DOI:10.15150/lt.2023.3295



Characteristics of a spot sprayer for the treatment of Rumex obtusifolius in meadows

Thomas Anken, Annett Latsch

Machine learning has enabled the long-sought breakthrough of automated single-plant weed detection. Ecorobotix ARA is one of the first commercially available spot sprayer that allows automated single-plant treatment of broad-leaved dock plants in meadows. Compared to the treatment of the whole surface with standard field crop sprayers, herbicide reductions of over 90% can be realised. The aim of the present research was to investigate the accuracy of plant recognition and spraying. The results of the measurements for three meadows show that over 90% of broad-leaved dock plants were correctly detected. Measurements using a fluorescent tracer in the spray liquid showed that 89% of the dock leaf surface was sprayed while 11% of the leaves were left out. Overall, the results are promising and prove that this technology, which has been the subject of research for over 40 years, is now ready for on-farm usage.

Keywords

Spot spraying, Rumex obtusifolius, plant recognition, machine learning, Ecorobotix ARA

Automated spot spraying of single weeds as an alternative to spraying the whole surface has long been a goal to reduce the use of herbicides. In the late 1980s, 'Detect spray' was developed in Australia (FELTON et al. 1987). The aim was to spray single weeds to keep water consuming vegetation out of fields, as even sparse weed populations can decrease the water and nutrients available to subsequent crops. Optical sensors using red (630–670 nm) and infrared (830–870 nm) spectral bands were used to discriminate the green plants from soil and residues (FELTON et al. 1992). The results indicated that, with scattered weeds, herbicide savings in sprayed areas could exceed 90%. BLACKSHAW et al. (1998) reported herbicide reductions of 50–78%, confirming the potential of this technology. In addition, spot spraying can better adapt to adverse application conditions, such as hot and windy weather and drought-stressed weeds, as the application rates can be increased without becoming overly expensive (FELTON et al. 1992). Thus, spot spraying for fallow weed control reached a highly technical level 30 years ago. However, despite possible savings of about 38 \$/ha (FELTON et al. 1992), this system has only experienced limited success on farms in the last three decades, likely due to the high required investment and low herbicide costs.

At nearly the same time, the development of the 'Weed Seeker', which is now commercialised by Trimble (Sunnyvale, USA), started in the USA (RUTTO and ARNALL 2009). Despite the limited uptake of these technologies in Europe, 'Weed it' (Weed-it, Steenderen, NL) emerged in the market in 1999. However, none of these spot sprayers could exclude planted crops from the spray, as they detected all green plants. Due to the low price of total herbicides, these spot sprayers were only used on large dryland farms, where saving water by minimising the water use of weeds is important.

^{© 2023} by the authors. This is an open access article distributed under the terms and conditions of the Creative Commons Attribution License (http://creativecommons.org/licenses/by/4.0).

Single plant recognition

The next step toward single-plant recognition was the invention of 'Sony Mavica', the first digital camera, which was released in 1981 (SCHRÖTER 2001). The first research projects using digital imaging techniques for row recognition were initiated during this period (REID and SEARCY 1988, TILLETT and HAGUE 1999). Based on this technology, the first camera-steered hoes were commercialised at the end of the 1990s (Tillet and Hague 1999, Sogaard and Olsen 2003, Handler and Nadlinger 2005). Using different classical image analysis algorithms, these tools were able to detect the lines of crop rows. Similar products from companies like Tillet and Hague (https://thtechnology.co.uk/) Ferrari (https://ferraricostruzioni.com), Steketee (www.steketee.com), Garford (https://garford.com), Claas (www.claas.com) and others followed. Many of these implements relied on the production of a binary image through a thresholding process (REID and SEARCY 1988). Unfortunately, under direct lighting conditions, shadows cast by the tractor or implement lead to poor results. SLAUGHTER et al. (1997) overcame this limitation by shading the entire image region. OLSEN (1995) proposed a calculation method that was largely unaffected by partial shading. SOGARD and OLSEN (2003) developed a system without segmentation to reduce the computational burden. Specifically, the segmentation step was replaced by the computation of centres of gravity for row segments in the image. All these different approaches illustrate the challenges in detecting crop rows and dealing with the high variability in crop fields. HANDLER and NADLINGER (2005) noted the following factors that decrease the accuracy of row recognition by camera systems: high soil coverage by weeds overlapping the crop rows; side wind moving the leaves; small, poorly visible crops combined with intense sunlight (midday at clear sky); and blue-coloured cabbage plants.

