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INSIGHT ARTICLE

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Site-specific weed management—constraints and opportunities for the weed research community: Insights from a workshop

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Abstract

The adoption of site-specific weed management (SSWM) technologies by farmers is not aligned with the scientific achievements in this field. While scientists have demonstrated significant success in real-time weed identification, phenotyping and accurate weed mapping by using various sensors and platforms, the integration by farmers of SSWM and weed phenotyping tools into weed management protocols is limited. This gap was therefore a central topic of discussion at the most recent workshop of the SSWM Working Group arranged by the European Weed Research Society (EWRS). This insight paper aims to summarise the presentations and discussions of some of the workshop panels and to highlight different aspects of weed identification and spray application that were thought to hinder SSWM adoption. It also aims to share views and thoughts regarding steps that can be taken to facilitate future implementation of SSWM.

KEYWORDS

actor-network, deep learning, integrated weed management, machine learning, phenotyping, precision agriculture, weed detection, weed mapping

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1 | INTRODUCTION

If research on site-specific weed management (SSWM) was to be evaluated by the criteria of farmer adoption, its success would be considered rather modest (Fernández-Quintanilla et al., 2018). Research to date has shown the potential of herbicide spot-spraying (Esau et al., 2018) and of variable rate application (Kempenaar et al., 2017) for reducing the quantities of herbicides required. There are also some indications that mechanical weed control may likewise benefit from the use of intelligent control techniques (Lati et al., 2015; Machleb et al., 2020). Furthermore, new phenotyping approaches can be applied to elucidate the interactions between weeds and their environment and to facilitate decision-making regarding the timing and choice of strategies for weed control (Comont and Neve, 2020). Nonetheless, despite the promise inherent in SSWM, the use of SSWM tools remains sporadic, which led us to pose the following questions: (a) *What is currently being done by the research community to develop and facilitate SSWM implementation by farmers?* (b) *What can be done by the research community to improve the situation*, and *how can research and development achievements be quantified or measured?* These questions were discussed at the 2019 workshop of the SSWM working group arranged by the European Weed Research Society in Odense, Denmark. Most of the 32 participants were scientists and students, but several field advisors also participated. The vast majority of presentations focused on image analysis and weed detection, and only a few related to the integration and adoption of precise tools in commercial farming systems, which still poses a major challenge. In this insight paper, we share and channel ideas and opinions about SSWM challenges that were discussed at the workshop and elaborate on some aspects of SSWM that are seldom covered in the scientific literature. The paper looks beyond the front-stage of SSWM research by providing readers with a peep into back stage aspects. It thus deals with the main factors that the weed research community believes are hindering the adoption of SSWM by farmers and presents some alternative social and scientific guidelines that could serve to mitigate the assimilation barrier.

2 | THE WEED DETECTION CHALLENGE

The implementation of SSWM relies on accurate weed monitoring. Thus, most SSWM research focuses on weed detection and discrimination from crop plants. Weed/crop classification procedures involve a wide range of technologies based on a variety of sensing devices, such as RGB, multispectral and hyperspectral cameras (Herrmann et al., 2013; Utstumo et al., 2018). As every sensor has strengths and weaknesses, integration (fusion) of several sensors into a single platform can provide robust classification capacities under a wide range of imaging conditions. For example, depth-cameras, which include RGB and depth perception, combine spectral and morphological (3D) weed characterisation. Other technologies that have been evaluated for weed detection include LiDAR, spectro-radiometry, radar systems, photogrammetry and thermal imaging (Andújar et al., 2016). The advantages of devices using these technologies include the capture of the information necessary to develop weed maps, upon which site-specific control strategies can be based (Peteinatos et al., 2014).

