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1 **Site-specific herbicide spraying can control weeds as well as full spraying in**
2 **the long-term. A simulation study**

3 Thibault Maillot¹, Jean-Baptiste Vioix², Nathalie Colbach¹

4

5

6 **ABSTRACT**

7 Site-specific herbicide spraying reduces herbicide use as it sprays only where weeds are detected.
8 We studied the long-term impact of this weed-control measure on weed-impact indicators (crop
9 yield loss, biodiversity, ...). We developed a submodel to simulate the effects of site-specific
10 spraying on weed floras and included this into the existing FLORSYS model. The latter simulates
11 multiannual multispecies weed dynamics and crop canopies at a daily time-step from cropping
12 system, weather and soil. Global sensitivity and uncertainty analyses, based on 30-year-long
13 simulations of different rotations and weather series, identified the most influential inputs and
14 the most sensitive outputs. The cropping system (rotation with associated sowing patterns,
15 herbicide products and treatment dates) was more influential than the spraying system
16 (geometrical spraying pattern, weed detection). Finally, a real-life case study was simulated to
17 demonstrate the feasibility of reconciling crop production with reduced herbicide use, thanks to
18 site-specific spraying.

19

20 Keywords: FLORSYS, patch spraying, site-specific spraying, global sensitivity analysis, weed
21 control

22

23 Highlights:

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-
- 24 • We modelled site-specific herbicide spraying in the weed-dynamics model FLORSYS
- 25 • We ran sensitivity analyses of weed dynamics and their impacts on crop production
- 26 • Cropping system had more influence on weed impacts than the spraying system
- 27 • Site-specific spraying controlled long-term weed infestation as well as full spraying
- 28 • Benefits of site-specific spraying mainly depend on the weed patch distribution
- 29

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30 **1 Introduction**

31 Because synthetic inputs (fertilizers, pesticides, etc.) damage the environment and human health
32 (Wilson and Tisdell, 2001), their use must be reduced, which is a major challenge for farmers.
33 This is particularly true for weed management as weeds are considered to be the most harmful
34 crop pest (Oerke, 2006). Herbicides must now be replaced as much as possible with a
35 combination of multiple, mostly preventive and partially efficient practices (Liebman et al., 1997;
36 Wezel et al., 2014). Site-specific herbicide spraying allows going even further by spraying only
37 where weeds are detected in the field (Esau et al., 2018; Fernández-Quintanilla et al., 2017;
38 Gerhards et al., 2022; Gonzalez-de-Soto et al., 2016; Johnson et al., 1995; Peña et al., 2013).
39 Most patch-spraying systems rely on weed detection procedures that locate and then treat weeds
40 in fields. Many detection systems are based on optical sensors (Gerhards and Christensen, 2003;
41 Gerhards and Oebel, 2006; Guerrero et al., 2017; Louargant et al., 2018). The algorithms used in
42 these systems are not yet perfect, either missing some weeds or erroneously considering bare soil
43 or crops as weeds. Detection rates can also be influenced by the way the system is used in the
44 field. Each detection method must thus be evaluated to check whether its detection rates are
45 adequate for a practical use in farmers' fields. For instance, in (Gonzalez-de-Soto et al., 2016),
46 authors working with a robotized patch-spraying system find that reducing herbicide use depends
47 on weed abundance (the higher the density is, the less herbicide is saved) and distribution (the
48 more weeds are aggregated, the more herbicide is save). The same trends were identified by
49 simulation (Villette et al., 2019). Other teams tackle the economic issue of site-specific weed
50 management and crop yield loss (Rider et al., 2006; Wilkerson et al., 2004). In their case study,
51 the costs of site-specific management were not compensated by the additional return (reduced
52 herbicide use). But the economic results varied enormously among considered fields.
53 Most of these studies focus on the short-term impact of this spraying strategy, simply looking at
54 weed reduction rates after spraying or, at the best, yield loss or gain in the sprayed crop. However,
55 weeds must be managed at the multiannual scale as their seeds survive for several years in the

56 soil (Lewis, 1973). Farmers are usually not so much focused on avoiding yield losses during a
57 given year, but rather on limiting weed seed return to the soil and yield losses in future years
58 (Macé et al., 2007). This is why weed dynamics models are essential to provide guidelines for
59 practical weed management at the multiannual scale (Holst et al., 2007). Only a few of these
60 models though consider site-specific spraying (Audsley, 1993; Barroso et al., 2004; Paice et al.,
61 1998; Wiles, 2009). Their simulations show, for instance, that for site-specific weed management
62 to be beneficial, weeds must be spatially aggregated and their densities relatively low. However,
63 these models focus on the impact of site-specific weed management on herbicide use and
64 economic return. They disregard interactions with other management techniques and weather as
65 well as impacts on other agronomic indicators such as crop production, weed harmfulness for
66 production or weed contribution to biodiversity.

67 Among the many weed dynamics models (Holst et al., 2007), FLORSYS is to date the one model
68 that quantifies the effects of the entire cropping system, in interaction with weather and soil
69 properties, on multiannual weed dynamics and crop canopies, as well as a series of agronomic
70 indicators (yield, weed harmfulness for production, weed contribution to biodiversity) (Colbach
71 et al., 2021, 2014a). This model is well adapted to evaluate multiple impacts of interacting
72 cropping techniques on weeds in the long-term, but it does not consider site-specific spraying.

73 Consequently, the objective of the present paper was to: 1) develop a patch-spraying submodel
74 for the FLORSYS model, 2) assess the sensitivity of the agronomic indicators predicted by the
75 model to the inputs of the new spraying submodel in order to identify the patch-spraying inputs
76 that must be determined as accurately as possible and/or can be modified to drive weed control,
77 3) use the new FLORSYS version including the spraying submodel in order to evaluate, in the
78 long-term, the use of a site-specific spraying system at the field scale. To achieve the second
79 goal, we used a combination of sensitivity and uncertainty analyses. Sensitivity analysis is
80 defined as "the study of how the uncertainty in the output of a model (numerical or otherwise)
81 can be apportioned to different sources of uncertainty in the model input" (Saltelli et al., 2004).

82 The uncertainty analysis aims to quantify the model output uncertainties that arise from the

83 uncertainty in inputs. By coupling these two analysis methods we can infer which are the least
84 robust outputs to the variations of the inputs (uncertainty analysis), and among these inputs which
85 are the ones that have the most influence on these outputs (sensitivity analysis). The combine use
86 of these two analysis methods was inspired by (Varella et al., 2012). This permitted identifying
87 the soil inputs needed for accurate model outputs and thus avoided the cost of measuring less
88 important inputs. For the third goal, a real patch-spraying system was analyzed, and its
89 characteristics were used in the new FLORSYS spraying submodel to assess its long-term impact
90 on crop production and biodiversity.

91

92 **2 The FLORSYS model**

93 **2.1 The current version**

94 **2.1.1 Model inputs**

95 FLORSYS is a virtual field on which cropping systems can be experimented and a large range of
96 crop, weed and environmental measures estimated. The structure of FLORSYS is presented in
97 detail in previous papers (Colbach et al., 2014b, 2014c, 2017, 2021; Gardarin et al., 2012;
98 Mézière et al., 2015; Munier-Jolain et al., 2013, 2014). Only a short summary is given here.
99 Further details can be found in section A of the supplementary material online.

100 The input variables of FLORSYS consist of (1) a description of the simulated field (daily weather,
101 latitude and soil properties); (2) all the simulated crops and management operations in the field,
102 with dates, tools and options; and (3) the initial weed seed bank which is either measured on soil
103 samples or, more feasible, estimated from regional flora assessments (Colbach et al., 2016).

104 In the following sections, parameters are fixed constants (e.g., base temperature of species X)
105 and inputs denote user-selected variables (e.g., date of mouldboard ploughing).

106

107 **2.1.2 The annual life cycle of crops and weeds**

108 These inputs influence the annual life cycle, which applies to annual weeds and crops, with a
109 daily time-step. Pre-emergent stages (surviving, dormant and germinating seeds, emerging
110 seedlings) are driven by soil structure, temperature and water potential. After emergence, the
111 crop-weed canopy is simulated in 3D with an individual representation of each crop and weed
112 plant. The canopy is discretized with voxels (3D pixels) and the precision of the plant location
113 and description decreases with increasing voxel size, which is an input chosen by the user (see
114 section A.3 online). Post-emergent processes (e.g., photosynthesis, respiration, growth,
115 etiolation) are driven by light availability and air temperature. At plant maturity, weed seeds are
116 added to the soil seed bank; crop seeds are harvested to determine crop yield. FLORSYS is
117 currently parameterized for 25 annual weed species.

118

119 **2.1.3 Impact of cultural techniques**

120 Life-cycle processes also depend on the dates, options and tools of management techniques
121 (tillage, sowing, herbicides, mechanical weeding, mowing, harvesting), in interaction with
122 weather and soil conditions on the day the operations are carried out (section A.4 online). For
123 instance, weed plant survival probabilities after a management operation (tillage, herbicides,
124 mechanical weeding, mowing, harvesting) are calculated deterministically depending on the
125 operation, biophysical environment as well as weed morphology and stage; the actual survival of
126 each plant is determined stochastically by comparing this probability to a random probability.

127 Herbicides can be sprayed over the whole simulated field, or only on either the crop rows or the
128 interrows (Colbach et al., 2017, details in section A.5 online). They enter plants via leaves
129 ("foliar" herbicides), shoot tips during emergence ("pseudo-root") or roots ("root"). Multiple
130 entry modes are possible ("multi-mode"). Foliar herbicides only kill emerged weeds on the day
131 of spraying, the other herbicides persist and act over several days and weeks. Killing rates depend
132 on the product's dosage and efficiency on each weed species, the farmer's availability and

133 equipment (spraying in adequate conditions or with outdated machinery reduces efficiency) and
134 decrease with canopy density (which keeps herbicide droplets from reaching their target).
135 Systemic herbicides circulate inside the target plant and their efficiency depends less on dosage.

136

137 **2.1.4 Model outputs**

138 All weed and crop state variables are available as outputs to understand the impacts of cultural
139 techniques. In addition, FLORSYS simulates crop yield as well as weed-borne agroecological
140 services and disservices (Mézière et al., 2015) (see section A.7 online). Indicators of weed
141 disservices describe weed harmfulness for crop production (e.g., yield loss due to weeds). Weed-
142 service indicators reflect the contribution that weeds make to biodiversity (e.g., the contribution
143 to feeding pollinators).

