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

Thibault Maillot[1], Jean-Baptiste Vioix[2], Nathalie Colbach[1]

ABSTRACT

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

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

Highlights:

[1] Agroécologie, INRAE, Institut Agro, Univ. Bourgogne, Univ. Bourgogne Franche-Comté, F-21000 Dijon, France.
thibault.maillot@agrosupdijon.fr
[2] Univ. Bourgogne, Route des plaines de l'Yonne, Auxerre, France.

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

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1 Introduction

Because synthetic inputs (fertilizers, pesticides, etc.) damage the environment and human health (Wilson and Tisdell, 2001), their use must be reduced, which is a major challenge for farmers. This is particularly true for weed management as weeds are considered to be the most harmful crop pest (Oerke, 2006). Herbicides must now be replaced as much as possible with a combination of multiple, mostly preventive and partially efficient practices (Liebman et al., 1997; Wezel et al., 2014). Site-specific herbicide spraying allows going even further by spraying only where weeds are detected in the field (Esau et al., 2018; Fernández-Quintanilla et al., 2017; Gerhards et al., 2022; Gonzalez-de-Soto et al., 2016; Johnson et al., 1995; Peña et al., 2013).

Most patch-spraying systems rely on weed detection procedures that locate and then treat weeds in fields. Many detection systems are based on optical sensors (Gerhards and Christensen, 2003; Gerhards and Oebel, 2006; Guerrero et al., 2017; Louargant et al., 2018). The algorithms used in these systems are not yet perfect, either missing some weeds or erroneously considering bare soil or crops as weeds. Detection rates can also be influenced by the way the system is used in the field. Each detection method must thus be evaluated to check whether its detection rates are adequate for a practical use in farmers' fields. For instance, in (Gonzalez-de-Soto et al., 2016), authors working with a robotized patch-spraying system find that reducing herbicide use depends on weed abundance (the higher the density is, the less herbicide is saved) and distribution (the more weeds are aggregated, the more herbicide is save). The same trends were identified by simulation (Villette et al., 2019). Other teams tackle the economic issue of site-specific weed management and crop yield loss (Rider et al., 2006; Wilkerson et al., 2004). In their case study, the costs of site-specific management were not compensated by the additional return (reduced herbicide use). But the economic results varied enormously among considered fields.

Most of these studies focus on the short-term impact of this spraying strategy, simply looking at weed reduction rates after spraying or, at the best, yield loss or gain in the sprayed crop. However, weeds must be managed at the multiannual scale as their seeds survive for several years in the

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

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

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

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

2 The FLORSYS model

2.1 The current version

2.1.1 Model inputs

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

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

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

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2.1.2 The annual life cycle of crops and weeds

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

2.1.3 Impact of cultural techniques

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

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

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

2.1.4 Model outputs

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

2.1.5 Model evaluation

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

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2.2 Introducing site-specific spraying into FLORSYS

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

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

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

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

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

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

The last two steps are the same as for any herbicide applied over the whole field. Crop plants are assumed not be affected by site-specific herbicide treatments. If the applied herbicide also presents pseudo-root or root-penetrating properties, the relative sprayed field area X is calculated from the spray map. A proportion Y of ungerminated seedlings (for which only density per m² is considered, disregarding coordinates) then dies because of the treatment.

3 Sensitivity and uncertainty analyses

3.1 Principle

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

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

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

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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

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3.2 Material and methods

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

3.2.1 Model inputs used in the sensitivity analysis

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

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

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

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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[$]	–	days
HD	Herbicide dose	0 – 100[$$]	–	%
SH	Spectrum of the used herbicide (qualitative)	monocotyledons (MONOCOT); dicotyledons (DICOT);	DEFAULT	

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		both (DEFAULT).		
HE	Herbicide efficiency (in optimal conditions)	0 – 100#	–	%

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

[&]percentage variation of the nominal value;

[$$] percentage of the recommended dose.

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

B. Interrow detection rates DR-IR and false detection rate FR in the case study, depending on the minimum detected weed size SW. Each combination of DR-IR, FR and SW corresponds to 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
Sens. 5	40	9	79	19
Sens. 6	38	9	77	18
Sens. 7	39	8	78	17
Sens. 8	33	6	66	12
Sens. 9	32	5	65	11
Sens. 10	22	4	44	8

3.2.2 Analysed outputs

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

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

3.2.3 Simulation plan and statistical analysis

3.2.3.1 Screening analysis

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

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

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oilseed rape/wheat/barley rotation (Herman et al., 2013; Morris, 1991). For each qualitative input, two sensitivity measures are computed (Campolongo et al., 2011). Considering the *i*-th input, μ_i^* and σ_i denote these measures. μ_i^* assesses the influence of the *i*-th input on the indicator values and σ_i is a measure of non-linear and/or interaction effects of the *i*-th input. The *i*-th input is considered as important if either μ_i^* or σ_i have a large value. As proposed in (Turati et al., 2016), to select important factors we first considered that a factor *i* has an important effect on an 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 of inputs. Arbitrarily, a threshold on σ was chosen equal to 1/3 of the maximum value to refine the selected important factors. In order to confirm the input selection, a visual analysis of σ values as a function of μ^* values was carried out. This analysis aimed to identify the different input groups that may have similar importance.

