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

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24 **Abstract**

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

35

36 **Key words:** actor-network, deep learning, integrated weed management, machine learning, precision
37 agriculture, phenotyping, weed detection, weed mapping.

38

39 **Introduction**

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

63 **The weed detection challenge**

64 The implementation of SSWM relies on accurate weed monitoring. Thus, most SSWM research
65 focuses on weed detection and discrimination from crop plants. Weed/crop classification procedures
66 involve a wide range of technologies based on a variety of sensing devices, such as RGB,
67 multispectral and hyperspectral cameras (Herrmann *et al.*, 2013; Utstumo *et al.*, 2018). As every
68 sensor has strengths and weaknesses, integration (fusion) of several sensors into a single platform can
69 provide robust classification capacities under a wide range of imaging conditions. For example,
70 depth-cameras, which include RGB and depth perception, combine spectral and morphological (3D)
71 weed characterization. Other technologies that have been evaluated for weed detection include
72 LiDAR, spectro-radiometry, radar systems, photogrammetry and thermal imaging (Andújar *et al.*,
73 2016). The advantages of devices using these technologies include the capture of the information
74 necessary to develop weed maps, upon which site-specific control strategies can be based (Peteinatos
75 *et al.*, 2014).

76 Although a wide variety of weed detection-specific sensors, procedures and methods are
77 commercially available, it is now generally agreed that the greatest potential for weed identification
78 lies in the use of image-based machine learning techniques. Powerful computers and extensive
79 development environments, such as TensorFlow (Abadi *et al.*, 2016) and Keras (Chollet *et al.*, 2018),
80 provide models for training hundreds of thousands of weights in artificial neural networks specifically
81 designed to meet image data requirements in so-called deep learning (DL) architectures (He *et al.*,
82 2016). DL may now lead to a new paradigm in the detection and classification of weeds with more
83 precise algorithms (Huang *et al.* 2018). When applying the models so developed on dedicated
84 hardware, such as specialized NVIDIA Jetson TX-embedded systems, objects in images can now be
85 identified in close to real time (Sa *et al.*, 2018). This rapid identification reduces post-processing time,
86 thereby reducing overall costs and increasing treatment efficacy (Fernández-Quintanilla *et al.*, 2018).

87 The boost in weed detection capacities offered by DL was reflected in the research presented at the
88 workshop showing improved weed detection success. Yet, only two presentations reported practice-
89 oriented farm experiments with SSWM, and these highlighted the difficulties in SSWM
90 implementation, as described in the next section. It was concluded that availability to end-users and
91 robustness in different environments are the major constraints to successful SSWM implementation
92 by farmers.

93 **The challenge of implementing SSWM**

94 Rasmussen *et al.*, (2019) reported on a demonstration project, in which farmers were offered cost-
95 free glyphosate application maps, based on UAV imagery, for spot-spraying against the field thistle
96 *Cirsium arvense*. The aim of the project was to show the farmer community that spot-spraying based
97 on prescription maps is technically and economically feasible (Rasmussen *et al.*, 2019). Weed
98 detection was carried out using Thistle Tool software, and other previously reported technical aspects
99 (Azim *et al.*, 2019; Rasmussen *et al.*, 2020). All the farmers had to do was to decide which cereal
100 fields they wanted to spot-spray after the crop harvest. They were also asked to save the log file from
101 the tractor computer after spraying so that the spatial accuracy of spraying could be evaluated. Help
102 was offered to farmers who encountered problems uploading the on-off application maps into their
103 tractor computers. In total, 20 farmers wanted to spot-spray *C. arvense*, but due to budget restraints,
104 only 7 fields were mapped. In the end, none of the fields was spot sprayed, with the main reason
105 being problems in uploading the application maps (shape files) into tractor computers. In another
106 farm study, spot-spraying was cancelled due to ISOXML-format issues, hindering correct opening
107 and closing of the sprayer boom sections. Even the company that manufactured the sprayer was
108 unable to upload the application files.