144

145 **2.1.5 Model evaluation**

146 FLORSYS was evaluated with independent field data, showing that crop yields, daily weed species
147 densities and, particularly, densities averaged over the years were generally well predicted and
148 ranked (Colbach et al., 2016; Pointurier et al., 2021). A corrective function was required to keep
149 weeds from flowering during winter in southern France (e.g. below 46°N). Higher crop yield
150 losses than those reported in previous field studies mostly result from the simulation plan. This
151 does not adapt practices to simulated weed floras and interannual weather variability (as farmers
152 or trial managers would do), in order to discriminate the effect of crop species and management
153 practices on weeds from the effect of weeds on the choice of crops and practices (Colbach and
154 Cordeau, 2018).

155

156 2.2 Introducing site-specific spraying into FLORSYS

157 Instead of spraying the whole simulated field (or entire crop rows or interrows), the new
158 submodel allows spraying only where weed plants are detected. Site-specific spraying is limited
159 to foliar herbicides, or multi-entry herbicides that also enter through leaves.

160 The new submodel first needs functions simulating weed detection. For this, the user chooses
161 (1) detection zones, e.g. crop row and interrow zones, and their widths (WR in Table 2), (2) weed
162 detection rates in each zone (DR-R and DR-IR), (3) the minimum plant diameter to be detected
163 (SW), which can be given per species, per clade (monocotyledonous vs dicotyledonous species),
164 or irrespective of species, and (4) the false detection rate (FR), i.e. the probability that a crop
165 plant is detected as a weed plant. Three other inputs describe the spraying system: (5) the width
166 of the spray (WS), (6) the distance from the detected weed at which the system starts to spray
167 (SD-B), and (7) stops spraying after the detected weed (SD-A).

168 Each time a site-specific treatment is applied in a FLORSYS simulation, a loop is run over all weed
169 plants to

- 170 • Determine in which detection zone (e.g., row or interrow) the plant is located. This
171 depends on the width chosen for the row detection (WR) and on the distance of the weed
172 to the crop row. Crop plant location depends on the sowing pattern chosen by the user, in
173 terms of sowing density, interrow width, sowing precision and orientation. Weeds are
174 placed in aggregated patches whose sizes increase with the species plant size.
- 175 • Deterministically calculate the detection rate from the weed's location (inside a detection
176 zone), species and size,
- 177 • Stochastically decide whether the plant is detected by comparing a random probability
178 from [0,1] to the detection rate,
- 179 • If a plant is detected, delimit the sprayed section depending on the plant's location and
180 size as well as the spray width (WS), the sprayed distance before and after the detected
181 weed (SD-B, SD-A). Sprayed sections do not overlap (i.e., no area is sprayed twice).

182 The same loop is run over crop plants, using the false detection rate to determine additional
183 sprayed sections. Once the field map of sprayed sections has been determined, another loop is
184 run over all emerged weed plants to:

- 185 • Deterministically determine whether the plant is sprayed, depending on whether it is
186 located inside a sprayed section. Undetected weeds close to detected ones can thus be
187 sprayed.
- 188 • Deterministically calculate the survival probability of the sprayed plant, depending on
189 weed species and stage, the sprayed herbicide product, dosage and type (systemic or not),
190 the farmer's availability and equipment, as well as the canopy density,
- 191 • Stochastically decide whether the plant survives by comparing a random probability from
192 $[0,1]$ to the survival probability.

193 The last two steps are the same as for any herbicide applied over the whole field. Crop plants are
194 assumed not be affected by site-specific herbicide treatments. If the applied herbicide also
195 presents pseudo-root or root-penetrating properties, the relative sprayed field area X is calculated
196 from the spray map. A proportion Y of ungerminated seedlings (for which only density per m^2 is
197 considered, disregarding coordinates) then dies because of the treatment.

198

199 **3 Sensitivity and uncertainty analyses**

200 **3.1 Principle**

201 We analyzed how key FLORSYS output indicators vary with variations in inputs of the patch
202 spraying submodel, combining sensitivity and uncertainty analyses.

203 For each considered output, we used a four-step method inspired by (Varella et al., 2012) (Table
204 1): 1) use a screening analysis to select the most important factors. The next steps were only
205 carried out for these important factors to minimize the number of simulation runs; 2) analyze the
206 global sensitivity indices of each input to rank input factors according to their impact on outputs;
207 3) compute coefficients of variation to analyze the uncertainties of the considered output

208 variables to select those that the most react to changes in inputs; 4) apply thresholds to sensitivity
209 indices and coefficients of variation to select the most influential inputs: when the uncertainties
210 of the input variables induce low variations of the considered output indicators, the results of the
211 sensitivity analysis (steps 1 and 2) should not be considered for this output.
212

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Table 1. Steps and principles for sensitivity and uncertainty analyses

Step	Simulation plan	Analysis	Aim
1. Screening analysis: identify non-influential inputs (section 3.2.3.1)			
1a	3 herbicide spectra × 3 seed banks × 2 rotations × LHS of 10 scenarios with random quantitative inputs	η^2 from ANOVA	Identify non- influential qualitative inputs
1b	~200 scenarios per rotation based on Morris sampling	μ_i^* and σ_i sensitivity indices	Identify non- influential quantitative inputs
2. Global sensitivity analysis: identify influential inputs (section 3.2.3.2)			
2a	50000 scenarios based on Saltelli's sampling, using influential inputs identified in steps 1 and 2	First-order and total sensitivity indexes S_i and St_i	Identify influential inputs
2b	3 spectra × 3 seed banks × 2 rotations × LHS of 100 scenarios with randomly chosen quantitative inputs	Sign of regression coefficients of linear regressions	Identify sign relations between inputs and outputs
3. Uncertainty analysis: identify sensitive outputs (section 3.2.3.3)			
3	Same as in step 2a	Coefficient of variation CV	Identify sensitive outputs
4. Conclusion (section 3.2.3.4)			
4	For sensitive outputs identified in step 3, influential inputs are identified based on step 2a	CV and St_i	Choose inputs per output

214 3.2 Material and methods

215 In the following we denote as *scenario* the cropping system given as input to FLORSYS and
216 *simulation* the FLORSYS execution of this scenario over several years with one weather series.

217

218 3.2.1 Model inputs used in the sensitivity analysis

219 We only considered inputs that influence the spraying process in FLORSYS: 13 quantitative
220 variables and two qualitative ones, i.e., the spectrum of the sprayed herbicide (*SH*) and the initial
221 weed seed bank (*IB*) (Table 2). The quantitative inputs and the herbicide spectrum determine
222 how weeds are detected and treated. The initial seed bank is an environmental constraint.

223 Three different spectra were associated to the herbicide used in simulations. The applied
224 herbicides only affect monocotyledons (*SH* = MONOCOT), only dicotyledons (*SH* = DICOT) or
225 both (*SH* = DEFAULT). We considered three initial seed banks associated to three French
226 regions: Aquitaine (*IB* = IBAQ), Burgundy (*IB* = IBBO) and Poitou-Charentes (*IB* = IBPC)
227 (details in section C of the supplementary material online).

228 Two different *scenarios*, with different complexities, were used hereafter, a maize monoculture
229 from Aquitaine (South-West France) and an oilseed rape/wheat/barley rotation from Burgundy
230 (Eastern France) (see details in (Colbach et al., 2014d, 2017)). Weeds were assumed to be
231 distributed in patches whose size was correlated to the maximum species plant height.
232 Simulations were run with soils and weather series typical of these two regions, using the
233 20190828 version of FLORSYS.2. Each scenario was run over 30 years and was repeated 10 times
234 with 10 different weather series consisting of 30 randomly chosen weather years recorded by
235 weather stations (and provided by the INRAE Climatik platform), using the same 10 series for
236 each scenario. To reduce simulation time, only a representative field sample of 6 m by 3 m was
237 simulated; the complete field (often covering several ha) then consisted of the repetition of the
238 basic sample.

239

240 Table 2: Definition of the 13 quantitative and 2 qualitative inputs with their ranges of variation.
 241 The column ‘case study value’ gives the input values used in the simulations of the case study in
 242 Section 4 combining systemic spraying on crop rows with patch-spraying in interrows
 243 A. Complete list

Label	Input	Range	Case study value	Unit
IB	Initial seed bank (qualitative)	Aquitaine (IBAQ); Burgundy (IBBO); Poitou-Charentes (IBPC)	IBAQ	
Spraying system				
WS	Width of spray	0 – 200	35	cm
SD-B	Sprayed distance before detected weed	0 – 200	5	cm
SD-A	Sprayed distance after detected weed	0 – 200	5	cm
Weed detection				
DR-R	Detection rate of weed in crop row	0 – 100	0	%
DR-IR	Detection rate of weed in inter-row	0 – 100	See Table 2B	%
FR	False detection rate	0 – 100	See Table 2B	%
WR	Width used for row detection	0 – 20	18	cm
SW	Minimum size of detected weeds	0 – 4	See Table 2B	cm
Crop plant location				
SD	Sowing density	-20 – 20 ^{&}	–	%
ID	Crop interrow (maize-based cropping system only)	25 – 120	75	cm
Herbicide characteristics				
TD	Treatment date	-5 – +5 ^s	–	days
HD	Herbicide dose	0 – 100 ^{ss}	–	%
SH	Spectrum of the used herbicide (qualitative)	monocotyledons (MONOCOT); dicotyledons (DICOT);	DEFAULT	

both (DEFAULT).

HE	Herbicide efficiency (in optimal conditions)	0 – 100 [#]	–	%
----	---	----------------------	---	---

244 [§]daily offset from the scheduled date in the simulated cropping systems.

245 [&]percentage variation of the nominal value;

246 ^{ss}percentage of the recommended dose.

247 [#]percentage of the efficiency published ACTA database (based on Mamarot and Rodriguez, 2003)

248 B. Interrow detection rates DR-IR and false detection rate FR in the case study, depending on
249 the minimum detected weed size SW. Each combination of DR-IR, FR and SW corresponds to
250 a WeedSeeker configuration: Sens. 5 to 10 (see section 4.1).