For a long period of time, commercial implements were restricted to row detection only. As a next step, single plant detection combined with intra-row hoeing of vegetables followed. These implements allowed the recognition of single rows, and if there was enough space between the crop plants, intra-row hoeing became possible. Tillet and Hague commercialised the first intra-row hoe in 2008 (https://thtechnology.co.uk/history/). Other companies followed, including like Ferrari, Ecodan and Steketee. In addition to hoeing between plants, it became possible to spray single vegetable plants with fungicides or insecticides (KELLER et al. 2020). In this approach, the same recognition technology can be used, but instead of hoeing the space around the plants, the plants themselves are sprayed.

In parallel to these developments, selective spot spraying of weeds was developed for crops and meadows. Many studies (GERHARDS et al. 1998, CHAPRON et al. 1999) attempted to recognise weeds using classical image analysis, but these attempts were unable to cope with the very high variability encountered in nature. KLUGE (2011) reported that a major issue for classical image recognition algorithms was overlapping leaves, as they are often recognised as a single surface and cannot easily be discriminated as different plants. Due to these issues, no commercial implement using classical image recognition for spot spraying has yet been commercialised.

In contrast to arable farming, single-plant recognition of weeds in meadows is even more challenging, as plant densities and overlapping are very high. The variability in meadows is also high, with up to several dozens of different plants growing irregularly. Hence, the recognition of weeds in meadows is more complex than recognising weeds in newly sown crops, which contrast with the bare, brown soil, as green weeds are overlapped by other green plants in meadows. Thus, discrimination based on colour only has failed. GEBHARDT and KÜHBAUCH (2007) used classification algorithms to attribute homogeneous regions of the images to different objects, such as docks (*Rumex obtusifolius*), plantain (*Plantago major*) or the soil surface. In a known environment, they achieved recognition rates for Rumex of 85–92%. They reported a calculation time of 2.5 to 45 s per image depending on the image size. VAN EVERT et al. (2011) presented the first robot for the treatment of dock plants. They used a texture-based method for plant detection based on the observation that grass leaves are long and narrow (several millimetres), whereas the leaves of broad-leaved dock are at least an order of magnitude larger. Consequently, image parts with grass contain more colour and intensity transitions than image parts with broad-leaved dock. This textural information can be used to discriminate grass and broad-leaved dock. This prototype was only capable of handling simple conditions in grass-dominated swards, including very few clover or herbs. It failed in meadows containing herbs like clover, common plantain (*Plantago major*) or dandelion (*Taraxacum officinale*). None of these prototypes have been commercialised, as they were not able to handle the high variability of plants encountered in practice. SLAUGHTER et al. (2008) presented a review of autonomous weed control during this era, observing that weed recognition was the bottleneck hampering automated single-weed control. BINCH and Fox (2017) conducted a large study on broad-leaved dock detection using classical computer vision methods.

To overcome the problem of recognizing a 'green plant in a green meadow', SEATOVIC et al. (2009), HOLPP et al. (2008) and BRUGGER and KOHL (2006) used three-dimensional point clouds to determine leaf surfaces. They achieved recognition rates of about 80%. Whereas this method helped to discriminate plants and the soil surface, it did not resolve the issue of overlapping leaves. Like classical image recognition algorithms, these approaches have not been commercialised. An exception is the Claas stereo camera for row detection. In addition to colour information, plant height is used for row detection (MÖLLER 2010).

Break-through of machine learning

None of the attempts to detect weeds and broad-leaved dock plants using classical image analysis made their way to industrialisation. The technical progress in the domain of machine learning changed the game. AITKENHEAD et al. (2003) published one of the first papers using neuronal networks for the discrimination of crops and weeds. They reported a recognition rate of 75% for carrots (Daucus caro-ta). Other studies (BAKHSHIPOUR et al. 2017) and reviews (HASAN et al. 2021) showed better and more robust recognition rates of over 90% when a large amount of labelled data were available. Wu et al. (2021) confirmed the superiority of machine learning techniques to classical image analysis.