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

3.2.3.2 Global sensitivity analysis

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

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

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

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

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

3.2.3.3 Uncertainty analysis

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

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

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

3.2.3.4 Final Input selection

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

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

3.3 Results

3.3.1 Screening analysis

3.3.1.1 Selection of qualitative inputs

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

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

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

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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 SH		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

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3.3.1.2 Quantitative inputs

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

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

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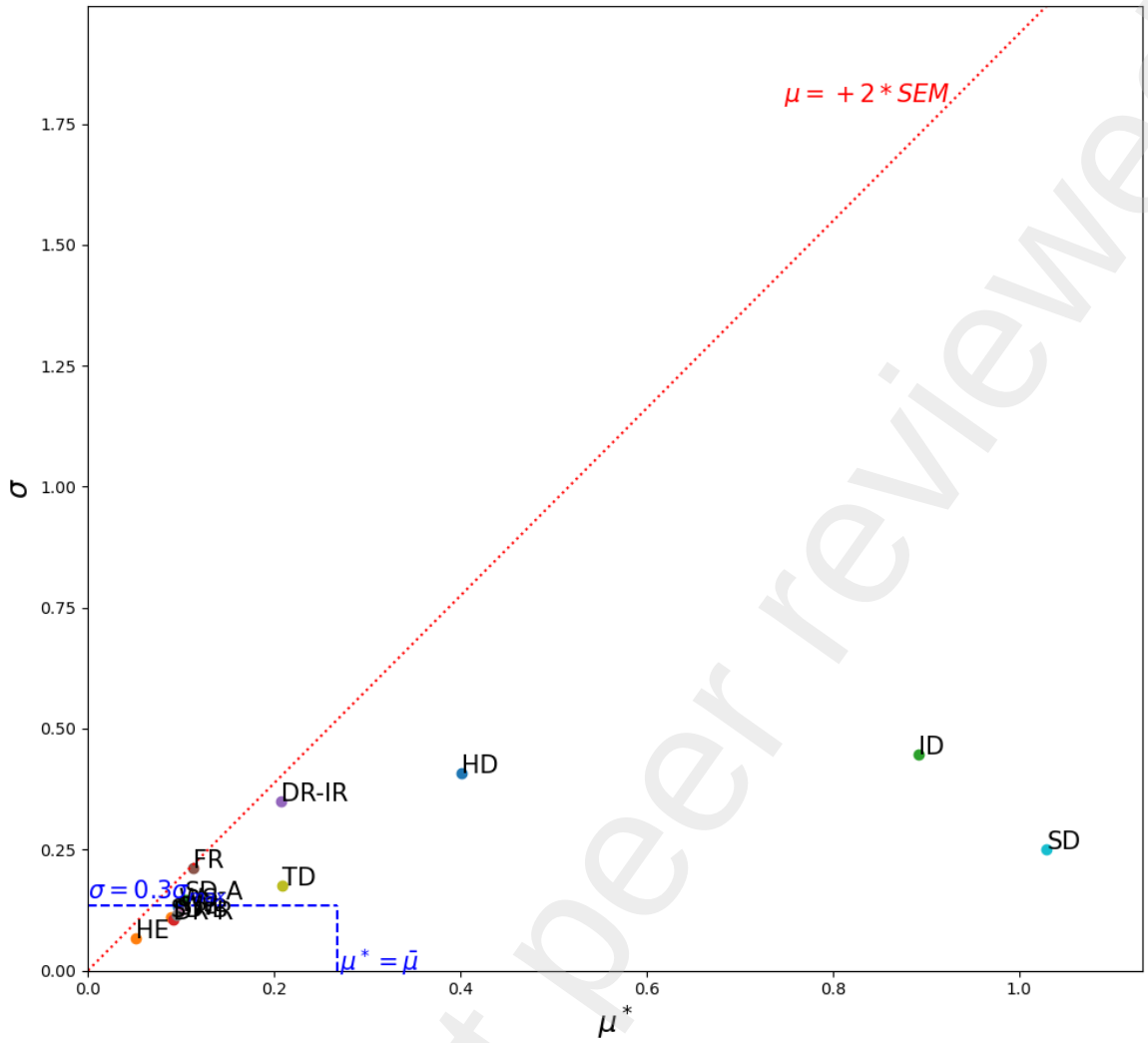

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Figure 1: Identifying influential quantitative input variables with the Morris screening method, using the weed-control variation due to site-specific spraying indicator in the maize-based cropping system as an example. Each dot represents, for an 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

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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

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3.3.2 Sensitivity analysis

3.3.2.1 The most influential inputs

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

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

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

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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

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the same effect as increased dosage or efficiency. In the spring-crop maize monoculture, the 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 intial 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												

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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

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correlated to at least one output are shown; effet 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

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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

