/pubs/chemweedguide.pdf. Accessed: October 2, 2023

Lenth R (2023) emmeans: Estimated Marginal Means, aka Least-Squares Means. R Package v. 1.8.6. https://CRAN.R-project.org/package=emmeans. Accessed: October 2, 2023

Maxwell BD, Luschei EC (2005) Justification for site-specific weed management based on ecology and economics. Weed Sci 53:221–227

McCarthy J (2007) What Is Artificial Intelligence? Stanford, CA: Computer Science Department, Stanford University. 2 p

Miranda JWA, Jhala AJ, Bradshaw J, Lawrence NC (2022) Control of acetolactate synthase-inhibiting herbicide-resistant Palmer amaranth (*Amaranthus palmeri*) with sequential applications of dimethenamid-P in dry edible bean. Weed Technol 36:325–333

Nguyen DV, Kuhnert L, Kuhnert KD (2012) Structure overview of vegetation detection. A novel approach for efficient vegetation detection using an active lighting system. Robot Auton Syst 60:498–508

Nunes AL, Lorenset J, Gubiani JE, Santos FM (2018) A multi-year study reveals the importance of residual herbicides on weed control in glyphosate-resistant soybean. Planta Daninha 36:e018176135

Nurse RE, Swanton CJ, Tardif F, Sikkema PH (2006) Weed control and yield are improved when glyphosate is preceded by a residual herbicide in glyphosate-tolerant maize (*Zea mays*). Crop Prot 25:1174–1179

Osorio K, Puerto A, Pedraza C, Jamaica D, Rodríguez L (2020) A deep learning approach for weed detection in lettuce crops using multispectral images. AgriEngineering 2:471–488

Owen MDK, Beckie HJ, Leeson JY, Norsworthy JK, Steckel LE (2015) Integrated pest management and weed management in the United States and Canada. Pest Manag Sci 71:357–376

Python (2023) Python 3.9.17 Documentation. https://docs.python.org/3.9/index.html. Accessed: October 2, 2023

QGIS (2023) Documentation for QGIS 3.22. https://docs.qgis.org/3.22/en/docs/. Accessed: October 2, 2023

Quigley N (2023) Bosch BASF Smart Farming and AGCO Announce Joint Development and Commercialization of Smart Spraying Capabilities. https://www.basf.com/global/en/media/news-releases/2023/04/p-23-159.html. Accessed: September 26, 2023

Ralašić I (2021) A Better mAP for Object Detection. https://towardsdatascience.com/a-better-map-for-object-detection-32662767d424. Accessed: September 27, 2023

R Core Team (2023) R: A Language and Environment for Statistical Computing. Vienna, Austria: R Foundation for Statistical Computing. https://www.R-project.org/. Accessed: October 2, 2023

Redmon J, Farhadi A (2018) YOLOv3: an incremental improvement. arXiv 1804.02767. doi: 10.48550/arXiv.1804.02767

Rozenberg G, Kent R, Blank L (2021) Consumer-grade UAV utilized for detecting and analyzing late-season weed spatial distribution patterns in commercial onion fields. Precis Agric 22:1317–1332

Ruigrok T, van Henten E, Booij J, van Boheemen K, Kootstra G (2020) Application-specific evaluation of a weed-detection algorithm for plant-specific spraying. Sensors 20:7262

Sanchez J, Gallandt ER (2020) Functionality and efficacy of Franklin Robotics' Tertill™ robotic weeder. Weed Technol 35:166–170

Sapkota B, Singh V, Cope D, Valasek J, Bagavathiannan M (2020) Mapping and estimating weeds in cotton using unmanned aerial systems-borne imagery. AgriEngineering 2:350–366

SciPy docs (2023) scipy.interpolate.griddata. https://docs.scipy.org/doc/scipy/reference/generated/scipy.interpolate.griddata.html. Accessed: October 2, 2023

Spaeth M, Sökefeld M, Schwaderer P, Gauer ME, Sturm DJ, Delatrée CC, Gerhards R (2024) Smart sprayer a technology for site-specific herbicide application. Crop Prot 177:106564

https://doi.org/10.1017/wsc.2025.10058

Turing A (1950) Computing machinery and intelligence. Mind 59:433–460
[USDA-NASS] U.S. Department of Agriculture–National Agricultural Statistics Service (2023a) 2023 Corn Yield, Kansas. https://www.nass.usda.gov/Statistics_by_State/Kansas/Publications/County_Estimates/22kscorn.pdf. Accessed: February 17, 2024
[USDA-NASS] U.S. Department of Agriculture–National Agricultural Statistics Service (2023b) 2023 Soybean Yield, Kansas. https://www.nass.usda.gov/Statistics_by_State/Kansas/Publications/County_Estimates/22KSsoy.pdf. Accessed: January 20, 2024
[USDA-NRCS] U.S. Department of Agriculture–Natural Resources Conservation Service (2023) Web Soil Survey. https://websoilsurvey.nrcs.usda.gov/app/. Accessed: September 26, 2023
van Stein B, Wang H, Kowalczyk W, Emmerich M, Bäck T (2020) Cluster-based Kriging approximation algorithms for complexity reduction. Appl Intell 50:778–791
Varella CAA, Gleriani JM, dos Santos RM (2015) Precision agriculture and remote sensing. Pages 185–203 *in* Santos F, Borém A, Caldas C, eds. Sugarcane: Agricultural Production, Bioenergy, and Ethanol. San Diego, CA: Elsevier.
Virtanen P, Gommers R, Oliphant TE, Haberland M, Reddy T, Cournapeau D, Burovski E, Peterson P, Weckesser W, Bright J, van der Walt SJ, Brett M, Wilson J, Millman KJ, Mayorov N, *et al.* (2020) SciPy 1.0: fundamental algorithms for scientific computing in Python. Nat Methods 17:261–272
Wenkel S, Alhazmi K, Liiv T, Alrshoud S, Simon M (2021) Confidence score: the forgotten dimension of object detection performance evaluation. Sensors 21:4350
Wiles LJ (2009) Beyond patch spraying: site-specific weed management with several herbicides. Precis Agric 10:277–290
Xie S, Hu C, Bagavathiannan M, Song D (2021) Toward robotic weed control: detection of nutsedge weed in bermudagrass turf using inaccurate and insufficient training data. IEEE Robot Autom Let 6:7365–7372
Yang MD, Tseng HH, Hsu YC, Yang CY, Lai MH, Wu DH (2021) A UAV open dataset of rice paddies for deep learning practice. Remote Sens 13:1358