The development of machine learning techniques was able to solve the problem of recognising broad-leaved docks in meadows as well. KOULANAKIS et al. (2019) showed that it is possible to detect broad-leaved dock in grassland using convolutional neural networks (CNN), achieving an accuracy around 85%. SCHORI et al. (2019) confirmed that a simple CNN could achieve recognition rates over 85%. VALENTE et al. (2019) showed that it was even possible to detect broad-leaved dock plants using images taken by unmanned aerial vehicles. All these results presented during the last few years prove that machine learning has been a big step forward in the domain of weed recognition.

This technical progress has had a distinct industrial impact. New products from Ecorobotix (www. ecorobotix.com), Allgäu Automation GmbH (www.allgaeuautomation.com) and Rumex GmbH (www. rumex-gmbh.com) have appeared on the market, including spot sprayers using RGB or multispectral cameras and machine learning for recognising dock plants. To create constant illumination conditions, Ecorobotix and Allgäu Automation GmbH exclude sunlight by using shields and flashes to illuminate images homogeneously. This allows constant working conditions, independent of daylight and meteorological conditions. Rumex GmbH works with daylight, which makes it possible to decrease the size of the machine and to mount it in the front of the tractor.

Agrifac (Steenwijk, NL, https://www.agrifac.de/condor/neue-innovationen/aicplus) equipped a conventional field sprayer with cameras for dock recognition. Compared to the special machines with working widths of about 6 m, large field sprayers offer high performance due to their large working width of over 30 m. However, the standard nozzle spacing of 50 cm or possibly 25 cm results in less accurate spraying compared to specialised spot sprayers. These have very low nozzle spacings which are 4 cm in the case of Ecorobotix. On their websites, Rumex GMBH and Allgäu Automation GmbH indicate 6.7 cm and 10 cm, respectively.

After about four decades of research and development, automated spot sprayers utilising neuronal networks and machine learning for recognition have been industrialised. Ecorobotix presented the ARA spot sprayer, capable of recognising and treating single broad-leaved dock plants in meadows. Compared to manual plant-by-plant treatment by humans using knapsack sprayers in meadows, this has resulted in a significant decrease in working time. Whereas manual single-plant treatment requires around three hours per hectare depending on the conditions, such a surface can be treated by the Ecorobotix ARA within just 15–20 minutes.

The goal of this work was to examine the performance of the spot sprayer Ecorobotix ARA. The level of dock plant recognition and the accuracy of the spraying operation were chosen to characterise the performance of this first broad-leaved dock spot sprayer.

Material and methods

Field trials were carried out with the Ecorobotix ARA spot sprayer (Ecorobotix, Yverdon, CH) to determine its accuracy in recognising broad-leaved dock (*Rumex obtusifolius*). In addition, indoor trials were performed to determine how accurately the spray liquid was applied on and around the target plants in comparison to the standard method, a manual knapsack sprayer.

Technical parameters of the Ecorobotix ARA

The ARA spot sprayer has a working width of 6 m, consisting of three identical functional units, each with a working width of 2 m (Figure 1). Two RGB cameras per unit take pictures of the vegetation, which are analysed in real time on an onboard Nvidia Jetson computer (Nvidia, Santa Clara, USA). To allow for homogeneous illumination and to keep sunlight out, the cameras are placed in three large boxes with an open bottom. LED flashes are used to illuminate the images. When broad-leaved dock plants are detected, the computer opens the single spray nozzle valves above the target plants, which are thus treated individually. The distance between the nozzles is 40 mm. According to the company, the nozzles can be switched on and off within 30 mm in the direction of travel. One nozzle sprays with a width of 80 mm and a height of 25 cm. This means that it is possible to treat 80 × 30 mm 'tiles' on the ground. The nozzles are flat spray nozzles with an opening angle of 25 ° (OD20RQX52, EUSpray, Sant Joan Despí, ES) and an output of 0.2 l/min at 3 bar. The application rate was determined by measuring cylinders placed directly under the nozzles, with a spray duration of 30 s at 2.6 bar. The average output was 184 ml per nozzle and minute. With a working width of 2 m with 52 nozzles and a forward speed of 1.94 m/s, this results in the following application rate: 0.184 l/60 s × 52 nozzles/ (1.94 m/s × 2 m width) × 10,000 = 411 l/ha.