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

3.3.3 Uncertainty analysis and input selection

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

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

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

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

3.4 Conclusion

The sensitivity analysis showed that cropping system, sowing density, herbicide dose, herbicide efficiency were the most influential inputs for all indicators. Furthermore, the herbicide site-specific spraying system inputs (weed detection and geometry of the spray pattern) influenced the sprayed area and the herbicide treatment frequency indicator. In the most complex cropping system, interactions among inputs were significant for all indicators, especially for weed-crop biomass ratio (the proxy for yield loss due to weeds), which was thus more complex to analyze. The sensitivity and uncertainty analyses did not highlight a single input that mainly influenced the studied weed-impact indicators. Moreover, the uncertainty analysis showed that it was not necessary to exactly know the value of the herbicide site-specific spraying system inputs (weed detection and geometry of the spray pattern) to predict the sprayed area and the herbicide treatment frequency. This last indicator mainly depended on herbicide dose.

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

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

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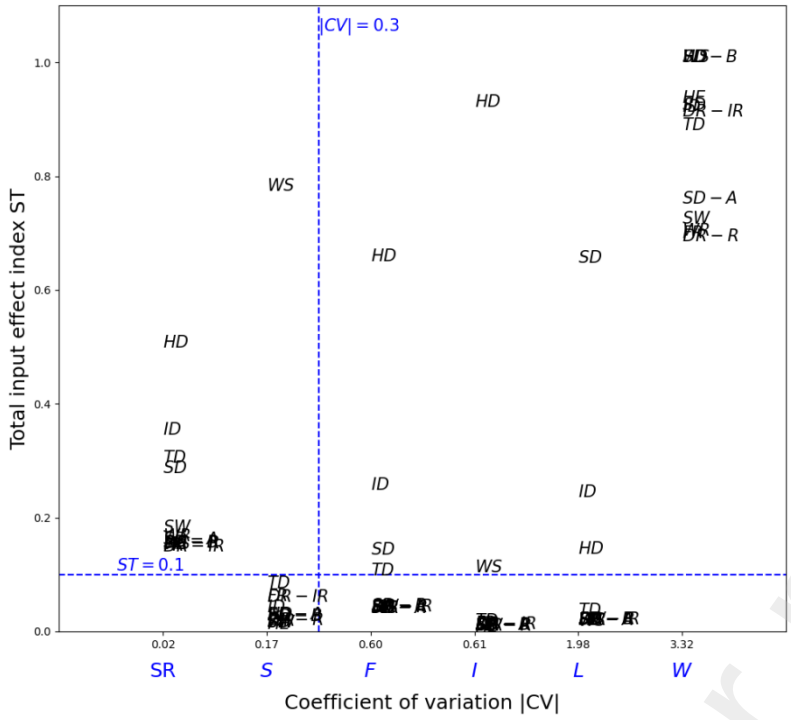

Figure 2: Identifying the important inputs to be determined accurately with an uncertainty analysis, using the maize-based cropping system as an example (see section D.3 online for the oilseed rape/wheat/barley rotation). For each indicator (species richness: SR, weed-control variation due to site-specific 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

4 Case study of an herbicide site-specific spraying system

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

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

4.1.1 A mobile platform based on WeedSeeker

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

4.1.2 Field experiments for calibration and evaluation

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

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

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

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4.1.3 Accuracy of the weed detection system

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

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

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

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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

