Performance simulation of real-time vision-based variable rate precision spraying

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Abstract: Herbicide application is one of the main methods of weed control in crop fields. With the development of sensing and control technologies, variable rate (VR) herbicide application is increasingly being adopted in the industry. Machine vision is commonly used for weed detection and identification in post-emergence VR herbicide application. The recent development of deep learning and artificial intelligence has greatly improved the accuracy and efficiency of weed detection, making cost-effective VR herbicide applications more feasible. In this paper, spraying simulation models were developed to simulate real-time machine vision-based variable-rate precision spraying. The objective of this study was to examine the influence of different design factors and spraying methods on the performance of VR precision spraying, such as the total amount of herbicide saved over the uniform application method. Different sprayer travel speeds and control zone sizes were incorporated into the models. The simulated spraying methods included on/off intermittent spraying, variable-rate spraying, and uniform low-dosage base rate plus variable-rate spraying. The results showed that travel speed had no influence on herbicide savings. For the two variable-rate spraying methods, herbicide saving decreased when the control zone size increased. However, for the on/off intermittent spraying method, there was no difference in herbicide savings across different control zone sizes. Overall, the on/off intermittent spraying method resulted in approximately 10% herbicide savings, whereas the variable-rate spraying method achieved up to 45% herbicide savings compared to the uniform spraying method. These results provide valuable suggestions for determining variable-rate application strategies for precision weed management in crop production.

Keywords: weed detection, herbicide application, simulation, variable rate application

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1 Introduction

Weeds cause the most losses in agricultural production compared to other biotic stressors, such as insects, diseases, and other pests (Sahrawat et al., 2020). Weeds are undesirable plants in crop fields that compete with crops for water, sunlight, and nutrients. Weeds can cause 100% yield loss if they are left untreated (Chauhan, 2020). The annual corn production loss due to weeds in the USA and Canada amounted to an average of $26.7B from 2007 to 2013 (Soltani et al., 2016). Herbicide application is one of the primary methods used for weed control and management in agricultural fields to maximize crop productivity and quality. In addition to improving productivity, herbicide application can reduce the amount of labor and machinery expenses related to

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mechanical weed control. In row-crop production, herbicides are mostly applied either as pre-emergence agents to prevent weed seed germination or as post-emergence agents to eliminate actively growing weeds. It was estimated that more than 76% of the pesticides applied in the United States are herbicides (Fernandez-Cornejo et al., 2014).

Despite its beneficial outcomes in improving crop productivity and reducing farming operation costs, herbicide application also has considerable negative impacts (Parven et al., 2025). These negative impacts include injury to off-target vegetation due to herbicide drift, degradation of soil and water quality caused by herbicide residues, evolution of herbicide-resistant weed populations, and even human health risks due to herbicide exposure.

Spray drift describes a situation of off-target spraying when herbicide is transported to unintendedly targeted crop and vegetation leading to crop damage and yield loss. For example, glyphosate, the most widely used herbicide in the world (Valavanidis, 2018), is a non-selective systemic herbicide with broad-spectrum activity for controlling weeds before planting crops and post-emergence applications in genetically modified glyphosate-resistant (GR) crops. One of the major concerns of glyphosate application is the risk of damage to non-GM crops, mainly because of the off-target drift of the application caused by unfavorable weather conditions. Crop injury from applied off-target herbicides has been studied extensively (Huang et al., 2015; Zhang et al., 2019).

Another major negative impact of herbicide application is its environmental impact, which causes a huge environmental burden on our farmland and the entire ecosystem. Van Bruggen et al. (2018) have shown that applied herbicide can become an environmental residual that contaminates surface and groundwater with persistent herbicide presence in soil and sediments. The widespread use of herbicides has also resulted in the development of herbicide-resistant weed populations, raising concerns about sustainability. The presence of herbicide-resistant weeds will eventually result in difficulties in the use of herbicides to control weeds (Schütte et al., 2017). There are 38 weed species that have evolved resistance to glyphosate, with their distribution across 37 countries in 34 different crops, and extending into six non-crop situations (Heap and Duke, 2018). To mitigate these negative impacts, it is essential to reduce herbicide usage in crop production while maintaining or improving the efficacy of herbicides in controlling weeds. To achieve this, an important approach is to implement precision spraying based on weed distribution data and apply herbicides based on the actual need in the field.

