European Journal of Agronomy 87 (2017) 59–73

Contents lists available at ScienceDirect

European Journal of Agronomy

journal homepage: www.elsevier.com/locate/eja

# A methodology for multi-objective cropping system design based on simulations. Application to weed management

Nathalie Colbach[a,*], Floriane Colas[a], Olivia Pointurier[a], Wilfried Queyrel[a], Jean Villerd[a,b]

[a] Agroécologie, AgroSup Dijon, INRA, Univ. Bourgogne Franche-Comté, F-21000 Dijon, France
[b] LAE, INRA, Université de Lorraine, F-54500 Vandoeuvre-lès-Nancy, France

ARTICLE INFO

*Keywords:*
Weed
Model
Cropping system
Design
Multi-criteria performance
Indicator
Agroecology

ABSTRACT

Weeds are harmful for crop production but important for biodiversity. In order to design cropping systems that reconcile crop production and biodiversity, we need tools and methods to help farmers to deal with this issue. Here, we developed a novel method for multi-objective cropping system design aimed at scientists and technical institutes, combining a cropping system database, decision trees, the "virtual field" model FlorSys and indicators translating simulated weed floras into scores in terms of weed harmfulness (e.g. crop yield loss, weed-borne parasite risk, field infestation), weed-mediated biodiversity (e.g. food offer for bees) and herbicide use intensity. 255 existing cropping systems were simulated with FlorSys, individual indicator values were aggregated into a multi-performance score, and decision trees were built to identify combinations of management practices and probabilities for reaching performance goals. These trees are used to identify the characteristics of existing cropping systems that must be changed to achieve the chosen performance goals, depending on the user's risk strategy. Alternative systems are built and simulated with FlorSys to evaluate their multi-criteria performance. The method was applied to an existing oilseed rape/wheat/barley rotation with yearly mouldboard ploughing from Burgundy which was improved to reconcile weed harmfulness control, reduced herbicide use and biodiversity promotion, based on a risk-minimizing strategy. The best alternative replaced a herbicide entering plants via shoot tips (during emergence) and roots after barley sowing by a spring herbicide entering via leaves, introduced crop residue shredding before cereals and rolled the soil at sowing, which reduced the risk of unacceptable performance from 90% to 40%. When attempting to reconcile harmfulness control and reduced herbicide use, the best alternative changed the rotation to oilseed rape/wheat/spring pea/wheat, replaced one herbicide in oilseed rape by mechanical weeding, delayed tillage before rape and applied the PRE herbicide before oilseed rape closer to sowing. This option reduced the risk of unacceptable performance to 30%. None of the initial or alternative cropping systems succeeded in optimal performance, indicating that more diverse cropping systems with innovative management techniques and innovative combinations of techniques are needed to build the decision trees. This approach can be used in workshops with extension services and farmers in order to design cropping systems. Compared to expert-based design, it has the advantage to go beyond well-known options (e.g. plough before risky crops) to identify unconventional options, with a particular focus on interactions between cultural techniques.

## 1. Introduction

Weeds are considered to be the most harmful pests among those targeted by pesticides, potentially leading to important crop production losses (Swinton et al., 1994; Oerke, 2006). Weeds can also host and propagate other bioagressors such as pathogen fungi (Wisler and Norris, 2005; Bonin et al., 2013) or parasitic plants (Gibot-Leclerc et al., 2003). Thanks to their efficacy and their relatively simple use, herbicides have been used widely and frequently in arable crops (Eurostat, 2016). As a result, they are now increasingly found in ground and surface water (Barbash et al., 2001; Lopez et al., 2015; Ulrich et al., 2015) and cause health problems (Vinson et al., 2011; Waggoner et al., 2013) while an increasing number of weed species are becoming resistant to a larger range of herbicide mode of actions (Heap, 2016). Moreover, weeds are the most important component of plant biodiversity in agricultural landscapes and contribute to feeding other components of agricultural biodiversity (Marshall et al., 2003; Petit et al., 2011). Consequently, French (http://agriculture.gouv.fr/plan-ecophyto-2015) and European

* Corresponding author. INRA, UMR1347 Agroécologie, BP 86510, 17 rue Sully, F-21065 Dijon Cedex, France.
*E-mail address:* Nathalie.Colbach@inra.fr (N. Colbach).

http://dx.doi.org/10.1016/j.eja.2017.04.005
Received 18 November 2016; Received in revised form 28 April 2017; Accepted 28 April 2017
Available online 20 May 2017
1161-0301/ 

legislation (CE) N°1107/2009 aim to restrict herbicide use and available products.