109 The second talk about SSWM field demonstrations presented the “RoboWeedMaps - automated
110 weed detection and mapping” system. The RoboWeedMaps focuses mainly on DL-based detection

111 of weed species in early growth stages in cereal fields (Jørgensen *et al.*, 2019). The system was
112 successfully used for spot spraying of annual grass weeds in winter cereals. However, here too, the
113 uploading of on-off herbicide application maps into sprayer consoles was a major issue that hampered
114 the spraying effort.

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

122 **Data sharing**

123 It was suggested that data sharing is a key element that could improve SSWM implementation
124 prospects. As mentioned above, the state of the art of SSWM methods (e.g., DL) relies mostly on
125 image-driven data, for which promising results have been obtained in weed recognition (Yu *et al.*,
126 2019) and in other precision-agriculture research fields (Kamilaris and Prenafeta-Boldú 2018). There
127 are, however, a number of problems that remain to be addressed in the development of DL models.
128 This development starts with a training stage that involves supervised learning, for which large
129 volumes of annotated training data are required to ensure high detection rates. However, such datasets
130 might not be sufficiently robust to ensure satisfactory results, due to limited representation of species,
131 environmental factors (e.g., soil type, temperature), and/or growth-stage-related morphological or
132 physiological changes. Additionally, human-related errors may be introduced during the training
133 stage, and non-professional trainers find it especially difficult to assign small seedlings to particular
134 species. These seedlings are often omitted or placed at genus level in both training and testing sets.

135 To overcome these limiting factors, workshop participants were encouraged to share data and
136 establish publicly available weed image datasets. Each research group was asked to generate a local
137 weed dataset by growing local populations of weeds. To avoid misclassifications, participants were
138 asked to grow specific weed species separately. The use of standardized imaging setup and image
139 acquisition methods was also encouraged. In addition, it was suggested that combined datasets
140 acquired under a wide range of environmental conditions might enable reliable comparisons between
141 different DL models and increase their robustness. The first step toward establishing a joint dataset
142 has been made by a Danish research group, who have developed the Open Plant Phenotyping
143 Database for common weeds in Denmark (Madsen *et al.*, 2020). It is the largest publicly available
144 dataset of its kind, and a valuable resource for future research in weed detection and plant
145 phenotyping.

146 **The challenge of shifting from technical to systemic approaches**

147 Bridging the gap between scientists' and end users' perspectives on SSWM was another issue
148 discussed during the workshop. In their publication addressing this gap, Roux *et al.*, (2006)
149 highlighted the tendency of consultants and other knowledge vendors to prefer working with clients
150 with levels of knowledge and technological capacities similar to their own. The larger the difference
151 between supplier and adopter of knowledge and skills, the lower the chance that the transfer would
152 be successful (Roux *et al.*, 2006). This idea has interesting implications from an actor-network
153 perspective, a social-science theory suggesting that farmers' actions are perceived as closely
154 interwoven within a network of other farmers, with no-one acting/deciding alone. Farmers' choices
155 are strongly dependent on the network as a whole, with its own goals and incentives. The more
156 farmers commit to the network, the more difficult it becomes for them to extricate themselves from
157 it, even if it is in their best interest (Gray and Gibson 2013). Research in SSWM can also be viewed
158 from a similar actor-network perspective, in which research is interwoven within an academic actor-

159 network with its own goals and incentives. Even within research in SSWM, there exist different actor-
160 networks, which impedes knowledge transfer across specialized disciplines. Each discipline has its
161 own terminology, goals and incentives. The debated questions then become: How well do farmer and
162 researcher networks interact, and how can the gap between networks be bridged? During the
163 workshop, it was argued that SSWM end-users seek user-friendly, robust and reliable technologies
164 that solve real-life problems, whereas scientists aim to develop new knowledge and tools that are
165 meritorious within their own networks. The extent to which these opposing goals constitute a barrier
166 to the adoption of SSWM remained an open question at the workshop, but it was agreed that systemic
167 approaches to SSWM should be emphasized in future research. A first step could be to bring end-
168 users and researchers in different domains into the same loop of development, training and
169 assimilation of the new technology and to acknowledge that the functionality of that loop should be
170 subjected to research. Developing SSWM technologies is a multidisciplinary task involving
171 participants with different levels of knowledge and skills. In such a research field, where scientists
172 are both suppliers and adopters of knowledge and skills, the need for discussions across scientific
173 disciplines is important. The workshop was an excellent opportunity for such an exchange of data
174 and ideas.