The traditional method of herbicide application is uniform, which assumes that weeds are evenly distributed in the field. However, weed distribution in crop fields is non-uniform. Weed distribution has previously been described as an aggregated spatial distribution pattern (Beck et al., 2015). Mathematically, the distribution pattern can be defined as a negative binomial distribution (Cardina et al., 1997). This pattern suggests that the spatial distribution of weeds can be best described as patchy rather than uniform or random. For an average weed density of 20% and a moderate patchy index, approximately 30% of the field was free of weeds based on the negative binomial distribution. Only 18% of the field had a weed density equal to or greater than 10%. The uniform application method can cause under- or over-dosage to the field, which can eventually cause yield loss or environmental stress. It is also evident that if herbicides are only applied to weed-infested areas, a large amount of herbicide can be saved. Thus, to address the spatial and temporal variability of weed populations, modern agriculture has evolved toward precision weed management (Monteiro and Santos, 2022) or site-specific weed management (Gerhards et al., 2022) for improved weed control and environmental protection.

There are two approaches to precision weed management. The first is a map-driven method that uses previously recorded information or remotely sensed data (Yao and Huang, 2013) of weed distribution to produce prescription maps for variable-rate precision spraying. Currently, unmanned aerial vehicles (UAV) are widely used for weed map generation (Castellano et al., 2023). The other approach is a real-time weed-sensing-based method, which uses a machine vision method to identify weeds in real time and implement precision spraying simultaneously. Machine vision techniques effectively identify weeds by analyzing the spatial, textual, and spectral information from the acquired images. Over the past decade, deep learning (DL) and artificial intelligence (AI) have been extensively used for weed sensing and identification. Neural networks have been trained to recognize weeds for precision spraying (Partel et al., 2019). A machine learning approach that implements lightweight vision transformers with multispectral imagery acquired using a UAV was applied to map weeds in crop fields (Castellano et al., 2023). In a recent study, a novel convolutional-based reparameterization module was integrated into the DL architecture to improve both the model performance and speed of real-time weed identification (Rai et al., 2024).

Precision weed management based on real-time weed detection and identification can save a considerable amount of herbicide. One study indicated that a real-time-based patch sprayer could save 43% of the spraying liquid in simulated experiments (Hussain et al., 2020). Zanin et al. (2022) pointed out that the amount of herbicide reduction in post-emergence applications could range from 15% to 53.7%, depending on the actual weed conditions and time of application. This study aimed to evaluate the potential herbicide savings associated with real-time vision-based variable-rate spraying in a simulated weed-infested environment with different spraying parameters, such as sprayer travel speed, nozzle control zone size, and different spraying methods.

2 Materials and methods

The configuration of a precision sprayer can vary significantly depending on the purpose and application of the operations. In this study, simulation models for variable-rate precision spraying were developed based on the configuration of a real-time precision sprayer similar to that of Tian et al. (1999), who used machine vision for weed detection and then implemented variable-rate spraying (Avent et al., 2024). For weed image acquisition, a camera boom was mounted in front of the spray boom along the travel direction (Figure 1). The distance between the camera boom and spray boom was defined so that the entire system had sufficient time to perform a sequence of tasks, including image acquisition, weed segmentation, and nozzle flow rate control, at a travel speed of up to 16 km h^{-1}. Two cameras were mounted on the camera boom. The cameras were positioned to capture images from a nadir view above the crops. Each camera could capture an image size of 2.64 m (along the travel direction) and 3.48 m (along the spray boom direction) at a time. The actual image size used by the computer for image processing was 2.44 m × 3.05 m. Each camera was designed to provide control information through an onboard computer to six nozzles, with an interval of 0.51 m between the nozzles. Each nozzle could spray an area of 0.51 m. The rectangle formed by this 0.51 m width and a variable length along the travel direction was called the control zone. Thus, each camera could provide information on six control zones along the spray boom. A solenoid valve with pulse-width modulation (PWM) was used to control the flow rate for each nozzle. The solenoid valve controller was programmed with different duty cycles to provide four flow rates: 0%, 33.3%, 66.7%, and 100%.