Although a wide variety of weed detection-specific sensors, procedures and methods are commercially available, it is now generally agreed that the greatest potential for weed identification lies in the use of image-based machine learning techniques. Powerful computers and extensive development environments, such as TensorFlow (Abadi et al., 2016) and Keras (Chollet, 2018), provide models for training hundreds of thousands of weights in artificial neural networks specifically designed to meet image data requirements in so-called deep learning (DL) architectures (He et al., 2016). DL may now lead to a new paradigm in the detection and classification of weeds with more precise algorithms (Huang et al. 2018). When applying the models so developed on dedicated hardware, such as specialised NVIDIA Jetson TX-embedded systems, objects in images can now be identified in close to real time (Sa et al., 2018). This rapid identification reduces post-processing time, thereby, reducing overall costs and increasing treatment efficacy (Fernández-Quintanilla et al., 2018). The boost in weed detection capacities offered by DL was reflected in the research presented at the workshop showing improved weed detection success. Yet, only two presentations reported practice-oriented farm experiments with SSWM, and these highlighted the difficulties in SSWM implementation, as described in the next section. It was concluded that availability to end-users and robustness in different environments are the major constraints to successful SSWM implementation by farmers.

3 | THE CHALLENGE OF IMPLEMENTING SSWM

Rasmussen et al., (2019) reported on a demonstration project, in which farmers were offered cost-free glyphosate application maps, based on UAV imagery, for spot-spraying against the field thistle *Cirsium arvense*. The aim of the project was to show the farmer community that spot-spraying based on prescription maps is technically and economically feasible (Rasmussen et al., 2019). Weed detection was carried out using Thistle Tool software, and other previously reported technical aspects (Azim et al., 2019; Rasmussen et al., 2020). All the farmers had to do was to decide, which cereal fields they wanted to spot-spray after the crop harvest. They were also asked to save the log file from the tractor computer after spraying so that the spatial accuracy of spraying could be evaluated. Help was offered to farmers who encountered problems uploading the on-off application maps into their tractor computers. In total, 20 farmers wanted to spot-spray *C. arvense*, but due to budget restraints, only seven fields were mapped. In the end, none of the fields was spot-sprayed, with the main reason being problems in uploading the application maps (shape files) into tractor computers. In another farm study, spot-spraying was cancelled due to ISOXML-format issues, hindering correct opening and closing of the sprayer boom sections. Even, the company that manufactured the sprayer was unable to upload the application files.

The second talk about SSWM field demonstrations presented the 'RoboWeedMaps - automated weed detection and mapping' system. The RoboWeedMaps focuses mainly on DL-based detection of weed species in early growth stages in cereal fields (Jørgensen, 2019). The system was successfully used for spot-spraying of annual grass weeds in winter cereals. However, here too, the uploading of on-off herbicide application maps into sprayer consoles was a major issue that hampered the spraying effort.

Both presentations showed that implementation and adoption of SSWM are far from constituting a simple technical process. While weed detection performance is often considered the main barrier to the adoption of SSWM (Lopez-Granados, 2011), many of the constraints hampering the implementation of SSWM are similar to those for other precision agriculture practices (Fernández-Quintanilla et al., 2018). Indeed, social and scientific constraints have been the focus of a number of studies aiming to identify the factors impacting adoption rates (Lindblom et al., 2017; Tey and Brindal, 2012).

4 | DATA SHARING

It was suggested that data sharing is a key element that could improve SSWM implementation prospects. As mentioned above, the state of the art of SSWM methods (e.g. DL) relies mostly on image-driven data, for which promising results have been obtained in weed recognition (Yu et al., 2019) and in other precision-agriculture research fields (Kamilaris and Prenafeta-Boldú, 2018). There are, however, a number of problems that remain to be addressed in the development of DL models. This development starts with a training stage that involves supervised learning, for which large volumes of annotated training data are required to ensure high detection rates. However, such datasets might not be sufficiently robust to ensure satisfactory results, due to limited representation of species, environmental factors (e.g. soil type, temperature) and/or growth-stage-related morphological or physiological changes. Additionally, human-related errors may be introduced during the training stage, and non-professional trainers find it especially difficult to assign small seedlings to particular species. These seedlings are often omitted or placed at genus level in both training and testing sets. To overcome these limiting factors, workshop participants were encouraged to share data and establish publicly available weed image datasets. Each research group was asked to generate a local weed dataset by growing local populations of weeds. To avoid misclassifications, participants were asked to grow specific weed species separately. The use of standardised imaging setup and image acquisition methods was also encouraged. In addition, it was suggested that combined datasets acquired under a wide range of environmental conditions might enable reliable comparisons between different DL models and increase their robustness. The first step towards establishing a joint dataset has been made by a Danish research group, who have developed the Open Plant Phenotyping Database for common weeds in Denmark (Madsen et al., 2020). It is the largest publicly available dataset of its kind, and a valuable resource for future research in weed detection and plant phenotyping.

