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Precision farming techniques for sustainable weed management

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Abstract

Weed management in modern agriculture is crucial to avoid yield losses and ensure food security. Climate change, intensive agricultural practices, and natural disasters change weed dynamics, requiring changes in weed management strategies. In addition to labor shortages, manual and chemical control options are no longer viable because of weed resistance to herbicides and the effects of eco-degradation and health hazards. As a result, weed management strategies that boost agricultural productivity are urgently needed. Precision agriculture has become one alternative for managing weeds, using tools and technologies to boost farm productivity. Recent innovations in precision application technology have made it possible to make smaller treatment units that can be applied to meet site-specific demands. These systems combine ground-based and aerial weed sensing systems (that are site-specific, need-specific, and cost-effective) with integrated weed management. Despite the viability of all of these strategies in today's agriculture, site-specific selections and the appropriate combination of these eco-friendly strategies can efficiently reduce herbicide use, and ensure environmental protection while enhancing weed control efficiency and crop yield.

Keywords aerial sensors, crop yield loss, ground-based sensors, precision agriculture, weed management

Introduction

During the last few decades, population growth has exerted a tremendous amount of pressure on crop production, which has forced farmers to intensify agriculture to meet rising food demands. Due to their competition and allopathic effects, weeds significantly reduce crop yields. Further, weeds serve as a habitat for insect pests, fungi, and bacteria that can harm nearby crops, and help support other biological components of the environment [1-3]. In modern agriculture, due to intensive management practices, ecological changes, and climate change, weed infestations and weed behaviors change very frequently [4-5]. Weed control can be done either mechanically with the application of herbicides or with specific cultivation practices [6]. However, intensive mechanization encourages soil erosion [7], leading to degradation in soil fertility. Herbicide use can pollute the air, food, soil, and water causing human and animal health hazards [8], creating weeds, herbicide-resistant, and unbalancing ecosystems. Find solutions to all these problems and increase agricultural productivity, robotics number and site-specific solutions used in precision agriculture have increased significantly in recent years. An expanding array of new technologies are being developed and implemented in agricultural practices, which are also crucial to progress toward sustainable weed management on an economic and environmental level. [6]. When weeds are controlled accurately, inputs are reduced without affecting the effectiveness of weed control [9]. Sensory, weeding and spraying technologies have brought about significant cost savings and technical advances, and some of these have been exploited commercially. [6]. Weed control methods used in precision agriculture are accurate and precise and intended to target specific weeds. The early twentieth century saw the advent of a new weed management approach that was site-specific. It started with grid sampling and mapping of weeds [10-11]. Through the mapping of weeds and spraying of herbicides in a site-specific manner in more than fifty field experiments with, maize, sugar beets, cereals, and peas, researchers saved 22%–89% in herbicide usage without compromising crop yields or increasing weed control costs in the succeeding years [6, 12-13]. It may be possible to reduce herbicide usage even more if these herbicides are site as well as species-specific [14]. Currently, numerous applications of this concept are being explored such as weed control using cameras, remote sensing-based patch spraying, and weeding using robotic technology.

Researchers are currently developing several other prototypes, including electrical weed control using sensor-based technology [15], unmanned aerial vehicle (UAV)-based mapping of weeds, and site-specific spraying of herbicides [16-17] and target-based weed control with controlled application of herbicides [18-19].

Weed detection/recognition by precision agriculture technology

Hyper-spectral/Multi-spectral imagery (Remote sensing)

Slaughter et al., [20] reportedly tried to differentiate between the tomato plant from nightshade weed (*Solanumnigrum* L.) using a broadband color classifier and a narrowband (10 nm bandwidth) visible region hyper-spectral classifier. In controlled spectrophotometer measurements of around 400 leaf samples, digitalized data from the 8-bit/band showed that the broadband color classification rate was 76% while the narrowband classification rate was 87%. Although the broadband color classifier accuracy did not change when digitalizing the data at 12-bits/band, the narrowband classifier performance increased to 95%. Borregaard et al., [21] reported an accuracy of 89-94% in crop versus weed classification at 694 nm and 970 nm wavelength using narrowband reflectance in comparison to other wavelengths while exploring the potential of ground-based hyperspectral machine vision systems. A similar study done by Feyaerts and van Gool [22] reported that when seventy hyperspectral images of sugar beet and 5 different weeds each were collected, the weed identification rate of 80% and 91% were recorded for sugar beet and weeds, respectively. Koger et al., [23] reported that multispectral imagery for weed identification was highly successful in weed-infested soybean as the differentiation rate was 88 to 92% for experiment 1, and for experiment 2, it was 85-96% across all the images.