Simulation models were built using Arena software (Rockwell Automation, Milwaukee, WI, USA). The following parameters were considered for the models:

1. Sprayer travel speed: The simulated travel speeds were set at 4.8 km h^{-1}, 8.1 km h^{-1}, and 16 km h^{-1}.

2. Control zone size: The control zone sizes for each nozzle were selected as 0.3 m × 0.51 m, 0.61 m × 0.51 m, and 1.22 m × 0.51 m.

3. Nozzle type: A flat fan nozzle was used in the model. The spray pattern of the flat fan nozzle is suitable for the control zone concept.

4. Spraying methods: Four spraying methods were

simulated in the model. The spraying methods were uniform spray, on/off intermittent spray, variable rate spray, and uniform low-dosage base rate plus variable rate spray. For each method, the model was run at different speeds with different control zone sizes.

4a. Uniform spray: This method was used for comparison. It provides a baseline for uniform application when no variable-rate spraying is implemented. In this case, all nozzles remained on with a 100% application rate applied to the control zone in the simulation. The other methods were compared to this method to determine the actual amount of herbicide saved.

4b. On/off intermittent spray: In this case, if weeds were found within the control zone, the respective nozzle would turn on and provide a 100% application rate to the control zone. If no weeds were found, the respective nozzle was turned off, resulting in a 0% application rate. The threshold for nozzle activation was a weed density of 1% or greater. Weed density is the percentage of a control zone area that is infested with weeds.

4c. Variable rate spray: If weeds were found within the control zone, the respective nozzle was turned on, and the application rate was related to the weed density of the control zone. Four spray levels were used in this method. These levels were 0%, 33.3%, 66.7%, and 100%. Weed densities corresponding to each spray level were 0%, 1-2%, 3-10%, and 11%. If no weeds were found or weed density was less than 1% within the control zone, the respective nozzle was turned off, resulting in a 0% spray rate.

4d. Uniform low-dosage base rate plus variable rate spray: This method combined uniform and variable-rate spraying methods. Ten percent of the total dosage was uniformly applied to the entire field. If weeds were found in the control zone, an additional variable rate dosage was added to the uniform rate. The variable rate levels were 0, 30%, 60%, and 90%, respectively, based on the above-mentioned weed densities.

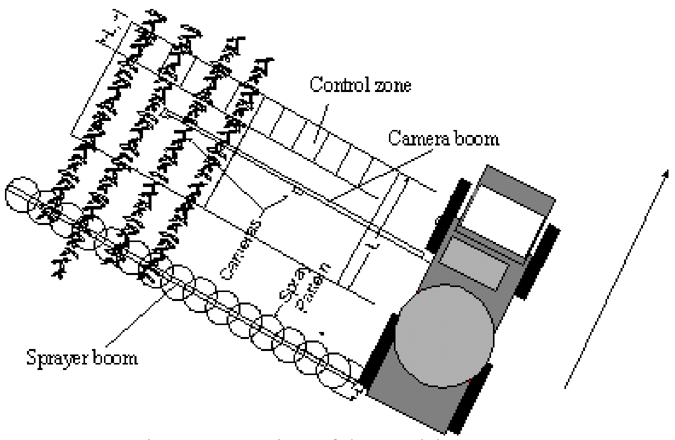

Figure 1 Top view of the precision sprayer

5. Weed detection accuracy: Weed detection accuracy describes the accuracy of weed detection using an image sensor. Without specifying the actual weed detection method, the detection accuracy for weed plants was chosen as 0.9, which was a moderate estimation of the overall weed-sensing capability. In real applications, this accuracy would change if different image processing methods were used.

6. Simulation field size: The simulation was performed on a one-acre field.

7. Error sources: Other error sources, such as wind speed, sprayer attitude, solenoid valve response delay, and mechanical system malfunction, were not considered in the models. System delays due to image acquisition, image processing, and valve control were not considered because the design specifications ensured that the sprayer would have sufficient time to process the data and issue control at the simulated speed.

For the evaluation of the results, the total amount of herbicide saved against uniform spraying was collected for each spraying method. The number of times the nozzle was switched on and off was also recorded to evaluate the influence of spraying methods, along with other factors such as speed and control zone size, on the durability of the nozzles and solenoid valves.