175 **Challenging the basic concept of SSWM**

176 Involvement of farmers in the development process can be taken a step further. At present, SSWM is
177 most often presented as a technology with fully automated weed detection and decision support
178 systems giving outputs to traditional actuation systems (sprayers, mechanical implements) or robots.
179 Sensors on the relevant vehicle, drone or satellite-based platform play a central role in this process.
180 They provide highly detailed data—from the whole crop level down to the individual plant level
181 (Dyrmann *et al.*, 2016; Pflanz *et al.*, 2018). In most studies, commercially available camera systems
182 are used, with the intention of providing inexpensive solutions for farming practices. However, as

183 these technologies are becoming increasingly complex, farmers (individuals and large-scale
184 cooperatives) might be less inclined to use them, as they leave little room for the application of
185 personal knowledge in decision making.

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

198 **Deeper insights into weed phenotyping**

199 Providing farmers with additional information on weeds, particularly how they respond to
200 management strategies could increase farmer interest in SSWM. Weeds – like all plants – are affected
201 by complex genome, environment and management (GxExM) interactions, which ultimately
202 determine their biotic and abiotic interactions and population dynamics. Substantial research efforts
203 have therefore been devoted to documenting the phenotypic plasticity of plant species (Nicotra *et al.*,
204 2010). Among these, several studies on weeds have focused on phenotypic and genotypic variations
205 in competitiveness, fitness (Matzrafi *et al.*, 2017; Vila-Aiub *et al.*, 2009) and herbicide resistance
206 (Comont *et al.*, 2020), yet, only few have used automated phenotyping technologies (Großkinsky *et*

207 *al.*, 2015). Nonetheless, the work that did use automated methods has uncovered complex interactions
208 between weeds in their dynamic environment. The combination of high spatial and temporal
209 resolution with the high capacity of automated weed phenotyping systems provides new opportunities
210 to obtain detailed and supplementary information on weed characteristics that can be used for future
211 integrated weed management. These new technological opportunities to monitor thousands of weed
212 plants may increase our understanding of weed species' competitiveness and adaptation to different
213 climates, soils and cropping systems.

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

226 **Funding and documentation**

227 Much of SSWM research is funded by short-term grants, which makes it extremely difficult to
228 establish strong research groups with long-term perspectives. The life cycle of funding fails to support
229 skill- and research capacity-building and collaboration timelines. Continuity is key here. To motivate
230 scientists and funding agencies, it is important to document “successful application cases”—what has

231 actually been achieved, what remains to be further improved, and what has the potential for
232 commercialization (Christensen *et al.*, 2009). In this context, a “successful application case” is one
233 characterized by the three key elements of SSWM, i.e., weed monitoring, translation of field
234 observations into decision guidelines, and precision weed control. Table 1 lists examples of successful
235 application cases, ranked according to maturity level, ranging from (1) “proof-of-concept
236 demonstrated under lab conditions” to (5) “fully adopted by end-users.” The examples given in
237 Table 1 cover a vast range of crops, sensing systems and precision levels. From these examples, it
238 appears that tractor-mounted sensors and on-the-go (real-time) SSWM implements have been most
239 successful so far. To facilitate the wider use of SSWM, the following recommendations should be put
240 into practice: The flexibility of SSWM, in terms of equipment cost, cropping system, application
241 timing and control mechanisms, should be highlighted. Farmers, stakeholders and regulators should
242 be made aware of the potential SSWM solutions for various cropping scenarios. Efforts should be
243 made to familiarize fellow scientists from other disciplines, who are not always aware of the current
244 SSWM status and its potential benefits, with this research field. Publications reporting on successful
245 or even unsuccessful studies and projects should disseminated widely via platforms ranging from
246 peer-reviewed journals through local farmer publications to public online web pages. Increasing the
247 awareness of different audiences to the successes of SSWM projects, and the contributions they offer
248 toward the overall goal of reducing herbicide usage, might assist in boosting funding and ensuring
249 research continuity.