Unmanned Arial Vehicle (Remote sensing)

Lee [24] reported that with SUMINV combined with ELG and CMP, the rate of true leaf recognition went from 38.0% to 62.0%, but the rate of cotyledon recognition decreased even more with a decline from 80% to 6.7%. These three factors also increased the weed recognition rate to 76.5%, while decreasing the recognition rate of miscellaneous tomato leaves to 0%. These results indicate that a high level of variability in shape patterns is observed when the shape is described by a top view of a single two-dimensional plant in an uncontrolled environment. Pflanz et al., [25] reported that a UAV platform with an altitude between 2.5 and 4.0 m yielded the best accuracy and precision for weed mapping. With 87% MATCH had the highest mapping precision and at lower altitudes, VIOAR and PAPRH obtained at par high precision values. As the altitude of the UAV increased the mapping precision drastically decreased and was even below 50%.

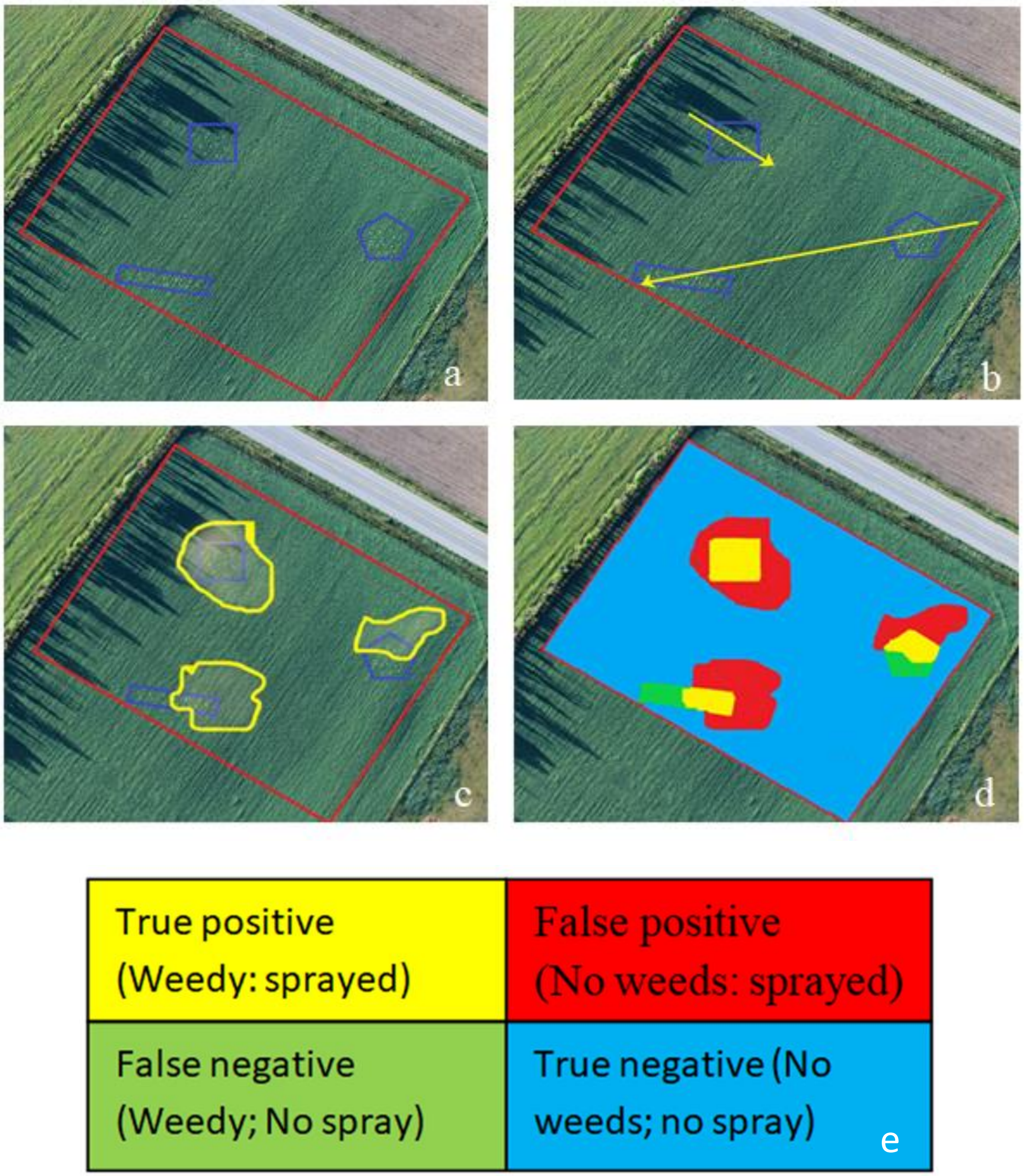

Figure 1. : Demonstration of integration of weed mapping and herbicide application by UAV's . (a). Random image of a field where weeds were mapped (blue area) (b) Specific flight paths (yellow arrows) generated to suit the areas in which the application of herbicide was needed (c). UAV images collected after the application of herbicide (d) and (e) Mapping of different areas of field categorized as true positive, false positive, false negative and true negative. These classifications help in determining the precision, accuracy and efficiency of the UAV's.

Robotic technology

A study performed by Tian et al., [26] and Lee et al., [27] explored two computer vision methods to improve species recognition based on leaf shape when used from a moving vehicle to identify crops from weeds in vivo. The recognition rate of the tomato cotyledons image sets was 40-60% in 1994 and 62-80% in 1997. While the weed recognition rate was more than 95% in 1994 and 69% in 1997. The difference in performance was due to the effort to obtain better weed and crop identification by controlled lightning in 1997. A self-governed robot made by Astrand and Baerveldt in 2002 [28] that discriminates sugar beets from weeds has proven to be one such advanced machine vision system. An analysis of color images of 214 sugar beet plants and 373 weed