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

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

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

4.3 Results

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

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

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

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

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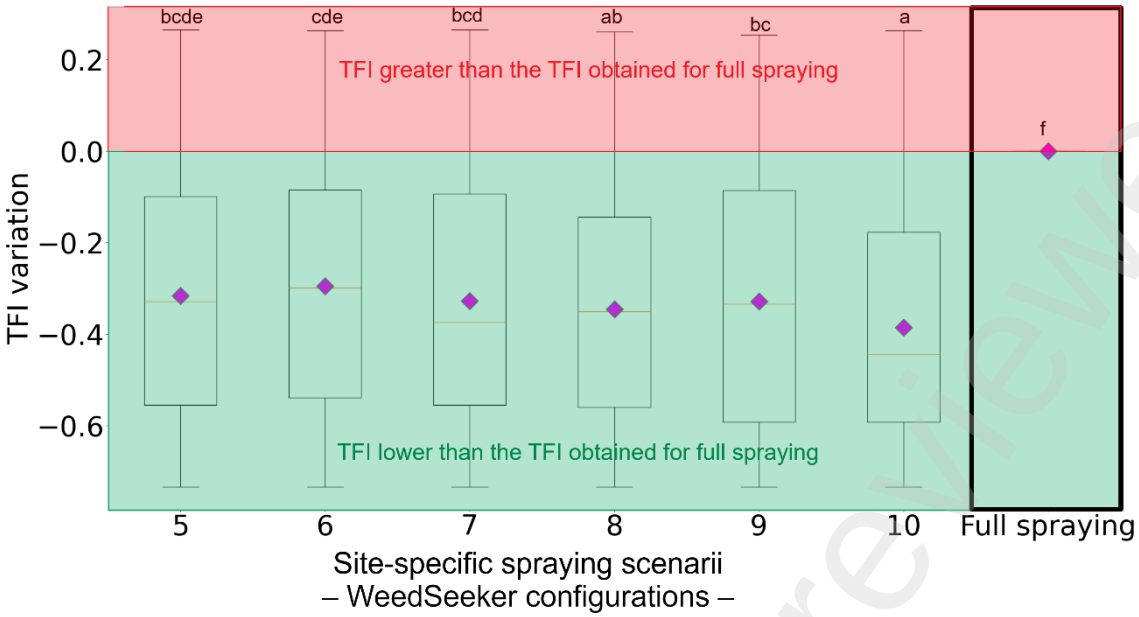
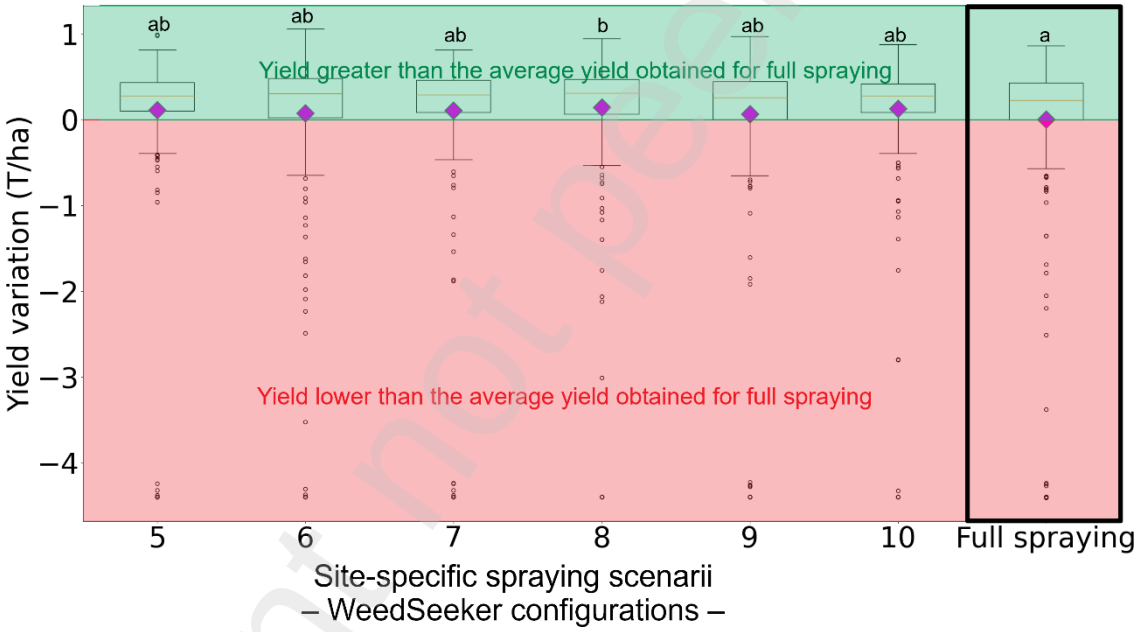


(A)



(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 × year × weather repetition). Letters show means that are not different at p=0.05 from One-way ANOVA tests.

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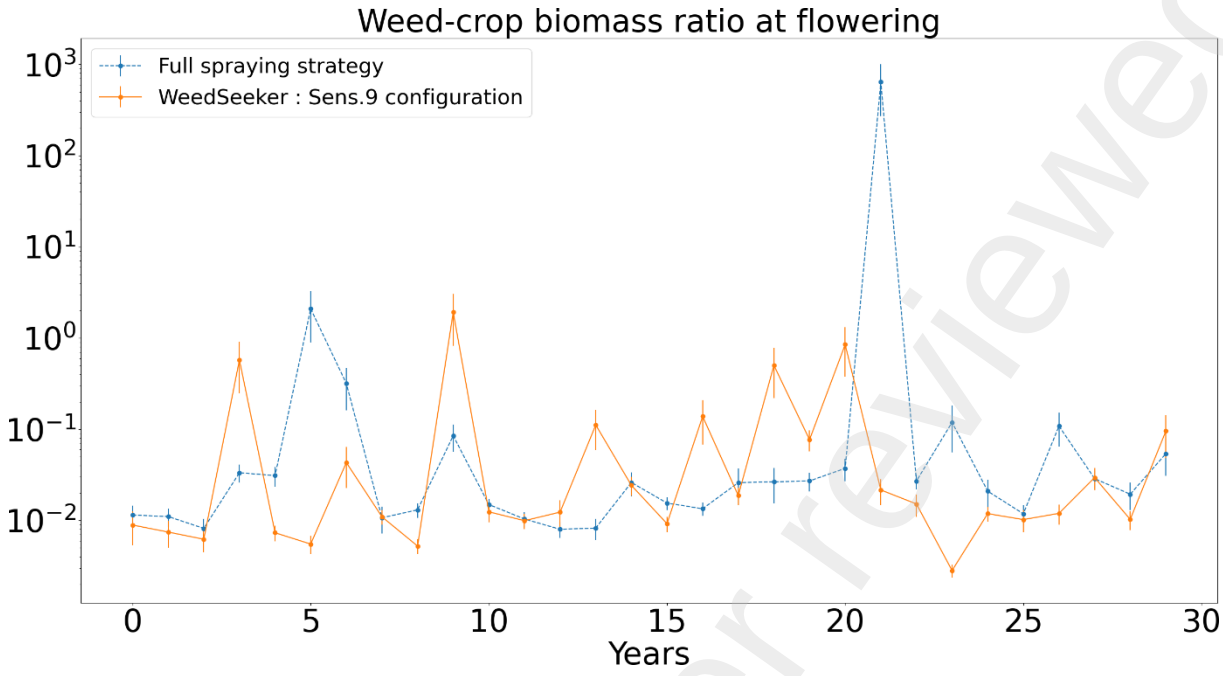