Figure 1: Spot sprayer Ecorobotix ARA treating broad-leaved dock plants in meadows (© Agroscope)

From the spray liquid tank, the liquid flows through the suction filter via the pump to the spray bar. Each electromagnetic valve mounted on the bar controls one nozzle. The liquid circulates permanently through the bar and from there back into the tank. The return line is equipped with a pressure-regulating valve and a pressure gauge for pressure control. Fresh water can be fed into the spray circuit via a three-way valve or into the tank via an internal cleaning nozzle. This can be used to mix the spray liquid or to rinse the sprayer. The output is not automatically adjusted to the forward speed; rather, it must be set manually via the pressure-regulating valve.

Determination of recognition rates

The first purpose of this investigation was to determine the proportion of correctly detected (true-positive) and non-detected and sprayed (true-negative) broad-leaved dock plants. Finally, the incorrectly sprayed plants (false-positive) were counted. For this purpose, the following steps were performed:

- 1) dye (see below) was added to the spray liquid, which made it possible to mark the sprayed locations in the field;
- 2) plant species in the sprayed locations were determined; and
- 3) the total number of broad-leaved dock plants in the whole field trial area were determined.

This procedure was repeated on three different fields where three test strips have been selected for the counting. The first was a newly sown meadow (Swiss ecological compensation area) in Dietwil (CH), and the two others were long-term meadows located in Taenikon (Table 1). At the Dietwil site, the plants were treated with 4% metsulfuron-methyl 'Ally Tabs' (Stähler Suisse SA, Zofingen, CH), using three tablets per 10 lt water and 'Ally' food colouring (3 ml/10 lt water). In Tänikon, pure water with 1% white dye (food colouring 6432077, Trawosa SA, St. Gallen, CH) was used.

Location	Botanical composition	Area
Dietwil 22.04.2021	Ecological compensation area, 4 ha with heavy abundance of dock plants (<i>Rumex obtusifolius</i>), stand height about 20 cm	960 m ² 3 strips 4 × 80 m
	Highly variable stand with about 70% grasses (English ryegrass, common bluegrass, meadowgrass)	
	1% clover (red/white clover) and approx. 30% herbs (common plantain, sorrel, dandelion, buttercup, horseweed, meadow sage, campion, knapweed, mallow, margerite, camomile, hornwort)	Coordinates: 47.1446 / 8.4040
Tänikon – Mühlewies 04.05.2021	Meadow, 3.7 ha area with moderate abundance of dock plants (<i>Rumex obtusifolius</i>), stand height 25 cm	1260 m ² 3 strips 6 × 70 m
	95% grasses (meadow foxtail, common fescue, tall fescue, English and Italian ryegrass, cocksfoot, downy oat, soft trespass)	
	1% white clover, 2% herbs (sorrel, dandelion, ivy speedwell, purple deadnettle, common hornwort, meadow foamwort, shepherd's purse) and 3% gaps	Coordinates: 47.4773 / 8.9101
Tänikon – Waldegg 04.05.2021	Meadow with moderate-to-low abundance of dock plants (<i>Rumex obtusifolius</i>), stand height 10 cm	1560 m ² 3 strips 6 × 65 m Coordinates: 47.4913 / 8.9203
	80% grasses (English ryegrass, common bluegrass, meadowgrass, meadowgrass, meadow fescue, cocksfoot)	
	10% clover (red and white clover), 5% herbs (dandelion, ivy speedwell, purple deadnettle, common plantain) and 5% gaps	

Table 1: Site characteristics of the investigated areas with indications of the most important species

Indoor determination of the accuracy of the spray treatment

To test the technical accuracy of the spray, freshly picked broad-leaved dock plants were placed on brown paper lanes inside a hall. Each spraying method was applied on four lanes with five plants each (Figure 2).

Two spraying methods were compared:

- Ecorobotix ARA
- Manual treatment with a knapsack sprayer with a hand pump, equipped with a Teejet 8002 flat spray nozzle with an 80° spraying angle (model: Iris, Birchmeier Sprühtechnik AG, Stetten, CH).