plants collected from many different sugar beet fields determined that the 5-NN classifier' green mean feature [g=G/ (R + G + B)] was efficient in distinguishing crops and weeds with 91% accuracy in cross-validation in comparison to color excluded, color features, Compactness, Elongation features Raja et al. (2020) [29] reported that the classification accuracy was 99.75% for lettuce plants and 83.74% for the weeds. Weeds classified as crop plants accounted for 14.37% of the total weeds, but these plants were not sprayable due to their proximity to the crop plants. As a result approx. 99% of weeds were distinguished for herbicide spraying while 98% of the weeds as sprayable. In critical in-field conditions such as high-density weeds, the algorithm provides significantly superior results than many existing methods when it comes to crop and weed detection and their discrimination used.

Influence of site-specific application/patch spraying on agroecosystem

Judicious use of herbicide

Gerhards and Oebel [13] after a six-year study on the use of herbicide with patch sprayer over different crops and fields reported that herbicide use in winter cereals was reduced by 60% against broad-leaved weeds and by 90% against grass weeds using this approach. In the case of sugar beet and maize crops, herbicide saving for grass weed was about 36% and 78% respectively. For broad-leaved weeds, the average savings for herbicide was about 11% in maize and 41% in sugar beet. In barley crops, herbicide saving ranged from 20-80% against broad-leaved weeds and 18-90% against grass weeds.

Christensen et al., [30] used a computerized decision model. This model was composed of a competition model, a herbicide dose-response model, and an algorithm to determine the economically optimal dose, among others. Five-year experiments showed that optimizing the herbicide dosage each year based on weed species composition and density decreased the use of herbicide by 45% to 67% without compromising the yields or affecting the weed population. Hamouz et al. (2013) [31] reported that using site-specific herbicide applications resulted in saving herbicide between 15.6% and 100%, depending upon the threshold and herbicide used. By using fluroxypyr, the highest savings (85.94-100%) were achieved since only a few cells were invaded by G. *aparine*.