5 | THE CHALLENGE OF SHIFTING FROM TECHNICAL TO SYSTEMIC APPROACHES

Bridging the gap between scientists' and end users' perspectives on SSWM was another issue discussed during the workshop. In their publication addressing this gap, Roux et al. (2006) highlighted the tendency of consultants and other knowledge vendors to prefer working with clients with levels of knowledge and technological capacities similar to their own. The larger the difference between supplier and adopter of knowledge and skills, the lower the chance that the transfer would be successful (Roux et al., 2006). This idea has interesting implications from an actor-network perspective, a social-science theory suggesting that farmers' actions are perceived as closely interwoven within a network of other farmers, with no-one acting/deciding alone. Farmers' choices are strongly dependent on the network as a whole, with its own goals and incentives. The more farmers commit to the network, the more difficult it becomes for them to extricate themselves from it, even if it is in their best interest (Gray and Gibson, 2013). Research in SSWM can also be viewed from a similar actor-network perspective, in which research is interwoven within an academic actor-network with its own goals and incentives. Even within research in SSWM, there exist different actor-networks, which impedes knowledge transfer across specialised disciplines. Each discipline has its own terminology, goals and incentives. The debated questions then become: How well do farmer and researcher networks interact, and how can the gap between networks be bridged? During the workshop, it was argued that SSWM end-users seek user-friendly, robust and reliable technologies that solve real-life problems, whereas, scientists aim to develop new knowledge and tools that are meritorious within their own networks. The extent to which these opposing goals constitute a barrier to the adoption of SSWM remained an open question at the workshop, but it was agreed that systemic approaches to SSWM should be emphasised in future research. A first step could be to bring end-users and researchers in different domains into the same loop of development, training and assimilation of the new technology and to acknowledge that the functionality of that loop should be subjected to research. Developing SSWM technologies is a multidisciplinary task involving participants with different levels of knowledge and skills. In such a research field, where scientists are both suppliers and adopters of knowledge and skills, the need for discussions across scientific disciplines is important. The workshop was an excellent opportunity for such an exchange of data and ideas.

6 | CHALLENGING THE BASIC CONCEPT OF SSWM

Involvement of farmers in the development process can be taken a step further. At present, SSWM is most often presented as a technology with fully automated weed detection and decision support systems giving outputs to traditional actuation systems (sprayers, mechanical implements) or robots. Sensors on the relevant vehicle, drone or satellite-based platform play a central role in this process. They provide highly detailed data—from the whole crop level down to the individual plant level (Dyrmann et al., 2016; Pflanz et al., 2018). In most studies, commercially available camera systems are used, with the intention of providing inexpensive solutions for farming practices. However, as these technologies are becoming increasingly complex, farmers (individuals and large-scale cooperatives) might be less inclined to use them, as they leave little room for the application of personal knowledge in decision making.

It was pointed out at the workshop that some farmers use new SSWM technologies simply as an adjunct tool to support their decision-making. One example that was presented is an assistance system for site-specific application of plant protection products (Pohl et al., 2020). This assistance system, which was developed by a German research group, is designed to identify and characterise specific areas within a field requiring precise applications. This system is based on an already existing infrastructure (e.g. farm management systems) but also integrates large quantities of geo-data, meta-data and sensor-based data. The system also includes an economic analysis and benchmarking process. It enables the farmer to monitor and optimise the costs of plant protection measures by means of comparison within and between farms. In this case, the particular components of the assistance system for SSWM (e.g. weed maps) to be used are defined solely by the farmer. We note that the possibility of monitoring the economic benefits of reduced herbicide use may improve the motivation to use more advanced technologies in the future.