To visualise the spray film, spray water was mixed with 1% fluorescent dye (Lumilux Dispersion Yellow CD 997; Honeywell, Seelze, DE) for both methods. After spraying, the treated area was illuminated with a sealed ultraviolett light box (UV) (fluorescent tubes, Sylvania Blacklight blue, F8W/ BLB T5 (Sylvania, Erlangen, DE)) and photographed from a distance of 75 cm with a standard reflex camera (Nikon D7500, with 28 mm lens (Nikon, Tokyo, JP)) mounted on the box. The spray images were evaluated using the image editing programme GIMP (version 2.10.24, Free Software Foundation, https://www.fsf.org/), which counts the number of pixels in the manually circled areas. The real pixel size in mm² was determined by photographing and converting scales placed in the image. The following parameters were determined for each image:

- Area sprayed around the dock leaves
- Leaf area of broad-leaved dock plants sprayed
- Leaf area of broad-leaved dock plants not sprayed

From the different areas, it was possible to determine the proportion of the leaf area of the dock plants actually sprayed and the size of the sprayed area outside the plants (Figure 2). A Welch t-test (unequal variances, $\alpha = 0.05$) was used to test the degree of difference between the two methods (Ecorobotix ARA and manual treatment) for the sprayed leaf area and the area outside the leaves.



Figure 2: Spraying accuracy: dock plants were placed on brown paper lanes and treated with a spray liquid containing a fluorescent tracer (left); the sprayed areas were highlighted using UV light; the sprayed area around the plants (outlined around the plant), sprayed leaf area of the dock plants and unsprayed leaf area were determined (right) (© Agroscope)

Results

Recognition rates

At the Dietwil site, Ecorobotix ARA detected broad-leaved dock plants at a rate of over 90% (true-positive), although they were often heavily covered by other plants (Figure 3). In the 'Mühlewies' and 'Waldegg' plots at the Tänikon site, the docks were detected with an accuracy of over 85% with one exception (strip 2, Mühlewies). Thus, the rates of non-recognition of dock plants (true-negative) were in the range of 10-15%.



Figure 3: Recognition rate of broad-leaved dock plants at three locations on three strips. Recognised dock plants (true-positive) and non-recognised plants (true-negative) are indicated.

Among the falsely treated species (false-positive), sorrel (Rumex acetosa) should be mentioned,

which was sprayed at the Dietwil site at a rate of over 75% (estimated value), especially in strip 2. Furthermore, the red light carnation (Silene dioica) was sporadically sprayed in this strip. Ribwort (Plantago lanceolata) was also repeatedly treated. However, this species was highly represented in Dietwil, especially in strip 1, so the nine plants that were treated here only constitute a small percentage. At Mühlewies and Waldegg, dandelion and common plantain were occasionally sprayed (< 5% estimate). The only two sorrel plants (Mühlewies, strip 2) were also treated.

Accuracy of the spray treatment

While manual treatment with a knapsack sprayer covered 95% of the leaf area of the dock plants with a spray film, the coverage using Ecorobotix ARA was significantly lower at 89% (t-test p = 0.006) (Figure 4). The unsprayed leaf area of the dock plants was thus somewhat higher with manual treatment (about 6%) than with the Ecorobotix device, where on average about 11% of the leaf area is not sprayed. During the indoor trials, the nozzles of the Ecorobotix ARA always opened about 3–14 cm (average 11.7 cm) before the dock leaves passed under the nozzles. Consequently, this area outside the leaves was unnecessarily sprayed. Nevertheless, the machine sprayed significantly less area outside the leaves (247%) (t-test, p = 0.007) on average than manual treatment (403%). This means that around the target plants an area of 2.47 resp. 4.03 fold the surface of the dock leaves has been unnecessarily treated.



Figure 4: Shares of the different sprayed areas (spray outside the Rumex plants / sprayed leaf area / unsprayed leaf area); leaf area of the dock plants = 100%; areas are represented true to scale

With both methods, the larger the broad-leaved dock plants, the less area outside the leaf area was sprayed (Figure 5). Two regression lines on the graph confirm that compared to the knapsack sprayer, Ecorobotix tended to treat a smaller area around the plants.



Figure 5: Sprayed area outside the Rumex leaves in % in function of the leaf area in cm², 100% = total sprayed area

Discussion

Good 'true-positive' recognition rates

Good recognition of broad-leaved dock plants was achieved for all three fields. At Mühlewies, the grass was about 25 cm long and partially covered with dock plants. There, the rate of correct plant treatment (true-positive) was around 80%. For the other two fields, the recognition rates were 90% and above, which is considered very good. These rates are comparable to those published by different research projects (KOULANAKIS et al. 2019, SCHORI et al. 2019, VALENTE et al. 2019). The conditions at these three meadows were not the easiest, as the average grass height was about 20–25 cm, which resulted in partial overlap of dock plants by other plants, making the detection more challenging. The research team concluded that if the treatment was done manually, more dock would be missed by humans than by the machine. In addition, the machine works the same way from morning to night, whereas humans quickly tire or may overlook individual plants. In terms of true-positive recognition, the machine exhibited good performance.