Figure 4: Annual evolution of the weed-crop biomass ratio at crop flowering (proxy for yield loss due to weeds) in a maize-based cropping system in Aquitaine depending on the type of spraying strategy (dashed blue = full, orange = site-specific spraying system based on the WeedSeeker system with the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

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5 Discussion

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

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

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

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

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

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

5.2 ….to produce more realistic conclusions

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

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

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

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

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

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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; Villette et al., 2019; Wiles, 2009)
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	
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)

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Herbicide efficiency	↗	None	More weeds killed	

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5.3 Implications for weed management in the field

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

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

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

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6 Conclusion

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

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Preprint not peer reviewed

This preprint research paper has not been peer reviewed. Electronic copy available at: https://ssrn.com/abstract=4435920

References

Ali, A., Streibig, J., Christensen, S., Andreasen, C., 2015. Image-based thresholds for weeds in maize fields. Weed Research 55, 26–33.

Andújar, D., Ribeiro, A., Carmona, R., Fernández-Quintanilla, C., Dorado, J., 2010. An assessment of the accuracy and consistency of human perception of weed cover: Human perception of weed cover. Weed Research 50, 638–647.

Andújar, D., Ribeiro, Á., Fernández-Quintanilla, C., Dorado, J., 2011. Accuracy and Feasibility of Optoelectronic Sensors for Weed Mapping in Wide Row Crops. Sensors 11, 2304–2318.

Andújar, D., Ribeiro, A., Fernández-Quintanilla, C., Dorado, J., 2013. Herbicide savings and economic benefits of several strategies to control Sorghum halepense in maize crops. Crop Protection 50, 17–23.

Audsley, E., 1993. Operational research analysis of patch spraying. Crop Protection 12, 111–119.

Barroso, J., Fernandez-Quintanilla, C., Maxwell, B.D., Rew, L.J., 2004. Simulating the effects of weed spatial pattern and resolution of mapping and spraying on economics of site-specific management. Weed Research 44, 460–468.

Barroso, J., Navarrete, L., Sánchez del Arco, M., FERNANDEZ-QUINTANILLA, C., Lutman, P., Perry, N., Hull, R., 2006. Dispersal of Avena fatua and Avena sterilis patches by natural dissemination, soil tillage and combine harvesters. Weed Research 46, 118–128.

Campolongo, F., Cariboni, J., Saltelli, A., 2007. An effective screening design for sensitivity analysis of large models. Environmental Modelling & Software 22, 1509–1518.

Campolongo, F., Saltelli, A., Cariboni, J., 2011. From screening to quantitative sensitivity analysis. A unified approach. Computer Physics Communications 182, 978–988.

Preprint not peer reviewed

This preprint research paper has not been peer reviewed. Electronic copy available at: https://ssrn.com/abstract=4435920

749 Christensen, S., Søgaard, H.T., Kudsk, P., Nørremark, M., Lund, I., Nadimi, E. s, Jørgensen,
750 R., 2009. Site-specific weed control technologies. Weed Research 49, 233–241.
751 Colbach, N., Bertrand, M., Busset, H., Colas, F., Dugué, F., Farcy, P., Fried, G., Granger, S.,
752 Meunier, D., Munier-Jolain, N.M., Noilhan, C., Strbik, F., Gardarin, A., 2016.
753 Uncertainty analysis and evaluation of a complex, multi-specific weed dynamics
754 model with diverse and incomplete data sets. Environmental Modelling & Software
755 86, 184–203.
756 Colbach, N., Biju-Duval, L., Gardarin, A., Granger, S., Guyot, S.H., Meziere, D., Munier-
757 Jolain, N., Petit, S., 2014a. The role of models for multicriteria evaluation and
758 multiobjective design of cropping systems for managing weeds. Weed Research 54,
759 541–555.
760 Colbach, N., Busset, H., Roger-Estrade, J., Caneill, J., 2014b. Predictive modelling of weed
761 seed movement in response to superficial tillage tools. Soil and Tillage Research 138,
762 1–8.
763 Colbach, N., Colas, F., Cordeau, S., Maillot, T., Queyrel, W., Villerd, J., Moreau, D., 2021.
764 The FLORSYS crop-weed canopy model, a tool to investigate and promote
765 agroecological weed management. Field Crops Research 261, 108006.
766 Colbach, N., Collard, A., Guyot, S.H., Mézière, D., Munier-Jolain, N., 2014c. Assessing
767 innovative sowing patterns for integrated weed management with a 3D crop: weed
768 competition model. European journal of agronomy 53, 74–89.
769 Colbach, N., Cordeau, S., 2018. Reduced herbicide use does not increase crop yield loss if it
770 is compensated by alternative preventive and curative measures. European Journal of
771 Agronomy 94, 67–78.
772 Colbach, N., Darmency, H., Fernier, A., Granger, S., Le Corre, V., Messéan, A., 2017.
773 Simulating changes in cropping practices in conventional and glyphosate-resistant