The lower savings for metsulfuron-methyl + tribenuron-methyl herbicide (15%-60%) were attributed to the greater abundance and homogeneity of V. *arvensis* and T. *inodorum*. As recorded, higher herbicide savings were obtained with higher application thresholds. Despite the crop field being vaguely distributed with weeds in the form of patches, the results suggest that with site-specific weed control, herbicide savings can be achieved, regardless of how high the mean weed infestation might be.

Increased crop yield

Hamouz et al., [31] reported that all the site-specific treatments recorded higher yields in comparison to the blanket spraying even though none of the treatments were statistically significant. Similar results were reported by Ritter et al., [32] where he explained that the insignificance in statistical analysis resulted because the data analyzed had a high total variance, indicating that there may be other factors affecting the grain yield. Giles et al., [33] reported that all herbicidal treatments that had glyphosate resulted in 20-30 fold higher yields than other treatments/controls. It was also observed that the highest yields (372.1ab) were from smaller doses of active ingredients indicating that there were more advantages to avoiding phytotoxicity than enhancing herbicide composition and application.

Enhanced weed control efficacy

Machleb et al., [34] reported that weed density with a Motorized finger weeder with 140 rpm and a Motorized finger weeder with 60 rpm reduced significantly to 15 and 19 plants per m sq. CFW had a weed population of 37 plants/m sq. Other than that there were no differences in weed density within the mechanical treatments except for the control, in the 2017 experiment. However, with the combination of mechanical treatment with a herbicide i.e. Herbicide along with motorized finger weeder (140 rpm) and Herbicide along with Motorized finger weeder (60 rpm) weed population significantly reduced to 1.7 and 1.3 plants per m sq. respectively. In the case of Herbicide along with Conventional finger weeder, a weed population of 5.3 plants per m sq. was recorded. Machleb et al., reported the highest weed control efficacy with herbicides treatments alone in 2017 and 2018 while the lowest weed control efficacy in 2017 was for the Conventional finger weeder (79%) and Herbicidal treatment along with Conventional finger weeder and also for conventional finger weeder alone in 2018 (77-78%).

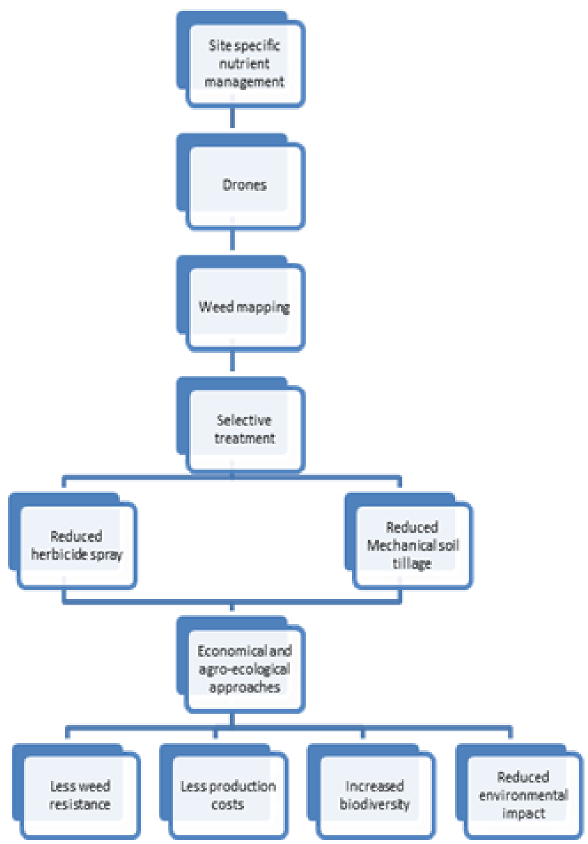

Figure 2. Economical and agro-ecological implications of using drones for site specific nutrient management