7 | DEEPER INSIGHTS INTO WEED PHENOTYPING

Providing farmers with additional information on weeds, particularly, how they respond to management strategies could increase farmer interest in SSWM. Weeds—like all plants—are affected by complex genome, environment and management (GxExM) interactions, which ultimately determine their biotic and abiotic interactions and population dynamics. Substantial research efforts have therefore been devoted to documenting the phenotypic plasticity of plant species (Nicotra et al., 2010). Among these, several studies on weeds have focused on phenotypic and genotypic variations in competitiveness, fitness (Matzrafi et al., 2017; Vila-Aiub et al., 2009) and herbicide resistance (Comont et al., 2020), yet, only few have used automated phenotyping technologies (Großkinsky et al., 2015). Nonetheless, the work that did use automated methods has uncovered complex interactions between weeds in their dynamic environment. The combination of high spatial and temporal resolution with the high capacity of automated weed phenotyping systems provides new opportunities to obtain detailed and supplementary information on weed characteristics that can be used for future integrated weed management. These new technological opportunities to monitor thousands of weed plants may increase our understanding of weed species' competitiveness and adaptation to different climates, soils and cropping systems.

Pioneering weed phenotyping studies have addressed issues of weed herbicide resistance and have begun to link variations in phenotype and genotype to variations in contemporary and historical management regimes (Comont et al., 2020). In particular, Comont and Neve (2020) have been able to unravel the drivers of target site and non-target site herbicide resistance and have demonstrated that herbicide mixtures and herbicide diversity can drive the evolution of a type of generalist, metabolic resistance. They have done so by integrating weed maps on a national scale, phenotypic and genetics-based assays of herbicide resistance, and long-term field management datasets at individual sites (Comont and Neve, 2020). Emerging approaches such as these can be augmented in the future by the automation of data collection for weed mapping (Lambert et al., 2018) and of sensor-based identification of herbicide resistance (Linn et al., 2019). Furthermore, the rapid development of weed phenotyping presents scientists with new opportunities to share large datasets and to work more closely on data relating to weed ecology and evolutionary biology (Mahaut et al., 2020).

8 | FUNDING AND DOCUMENTATION

Much of SSWM research is funded by short-term grants, which makes it extremely difficult to establish strong research groups with long-term perspectives. The life cycle of funding fails to support skill and research capacity-building and collaboration timelines. Continuity is key here. To motivate scientists and funding agencies, it is important to document 'successful application cases'—what has actually been achieved, what remains to be further improved and what has the potential for commercialisation (Christensen et al., 2009). In this context, a 'successful application case' is one characterised by the three key elements of SSWM, that is, weed monitoring, translation of field observations into decision guidelines and precision weed control. Table 1 lists examples of successful application cases, ranked according to maturity level, ranging from (1) 'proof-of-concept demonstrated under laboratory conditions' to (5) 'fully adopted by end-users'. The examples given in Table 1 cover a vast range of crops, sensing systems and precision levels. From these examples, it appears that tractor-mounted sensors and on-the-go (real-time) SSWM implements have been most successful so far. To facilitate the wider use of SSWM, the following recommendations should be put into practice: The flexibility of SSWM, in terms of equipment cost, cropping system, application timing and control mechanisms, should be highlighted. Farmers, stakeholders

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TABLE 1 Examples of Site-Specific Weed Management (SSWM) cases with maturity levels ranging from (1) 'Proof-of-concept demonstrated in laboratory conditions' to (5) 'Fully adopted by end-users'. (1 = Proof-of-concept demonstrated in laboratory conditions; 2 = Proof-of-concept demonstrated in field conditions; 3 = Tested in field by end-users; 4; Available at the market, but limited uptake by end-users; 5 = Fully adopted by end-users)