WeedSeeker configuration	Minimum detected weed size			
	SW1 = 0 cm		SW2 = 3 cm	
	DR-IR	FR	DR-IR	FR
<i>Sens. 5</i>	40	9	79	19
<i>Sens. 6</i>	38	9	77	18
<i>Sens. 7</i>	39	8	78	17
<i>Sens. 8</i>	33	6	66	12
<i>Sens. 9</i>	32	5	65	11
<i>Sens. 10</i>	22	4	44	8

251

252

253 3.2.2 Analysed outputs

254 The analysed performance indicators assess (1) weed-control variation due to site-specific
255 spraying relatively to a fully sprayed field, i.e. crop yield from patch-sprayed simulations – crop
256 yield from fully sprayed simulations, for each scenario, weather repetition and year, (2) weed
257 harmfulness for production: weed-crop biomass ratio at crop flowering as a proxy of weed-
258 caused yield loss (Colbach and Cordeau, 2018), (3) field infestation; (4) weed contribution to
259 biodiversity: wild plant species richness; and (5) herbicide use intensity: proportion of sprayed

260 field area, and treatment frequency indicator (TFI). Indicators of types (2)-(5) are directly
261 calculated by FLORSYS (section 2.1.4).

262

263 **3.2.3 Simulation plan and statistical analysis**

264 3.2.3.1 Screening analysis

265 A screening analysis aims to identify non-influential model inputs with a reduced number of
266 simulations (Iooss and Lemaître, 2015; Saltelli et al., 2008; Wallach et al., 2013). In the following
267 we used a two-step screening approach to identify non-influential inputs defining patch spraying.
268 First, for each combination of herbicide spectrum (3 possibilities), initial seed bank (3) and crop
269 rotation (2), a Latin Hypercube Sampling (LHS) simulation plan (McKay et al., 1979) consisting
270 of 10 scenarios was built by drawing the quantitative inputs of Table 2 in a uniform distribution
271 inside the ranges listed. As explained in section 3.2.1, each scenario was simulated over 30 years
272 and repeated with 10 weather series. For each crop rotation, simulated outputs were analyzed
273 with an analysis of variance (ANOVA) as a function of herbicide spectrum and initial weed seed
274 bank to differentiate qualitative inputs, which have negligible effects, via the eta-squared (η^2)
275 measure of effect size. The value for eta-squared is between 0 and 1: the closer the value is to 1,
276 the higher the proportion of variance that can be explained by a given variable in the model is.
277 To select the qualitative factors that have the greatest impact on outputs an uncertainty analysis
278 using absolute value of the coefficient of variation (see Section 3.2.3.3) and a threshold of 0.2
279 was made to highlight most influential inputs.

280 In a second step, using the analysis of variance results, we applied the screening method proposed
281 by Morris and improved by Campolongo et al. (Campolongo et al., 2007; Morris, 1991). This
282 method permits to differentiate quantitative inputs that have negligible effects, inputs with large
283 linear effects without interactions and inputs with large non-linear and/or interaction effects. The
284 analysis was based on a simulation plan based on the Morris sampling method which reduces the
285 total number of simulations needed to 210 scenarios for the maize monoculture and 195 for the

286 oilseed rape/wheat/barley rotation (Herman et al., 2013; Morris, 1991). For each qualitative
287 input, two sensitivity measures are computed (Campolongo et al., 2011). Considering the i -th
288 input, μ_i^* and σ_i denote these measures. μ_i^* assesses the influence of the i -th input on the indicator
289 values and σ_i is a measure of non-linear and/or interaction effects of the i -th input. The i -th input
290 is considered as important if either μ_i^* or σ_i have a large value. As proposed in (Turati et al.,
291 2016), to select important factors we first considered that a factor i has an important effect on an
292 indicator if μ_i^* is larger than the average of the μ^* values, *i.e.* $\mu_i^* > \frac{1}{K} \sum_{k=1}^K \mu_k^*$, with K the number
293 of inputs. Arbitrarily, a threshold on σ was chosen equal to 1/3 of the maximum value to refine
294 the selected important factors. In order to confirm the input selection, a visual analysis of σ values
295 as a function of μ^* values was carried out. This analysis aimed to identify the different input
296 groups that may have similar importance.

297 Screening analysis were performed using Python and the SciPy and SALib libraries (Herman and
298 Usher, 2017; Oliphant, 2007).

299

300 3.2.3.2 Global sensitivity analysis

301 Once the most important factors were selected thanks to the screening analysis, a global
302 sensitivity analysis was performed to estimate the global sensitivity indices of each input in order
303 to rank them according to their impact on outputs.

304 Among the different methods to compute global sensitivity indices (Gan et al., 2014; Iooss and
305 Lemaître, 2015; Saltelli et al., 2008), the variance-based sensitivity analysis is appropriate for a
306 non-linear model like FLORSYS (Saltelli, 2002; Saltelli et al., 2008). We choose to use the Sobol
307 sensitivity indices estimated with Saltelli's sampling method with 50000 sample points
308 distributed in ranges given in Table 2 (Iooss and Lemaître, 2015; Saltelli, 2002; Saltelli et al.,
309 2010). This method calculates a first-order sensitivity index (S_i) which represents the main-effect
310 contribution of input i to the variance of the considered indicator (without interaction with other
311 variables) and a total effect index (ST_i) which describes the proportion of the variance of the

312 indicator explained by input i individually plus effects due to the interactions with all other factors
313 (Saltelli et al., 2008).

314 First and total Sobol indexes were computed using Python with the SALib library (Herman and
315 Usher, 2017).

316
317 Finally, in order to estimate sign relations between considered inputs and outputs, for each
318 combination of herbicide spectrum (3 possibilities), initial seed bank (3) and crop rotation (2), a
319 Latin Hypercube Sampling (LHS) simulation plan (McKay et al., 1979) consisting of 100
320 scenarios was built by drawing the quantitative inputs of Table 2 in a uniform distribution inside
321 the ranges listed in Table 2. Simulations results was analysed with a linear regression model.

322
323 3.2.3.3 Uncertainty analysis

324 The uncertainty analysis aims to quantify uncertainty in model outputs (Saltelli et al., 2008). For
325 this purpose, using the simulations used to estimate the global sensitivity indices (section
326 3.2.3.2), uncertainty analysis of each output indicator Y was achieved by computing the absolute
327 value of the coefficient of variation (Varella et al., 2012):

328
$$CV(Y) = \frac{\sqrt{V(Y)}}{\bar{Y}} = \frac{\sigma(Y)}{\bar{Y}}$$

329 with $\sigma(Y)$ the standard deviation of the variable Y , \bar{Y} its mean and $V(Y)$ its total variance.

330
331 3.2.3.4 Final Input selection

332 In order to select the influential inputs that must be determined accurately for the estimation of a
333 given indicator, the coefficient of variation of section 3.2.3.3 was analyzed with regard to the
334 total effect index of each input. Two thresholds were set to select the inputs that have the greatest
335 influence on the indicator uncertainty. A first threshold was set to 10% for the total effect index
336 (Makowski et al., 2006). An arbitrary value of 0.3 was taken for the threshold on the coefficient

337 of variation. The weed-impact indicators with a coefficient of variation less than this threshold
338 are considered robust with regards to changes in considered inputs. Otherwise, all inputs with a
339 total effect index greater than 10% were considered as influential.

340

341 **3.3 Results**

342 **3.3.1 Screening analysis**

343 3.3.1.1 Selection of qualitative inputs

344 Irrespective of the rotation, the output indicators that were the most influenced (based on the
345 analysis of the coefficient of variance available in section D.1 of the supplementary material
346 online) by the qualitative inputs were weed-control variation due to site-specific spraying, weed-
347 crop biomass ratio at flowering, the herbicide treatment frequency indicator and field infestation.
348 Weed species richness and the herbicide-sprayed area were little influenced.

349 Among the two tested qualitative inputs, the spectrum of the used herbicide (SH) had a negligible
350 influence on the considered indicators in both rotations (see Table 3, details in section D.1 of the
351 supplementary material online). The impact of the initial weed seed bank (IB) was significant (p-
352 value < 0.05) with a large impact on outputs (high η^2 in Table 3) for all output indicators in the
353 diversified oilseed rape/wheat/barley rotation. In the maize monoculture, it only influenced
354 weed-control variation due to site-specific spraying and weed species richness.

355 In view of these results, in the following steps, we set the herbicide spectrum *SH* to *DEFAULT*
356 (targeting all weeds irrespective of clade) for all outputs and rotations. The initial seed bank *IB*
357 input was set to the Burgundy seed bank (*IBBO*) when analysing the species-richness and
358 sprayed-area outputs for the oilseed rape/wheat/barley rotation (typical of Burgundy) whereas all
359 possible *IB* values were considered when analysing the other outputs. For the maize-based system
360 (typical of Aquitaine), we set the value of *IB* to *IBAQ* for all output indicators.