Other precision weed management tools

Sensor based technologies

Machleb et al., [34] reported higher sugar beet yield for four treatments Herbicide along with Conventional finger weeder, Herbicide along with motorized finger weeder (60 rpm), H2017, Herbicide along with motorized finger weeder (140 rpm) between 75-79 t/ha while the untreated control gave 6.9 t/ha yield(2017) and Motorized finger weeder with 140 rpm and Motorized finger weeder with 60 rpm yielded 48.5 t/ha and 52.4 t/ha, respectively while Conventional finger weeder yielded 36.2 t/ha. Low yield in Motorized finger weeder and conventional finger weeder was due to the high weed population problem. Untreated control recorded a yield loss of 91% compared to the most successful treatment of all.

UAV-IS

Hunter et al., [35] reported that the broadcast system applied herbicide to 92% of the areas where weed was absent while UAV-IS applied herbicide in only 30% of such areas, showing its much higher efficiency compared to the normal broadcast system. Only 1/3rd of the total plot area was treated with UAV-IS because of the larger weed cover.

Robotic technology

Lamm et al., [36] reported that the robots sprayed 88.8% of all weeds while identifying and leaving 78.7% of cotton plants untouched. The total error from the sum proportional to the number of weeds and cotton plants corresponded to 13.1%. The primary source of error was the misclassification of plants and weeds by the system. Secondly, the spray placement was incorrect after the target was identified by the vision system. Astrand and Baerveldt [37-39] reported that a robotic weed control system was tested in the sugar beet field. It was reported that 99% of sugar beet plants had not been taken out while 41-53% of weeds had been taken out. 31% of the weeds were growing very close to the plants and therefore were not removed while 18% of the weeds which were growing in places where sugar beet was supposed to germinate were also not taken out. Blasco et al., [40] reportedly made an electrical weed control system (robotic). An electrical discharge of 15 kV killed the weeds with the robotic end-effector. In addition to the machine vision system used for weed detection in field images, the end-effector was provided with trajectory information during the electrical probe's positioning in another method. The system detected weeds based on their size (blobs that were much bigger than crop plants), ignoring the weeds that touched lettuce plants. A field test revealed that the computerized vision system identified 84% of weeds and 99% of lettuce plants, at a computation speed of 482ms per image.

Conclusion

In conventional farms, Precision agriculture technologies for weed management will be adopted primarily because of the reduction of herbicide use and the benefits to the environment. It will also be beneficial economically by reducing the costs of herbicides as well as yield losses due to herbicide-resistant weed populations. These robust technologies have accurate weed detection and identification and mapping methods but still putting these technologies to practical use requires them to become more resilient under practical conditions. During the first years of operation, farmers must be assisted in learning about new technologies through on-farm research.

For an entire field to be monitored on an individual plant level there will need to be communications, mobile devices, and decision support software, which are factors of swarm technology. It may eventually become more important to control individual crop plants or swarms through fields using coordinated robotics than to use genetically engineered seeds or new fertilizer formulations, so further research is needed to optimize these tools and technologies for improvements in efficiency and practicability.

References

[1] J. D. Smith, T. Dubois, R. Mallogo, E. F. Njau, S. Tua and R. Srinivasan **(2019)**. Host range of the invasive tomato pesttutaabsolutameyrick (Lepidoptera: Gelechiidae) on solanaceous crops and weeds in Tanzania. Fla. Entomol., **101:** 573-579.

[2] P. Roshan, A. Kulshreshtha and V. Hallan **(2019)**. Global Weed-Infecting Geminiviruses. In: Kumar, R. (eds) Geminiviruses. Springer, Cham. doi: 10.1007/978-3-030-18248-9_6.

[3] R. Srinivasan, F. A. Cervantes and J. M. Alvarez **(2013)**. Aphid-borne virus dynamics in the potato-weed pathosystem. Insect Pests Potato.

[4] B. S. Chauhan, G. S. Gill and C. Preston **(2006)**. Tillage system effects on weed ecology, herbicide activity and persistence: a review. Aust. J. Exp. Agric., **46:** 1557-1570.