250 In conclusion, reluctance of farmers to adopt SSWM is not limited exclusively to economic and
251 technological reasons; deeper social aspects are involved. We must therefore involve the agricultural
252 community in the development and assimilation stages of new SSWM tools. By so doing, a more
253 technology-oriented generation of farmers, likely to be more open to the adoption of new ideas, will
254 evolve. Stronger interactions between farmer and scientist networks should be established, and

255 mutual goals should be identified. The objectives of SSWM research should be updated, and
256 provision to farmers of decision-making tools should become the primary target. In addition, the
257 sharing of ideas and data can improve the performance of advanced DL and other image-driven
258 models and increase the robustness of SSWM tools, while phenotyping-gained insights and data may
259 increase their attractiveness. Finally, the documentation of SSWM studies and developments must be
260 disseminated to a wider audience with the aim to cultivate collaborative efforts, expand funding
261 options, and ensure research continuity.

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393 **Table 1.** Examples of Site Specific Weed Management (SSWM) cases with maturity levels ranging
394 from (1) “Proof-of-concept demonstrated in lab conditions” to (5) “Fully adopted by end-users”. (1
395 = Proof-of-concept demonstrated in lab conditions; 2 = Proof-of-concept demonstrated in field
396 conditions; 3 = Tested in field by end-users; 4; Available at the market, but limited uptake by end-
397 users; 5 = Fully adopted by end-users).

Weed control tactic	Application type*	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 <i>et al.</i> , 2016
Herbicides (selective)	Map-based (VAR)	Cereals (seed-propagated juvenile weeds)	3	ATV-mounted camera-> machine vision algorithm-> application file -> farmers’ field sprayer	Somerville <i>et al.</i> , 2019
Herbicides (selective)	Map-based (on/off)	Winter wheat, maize	2	Manual mapping-> prescription maps-> GPS-controlled multiple-tank sprayer	Gutjahr <i>et al.</i> , 2012
Herbicides (selective)	Real-time (on/off)	Primarily cereals (seed-	3	Tractor-mounted	Berge <i>et al.</i> , 2012

		propagated juvenile weeds)			
Physical (weed harrowing)	Real-time (VAR)	Maize (seed- propagated juvenile weeds)	2	Tractor-mounted	Rueda- Ayala <i>et al.</i> , 2015
Hoeing	Real-time (on/off)	Row crops** (<i>intra</i> -row weeds)	5	Tractor-mounted	Merfield, 2016
Physical (hoeing)	Real-time (on/off)	Row crops (<i>inter</i> -row weeds)	5	Tractor-mounted	Melander <i>et</i> <i>al.</i> , 2015
Thermal (flaming)	Real-time (on/off)	Row crops (<i>intra</i> -row weeds)	2	Tractor-mounted	Lati <i>et al.</i> , 2015
Herbicide	Real-time (on/off)	Row crops****	2	Tractor-mounted	Westwood <i>et al.</i> , 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)*****	4	Tractor-mounted	Merfield, 2016

Herbicides (non-selective and selective)	Real-time (on/off)	Seeded root vegetables	2-3	Self-propelled robot	Utstumo <i>et al.</i> , 2018
Combination of two tactics (spraying and stamping)	Real-time (on/off)	Sugar beet (intra-row weeds)	2	Self-propelled (?) robot	Wu <i>et al.</i> , 2020
Physical (chopping)	Real-time (on/off)	Grassland (taproot of docks)	2	Self-propelled robot	van Evert <i>et al.</i> , 2020

398 *Map-based or on-the-go (on/off) or variable rate of application (VRA), ** Transplanted crops such
399 as lettuce, cabbage, celery; *** Initially the machine is aimed at treating potatoes growing in
400 carrots, parsnips, onions or leeks but the interest and usage requirements are spreading to general
401 weed control in all varieties of crops; ***** e.g., cotton

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