361

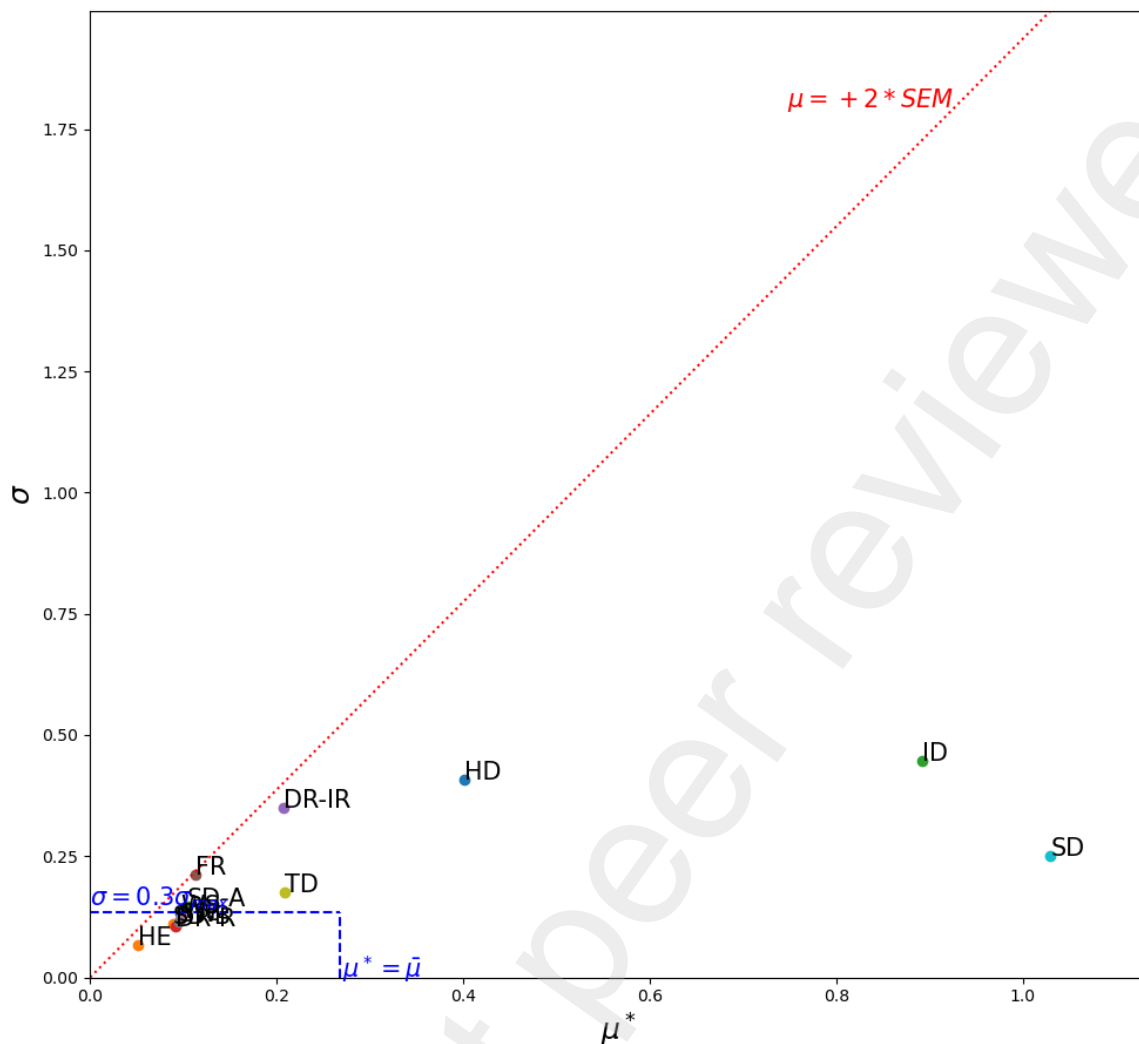
Table 3: Identification of key qualitative input variables and the most influenced outputs of the FLORSYS patch-spraying submodel based on analyses of variance of data from simulations based on LHS sampling on qualitative inputs. In green, CV values greater than 0.2. ns = effect of simulation factor not significant at p=0.05

Analysed output indicators values averaged over 30 years	Herbicide spectrum		Initial weed seed bank IB		Total	Coefficient of variance
	η^2		η^2		R ²	CV
	A. Maize monoculture					
Weed species richness	0.01	ns	0.95		0.96	0.024
Weed-control variation due to site-specific spraying	0.02	ns	0.81	ns	0.83	1.4
Field infestation	0.04	ns	0.51	ns	0.55	0.67
Sprayed area	0.08	ns	0.51	ns	0.58	0.066
Herbicide Treatment Frequency Index	0.02	ns	0.53	ns	0.55	0.64
Weed-crop biomass ratio at flowering (proxy for yield loss due to weeds)	0.34	ns	0.01	ns	0.36	2.4
B. Oilseed rape/wheat/barley rotation						
Weed species richness	0.01	ns	0.96		0.97	0.027
Weed-control variation due to site-specific spraying	0.01	ns	0.97		0.98	0.28
Field infestation	0.03	ns	0.93		0.96	0.45
Sprayed area	0.06	ns	0.77	ns	0.83	0.13
Herbicide Treatment Frequency Index	0.03	ns	0.74	ns	0.87	0.32
Weed-crop biomass ratio at flowering (proxy for yield loss due to weeds)	0.10	ns	0.81		0.92	0.89

363 3.3.1.2 Quantitative inputs

364 Figure 1 shows an example of how the impact of quantitative inputs was analysed (further results
365 in section D.1 online). In the case of weed-control variation due to patch-spraying, the least
366 influential inputs (low values of μ^* and σ) were related to the detection and patch-spraying
367 system, i.e., on-row weed detection rate (DR-R), before-weed sprayed distance (SD-B),
368 minimum detected weed size (SW), row-width (WR), and spray-width (WS). The only other non-
369 influential input was herbicide efficiency (HE). The most influential inputs were herbicide dose
370 (HD) or related to crop-plant location, i.e., sowing density (SD) and interrow distance (ID). These
371 three presented large μ^* values and were located far below the $2 \times \text{SEM}$ line, indicating a linear
372 relation with the considered output and little interaction with other inputs. The other inputs
373 (interrow detection rate (DR-IR), treatment date (TD), false detection rate (FR), after-weed
374 sprayed distance (SD-A)) were less influential (lower μ^* values), their effects were non-linear
375 and/or depended more on other inputs (location close to the $2 \times \text{SEM}$ line).

376 The results for all indicators and cropping systems are summarized in Table 4. The most
377 influential variables were the same in both systems. But, the more complex cropping system
378 presented more influential inputs, more non-linear input-output relationships and/or more
379 interactions among inputs. There was no input that had no influence at all on any output in any
380 system. So, all the input variables were considered for both cropping systems in the next step.



381

Figure 1: Identifying influential quantitative input variables with the Morris screening method, using the weed-control variation due to site-specific spraying indicator in the maize-based cropping system as an example. Each dot represents, for an input given by its abbreviation (see Table 2 for the meaning of the input abbreviations), the sensitivity measures (the σ (ordinate) and μ^* (on the x-axis) values) computed with the Morris screening method. μ^* assesses the influence of the input on the indicator values and σ is a measure of non-linear and/or interaction effects of the input. The horizontal dashed blue line (at 0.3 of the maximum σ values) and the vertical one (the average of the μ^* values) correspond to the thresholds used on μ^* and σ to select the most influential inputs: if a (μ^*, σ) -dot is below these two lines, the associated input is considered as having no influence on the output (and thus as of no interest for the sensitivity analysis). Dots near or above the dotted red line (twice the estimated Standard Error of the Mean) show inputs with a non-linear relationship with the output or with interactions with other inputs.

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Table 4: The most influential inputs of the patch-spraying submodel identified with the Morris screening method results (detailed results in section D.1.2 online). Inputs related to weed detection (green, details in Table 2), spraying system (red), herbicide characteristics (blue), crop-plant location (purple). NI: not important; LI: linear relation with the output; NLI: non-linear relation with the output or interaction with other inputs

	Analysed output indicators values averaged over years					
Input	Weed species richness	Weed-control variation §	Field infestation	Weed-crop biomass ratio §	Sprayed area	Herbicide TFI &
A. Maize monoculture						
DR-IR FR	NLI	NLI	NLI	NLI	NLI	NLI
HD	NLI	NLI	LI	NLI	NI	LI
WS	NLI	NI	NI	NLI	LI	LI
SD ID	NLI	LI	LI	NLI	NI	NI
SD-A TD	NLI	NLI	NLI	NLI	NI	NI
SD-B WR SW HE	NLI	NI	NI	NLI	NI	NI
DR-R	NLI	NI	NI	NI	NI	NI
B. Oilseed rape/wheat/barley rotation						
WS DR-IR FR WR TD	NLI	NLI	NLI	NLI	NLI	NLI

DR-R	NLI	NLI	NLI	NLI	NLI	NI
HD	NLI	NLI	NLI	NLI	NI	LI
SD-B SD-A SW SD HE	NLI	NLI	NLI	NLI	NI	NI

382 [§] due to site-specific spraying, [§] at flowering, proxy for yield loss due to weeds, & Treatment Frequency Index

383

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384

385 3.3.2 Sensitivity analysis

386 3.3.2.1 The most influential inputs

387 The Sobol sensitivity indexes were then used to rank the different inputs according to their
388 influence on the analysed output indicators (Table 5). For weed-control variation due to site-
389 specific spraying, the two variables determining crop-plant location in the field, sowing density
390 (SD) and the crop interrow distance (ID), contributed the most to the variance output in the maize
391 monoculture (Table 5.A). Among the inputs of the spraying strategy, only the herbicide dose
392 (HD) influenced this indicator. These impacts were all almost entirely due to first-order effects
393 (i.e., first-order sensitivity was almost equal total sensitivity).

394 Unlike for the maize-based system, the oilseed rape/wheat/barley rotation showed a high rate of
395 interactions between inputs (except for the sprayed area and the herbicide treatment frequency
396 index) (Table 5.B). For the two cropping systems, the sprayed area and the herbicide treatment
397 frequency indexes were mainly influenced by the same inputs: width of spray (WS) and treatment
398 date (TD) for the first indicator and herbicide dose (HD) and width of spray (WS) for the second.
399 For the other indicators and for both cropping systems, the herbicide dose (HD) was one of the
400 most influential inputs. The two cropping systems mainly differed in terms of the influence of
401 the herbicide efficiency (HE), which was low in the maize-based system but among the key inputs
402 for the diversified rotation.

403 The initial weed seed bank did not change the inputs that the most influenced herbicide treatment
404 frequency index in the oilseed rape/wheat/barley rotation (section D.2.2 online). This did not
405 apply to the other indicators for which the screening analysis showed a potential effect of the
406 initial seed bank (Table 3): when changing from the Aquitaine seed bank (IBAQ) to the Burgundy
407 one (IBBO), the first-order effect of the others inputs changed (section D.2.2 online). For
408 instance, with the Burgundy seed bank, the sowing density (SD) had a direct influence on the

409 weed-control variation due to site-specific spraying, the field infestation and the weed-crop
410 biomass ratio at flowering; this was not the case when the Aquitaine seed bank was used.

411

412 3.3.2.2 Which input choices improve weed control and reduce sprayed herbicide amounts?