While the model was running, the weed density was calculated based on the negative binomial distribution. The negative binomial distribution is described by the following Equation (Davis, 1994):

$$P(x) = \frac{(k+x-1)!}{x!(k-1)!} p^x q^{-(x+k)}$$

x=0, 1, 2, …

$$p = \frac{\mu}{k}, \quad q = 1 + p$$

where μ is the mean weed density of the entire field, and k is the weed patchy index. The smaller the k, the greater the number of aggregated weeds. x is weed density. P(x) is the probability distribution as a function of the weed density.

Weed density was randomly generated within each control zone based on the above distribution using the following process. In this paper, μ was set to 20%, and k was set to 0.3. Weed distribution was initially generated for a control zone size of 0.3 m × 0.51 m. Each 0.3 m × 0.51 m control zone was subdivided into 10 small areas. Weed density was generated for each small area based on the above distribution. The weed density of each 0.3 m × 0.51 m control zone was the average weed density of the 10 small areas. For the 0.61 m × 0.51 m control zone size, the weed density of two consecutive 0.3 m × 0.51 m control zones along the travel direction were averaged, and the number was assigned to the new 0.61 m × 0.51 m control zone as its weed density. The same parameters were applied to the 1.22 m × 0.51 m control zone. To simplify the models, weed density was generated at only 10 levels. The final spray level for variable spraying was set to four based on the above variable spray criteria.

Two processes were created while the model was running. One process simulated the image processing procedure, which determined the weed density in the control zone and issued spray level commands to the nozzle controller. The other process simulated the nozzle controller for each solenoid valve and changed the pulse width based on the computed spray level for each nozzle. The total amount of herbicide used (in relative terms, i.e., for each control zone, 1 with 100% rate application, 0 with 0% rate), and the average nozzle on/off counts were recorded in the controller process.

3 Results and discussion

Table 1 shows the probability distributions for the 10 weed density levels described in the Methods section. The weed density for each weed level is listed in the table. The resulting probability distribution of weeds indicated that 28.2% of the field was free of weeds. Only 14.5% of the field had weed density greater than the average field weed density, which is 20%. It is obvious that uniform spraying at 100% rate would cause considerable waste of herbicide.

Table 1 Weed density levels, used in the models

Levels	0	1	2	3	4	5	6	7	8	9
Weed density (%)	0	1	2	3 -4	5 -6	7 -10	11 -20	21 -40	41 -60	61 -100
Probability distribution (%)	28.2	13.9	9.1	10.3	6.3	7.1	10.6	8.4	3.5	2.6

Tables 2, 3, and 4 show the herbicide saving results under different sprayer travel speeds and control zone sizes for the on/off intermittent spraying method, variable rate spraying method, and uniform low-dosage base rate plus variable rate spraying, respectively. A common feature of all three methods is that the sprayer travel speed has almost no influence on the total amount of herbicide saved. For the on/off intermittent spraying (Table 2), herbicide saving did not change for different control zone sizes and different travel speeds. For the variable rate spraying (Table 3) and uniform low-dosage base rate plus variable rate spraying (Table 4) methods, herbicide savings decreased as the control zone size increased. Specifically, for the variable-rate spraying method, the percentage of savings increased from 40.6% when the control zone size was 1.22 m× 0.51 m to 45.1% when the control zone size was 0.3 m× 0.51 m. Similarly, for the uniform low-dosage base rate plus variable rate spraying method, the percentage of saving increased from 36.6% when the control zone size was 1.22 m × 0.51 m to 40.6% when the control zone size was 0.3 m× 0.51 m. These results suggest that a smaller control zone size will save more herbicides than larger control zones.

Table 2 On/off intermittent spray: percentage saved over uniform spray

Control zone size (m x m)	Speed (km h^{-1})		
	4.8	8.1	16
(0.3 x 0.51)	9.7	9.7	9.9
(0.61 x 0.51)	9.3	9.4	9.6
(1.22 x 0.51)	9.4	9.5	9.5

Table 3 Variable rate spray: percentage saved over uniform spray

Control zone size (m x m)	Speed (km h^{-1})		
	4.8	8.1	16
(0.3 x 0.51)	45.1	45.1	45.1
(0.61 x 0.51)	43.0	43.1	43.1
(1.22 x 0.51)	40.6	40.6	40.6

Table 4 Base+variable rate spray: percentage saved over uniform spray

Control zone size (m x m)	Speed (km h^{-1})		
	4.8	8.1	16
(0.3 x 0.51)	40.6	40.6	40.6
(0.61 x 0.51)	38.7	38.8	38.8
(1.22 x 0.51)	36.6	36.6	36.5