Preprint not peer reviewed

This preprint research paper has not been peer reviewed. Electronic copy available at: https://ssrn.com/abstract=4435920

maize. II. Weed impacts on crop production and biodiversity. Environmental Science and Pollution Research 24, 13121–13135.

Colbach, N., Granger, S., Guyot, S.H.M., Mézière, D., 2014d. A trait-based approach to explain weed species response to agricultural practices in a simulation study with a cropping system model. Agriculture, Ecosystems & Environment 183, 197–204.

Dicke, D., Gerhards, R., Büchse, A., Hurle, K., 2007. Modeling spatial and temporal dynamics of Chenopodium album L. under the influence of site-specific weed control. Crop Protection 26, 206–211.

Esau, T., Zaman, Q., Groulx, D., Farooque, A., Schumann, A., Chang, Y., 2018. Machine vision smart sprayer for spot-application of agrochemical in wild blueberry fields. Precision Agriculture 19, 770–788.

Fernández-Quintanilla, C., Peña, J.M., Andújar, D., Dorado, J., Ribeiro, A., López-Granados, F., 2017. Is the current state of the art of weed monitoring suitable for site-specific weed management in arable crops? Weed Research 58, 259–272.

Gan, Y., Duan, Q., Gong, W., Tong, C., Sun, Y., Chu, W., Ye, A., Miao, C., Di, Z., 2014. A comprehensive evaluation of various sensitivity analysis methods: A case study with a hydrological model. Environmental Modelling & Software 51, 269–285.

Gardarin, A., Dürr, C., Colbach, N., 2012. Modeling the dynamics and emergence of a multispecies weed seed bank with species traits. Ecological Modelling 240, 123–138.

Gauchi, J.-P., Bensadoun, A., Colas, F., Colbach, N., 2017. Metamodeling and global sensitivity analysis for computer models with correlated inputs: A practical approach tested with a 3D light interception computer model. Environmental Modelling & Software 92, 40–56.

Preprint not peer reviewed

This preprint research paper has not been peer reviewed. Electronic copy available at: https://ssrn.com/abstract=4435920

797 Gerhards, R., Andújar Sanchez, D., Hamouz, P., Peteinatos, G.G., Christensen, S., Fernandez-
798 Quintanilla, C., 2022. Advances in site-specific weed management in agriculture—A
799 review. Weed Research 62, 123–133.
800 Gerhards, R., Christensen, S., 2003. Real-time weed detection, decision making and patch
801 spraying in maize, sugarbeet, winter wheat and winter barley. Weed Research 43,
802 385–392.
803 Gerhards, R., Oebel, H., 2006. Practical experiences with a system for site-specific weed
804 control in arable crops using real-time image analysis and GPS-controlled patch
805 spraying. Weed Research 46, 185–193.
806 Gonzalez-de-Soto, M., Emmi, L., Perez-Ruiz, M., Aguera, J., Gonzalez-de-Santos, P., 2016.
807 Autonomous systems for precise spraying – Evaluation of a robotised patch sprayer.
808 Biosystems Engineering 146, 165–182.
809 González-Díaz, L., Blanco-Moreno, J.M., González-Andújar, J.L., 2015. Spatially explicit
810 bioeconomic model for weed management in cereals: validation and evaluation of
811 management strategies. Journal of Applied Ecology 52, 240–249.
812 Guerrero, J.M., Ruz, J.J., Pajares, G., 2017. Crop rows and weeds detection in maize fields
813 applying a computer vision system based on geometry. Computers and Electronics in
814 Agriculture 142, 461–472.
815 Herman, J., Kollat, J., Reed, P., Wagener, T., 2013. Method of Morris effectively reduces the
816 computational demands of global sensitivity analysis for distributed watershed
817 models. Hydrology and Earth System Sciences 17, 2893–2903.
818 Herman, J., Usher, W., 2017. SALib: An open-source Python library for Sensitivity Analysis.
819 The Journal of Open Source Software 2.
820 Holst, N., Rasmussen, I.A., Bastiaans, L., 2007. Field weed population dynamics: a review of
821 model approaches and applications. Weed Research 47, 1–14.