A varied picture emerged for the incorrectly treated plants. The front-runner was sorrel (*Rumex acetosa*), which was treated falsely to a very large extent. In addition, plantain (*Plantago major*) was treated sporadically, as were dandelion (*Taraxacum officinale*), white clover (*Trifolium repens*), day-light carnation (*Lychnis flos cuculi*) and meadow foxtail (*Phleum pratense*). Sorrel is similar to broad-leaved dock and was probably mislabelled during the annotation process (oral communication of Ecorobotix). In the case of the falsely sprayed daylight carnation and meadow foxtail, red-coloured stems and flowers were visible, respectively. The red colouring of the plants was above average due to this year's strong and long-lasting late frosts. Such red colouration is also quite common for broad-leaved docks and might be the reason for the incorrect classification by the system. Another drastic

misclassification was observed during the indoor trials for the measurement of spray accuracies. The brown paper lanes on which the dock plants were placed were fixed on the grey concrete floor using yellow duct tape. These strips, which were about 10 cm in length, were erroneously sprayed by the machine. This misclassification seems to be to the fact that these environments were not included in the image training data base, which has been confirmed by Ecorobotix. This shows that unexpected recognition results may be obtained in an untrained environment. However, by expanding the image database, such misclassifications can be corrected.

According to Ecorobotix, thousands of dock plants have been trained. In environments that are similar to those included in the trained database, the recognition rates are good. Compared to studies conducted in meadows dominated by grasses (van Everr et al. 2011), the current trials took place in meadows containing many other plant species, which increased the difficulty in discriminating broad-leaved dock plants from other broad-leaved plants. Not surprisingly, nearly no grasses with narrow leaves were treated by the machine. GEBHARD and KÜHBAUCH (2007) and SCHORI et al. (2019) found that most misclassifications of dock plants were caused by plantain and dandelion, which is consistent with the present results. Thus, correct recognition of similar-looking plants is not only difficult for humans but also for technical systems. It must be remembered that machine learning can only learn what humans have annotated on the images. Therefore, incorrect annotations are a source of error.

Our results show, that it is challenging to control the high natural variability of plants and that unseen field conditions, as in the case of Dietwil, mainly increase the number of false-positive cases. Hence, it is not only important to classify many images but also to include the largest possible variability of different environments into the machine learning training database. However, taking into account that these first machines represent a new technology for spot spraying in meadows, the results are promising. Moreover, compared to other sectors (e.g., autonomous driving), a much higher error tolerance is acceptable.

Accuracy of the spraying process

The accuracy of hitting the target plant with the spray of the Ecorobotix ARA differed only slightly compared to standard manual treatment with a knapsack sprayer. Whereas the latter sprayed the leaves of the dock plants more completely, it also sprayed more of the area around them. Both sprayed areas were smaller with the Ecorobotix ARA. In terms of treatment efficiency on dock plants, no differences are expected.

The driving speed of the spot sprayer of 1.94 m/s requires very fast valve switching times. At this speed, a distance of 19.4 cm passes in one-tenth of a second. The company indicates that the shortest possible switching distance in the direction of travel is 3 cm. During the tests, this accuracy was not achieved using the chosen set-up. The nozzles usually opened too early. Relatively speaking, the area sprayed around plants became smaller with increasing leaf areas. In absolute terms, the error in switching the valve on and off remained constant and did not change as a function of the leaf area. Thus, no correlation could be found between the leaf area and the opening of the nozzles (data not shown). However, there is potential for technical optimisation, as more than twice the leaf area of the dock plants was unnecessarily treated by the machine.