Table 5 On/off intermittent spray: average nozzle on/off count

Control zone size (m x m)	Speed (km h^{-1})		
	4.8	8.1	16
(0.3 x 0.51)	385	385	263
(0.61 x 0.51)	187	187	187
(1.22 x 0.51)	94	94	94

Table 6 Variable rate spray: average nozzle on/off count

Control zone size (m x m)	Speed (km h^{-1})		
	4.8	8.1	16
(0.3 x 0.51)	9655	5793	2897
(0.61 x 0.51)	9682	5808	2904
(1.22 x 0.51)	9684	5811	2906

Although the uniform low-dosage base rate plus variable rate spraying method applied almost 10% more herbicide than the variable rate spraying method, there was only a 5% increase in total herbicide spending over the variable rate spraying method. This method provides a practical approach to using variable rate technology (VRT) because it ensures that some level of herbicide is applied across the field, even if the variable application part of the sprayer is not working properly. For the on/off intermittent spraying method, there was no difference in herbicide saving for different control zone sizes when the threshold (weed density) for turning on the nozzle was 1%.

Tables 5 and 6 show the average nozzle on/off switch counts for the on/off intermittent and variable-rate spraying methods, respectively. For the on/off intermittent spraying method, speed did not influence the number of times the nozzle switched on and off (except when the control zone size was 0.3 m × 0.51 m and speed was 16 km h^{-1}). For the same speed, the average nozzle on/off counts decreased when the control zone size increased. However, for the variable-rate spraying method, the control zone size had no influence on the average valve switch count. For the same control zone size, the nozzle on/off count decreased as the sprayer speed increased. High nozzle on/off counts may pose challenges to sprayer hardware, such as shortening the lifespan of the nozzles and solenoid valves.

4 Conclusion

To combat the ever-increasing costs of herbicide applications and to accommodate better environmental protection, variable-rate herbicide applications are increasingly used in the agricultural industry. In this study, spraying simulation models were built to simulate precision spraying using real-time weed detection and variable-rate herbicide application. Various design factors, such as sprayer speed and control zone size, were examined to evaluate their impact on the total amount of herbicide saved across different spraying methods. The results showed that travel speed had no effect on herbicide savings. For the two variable rate spraying methods, herbicide saving decreases when control zone size increases. However, there was no difference in herbicide savings with different control zone sizes for the on/off intermittent spraying method. For the on/off intermittent spraying model, a larger control zone size could decrease the number of nozzle on/off counts. For the variable-rate spraying model, higher speeds decreased the number of nozzle on/off counts. In total, the variable-rate spraying method could save up to 45% of herbicide, while the on/off intermittent spraying method could save approximately 10% compared to the uniform spraying method. These findings are expected to provide guidance for the development of real-time machine-vision-based variable-rate application strategies for precision weed management in crop production.

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References

Avent, T. H., J. K. Norsworthy, W. L. Patzoldt, L. M. Schwartz-Lazaro, M. M. Houston, T. R. Butts, and A. R. Vazquez. 2024. Comparing herbicide application methods with See & Spray^{TM} technology in soybean. *Weed Technology*, 38: e74.

Beck, E. A., A. M. Lefcourt, Y. M. Lo, and M. S. Kim. 2015. Use of a portable fluorescence imaging device to facilitate cleaning of deli slicers. *Food Control*, 51: 256–262.

Cardina, J., G. A. Johnson, and D. H. Sparrow. 1997. The nature and consequence of weed spatial distribution. *Weed Science*, 45(3): 364–373.

Castellano, G., P. De Marinis, and G. Vessio. 2023. Weed mapping in multispectral drone imagery using lightweight vision transformers. *Neurocomputing*, 562: 126914.

Chauhan, B. S. 2020. Grand Challenges in Weed Management. *Frontiers in Agronomy*, 1: 3.

Davis, P. M. 1994. Statistics for Describing Populations. In *Handbook of Sampling Methods for Arthropods in Agriculture*, eds. L. P. Pedigo, and G.D. Buntin, ch. 3, 38-40. Boca Raton, FL: CRC Press.