To date no alternative curative weed control technique is as efficient and robust as herbicides. The most frequent alternative, i.e. mechanical weeding, is less or not efficient at all in the crop row, less selective of weed vs. crop plants, often damages weed plants insufficiently and requires several successive operations for sufficient efficacy (Chicouene, 2007). Herbicide-parsimonious weed management strategies need to combine all cropping system components aiming at weed control (Liebman and Gallandt, 1997). Various long-term field trials currently assess innovative cropping systems and weed flora impact on crop production and biodiversity (e.g. Gerowitt, 2003; Chikowo et al., 2009; Davis et al., 2012) but they can only test a small number of systems in a small number of locations. Recently, the DEPHY farm network was set up in France to monitor hundreds of farms over time but with little or no access to biophysical state variables (Pillet et al., 2014). In addition to these methods, *in silico* approaches test a large range of agricultural systems with simulation models to identify those answering to objectives (Loyce and Wéry, 2006). Models allow us to assess many and diverse cropping systems at the long-term and with different weather data for their impact on weed flora (Storkey and Cussans, 2007; Colbach et al., 2014a).

Different approaches exist for model-based cropping system design but all follow the same basic steps (Bergez et al., 2010): (1) generation of candidate cropping systems, (2) simulation, (3) evaluation and selection, and (4) possibly further loops where new candidates are generated based on the first results. If the list of possible candidates is small, then the candidate systems can present the complete list of all possibilities (e.g. a list of crop rotation in ROTAT, Dogliotti et al., 2003; or a list of rotations with herbicide programmes in ECOHERBI, http://ecoherbi.florad.org/; or rotation including cover crop and no till in PRACT, Naudin et al., 2015), but this cannot apply to cropping systems which combine many components with many possible options. Candidate systems are thus often proposed by experts in workshops aiming to design cropping systems (Hossard et al., 2013; Reckling et al., 2016), with the risk of missing innovative approaches that are outside the imagination and expertise of the workshop participants. Optimizing an objective via mathematical or numerical algorithms can overcome this obstacle, e.g. using a linear combination of crop proportions weighted by their agronomical values and penalties for their disadvantages to optimize crop rotations (Schönhart et al., 2011) Cropping system design though is a multi-criteria problem requiring a multi-objective optimization where several objectives and inputs are simultaneously optimized (Ould-Sidi and Lescourret, 2011). Solving optimization problems with complex models is a tedious task requiring to find compromise solutions to integrate antagonisms and synergies between the model performance criteria (deVoil et al., 2006; Groot and Rossing, 2011; Ould-Sidi and Lescourret, 2011; Grechi et al., 2012). Automatic optimization based on algorithms would be difficult in our case because we have to optimize many and often antagonistic objectives as well as many management levers with many options. Moreover, modelling weed dynamics is complex and their simulation is slow. Indeed, weed dynamics must be considered at a multi-annual scale, and a larger number of inputs are necessary to realistically predict them in cropping systems (Colbach, 2010).

Consequently, the objective of the present paper was to develop a method for simulation-based multi-criteria design of cropping systems and to apply it to designing systems reconciling weed harmfulness control, herbicide use reduction and promotion of weed-mediated biodiversity. Instead of an automatic algorithm-based optimization, we propose a manual method that combines the knowledge produced by a large-scale evaluation of existing cropping systems and expert knowledge. The method is aimed at scientists and technical institutes that design agroecological cropping systems. The weed dynamics model used in the present study was FlorSys which is a process-based cropping system model that answers all our requirements, i.e. it predicts the dynamics of a multi-specific weed flora and its impact on crop production and biodiversity (Colbach et al., 2014a).

## 2. Material and methods

### 2.1. A short presentation of FlorSys

#### 2.1.1. Weed and crop life cycle

FlorSys is a virtual field on which cropping systems can be experimented and a large range of crop, weed and environmental measurements estimated. The structure of FlorSys is presented in detail in previous papers (Gardarin et al., 2012; Munier-Jolain et al., 2013; Colbach et al., 2014b; Colbach et al., 2014c; Munier-Jolain et al., 2014; Mézière et al., 2015b).

The input variables of FlorSys consist of (1) a description of the simulated field (daily weather, latitude and soil characteristics); (2) all the simulated crops (including cash, undersown, associated, cover and multi-annual crops) and cultivation 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). These input variables 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. 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 (in t/ha and in MJ/ha). In case of multi-annual crops (e.g. lucerne, ryegrass), seedlings can also be the offspring of vegetative older plants. Perennial weeds are not included in FlorSys.