Economic considerations

Considering an average dock plant presenting a leaf area of 530 cm², the sprayed area per plant results in 530 cm² × 2.47 (times the area sprayed) = 1,309 cm². Multiplied by an average number of 10,000 plants/ha, 13% of the area will be sprayed. Thus, compared to the use of standard boom sprayers, herbicide use can be reduced by 87%. Boom sprayers are recommended when the dock abundancy is higher than 10,000 plants/ha (HEBEISEN et al. 2011a). The herbicide cost for the treatment of 1 ha (45 g/ha Thiensulfuron-methyl) is € 129/ha (HEBEISEN et al. 2011b). Thus, a reduction of 87% in herbicide use would save € 112/ha. Due to the high investment required, spot sprayers are mostly owned by contractors, which offer full-service treatment for about € 200/ha (https://www.landiweinland.ch/landwirtschaft/pflanzenschutz). In the presented case, that means that about € 88/ha would be available to cover the labour costs for manual treatment, without considering the larger sprayed area in case of manual treatment. It is estimated that a manual treatment of 1 ha with 10,000 plants would take about five hours. The success of the spot spraying technique in Switzerland shows that many farmers are willing to pay for the service of a contractor. Moreover, compared to spraying the whole surface, spot spraying reduces yield depressions caused by the herbicides and spray residues on feed.

Conclusions

After decades of research by various institutes and companies, the spot spraying of single plants in meadows has found its way into practice. Specifically, technical developments in the domains of computer vision and machine learning have enabled this breakthrough. Ecorobotix ARA has achieved high recognition rates and is ready for practical application. There is still potential for reducing the number of falsely sprayed plants and improving the accuracy of the spray application on the target plants. This technology is an important milestone on the path to sustainable weed regulation and herbicide-free technologies, many of which rely on weed recognition.

References

- Aitkenhead, M. J.; Dalgetty, I. A.; Mullins, C. E.; McDonald, A. J. S.; Strachan, N. J. C. (2003): Weed and crop discrimination using image analysis and artificial intelligence methods. Computers and Electronics in Agriculture 39(3), pp. 157–171
- Bakhshipour, A.; Jafari, A.; Nassiri, S. M.; Zare, D. (2017): Weed segmentation using texture features extracted from wavelet sub-images. Biosystems Engineering 57(1), pp. 1–12
- Binch, A.; Fox, C. W. (2017): Controlled comparison of machine vision algorithms for Rumex and Urtica detection in grassland. Computers and Electronics in Agriculture 140, pp. 123–138
- Brugger, D.; Kohl, M. (2006): Miniatur-Laserscanner für mobile Anwendungen. Dissertation, Universität Karlsruhe
- Blackshaw, R.; Molnar, L.; Lindwall, C. (1998): Merits of a weed-sensing sprayer to control weeds in conservation fallow and cropping systems. Weed Science 46(1), pp. 120–126
- Chapron, M.; Requena-Esteso, M.; Boissard, P.; Assemat, L. (1999): A method for recognizing vegetal species from multispectral images. Precision Agriculture 1999, 2nd European Conference on Precision Agriculture, edited by J. Stafford (Sheffield Academic Press, Sheffield, UK), pp. 239–248
- Felton, W. L.; McCloy, K. R.; Doss, A. F.; Burger, A. E. (1987): Evaluation of a weed detector. Proceedings of the Eighth Australian Weeds Conference, Sydney, New South Wales, Australia, 21–25 September, pp. 80–84

Felton, W. L.; McCloy, K. R. (1992): Spot spraying. Agricultural Engineering 73, pp. 9-12

- Gebhardt, S.; Kühbauch, W. (2007): A new algorithm for automatic Rumex obtusifolius detection in digital images using colour and texture features and the influence of image resolution. Precision Agriculture 8(1), pp. 1–13
- Gerhards, R.; Sökefeld, M.; Kühbauch, W. (1998): Einsatz der digitalen Bildverarbeitung bei der teilschlagspezifischen Unkrautkontrolle. Zeitschrift für Pflanzenkrankheiten und Pflanzenschutz, Sonderheft 16, pp. 273-278

Handler., F.; Nadlinger, M. (2005): Automatische Lenkungen für Hackgeräte. Gemüsebaupraxis 2, pp. 24-25