Weed control tactic	Application type[a]	Crop species (target weeds)	Level	Platforms	Reference
Herbicides (non-selective)	Real-time (on/off)	Cereal stubble and close to harvest (all green weeds)	5	Field sprayer with WeedSeeker units	Yorgey et al. (2016)
Herbicides (selective)	Map-based (VAR)	Cereals (seed-propagated juvenile weeds)	3	ATV-mounted camera-> machine vision algorithm-> application file -> farmers' field sprayer	Somerville et al. (2019)
Herbicides (selective)	Map-based (on/off)	Winter wheat, maize	2	Manual mapping-> prescription maps-> GPS-controlled multiple-tank sprayer	Gutjahr et al. (2012)
Herbicides (selective)	Real-time (on/off)	Primarily cereals (seed-propagated juvenile weeds)	3	Tractor-mounted	Berge et al. (2012)
Physical (weed harrowing)	Real-time (VAR)	Maize (seed-propagated juvenile weeds)	2	Tractor-mounted	Rueda-Ayala et al. (2015)
Hoeing	Real-time (on/off)	Row crops[b] (*intra*-row weeds)	5	Tractor-mounted	Merfield (2016)
Physical (hoeing)	Real-time (on/off)	Row crops (*inter*-row weeds)	5	Tractor-mounted	Melander et al. (2015)
Thermal (flaming)	Real-time (on/off)	Row crops (intra-row weeds)	2	Tractor-mounted	Lati et al. (2015)
Herbicide	Real-time (on/off)	Row crops[c]	2	Tractor-mounted	Westwood et al. (2018)
Physical	Real-time (on/off)	Sugar beet	2	Self-propelled robot	Åstrand and Baerveldt (2002)
Herbicide	Real-time (on/off)	Field vegetables (volunteer potato)[d]	4	Tractor-mounted	Merfield (2016)
Herbicides (non-selective and selective)	Real-time (on/off)	Seeded root vegetables	2–3	Self-propelled robot	Utstumo et al. (2018)
Combination of two tactics (spraying and stamping)	Real-time (on/off)	Sugar beet (intra-row weeds)	2	Self-propelled (?) robot	Wu et al. (2020)
Physical (chopping)	Real-time (on/off)	Grassland (taproot of docks)	2	Self-propelled robot	van Evert et al. (2020)

[a]Map-based or on-the-go (on/off) or variable rate of application (VRA).

[b]Transplanted crops such as lettuce, cabbage, celery.

[c]Initially the machine is aimed at treating potatoes growing in carrots, parsnips, onions or leeks, but the interest and usage requirements are spreading to general weed control in all varieties of crops.

[d]For example, cotton.

and regulators should be made aware of the potential SSWM solutions for various cropping scenarios. Efforts should be made to familiarise fellow scientists from other disciplines, who are not always aware of the current SSWM status and its potential benefits, with this research field. Publications reporting on successful or even unsuccessful studies and projects should disseminated widely via platforms ranging from peer-reviewed journals through local farmer publications to public online web pages. Increasing the awareness of different audiences to the successes of SSWM projects, and the contributions they offer toward the overall goal of reducing herbicide usage, might assist in boosting funding and ensuring research continuity.

In conclusion, reluctance of farmers to adopt SSWM is not limited exclusively to economic and technological reasons; deeper social aspects are involved. We must therefore involve the agricultural community in the development and assimilation stages of new SSWM tools. By so doing, a more technology-oriented generation of farmers, likely to be more open to the adoption of new ideas, will evolve. Stronger interactions between farmer and scientist networks should be established, and mutual goals should be identified. The objectives of SSWM research should be updated, and provision to farmers of decision-making tools should become the primary target. In addition, the sharing of ideas and data can improve the performance of advanced DL and other image-driven models and increase the robustness of SSWM tools, while phenotyping-gained insights and data may increase their attractiveness. Finally, the documentation of SSWM studies and developments must be disseminated to a wider audience with the aim to cultivate collaborative efforts, expand funding options and ensure research continuity.

PEER REVIEW

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