Life cycle processes also depend on management practices, in interaction with weather and soil conditions on the day the operations are carried out. Herbicides can enter plants via leaves ("foliar"), shoot tips during emergence ("pseudo-root") or roots ("root"). Multiple entry modes are possible. Foliar herbicides only kill emerged weeds on the day of spraying, the other herbicides persist and act over several days and weeks. Systemic herbicides circulate inside the target plant and their efficiency depends less on dosage. FlorSys parameters are currently available for 25 frequent and contrasting weed species. Further details can be found in section A of the supplementary material online.

#### 2.1.2. Domain of validity

FlorSys was evaluated with independent field data from a large range of contrasting cropping systems from several regions and years, including innovative techniques such as conservation agriculture or cover crops as well as those options that were identified as potential solutions in the present study (e.g. fallow mowing, rolling etc). The evaluation showed that daily species densities and, particularly, densities averaged over the years were generally well predicted and ranked in the model's original region, i.e. Burgundy (Colbach et al., 2016). At more southern latitudes, a corrective function was used to keep weeds from flowering during winter. This correction improved prediction quality sufficiently so that FlorSys could be used here to assess cropping systems in terms of weed flora and crop yield.

#### 2.1.3. Assessing weed impacts on crop production and biodiversity

The weed densities simulated by FlorSys are translated into a set of indicators depicting the weed flora impact on crop production and biodiversity (Mézière et al., 2015b; Colbach et al., 2017a) (see section A.4 online). Weed harmfulness indicators consider direct harmfulness for crop production (crop yield loss, harvest pollution by weed debris), technical harmfulness (harvesting problems due to green weed biomass blocking the harvest combine), indirect harmfulness due to pest survival and dispersal by weeds (increase in yield loss due to weed-

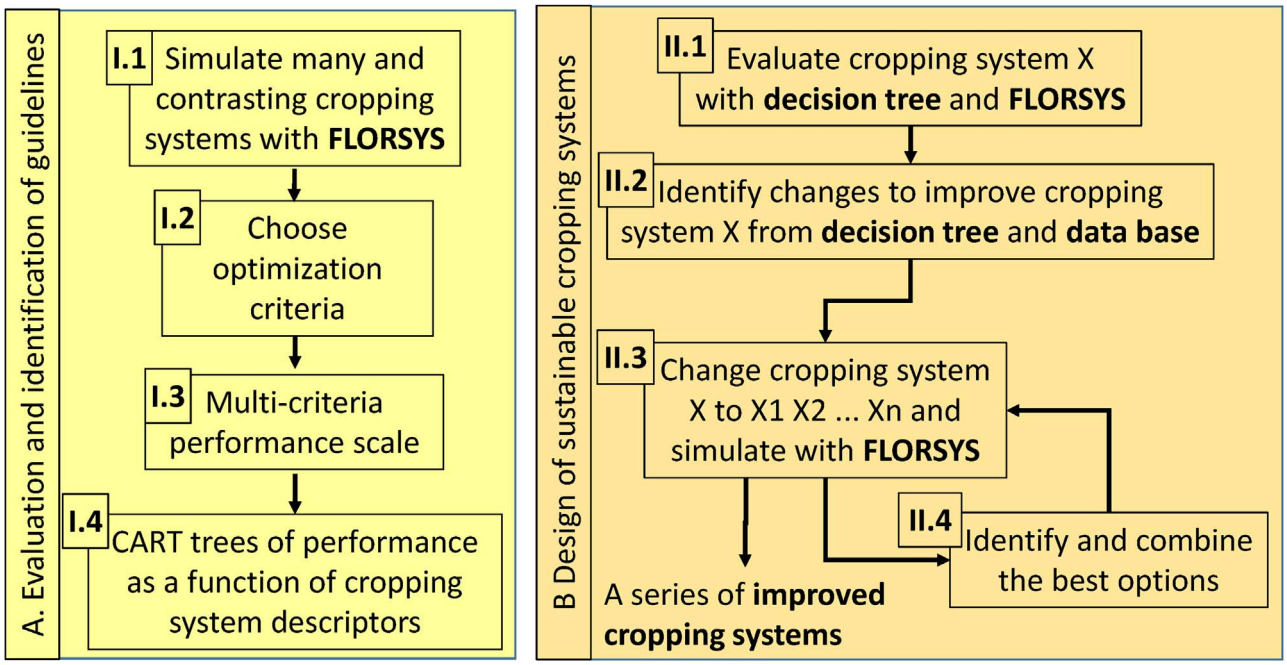


**Fig. 1.** Step-wise methodology for using FlorSys to design cropping system aiming to reconcile multiple weed impact objectives, based on the evaluation current or probable farming practices (Nathalie Colbach © 2017).

borne take-all disease in cereals, parasite risk due to the holoparasitic plant *Phelipanche ramosa*), and sociological harmfulness (field infestation by weed biomass during crop growth) which reflects the farmer's worry of being thought incompetent by his peers even if there is no effect on yield loss.