Preprint not peer reviewed

This preprint research paper has not been peer reviewed. Electronic copy available at: https://ssrn.com/abstract=4435920

822 Iooss, B., Lemaître, P., 2015. A review on global sensitivity analysis methods. In: Meloni, C.,
823 Dellino, G. (Eds.), Uncertainty Management in Simulation-Optimization of Complex
824 Systems: Algorithms and Applications. Springer.
825 Johnson, G.A., Mortensen, D.A., Martin, A.R., 1995. A simulation of herbicide use based on
826 weed spatial distribution. Weed Research 35, 197–205.
827 Lewis, J., 1973. Longevity of crop and weed seeds: survival after 20 years in soil. Weed
828 research 13, 179–191.
829 Liebman, M., Gallandt, E.R., Jackson, L., 1997. Many little hammers: ecological management
830 of crop-weed interactions. Ecology in agriculture 1, 291–343.
831 Louargant, M., Jones, G., Faroux, R., Paoli, J.-N., Maillot, T., Gée, C., Villette, S., 2018.
832 Unsupervised Classification Algorithm for Early Weed Detection in Row-Crops by
833 Combining Spatial and Spectral Information. Remote Sensing 10.
834 Macé, K., Morlon, P., Munier-Jolain, N., Quéré, L., 2007. Time scales as a factor in decision-
835 making by French farmers on weed management in annual crops. Agricultural
836 Systems 93, 115–142.
837 Maillot, T., Gée, C., Gobin, B., Villette, S., Vioix, J.-B., JONES, G., Paoli, J.-N., 2016. I-
838 Weed robot : un outil pour l'étude de population de plantes adventices. In: 23.
839 Conférence Du COLUMA - Journées Internationales Sur La Lutte Contre Les
840 Mauvaises Herbes. AFPP - Association Française de Protection des Plantes, Dijon,
841 France, pp. 191–199.
842 Makowski, D., Naud, C., Jeuffroy, M.-H., Barbottin, A., Monod, H., 2006. Global sensitivity
843 analysis for calculating the contribution of genetic parameters to the variance of crop
844 model prediction. Reliability Engineering & System Safety 91, 1142–1147.
845 Mamarot, J., Rodriguez, A., 2003. Sensibilité des mauvaises herbes aux herbicides en grandes
846 cultures. ACTA.

Preprint not peer reviewed

This preprint research paper has not been peer reviewed. Electronic copy available at: https://ssrn.com/abstract=4435920

847 Manalil, S., Busi, R., Renton, M., Powles, S.B., 2011. Rapid Evolution of Herbicide
848 Resistance by Low Herbicide Dosages. Weed Science 59, 210–217.
849 McKay, M.D., Beckman, R.J., Conover, W.J., 1979. A Comparison of Three Methods for
850 Selecting Values of Input Variables in the Analysis of Output from a Computer Code.
851 Technometrics 21, 239–245.
852 Medlin, C.R., Shaw, D.R., 2000. Economic comparison of broadcast and site-specific
853 herbicide applications in nontransgenic and glyphosate-tolerant Glycine max. Weed
854 Science 48, 653–661.
855 Meyer, G.E., Neto, J.C., 2008. Verification of color vegetation indices for automated crop
856 imaging applications. Computers and Electronics in Agriculture 63, 282–293.
857 Mézière, D., Petit, S., Granger, S., Biju-Duval, L., Colbach, N., 2015. Developing a set of
858 simulation-based indicators to assess harmfulness and contribution to biodiversity of
859 weed communities in cropping systems. Ecological Indicators 48, 157–170.
860 Morris, M.D., 1991. Factorial Sampling Plans for Preliminary Computational Experiments.
861 Technometrics 33, 161–174.
862 Munier-Jolain, N., Guyot, S., Colbach, N., 2013. A 3D model for light interception in
863 heterogeneous crop:weed canopies. Model structure and evaluation. Ecological
864 modelling 250, 101–110.
865 Munier-Jolain, N.M., Collard, A., Busset, H., Guyot, S.H., Colbach, N., 2014. Investigating
866 and modelling the morphological plasticity of weeds. Field Crops Research 155, 90–
867 98.
868 Neve, P., Powles, S., 2005. High survival frequencies at low herbicide use rates in populations
869 of Lolium rigidum result in rapid evolution of herbicide resistance. Heredity 95, 485–
870 492.

Preprint not peer reviewed

This preprint research paper has not been peer reviewed. Electronic copy available at: https://ssrn.com/abstract=4435920

Nikolić, N., Rizzo, D., Marraccini, E., Gotor, A.A., Mattivi, P., Saulet, P., Persichetti, A., Masin, R., 2021. Site and time-specific early weed control is able to reduce herbicide use in maize-a case study. Italian Journal of Agronomy 16, 1780.

Oerke, E.-C., 2006. Crop losses to pests. The Journal of Agricultural Science 144, 31–43.

Oliphant, T.E., 2007. Python for scientific computing. Computing in Science & Engineering 9, 10–20.

Paice, M.E.R., Day, W., Rew, L.J., Howard, A., 1998. A stochastic simulation model for evaluating the concept of patch spraying. Weed Research 38, 373–388.

Peña, J.M., Torres-Sãnchez, J., de Castro, A.I., Kelly, M., López-Granados, F., 2013. Weed Mapping in Early-Season Maize Fields Using Object-Based Analysis of Unmanned Aerial Vehicle (UAV) Images. PLoS ONE 8, e77151.