413 Finally, linear regressions were done with all inputs in order to estimate the direction of the
414 relationship between inputs and outputs, i.e., whether an increase in the input led to an increase
415 or a decrease in the output (Table 6). Regardless of the rotation, increasing the spraying width
416 (WS) and the sprayed areas before and after the detected weed (SD-B and SD-A) increased the
417 sprayed field area and the herbicide treatment frequency index (TFI), but had no influence on the
418 other output indicators. Notably, there was no decrease in the weed/crop biomass ratio (i.e., the
419 proxy for crop yield loss due to weeds) or in the weed-control variation due to patch spraying.
420 Similarly, increasing the detection rates, particularly in the interrow (DR-IR), and decreasing the
421 minimum size to detected a weed (SW) increased sprayed area and TFI without improving weed
422 control. Only the weed species richness deteriorated in the maize monoculture.

423 Crop-plant location, on the other hand, was crucial for all outputs: the more crop plants there
424 were (high SD) and the closer they were located (small ID), the better weeds were controlled in
425 general (lower field infestation and weed/crop biomass ratio) and relatively to whole-field
426 spraying (larger weed-control variation). This came with a cost in terms of lower weed species
427 richness and larger amounts of sprayed herbicide (larger sprayed area, TFI), particularly for
428 smaller interrows (low ID).

429 Unsurprisingly, increased herbicide doses (HD) improved weed control, deteriorated weed
430 species richness and increased TFI, though the sprayed area was reduced (in maize monoculture
431 only). Increased herbicide efficiency had the same effects on weeds, though less visible in the
432 maize rotation and without the cost in terms of TFI. The effect of treatment date depended on the
433 rotation. In the winter-crop rotation (oilseed rape/wheat/barley), delayed spraying (large TD) had

434 the same effect as increased dosage or efficiency. In the spring-crop maize monoculture, the
435 effect was opposite, except that herbicide usage (TFI) did not decrease.

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Table 5: Identifying influential quantitative input variables with the Sobol sensibility analysis for the maize monoculture (A) and the oilseed rape/wheat/barley rotation using the initial weed seed bank from Burgundy (IB = IBBO; for IB = IBAQ and IB = IBAQ see section D.2.2 online) (B). Evaluation indicators are S1 (main-effect contribution without interaction) and ST (total contribution including interactions with other inputs). See Table 2 for the meaning of the input abbreviations.

		Analysed output indicators values averaged over years											
Input	Weed species richness		Weed-control variation due to site-specific spraying		Field infestation		Weed-crop biomass ratio at flowering (proxy for yield loss due to weeds)		Sprayed area		Herbicide Treatment Frequency Index		
	S1	ST	S1	ST	S1	ST	S1	ST	S1	ST	S1	ST	
A. Maize monoculture (initial weed seed bank IB = IBAQ)													
Spraying system													
WS	0.00	0.14	0.00	0.01	0.00	0.03	0.00	1.00	0.76	0.77	0.06	0.1	
SD-B	0.00	0.15	0.00	0.01	0.00	0.04	0.00	1.00	0.02	0.02	0.00	0.00	
SD-A	0.00	0.15	0.00	0.01	0.00	0.03	0.00	0.75	0.00	0.02	0.00	0.00	
Weed detection													
DR-R	0.00	0.15	0.00	0.01	0.00	0.03	0.00	0.69	0.00	0.01	0.00	0.00	
DR-IR	0.00	0.14	0.00	0.01	0.00	0.04	0.00	0.90	0.03	0.05	0.00	0.00	
FR	0.00	0.14	0.00	0.01	0.01	0.03	0.03	0.69	0.04	0.05	0.00	0.01	
WR	0.00	0.16	0.01	0.01	0.00	0.03	0.03	0.70	0.00	0.01	0.00	0.00	
SW	0.00	0.17	0.00	0.01	0.00	0.04	0.02	0.72	0.00	0.01	0.00	0.00	
Crop plant location													

SD	0.05	0.28	0.63	0.65	0.10	0.13	0.03	0.92	0.00	0.01	0.00	0.00
ID	0.14	0.35	0.23	0.24	0.24	0.25	0.00	0.91	0.00	0.03	0.00	0.00
Herbicide characteristics												
TD	0.13	0.30	0.02	0.03	0.07	0.10	0.00	0.88	0.06	0.08	0.01	0.01
HD	0.31	0.50	0.11	0.14	0.57	0.65	0.10	1.00	0.00	0.02	0.89	0.92
HE	0.00	0.14	0.00	0.01	0.00	0.03	0.01	0.93	0.00	0.00	0.00	0.00
B. Oilseed rape/wheat/barley rotation (initial weed seed bank IB = IBBO)												
Spraying system												
WS	0.00	0.52	0.00	0.60	0.02	0.80	0.04	0.72	0.70	0.68	0.06	0.05
SD-B	0.00	0.50	0.00	0.66	0.00	0.87	0.00	0.69	0.00	0.04	0.00	0.00
SD-A	0.01	0.55	0.03	0.63	0.05	0.80	0.00	0.69	0.02	0.04	0.00	0.00
Weed detection												
DR-R	0.01	0.54	0.00	0.62	0.00	0.82	0.00	0.68	0.00	0.04	0.00	0.00
DR-IR	0.07	0.53	0.00	0.62	0.00	0.77	0.00	0.72	0.03	0.05	0.00	0.00
FR	0.00	0.50	0.00	0.68	0.00	0.91	0.03	0.68	0.02	0.05	0.00	0.00
WR	0.00	0.54	0.00	0.59	0.00	0.81	0.00	0.68	0.00	0.03	0.00	0.00
SW	0.01	0.58	0.00	0.62	0.05	0.77	0.04	0.68	0.08	0.13	0.00	0.01
Crop plant location												
SD	0.07	0.55	0.08	0.65	0.07	0.83	0.08	0.78	0.02	0.03	0.00	0.00
Herbicide characteristics												
TD	0.00	0.54	0.00	0.61	0.00	0.76	0.04	0.69	0.19	0.25	0.00	0.01
HD	0.16	0.65	0.09	0.64	0.09	0.76	0.09	0.73	0.00	0.03	0.97	0.98
HE	0.38	0.93	0.31	0.89	0.23	0.99	0.18	0.85	0.01	0.03	0.00	0.00

Table 6: Identifying relationships between input variables and indicators with linear regressions for the maize monoculture (A) and the Oilseed rape/wheat/barley rotation (B). See Table 2 for the meaning of the input abbreviations. ns = effect of simulation factor not significant at $p=0.05$. Only inputs significantly

correlated to at least one output are shown; effect of seed bank inputs and spectrum of the used herbicide can be found in section D.2.3 online. Input-output combinations with positive (resp. negative) correlation are shown in green (resp. red). Input-output combinations that were identified as crucial in section 3.3.3 (i.e., sensitive outputs, influential inputs) are shown in bold.

Input	Analysed output indicators values averaged over years					
	Weed species richness (number of species)	Weed-control variation \$ (t dry matter/ha)	Field infestation (t dry matter/ha)	Weed-crop biomass ratio § (t/t)	Sprayed area (%)	Herbicide TFI &
A. Maize monoculture						
R ²	0.62	0.79	0.57	0.16	0.53	0.94
Spraying-system inputs						
WS (cm)	ns	ns	ns	ns	0.154	0.0008
SD-B (cm)	ns	ns	ns	ns	0.0216	0.0001
SD-A (cm)	ns	ns	ns	ns	0.0194	0.0001
Weed-detection inputs						
DR-R (%)	ns	ns	ns	ns	3.17	ns
DR-IR (%)	-0.0674	ns	ns	ns	5.97	0.0304
FR (%)	ns	ns	ns	ns	7.33	0.0338
Crop-location inputs						
SD (%)	-1.04	2.81	-0.289	-19.6	ns	ns
ID (cm)	0.0045	-0.0057	0.0016	0.0806	-0.0529	-0.0002
Herbicide characteristics						
TD (days)	0.0284	-0.0105	0.0057	0.265	0.637	0.0034
HD (%)	-0.623	0.332	-0.208	-21.5	-2.40	0.855
HE (%)	ns	ns	Ns	-4.03	ns	ns
B. Oilseed rape/wheat/barley rotation						
R ²	0.88	0.92	0.84	0.54	0.37	0.96
Spraying-system inputs						
WS (cm)	ns	ns	ns	ns	0.134	0.0004

SD-B (cm)	ns	ns	ns	ns	0.0260	7.61E-05
SD-A (cm)	ns	ns	ns	ns	0.0232	ns
Weed-detection inputs						
DR-IR (%)	ns	ns	ns	ns	5.48	ns
SW (cm)	ns	ns	ns	ns	-5.11	-0.0142
Crop-location inputs						
SD (%)	-0.0938	0.809	-0.200	-22.1	ns	ns
Herbicide characteristics						
TD (days)	-0.0018	0.0048	ns	ns	1.05	0.0028
HD (%)	-0.151	0.268	-0.115	-11.5	ns	1.07
HE (%)	-0.291	0.535	-0.155	-8.07	ns	ns

436 § due to site-specific spraying, § at flowering, proxy for yield loss due to weeds, & Treatment Frequency Index

437

438 3.3.3 Uncertainty analysis and input selection

439 In order to select the influential inputs that must be determined accurately for the estimation of a
 440 given indicator, the coefficient of variation was analyzed with regard to the total effect index of
 441 each input.

442 For the maize-based system (Figure 2), the uncertainty in the considered inputs had little
 443 influence on simulated species richness and sprayed area. Indeed, even if some inputs (like *HD*
 444 or *WS*) influenced indicator values (i.e., their *ST* values exceeded 0.5), the indicator variations
 445 remained low (i.e., the associated coefficients of variation were lower than 0.3). The herbicide
 446 dose (*HD*) and the width of spray (*WS*) were the only inputs that needed to be accurately
 447 determined to estimate the herbicide treatment frequency indicator, i.e., they were the only inputs
 448 whose *ST* value exceeded 10%. For weed-crop biomass ratio at flowering (i.e., a proxy for crop
 449 yield loss due to weeds), the coefficient of variation was over 0.3 and all input *ST* indexes
 450 exceeded 10% (Figure 2) and therefore, all inputs had to be accurately defined.

451 For the oilseed rape/wheat/barley rotation (section D.3.2 online), conclusions were similar for
 452 species richness and sprayed area. However, this more complex cropping system needed more

453 inputs to accurately simulate some indicators. For instance, for the weed-control variation due to
454 site-specific spraying indicator, all inputs had to be precisely set.