Fernandez-Cornejo, J., R. F. Nehring, C. Osteen, S. Wechsler, A. Martin, and A. Vialou. 2014. Pesticide Use in U.S. Agriculture: 21 Selected Crops, 1960-2008. Economic Information Bulletin No. 124. Washington, DC: U.S. Department of Agriculture, Economic Research Service.

Gerhards, R., D. Andújar Sanchez, P. Hamouz, G. G. Peteinatos, S. Christensen, and C. Fernandez-Quintanilla. 2022. Advances in site-specific weed management in agriculture—A review. *Weed Research*, 62(2): 123–133.

Heap, I., and S. O. Duke. 2018. Overview of glyphosate-resistant weeds worldwide. *Pest Management Science*, 74(5): 1040–1049.

Huang, Y., K. N. Reddy, S. J. Thomson, and H. Yao. 2015. Assessment of soybean injury from glyphosate using airborne multispectral remote sensing. *Pest Management Science*, 71(4): 545–552.

Hussain, N., A. A. Farooque, A. W. Schumann, A. McKenzie-Gopsill, T. Esau, F. Abbas, B. Acharya, and Q. Zaman. 2020. Design and Development of a Smart Variable Rate Sprayer Using Deep Learning. *Remote Sensing*, 12(24): 4091.

Monteiro, A., and S. Santos. 2022. Sustainable Approach to Weed Management: The Role of Precision Weed Management. *Agronomy*, 12(1): 118.

Partel, V., S. Charan Kakarla, and Y. Ampatzidis. 2019. Development and evaluation of a low-cost and smart technology for precision weed management utilizing artificial intelligence. *Computers and Electronics in Agriculture*, 157: 339–350.

Parven, A., I. M. Meftaul, K. Venkateswarlu, and M. Megharaj. 2025. Herbicides in modern sustainable agriculture: environmental fate, ecological implications, and human health concerns. *International Journal of Environmental Science and Technology*, 22(2): 1181–1202.

Rai, N., Y. Zhang, M. Villamil, K. Howatt, M. Ostlie, and X. Sun. 2024. Agricultural weed identification in images and videos by integrating optimized deep learning architecture on an edge computing technology. *Computers and Electronics in Agriculture*, 216: 108442.

Sahrawat, A., S. N. Rahul, S. K. Singh, and S. Patel. 2020. The potential benefits of weeds: A comparative study: A review. *International Journal of Chemical Studies*, 8(2): 148–154.

Schütte, G., M. Eckerstorfer, V. Rastelli, W. Reichenbecher, S. Restrepo-Vassalli, M. Ruohonen-Lehto, A. W. Saucy, and M. Mertens. 2017. Herbicide resistance and biodiversity: agronomic and environmental aspects of genetically modified herbicide-resistant plants. *Environmental Sciences Europe*, 29(1): 5.

Soltani, N., J. A. Dille, I. C. Burke, W. J. Everman, M. J. VanGessel, V. M. Davis, and P. H. Sikkema. 2016. Potential Corn Yield Losses from Weeds in North America. *Weed Technology*, 30(4): 979–984.

Tian, L., J. F. Reid, and J. W. Hummel. 1999. Development of a precision sprayer for site-specific weed management. *Transactions of the ASAE*, 42(4): 893–900.

Valavanidis, A. 2018. Glyphosate, the most widely used herbicide. *Scientific Reviews*, 1: 1-36.

Van Bruggen, A. H. C., M. M. He, K. Shin, V. Mai, K. C. Jeong, M. R. Finckh, and J. G. Morris. 2018. Environmental and health effects of the herbicide glyphosate. *Science of The Total Environment*, 616: 255–268.

Yao, H., and Y. Huang. 2013. Remote Sensing Applications for Precision Farming. In *Remote Sensing of Natural Resources*, eds. G. Wang, and Q. Wen, ch. 18, 333-352. Boca Raton: CRC Press.

Zanin, A. R. A., D. C. Neves, L. P. R. Teodoro, C. A. Da Silva Júnior, S. P. Da Silva, P. E. Teodoro, and F. H. R. Baio. 2022. Reduction of pesticide application via real-time precision spraying. *Scientific Reports*, 12(1): 5638.

Zhang, J., Y. Huang, K. N. Reddy, and B. Wang. 2019. Assessing crop damage from dicamba on non-dicamba-tolerant soybean by hyperspectral imaging through machine learning. *Pest Management Science*, 75(12): 3260–3272.