Pointurier, O., Moreau, D., Pagès, L., Caneill, J., Colbach, N., 2021. Individual-based 3D modelling of root systems in heterogeneous plant canopies at the multiannual scale. Case study with a weed dynamics model. Ecological Modelling 440, 109376.

Rees, S., McCarthy, C., Fillols, E., Baille, C., Staier, T., 2013. Evaluating commercially available precision weed spraying technology for detecting weeds in sugarcane farming systems. Sugar research, Pest, Disease and Weed Management.

Renton, M., 2013. Shifting focus from the population to the individual as a way forward in understanding, predicting and managing the complexities of evolution of resistance to pesticides. Pest management science 69, 171–175.

Rider, T.W., Vogel, J.W., Dille, J.A., Dhuyvetter, K.C., Kastens, T.L., 2006. An economic evaluation of site-specific herbicide application. Precision Agriculture 7, 379–392.

Saltelli, A., 2002. Making best use of model evaluations to compute sensitivity indices. Computer Physics Communications 145, 280–297.

Preprint not peer reviewed

This preprint research paper has not been peer reviewed. Electronic copy available at: https://ssrn.com/abstract=4435920

895 Saltelli, A., Annoni, P., Azzini, I., Campolongo, F., Ratto, M., Tarantola, S., 2010. Variance
896 based sensitivity analysis of model output. Design and estimator for the total
897 sensitivity index. Computer Physics Communications 181, 259–270.
898 Saltelli, A., Ratto, M., Andres, T., Campolongo, F., Cariboni, J., Gatelli, D., Saisana, M.,
899 Tarantola, S., 2008. Global Sensitivity Analysis. The Primer. Wiley.
900 Saltelli, A., Tarantola, S., Campolongo, F., Ratto, M., 2004. Sensitivity Analysis in Practice:
901 A Guide to Assessing Scientific Models. Halsted Press, New York, NY, USA.
902 Sudret, B., 2008. Global sensitivity analysis using polynomial chaos expansions. Reliability
903 Engineering & System Safety 93, 964–979.
904 Sudret, B., Caniou, Y., 2013. Analysis of covariance (ANCOVA) using polynomial chaos
905 expansions. In: Safety, Reliability, Risk and Life-Cycle Performance of Structures and
906 Infrastructures. ETH Zürich, pp. 3275–3281.
907 Sui, R., Thomasson, J.A., Hanks, J., Wooten, J., 2008. Ground-based sensing system for weed
908 mapping in cotton. Computers and Electronics in Agriculture 60, 31–38.
909 Timmermann, C., Gerhards, R., Kühbauch, W., 2003. The Economic Impact of Site-Specific
910 Weed Control. Precision Agriculture 4, 249–260.
911 Turati, P., Pedroni, N., Zio, E., 2016. Dimensionality reduction of the resilience model of a
912 critical infrastructure network by means of elementary effects sensitivity analysis. In:
913 European Safety and RELiability Conference (ESREL) 2016, Risk, Reliability and
914 Safety: Innovating Theory and Practice: Proceedings of ESREL 2016. Glasgow,
915 United Kingdom, pp. 2797–2804.
916 Varella, H., Buis, S., Launay, M., Guérif, M., 2012. Global sensitivity analysis for choosing
917 the main soil parameters of a crop model to be determined. Agricultural Sciences 03,
918 949–961.

Preprint not peer reviewed

This preprint research paper has not been peer reviewed. Electronic copy available at: https://ssrn.com/abstract=4435920

Villette, S., Maillot, T., Douzals, J., Jones, G., Paoli, J., Guillemin, J., 2019. Use of simulations to study herbicide site-specific spraying. In: Precision Agriculture'19. Wageningen Academic Publishers, pp. 171–181.

Wallach, D., Makowski, D., Jones, J.W., Brun, F., 2013. Working with Dynamic Crop Models: Methods, Tools and Examples for Agriculture and Environment. Academic Press.

Wezel, A., Casagrande, M., Celette, F., Vian, J.-F., Ferrer, A., Peigné, J., 2014. Agroecological practices for sustainable agriculture. A review. Agronomy for sustainable development 34, 1–20.

Wiles, L.J., 2009. Beyond patch spraying: site-specific weed management with several herbicides. Precision Agriculture 10, 277–290.

Wilkerson, G.G., Price, A.J., Bennett, A.C., Krueger, D.W., Roberson, G.T., Robinson, B.L., 2004. Evaluating the potential for site-specific herbicide application in soybean. Weed Technology 18, 1101–1110.

Wilson, C., Tisdell, C., 2001. Why farmers continue to use pesticides despite environmental, health and sustainability costs. Ecological economics 39, 449–462.

Preprint not peer reviewed

This preprint research paper has not been peer reviewed. Electronic copy available at: https://ssrn.com/abstract=4435920

936

Preprint not peer reviewed

This preprint research paper has not been peer reviewed. Electronic copy available at: https://ssrn.com/abstract=4435920