455

456 **3.4 Conclusion**

457 The sensitivity analysis showed that cropping system, sowing density, herbicide dose, herbicide
458 efficiency were the most influential inputs for all indicators. Furthermore, the herbicide site-
459 specific spraying system inputs (weed detection and geometry of the spray pattern) influenced
460 the sprayed area and the herbicide treatment frequency indicator. In the most complex cropping
461 system, interactions among inputs were significant for all indicators, especially for weed-crop
462 biomass ratio (the proxy for yield loss due to weeds), which was thus more complex to analyze.

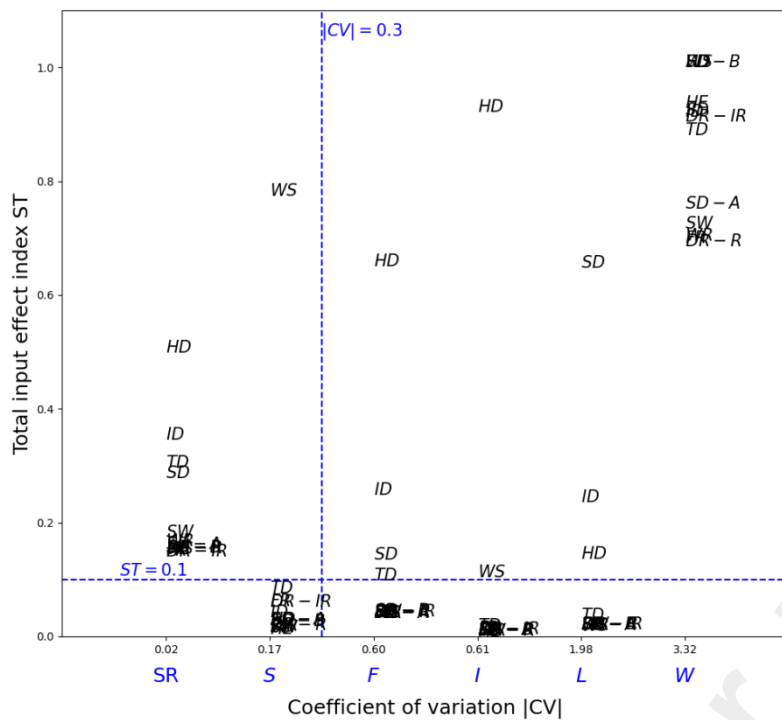
463 The sensitivity and uncertainty analyses did not highlight a single input that mainly influenced
464 the studied weed-impact indicators. Moreover, the uncertainty analysis showed that it was not
465 necessary to exactly know the value of the herbicide site-specific spraying system inputs (weed
466 detection and geometry of the spray pattern) to predict the sprayed area and the herbicide
467 treatment frequency. This last indicator mainly depended on herbicide dose.

468 Moreover, the uncertainty analysis showed that the considered inputs had little impact on wild
469 plant species richness and sprayed area. Conversely, all inputs were needed to estimate the weed-
470 control variation due to site-specific spraying and the weed-crop biomass ratio.

471 The initial seed bank had an influence on the input uncertainties of the field infestation indicator:
472 for the complex cropping system where all inputs had little influence on the indicator, when the
473 Burgundy and Poitou-Charentes initial seed banks were used, all were necessary to estimate the
474 indicator when the Aquitaine initial seed bank was used.

475

476



477

Figure 2: Identifying the important inputs to be determined accurately with an uncertainty analysis, using the maize-based cropping system as an example (see section D.3 online for the oilseed rape/wheat/barley rotation). For each indicator (species richness: SR, weed-control variation due to site-specific spraying: L, field infestation: F, weed-crop biomass ratio at flowering: W, sprayed field area: S, herbicide treatment frequency indicator: I), absolute value of coefficient of variation (unitless) is on the horizontal axis and the corresponding input total effects index (ST) are on the vertical axis (unitless). For each indicator, inputs are represented with their labels (see Table 1 for meanings). Any input whose $|CV|$ value exceeded 0.3 (vertical dashed line) and whose ST exceeded 10% (horizontal dashed line) needed to determine accurately to ensure satisfactory indicator predictions. These combinations were highlighted in Table 6

478

479 4 Case study of an herbicide site-specific spraying system

480 The interest of the new patch-spraying submodel of FLORSYS was illustrated here with an
 481 autonomous mobile platform, which has been presented and evaluated in (Maillot et al., 2016)
 482 and summarized here in section 4.1.

483

484 4.1 Patch-spraying platform presentation and *in situ* evaluation

485 4.1.1 A mobile platform based on WeedSeeker

486 The studied mobile platform aims to detect and treat the vegetation in the inter-row: spraying is
487 triggered only where a plant is detected. The spray system is based on a WeedSeeker system
488 (Trimble) including an optical sensor and a spray nozzle positioned at 30 cm from the soil
489 surface. At this height, with a nozzle of 65°, the width of spray is about 35 cm. The optical sensor
490 distinguishes green plants from the soil using their spectral properties. It uses its own light
491 emission and measures the spectral reflection in the red and the near infrared to calculate a
492 vegetation index.

493 494 4.1.2 Field experiments for calibration and evaluation

495 Field experiments were carried out on a 120 m² plot at L'Institut Agro Dijon (47°18'30.0"N
496 5°03'53.2"E). The plot was composed of a deep clay-limestone soil. Maize was sown in mid-
497 June with a row spacing of 0.75 m. Mechanical weeding was carried out after emergence, at the
498 3-4 leaf stage. The experiments were carried out at the 4-6 leaf stage, with 24 passages in three
499 different inter-rows of 12 m in length. The working speed was 1–2 km/h.

500 The positioning of the WeedSeeker was such that the detection zone (length 20 cm x width 2 cm
501 at 30 cm height) of its optical sensor was centered on the middle of the inter-row. Calibration
502 and configuration of the optical sensor were performed using the WeedSeeker control panel on
503 bare ground. Ten sensor-configuration values (chosen via the control panel) were tested, ranging
504 from *Sens. 1* (lowest sensitivity) to *Sens. 10* (highest).

505 Weeds detected and treated by the WeedSeeker were geolocated using an GPS RTK signal. These
506 weed positions were compared to a weed map constructed the same day using the Excess Green
507 Vegetation Index (ExG) (Meyer and Neto, 2008) computed using multispectral sensor images.

508

509 4.1.3 Accuracy of the weed detection system

510 The configurations *Sens. 1* to *Sens. 4* led to too many false positives (i.e., > 20%), identifying
511 bare soil or plant residues as living vegetation, and were not considered hence. The in-field
512 measured accuracy of the other configurations of the weed-detection system are shown in Table
513 7. The sensor sensitivity corresponds to the number of plants correctly detected and therefore
514 treated. Sensor specificity indicates the ability of the system to avoid false positives, and thus to
515 save pesticides and to reduce environmental impacts. The overall precision of the system was
516 computed by the ratio of the sum of the true positives and the true negatives by the sum of the
517 positive and negative real cases.

518 In our experiments, configuration *Sens. 7* of the WeedSeeker led to a good compromise between
519 the average sensor sensitivity and the average sensor specificity (Table 7). This configuration
520 had already been noted for its ability to detect plants in the field (Rees et al., 2013; Sui et al.,
521 2008). Our results are similar to those obtained in (Andújar et al., 2011). The overall accuracy
522 obtained during these tests is comparable to studies using human perception (Andújar et al.,
523 2010).

524 These field trials showed that for each WeedSeeker configuration, the spraying system ignored
525 some weeds (22% for the *Sens.7* configuration) which were therefore not treated. Potentially,
526 these weeds compete with the crops for resources, thus reducing the yield, and replenish the soil
527 seed bank, thus increasing the risk of reducing yields in subsequent years. To evaluate these risks,
528 simulations were carried out in the next step.

Table 7: Sensor sensibility (true positive rate) and specificity (true negative rate) analysis of the weed detection system measured in field measurements. The overall precision gives an estimate of the propensity of the system to correctly detect true positives and negatives (Maillot et al., 2016)

WeedSeeker configuration	Average sensor sensitivity* (%)	Average sensor specificity** (%)	Overall precision*** (%)
Sens. 5	79	81	81
Sens. 6	77	82	82
Sens. 7	78	83	82
Sens. 8	66	88	87
Sens. 9	65	89	84
Sens. 10	44	92	84

529 * % of detected weeds (true positive detections)

530 ** 100% - % of crops or bare soil identified as weeds (true negative detections)

531 *** Overall precision is the ratio of correct detections (true positive and true negative) by the total of detections

532

533 4.2 Virtual experiments with FLORSYS

534 Virtual experiments were carried out with FLORSYS to assess how well herbicide site-specific
 535 spraying systems applied to the interrow combined with a continuous row spraying manage
 536 weeds compared to a full spraying over several years. Simulations were run with the seedbank,
 537 pedoclimate and maize-based cropping system from Aquitaine (see section 3.2.1).

538 Six spraying scenarios were tested (Table 2), corresponding to six WeedSeeker configurations
 539 (*Sens. 5 to Sens. 10*) with different weed detection (*DR-IR*) and false detection (*FR*) rates in the
 540 interrow measured in the experiment of section 4.1.2. Two values were given for the *DR-IR* and
 541 *FR* inputs to take into account the size weed dependent efficiency of the WeedSeeker thanks to
 542 the minimum size of detected weeds input (*SW*) (Rees et al., 2013). As site-specific spraying was
 543 limited to the interrow and the crop row was continuously sprayed, the detection rate of weed in
 544 crop row input (*DR-R*) was set to 0. A seventh spraying scenario simulated a full spraying

545 treatment and was used as a reference to calculate weed-control variation due to the site-specific
546 spraying scenarios compared to a full treatment.

547 The treatment date (TD) and all other cropping-system components remained unchanged,
548 including those that interact with patch spraying, i.e. sowing density (*SD*), herbicide dose (*HD*),
549 herbicide efficiency (*HE*), crop interrow (*ID*), spectrum of the used herbicide (*SH*, which was set
550 to the *DEFAULT* spectrum targeting both monocotyledons and dicotyledons), and initial seed
551 bank *IB*, which was set to *IBAQ* (see Table 2).

552 Each scenario was simulated over 30 years and was repeated 10 times with 10 different weather
553 series consisting of 30 randomly chosen weathers years from the Aquitaine region. The simulated
554 weed-impact indicators were averaged over the 30 simulated years and analyzed with ANOVA
555 as a function of spraying scenario and weather repetition. Indicator means were compared using
556 t-tests (for one-to-one comparison), or One-way ANOVA tests (for multiple comparison).
557 Synergies and antagonisms between indicators were analysed using Pearson correlation. All
558 statistical analyses were performed using Python and the statistical functions of the SciPy library
559 (Oliphant, 2007).