[5] B. S. Chauhan and G. S. Gill **(2014)**. Ecologically based weed management strategies. *In* Recent Advances in Weed Management, eds B. S. Chauhan and G. Mahajan. New York: Springer, pp1-11. doi: 10.1007/978-1-4939-1019-9_1.

[6] S. Christensen, H.T. Søgaard, P. Kudsk, M. Nørremark, I. Lund, E.S. Nadimi and R. Jørgensen **(2009)**. Site-specific weed control technologies. Weed Res., **49:** 233-241.

[7] G. Guccione and G. Schifani **(2001)**. Technological innovation, agricultural mechanization and the impact on the environment: Sod seeding and minimum tillage. Prospettive e propostemediterranee. J. Econ. Agric. Environ., **3:** 29-36.

[8] P. Ribas and A. Matsumura **(2009)**. A química dos agrotóxicos: Impactosobre a saúde e meio ambiente. The chemistry of pesticides: Impact on health and the environment. Rev. Lib., **10:** 149-158.

[9] S. L. Young, F. J. Pierce **(2014)**. Automation: The Future of Weed Control in Cropping Systems; Springer: Berlin/Heidelberg, Germany; pp249-259.

[10] E. J. P. Marshall **(1988)**. Field-scale estimates of grass populations in arable land. Weed Res., **28:** 191-198.

[11] L. J. Wiles, G. W. Oliver, A. C. York, H. J. Gold and G. G. Wilkerson **(1992)**. Spatial distribution of broadleaf weeds in North Carolina soybean (Glycine max) fields. Weed Sci., **40:** 554-557.

[12] T. W. Berge, S. Goldberg, K. Kaspersen and J. Netland **(2012)**. Towards machine vision based site-specific weed management in cereals. Comput. Electron. Agric., **81:** 79-86.

[13] R. Gerhards and H. Oebel **(2006)**. Practical experiences with a system for site specific weed control in arable crops using real-time image analysis and GPS-controlled patch spraying. Weed Res., **46:** 185-193.

[14] L. J. Wiles **(2009)**. Beyond patch spraying: site-specific weed management with several herbicides. Precision Agric., **10:** 277-290.

[15] D. Reiser, E. S. Sehsah, O. Bumann, J. Morhard and H. W. Griepentrog **(2019)**. Development of an autonomous electric robot implement for intra-row weeding in vineyards. Agriculture, 9: 18. doi: 10.3390/agriculture9010018.

[16] R. Mink, A. Dutta, G. Peteinatos, M. Sökefeld, J. Engels, M. Hahn and R. Gerhards (2018). Multi-temporal site-specific weed control of *Cirsium arvense* (L.) Scop and *Rumex crispus* L. in maize and sugar beet using unmanned aerial vehicle based mapping. Agriculture, 8: 65. doi: 10.3390/agriculture8050065.

[17] J. Rasmussen, J. Nielsen, F. Garcia-Ruiz, S. Christensen and J. C. Streibig **(2013)**. Potential uses of small unmanned aircraft systems (UAS) in weed research. Weed Res., **53:** 242-248.

[18] J. P. Pohl, D. Rautmann, H. Nordmeyer, D. Hoersten **(2019)**. Direkteinspeisungim Präzisionspflanzenschutz Teilflächenspezifische application von Pflanzenschutzmitteln (Direct Injection for site-specific application of pesticides). Gesunde Pflanzen, **71:** S51-S55.

[19] T. Ruigrok, E. van Henten, J. Booij, K. van Boheemen, and G. Kootstra (2020). Application-specific evaluation of a weed-detection algorithm for plant-specific spraying. Sensors, 20: 7262. doi: 10.3390/s20247262.