- Hasan, A. S. M. M.; Sohel, F.; Diepeveen, D.; Laga, H.; Jones, M. G. K. (2021): A survey of deep learning techniques for weed detection from images. Computers and Electronics in Agriculture 184, https://doi.org/10.1016/j. compag.2021.106067
- Hebeisen, H.; Gago, R.; Jeangros, B.; Lüscher, A. (2011a): Wiesenblacke und Alpenblacke vorbeugen und bekämpfen. AGFF-Merkblatt 7, Arbeitsgemeinschaft zur Förderung des Futterbaus, Zürich
- Hebeisen, H.; Gago, R.; Jeangros, B.; Lüscher, A. (2011b): Bewilligte Herbizide gegen Wiesenblacken und Alpenblacken in Wiesen und Weiden des ÖLN-Betriebes. Anhang zu AGFF-Merkblatt 7, Arbeitsgemeinschaft zur Förderung des Futterbaus, Zürich
- Holpp, M.; Anken, T.; Seatovic, D.; Grüninger, R.; Hüppi, R. (2008): 3D object recognition, localization, and treatment of Rumex obtusifolius in its natural environment. Proceedings of the 9th International Conference on Precision Agriculture, July 2008, Denver
- Keller, M.; Haberey, P.; Hodel, D.; Collet, L.; Steiner, R.; Bucher, C.; Möri, H.; Wyssa, T.; Duckert, F.; Hauenstein, S.; Matter, R.; Anken, T.; Total, R. (2020): Spot Spraying im Gemüsebau: Deutliche Pflanzenschutzmittelreduktion möglich, aber anspruchsvoll. Agroscope Transfer 353, https://doi.org/10.34776/at353g
- Kluge, A. (2011): Methoden zur automatischen Unkrauterkennung für die Prozesssteuerung von Herbizidmaßnahmen. Dissertationen aus dem Julius Kühn-Institut., Braunschweig
- Kounalakis, T.; Triantafyllidis, G. A.; Nalpantidis, L. (2019): Deep learning-based visual recognition of rumex for robotic precision farming. Computers and Electronics in Agriculture 165, pp. 1–11. https://doi.org/10.1016/j. compag.2019.104973
- Möller, J. (2010): Computer vision a versatile technology in automation of agricultural machinery. Journal of Agricultural Engineering 47(4), pp. 28–36
- Reid, F. J.; Searcy, W. S. (1988): An algorithm for separating guidance information from row crop images. Transactions of the ASAE 31(6), pp. 1624–1632
- Rutto, E.; Arnall, B. (2009): History of GreenSeeker Technology. Oklahoma Extension Service PSS-2260
- Schori, D.; Anken, T.; Seatovic, D. (2019): Using fully convolutional networks for Rumex obtusifolius segmentation, a preliminary report. 2019 International Symposium ELMAR, 2019, pp. 119–122, https://doi.org/10.1109/ ELMAR.2019.8918914
- Seatovic, D.; Kutterer, H.; Anken, T.; Holpp, M. (2009): Automatic weed detection in grassland SmartWeeder, let the machines do the job! VDI-Berichte, 2060, pp. 187–192
- Slaughter, D.C.; Giles, D.K.; Downey, D. (2008): Autonomous robotic weed control systems: a review. Computers and Electronics in Agriculture 61, pp. 63–78
- Sogaard, H. T.; Olsen, H. J. (2003): Determination of crop rows by image analysis without segmentation. Computers and Electronics in Agriculture 38(2), pp. 141–158
- Tillett, N. D.; Hague, T. (1999): Computer-vision-based hoe guidance for cereals/an initial trial. Journal of Agricultural Engineering Research 74, pp. 225–236
- Valente, J.; Doldersum, M.; Roers, C.; Kooistra, L. (2019): Detecting Rumex obtusifolius weed plants in grasslands from UAV RGB imagery using deep learning. ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences 4(2), pp. 179–185
- van Evert, F. ; Samsom, J.; Polder, G.; Vijn, M.; van Dooren, H.-J.; Lamaker, A.; van der Heijen, G.; Kempenaar, C.; van der Zalm, T.; Lotz, L. (2011): A robot to detect and control broad-leaved dock (Rumex obtusifolius L.) in Grassland. Journal of Field Robotics 28(2), pp. 264–277
- Wu, Z. N.; Chen, Y. J.; Zhao, B.; Kang, X. B.; Ding, Y. Y. (2021): Review of weed detection methods based on computer vision. Sensors 21(11), 3647. https://doi.org/10.3390/s21113647

Authors

Dr Thomas Anken is a group leader and **Dipl. biol. Annett Latsch** is a scientific collaborator at Agrosocope, Tänikon 1, CH-8356 Ettenhausen. Email: thomas.anken@agroscope.admin.ch

Acknowledgments

We would like to thank Alfons Beerli of 'Estermann AG', Eschenbach and Lorenz Büchel, 'fenaco', Aesch for making the equipment available and for assisting with the trials. We are also grateful for the cooperation of Ecorobotix.