560

561 **4.3 Results**

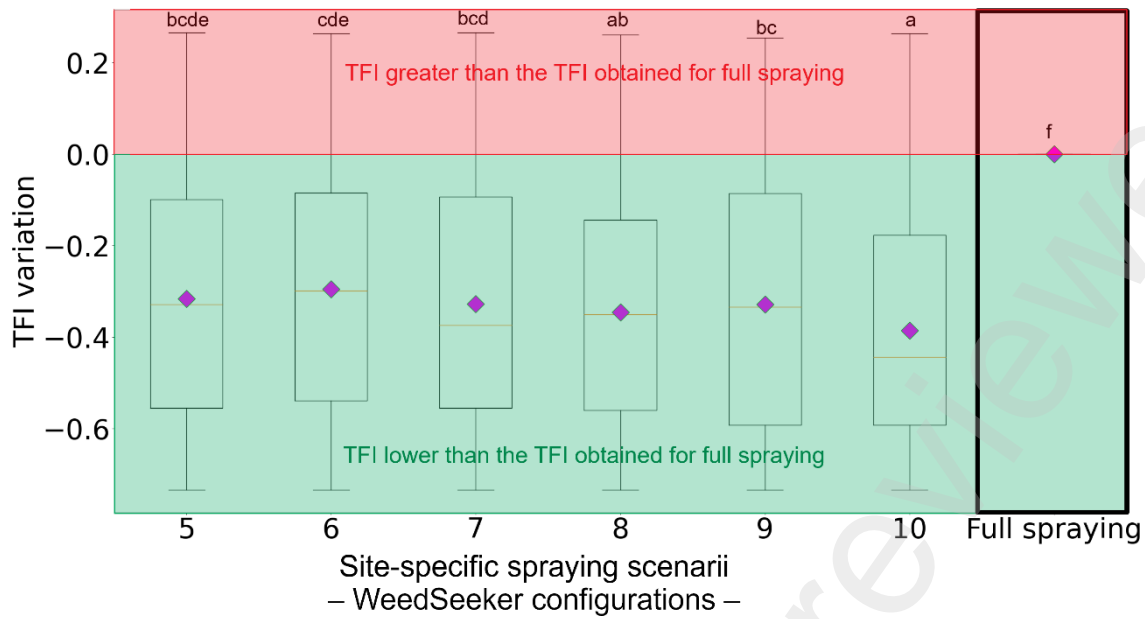
562 Analyses of variances of output indicators averaged over the simulated 30 years showed that the
563 spraying strategies (i.e., the 6 scenarios of Table 7 and the full spraying scenario) did not
564 influence any of the weed-impact indicators, i.e., the weed-crop biomass ratio at crop flowering
565 (as a proxy for yield loss due to weeds), weed-control variation due to site-specific spraying, i.e.,
566 the yield in patch-sprayed vs full-field sprayed fields, field infestation by weeds, or weed species
567 richness (details in section E online). Only the indicators related to herbicide use intensity were
568 influenced, i.e., the sprayed field area and the herbicide treatment frequency index (TFI) varied
569 with the spraying strategies.

570 The comparison of the six site-specific spraying strategies of Table 7 showed that the TFI and
571 the sprayed area were not influenced by the WeedSeeker configuration (p-value: 0.2 for sprayed
572 area and 0.18 for TFI). These two indicators were highly correlated (Pearson correlation
573 coefficient = 0.99) as the cropping system was a monoculture with the same herbicide strategy
574 each year. In conclusion, the two indicators related to herbicide use intensity were impacted by
575 switching from a full spraying strategy to a site-specific strategy but not by the configuration of
576 the site-specific strategy.

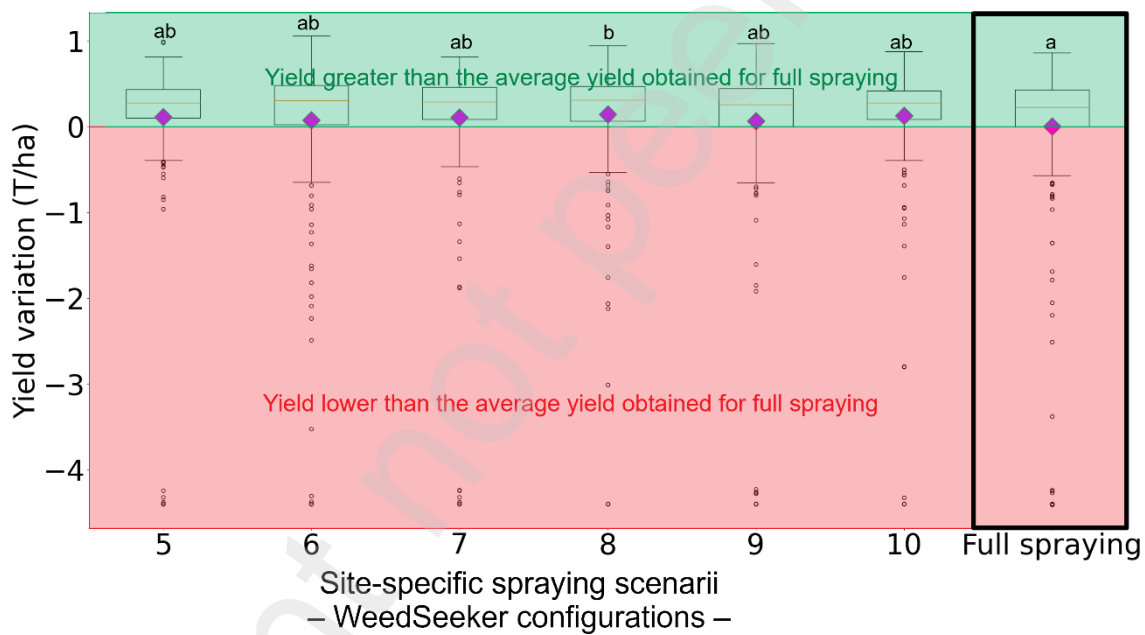
577
578 In average over all years, weather repetitions and site-specific spraying strategies, the averaged
579 sprayed field area dropped from 100% for the whole-field treatment to 66% (details in section E
580 online). The continuous treatment of the crop rows accounted for about 26% of the sprayed field
581 area. Similarly, the herbicide TFI was reduced by 34% when switching from whole-field to site-
582 specific spraying, without any significant difference depending on the WeedSeeker
583 configurations (Figure 3.A).

584 This reduction affected neither crop yield (Figure 3.B) nor yield loss due to weeds (analysed via
585 the weed-crop biomass ratio at crop flowering) (details in section E online). However, weed-
586 impact indicator values, such as yield loss due to weeds, varied more strongly between years in
587 the case of site-specific spraying (Figure 4), and thus also the yield and the farmer's income.
588 Peaks of weed infestation were nevertheless controlled and the overall infestation remained
589 stable in the long term. It should also be highlighted that those peaks of weed infestation were
590 also possible for a full spraying strategy (years 5 and 21) and that it took several years (e.g. years
591 6 to 9) for the infestation to stabilize again at a low level (years 10 to 20).

592



(A)



(B)

Figure 3: Effect of site-specific herbicide spraying scenarios compared to a whole-field spraying strategy for different weed-detection sensitivities in a maize monoculture in Aquitaine for herbicide treatment frequency index TFI (A) and crop yield (B). On the x-label, WS Sens.x stands for the configuration Sens.x of the WeedSeeker: the lower the sensitivity value, the more sensitive the spray system is to weed color variations. The purple dots represent the averages of the TFI or yield variations obtained, for each simulation (scenario \times year \times weather repetition). Letters show means that are not different at $p=0.05$ from One-way ANOVA tests.

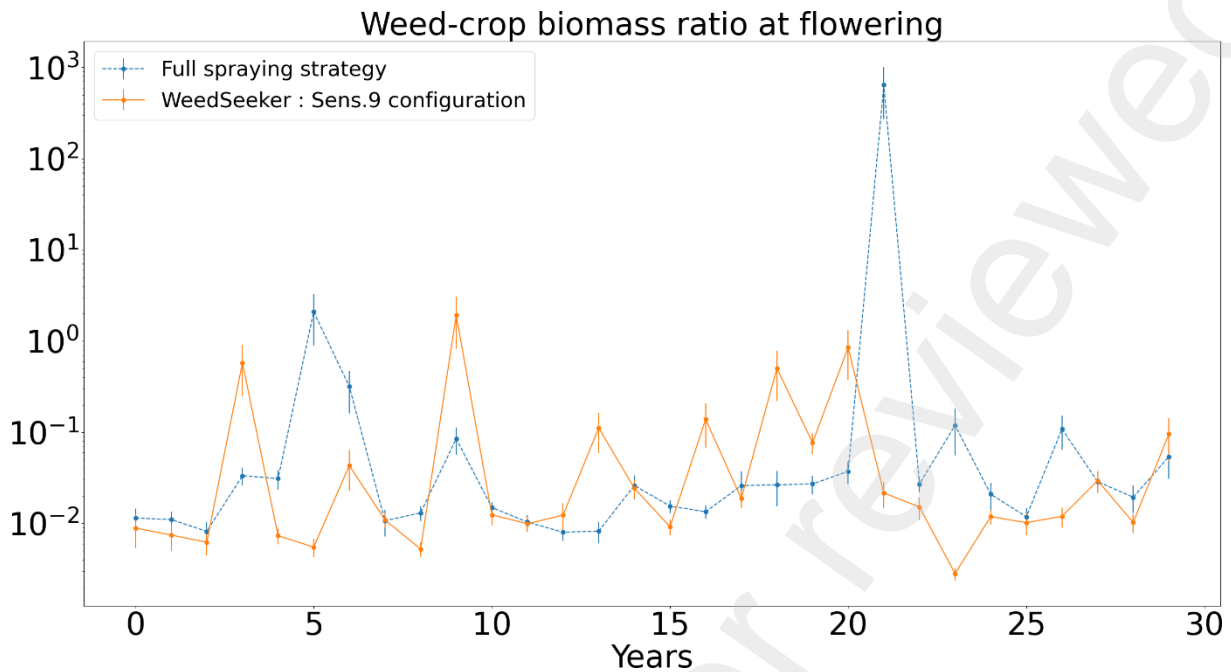


Figure 4: Annual evolution of the weed-crop biomass ratio at crop flowering (proxy for yield loss due to weeds) in a maize-based cropping system in Aquitaine depending on the type of spraying strategy (dashed blue = full, orange = site-specific spraying system based on the WeedSeeker system with the Sens. 9 configuration). The vertical segments represent the 68% confidence interval, resulting from the 10 weather repetitions.