[20] D. C. Slaughter, W. T. Lanini and D. K. Giles **(2004)**. Discriminating weeds from processing tomato plants using visible and near-infrared spectroscopy. Trans. ASAE., **47:** 1907-1911.
[21] T. Borregaard, H. Nielsen, L. Norgaard and H. Have **(2000)**. Crop–weed discrimination by line imaging spectroscopy. J. Agric. Eng. Res., **75:** 389-400.
[22] F. Feyaerts and L. van Gool **(2001)**. Multi-spectral vision system for weed detection. Pattern Recognit. Lett., **22:** 667-674.
[23] C. Koger, D. Shaw, C. Watson and K. Reddy **(2003)**. Detecting Late Season Weed infestations in Soybean (*Glycine max*). Weed Technol., **17:** 696-704. doi: 10.1614/WT02-122.
[24] W. S. Lee **(1998)**. Robotic weed control system for tomatoes. Ph.D. dissertation, University of California, Davis.
[25] M. Pflanz, H. Nordmeyer and M. Schirrmann **(2018)**. Weed mapping with UAS imagery and a bag of visual words based image classifier. Remote Sens., **10:** 1530. doi: 10.3390/rs10101530.
[26] L. Tian, D. C. Slaughter and R. F. Norris **(1997)**. Outdoor field machine vision identification of tomato seedlings for automated weed control. Trans. ASAE, **40:** 1761-1768.
[27] W. S. Lee, D. C. Slaughter and D. K. Giles **(1999)**. Robotic weed control system for tomatoes. Precision Agric. 1: 95-113.
[28] B. Astrand and A. J. Baerveldt **(2002)**. An agricultural mobile robot with vision-based perception for mechanical weed control. Auton. Robots, **13:** 21-35.
[29] R. Raja, T. T. Nguyen, D. C. Slaughter and S. A. Fennimore **(2020)**. Real-time weed-crop classification and localisation technique for robotic weed control in lettuce, Biosyst. Eng., **192:** 257-274.
[30] S. Christensen, T. Heisel, A. Walter and E. Graglia **(2003)**. A decision algorithm for patch spraying.Weed Res., **43:** 276-284.
[31] P. Hamouz, K. Hamouzová, J. Holec and L. Tyšer **(2013)**. Impact of site-specific weed management on herbicide savings and winter wheat yield. Plant, Soil and Environ., **59:** 101-107.
[32] C. Ritter, D. Dicke, M. Weis, H. Oebel, H.P. Piepho, A. Büchse and R. Gerhards **(2008)**. An on-farm approach to quantify yield variation and to derive decision rules for site-specific weed management. Precision Agric., **9:** 133-146.
[33] D.K., Giles, D. Downey, D.C. Slaughter, J.C. Brevis-Acuna, W.T. Lanini **(2004)**. Herbicide micro-dosing for weed control in field grown processing tomatoes. Appl. Eng. Agric., **20:** 735-743.
[34] J. Machleb, G.G. Peteinatos, M. Sökefeld and R. Gerhards **(2021)**. Sensor-based intrarow mechanical weed control in sugar beets with motorized finger weeders. Agronomy, **11:** 1517. doi: 10.3390/agronomy11081517.
[35] J. E. Hunter, T. W. Gannon, R. J. Richardson, F. H. Yelverton and R. G. Leon **(2020)**. Integration of remote-weed mapping and an autonomous spraying unmanned aerial vehicle for site-specific weed management. Pest Manag. Sci., **76:** 1386-1392.
[36] R. D. Lamm, D. C. Slaughter and D. K. Giles **(2002)**. Precision weed control system for cotton. Trans. ASAE., **45:** 231-238.
[37] B. Astrand and A. J. Baerveldt **(2002)**. An agricultural mobile robot with vision-based perception for mechanical weed control. Auton. Robots, **13:** 21-35.
[38] B. Astrand and A. J. Baerveldt **(2004)**. Plant recognition and localization using context information and individual plant features. In: Proc. of the IEEE Conf. Mechatronics and Robotics 2004-special session Autonomous Machines in Agriculture, Aachen, Germany, September 13-15, pp1191-1196.
[39] B. Astrand and A.J. Baerveldt **(2005)**. Paper IV-Plant recognition and localization using context information and individual plant features. In: Vision Based Perception for Mechatronic Weed Control. Astrand B. Doctor of Philosophy Thesis, Chalmers University of Technology and Halmstad University, Sweden.
[40] J. Blasco, N. Aleixos, J. M. Roger, G. Rabatel and E. Molto **(2002)**. Robotic weed control using machine vision. Biosyst. Eng., **83:** 149-157.