595 5 Discussion

596

597 5.1 A more realistic model of weed-crop dynamics and site-specific spraying systems...

598 The present study combined (1) a complex multiannual multispecies model acting as a virtual
599 experimental field to allow large-scale virtual experiments ranging through thousands of virtual
600 site-specific herbicide-spraying systems and crop-sowing patterns in contrasting real-life
601 rotations, weed floras, soils and weather conditions, and (2) actual field measurements to
602 characterize a site-specific herbicide-spraying platform. The complex experimental plan was
603 analysed with a series of statistical methods to identify which weed impacts are the most sensitive
604 to patch spraying, which are the most influential patch-spraying characteristics, how they interact
605 with crop rotation and management, and whether site-specific spraying allows sufficient weed
606 control in the long-term to ensure crop production while reducing herbicide use.

607 To date, site-specific spraying is usually evaluated in the short term in actual fields (see
608 introduction). Even among the teams that work *in silico*, few look beyond the amount of herbicide
609 savings, applying different thresholds for triggering spraying to maps of weed patches established
610 from manual countings, drones and other unmanned vehicles and combining them with yield-
611 loss functions (Ali et al., 2015; Andújar et al., 2013). Those that use simulation models to
612 evaluate site-specific spraying focus on the short term only, working with weed emergence
613 models (Nikolić et al., 2021) and/or very basic weed-dynamics models, with one crop or one
614 weed only (Dicke et al., 2007). The tested spraying system was usually simplistic, i.e.
615 disregarding technical details such spraying width and distances to the detected vegetation, or
616 the distinction of detection zones relatively to crop rows, as we did here.

617 Despite its complexity, FLORSYS presents a major short-coming for evaluating site-specific
618 spraying. In the simulations, weed plants are distributed in patches whose size depends on the
619 species plant height, regardless of tillage and harvest operations, even though these are known to
620 displace weed seeds inside fields (Barroso et al., 2006). Very few models simulate weed-seed

621 dispersal and plant distribution mechanistically, and with enough details to evaluate site-specific
622 spraying (González-Díaz et al., 2015; Paice et al., 1998). But these models only consider one
623 weed in one crop type. And while they can be very precise in terms of plant location (e.g., 5 cm
624 in Paice et al., 1998), the simulated field is simply split into cells in which the weed life-cycle
625 submodel runs simultaneously and independently. The 3D-interactions between neighbouring
626 individual plants and the effect on morphological plasticity are disregarded, even though this
627 scale is now deemed necessary to realistically model weed dynamics (Renton, 2013). Moreover,
628 the resolution (“grain”) of these cell-based models is often too imprecise for testing actual
629 modern spraying equipment (e.g., ~1 m² in González-Díaz et al., 2015).

630 Even though FLORSYS considers many more technical details to describe site-specific spraying
631 than its predecessors, it only accepts a spray nozzle with a uniform spraying pattern. Although
632 the spraying system studied in section 4 may be equipped with such a nozzle, the actual pattern
633 may differ and lead to a weed-control failure because the spray deposit under a single nozzle is
634 not constant and weeds may be exposed to a sublethal application rate. Studies like (Villette et
635 al., 2019) could help to refine the analysis.

636

637 **5.2to produce more realistic conclusions**

638 The high degree of realism of the crop-weed interactions and the site-specific spraying submodels
639 in FLORSYS made it possible to produce novel conclusions. The sensitivity and uncertainty
640 analyses showed that the studied weed-impact indicators were not influenced by a single
641 individual spraying input, but the degree of weed control resulted from the interaction of several
642 inputs. Table 8 summarizes the discussion hereafter in focusing on inputs impact on crop
643 production and herbicide use.

644 Using a complex mechanistic model allowed explaining these interactions. For example, the
645 impact of the weed-detection rate or the minimum detectible weed size decreases with the
646 spraying width: the larger the latter is, the more undetected weeds are treated together with a

647 detected weed. The dominant effect of spraying width was most visible when looking at the
648 sprayed field area. These results confirm previous findings that the sprayed area depends on the
649 spraying strategy (spraying durations and target size) and weed distribution (Wiles, 2009). But
650 otherwise, inputs specific to site-specific spraying (i.e., spraying-system and weed-detection
651 inputs) had negligible first-order effects, particularly compared to differences among cropping
652 systems. This is consistent with literature (Timmermann et al., 2003; Wiles, 2009) reporting that
653 the impact of the production situation greatly exceeds that of the characteristics site-specific
654 spraying.

655 Unsurprisingly, the weight of the interactions was the most important for the weed-crop biomass
656 ratio at crop flowering (i.e., the proxy for yield loss due to weeds). This indicator is the result of
657 processes not only related to weeds, but also to crop-weed interactions, all of which strongly
658 interact with weather and cropping system. A more complex method should be used in order to
659 consider stochasticity and identify correlations between input variables (Gauchi et al., 2017;
660 Sudret, 2008; Sudret and Caniou, 2013).

661 The number of the relevant inputs and the weight of the interactions were larger in the complex
662 cropping system, notably when looking at indicators like the field infestation and the weed-
663 control variation due to site-specific spraying. The rotation consisted of different crop species
664 sown in different seasons, resulting in more diverse weed floras which, moreover, varied over
665 the years. As a result, both the weed-detection and the herbicide-efficiency rates varied over time.
666 The different crops were also sown with different interrows, influencing the proportion of patch-
667 sprayed field area. These results are consistent with (Audsley, 1993; Christensen et al., 2009;
668 Rider et al., 2006; Wiles, 2009) who concluded that, to increase the effectiveness of site-specific
669 management, spraying systems need information about weed species composition and density.
670 The latter vary between fields and over time, hence the relevance of multiannual multispecies
671 models such as FLORSYS to predict them.

Table 8: Results and discussion summary considering inputs impact on crop production and herbicide use

Increase in ...	Impact on crop production	Impact on herbicide use	Reason	Similar findings in literature
Spraying width & length	None	↗	Sprays more area	(Timmermann et al., 2003;
True and false detection rate (particularly interrow)	None	None	Controlled impact of weed infestation and long-term overall infestation remained stable in the long term	Villette et al., 2019; Wiles, 2009)
Sowing density	↗	None	Fewer resources for weeds (depend on weed competitiveness)	(Audsley, 1993; Rider et al., 2006)
Interrow width	↘ (spring crop)	None	Fewer crop rows	
Treatment date	None (spring crop), ↗ (winter crop)	None	More emerged weeds to detect, but more difficult to destroy in spring crops	
Herbicide dosage	↗	↗	More product sprayed → more weeds killed Low herbicide use rate can lead to non-target site-based resistance	(Audsley, 1993; Manalil et al., 2011; Neve and Powles, 2005)

Herbicide efficiency	↗	None	More weeds killed	
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674

675 **5.3 Implications for weed management in the field**

676 The maize-based case study confirmed the main conclusions of the sensitivity and uncertainty
677 analyses: except for the sprayed field area and the herbicide amount (via the treatment frequency
678 index TFI), modifications in the spraying strategies (spraying pattern, weed detection) had no
679 effect on weed-impact indicators. Most importantly, average crop production was as good in the
680 site-specific spraying than in fully sprayed scenarios.

681 The analysis of indicator values during the 30 simulated years explains why the accuracy of the
682 detection system had no effect. The sprayed area increased with the field infestation. In other
683 words, when the weed infestation increased too much, the spray system adapted by spraying
684 more herbicide, regardless of its sensitivity (Villette et al., 2019; Wiles, 2009). This avoided any
685 drop in crop production at the cost of spraying the whole field in some years or weather
686 repetitions. But, on average herbicide used decreased by 34% compared the full spraying
687 strategy, very similar to the 35% reported by (Wiles, 2009) or the 40% in average in (Medlin and
688 Shaw, 2000).

689 Thus, the site-specific spraying can be useful to reduce herbicide use while allowing a robust
690 long-term management of weeds. However, as highlighted in previous works (Barroso et al.,
691 2004; Timmermann et al., 2003; Wiles, 2009), income of this strategy mainly depends on the
692 weed patch distribution. Site-specific weed management certainly will be the most advantageous
693 when preventive weed management options reduce weed infestation to residual patches rather
694 than a continuous dense weed canopy. Moreover, an economic study remains to be done to check
695 that the investment in the site-specific spraying system is cancelled out by the reduction in
696 herbicide costs.

697

698 **6 Conclusion**

699 The present study used a novel approach combining (1) a complex multispecies multiannual
700 model (FLORSYS) producing detailed realistic predictions of crop-weed canopies, (2) a new
701 submodel to simulate the detection and site-specific treatment of weeds, and (3) field
702 measurements to characterize a site-specific herbicide-spraying platform. A global sensitivity
703 analysis combined with an uncertainty analysis were used to identify the most influential inputs
704 and the most sensitive output indicators evaluating crop production, weed harmfulness and
705 benefits as well as herbicide use intensity. The general conclusions were consistent with
706 literature, i.e., cropping system (rotation with associated sowing patterns, herbicide products and
707 treatment dates) was much more influential than the characteristics of the spraying system in
708 terms of geometrical spraying pattern and weed detection. But thanks to the realism of the
709 FLORSYS model and the complexity of the simulation plan, we were able to go much further in
710 exploring different cropping systems and weed floras and understanding interactions. Finally, a
711 real-life case study was used to demonstrate the feasibility of reconciling crop production with
712 reduced herbicide use, thanks to site-specific spraying, at a multiannual scale. This is a major
713 step forward compared to previous studies focusing on short-term (annual) herbicide savings,
714 disregarding risk for future crops due to weed-seed production of missed or surviving weeds. The
715 next steps will be to explore more cropping systems to identify in which situations and with
716 which weeds floras site-specific spraying will be the most beneficial.

717

718

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723

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