The second series of indicators concern weed-mediated biodiversity. Two indicators assess plant biodiversity, i.e. species richness (the number of weed species), and species equitability (Pielou's index). Three other indicators assess weed contribution to feed other organisms in the agro-ecosystems, considering the seasons of activity and food shortage: weed seeds on soil surface in autumn and winter to feed field birds, lipid-rich seeds on soil surface in summer to feed carabids, and weed flowers in spring and summer to feed domestic bees.

### 2.2. Methodology

#### 2.2.1. The different steps

The method was based on two different parts, each with four steps (Fig. 1). The objective of the first part is to establish guidelines for choosing cultural techniques, based on the effects of combinations of techniques on weed impact and herbicide use. Step I.1 simulates indicators of weed impact in existing cropping systems with FlorSys, step I.2 chooses the optimization criteria, step I.3 sets up a multi-criteria performance scale and I.4 builds decision trees that identify combinations of management practices for reaching performance goals.

The second part uses the decision tree and the database to improve existing cropping systems step by step, aiming to optimize the chosen optimization criteria. For each existing cropping system that is to be improved, step II.1 evaluates the performance of the existing system. Step II.2 identifies inappropriate practices in the existing cropping system and pertinent changes to improve the system's performance, depending on the performance goal and risk strategy. Step II.3 uses the conclusions of steps II.1 and II.2 to propose alternative systems and to test them with FlorSys. Based on these results, II.4 combines and tests the best options in a further series of alternative systems.

#### 2.2.2. Simulate weed impact indicators in cropping systems (step I.1)

A total of 255 arable cropping systems was simulated with FlorSys during the evaluation step which was described in a previous paper (Colbach et al., 2017a). These systems covered six contrasting regions from France (Burgundy, Paris Basin, Aquitaine, Poitou-Charentes, Lorraine, Picardie) and Spain (Catalonia). They mainly differed in terms of rotational diversity, tillage and herbicide use intensity (section B online).

Each cropping system was simulated over 27 years to evaluate long-term efficiency of weed control, repeating the basic rotational pattern (e.g. oilseed rape/wheat/barley) over time, starting with typical regional seed banks and soils. Each cropping system was repeated with 10 weather series consisting of 27 randomly chosen weather years from the INRA Climatik platform, using the same 10 series for the cropping systems of each region.

#### 2.2.3. Choose optimization criteria (step I.2)

Most users only aim to optimize a few weed impact criteria. For instance, farmers would be mostly interested in controlling weed harmfulness, ecologists would focus on promoting weed contribution to biodiversity whereas French legislation requires a reduction in herbicide use. The major concerns of farmers were identified from surveys and interviews of farmers and advisors (Colas et al., 2015; Mézière et al., 2015b). Weed-related biodiversity functions were identified from ecological studies (Ricou et al., 2014). Proxies for herbicide impact on ground and surface water were taken from farm network studies on herbicide use intensity (Lechenet et al., 2014). The simplest proxy is the treatment frequency index (TFI), i.e. the number of herbicide treatments applied at regulatory dosage per year. For instance, a herbicide applied at half dosage of the whole field, or at full dosage over half the field counts as 0.5. Antagonisms and synergies among the chosen optimization criteria were investigated with Principal Component Analyses (PCA) on weed impact indicators averaged over the 27 simulated years for each “cropping system x weather repetition”.

#### 2.2.4. Set-up a multi-criteria performance scale (step I.3)

To make weed impact indicator performances comparable, the values calculated by FlorSys for each cropping system and weather repetition were averaged over the 27 simulated years and translated to class-based scores, ranging from A (best) to E (worst) (see examples in Table 1.A). Indicator values were transformed into values relative to the

**Table 1**
Performance thresholds for scoring individual (A) and overall (B) weed impact in the simulation study. Class thresholds were chosen to discriminate the best performance. Less stringent thresholds were used for biodiversity indicators whose maximum values were often extreme outliers, with few cropping systems achieving these results.

A. Individual weed impact score

| Score | Relative to maximum observed or possible value | |
|---|---|---|
| | Harmfulness and herbicide use | Biodiversity |
| A (best) | < 5% | > 75% |
| B | 5-10% | 70-75% |
| C | 10-20% | 60-70% |
| D | 20-30% | 50-60% |
| E (worst) | > 30% | < 50% |

B. Combined, overall score

| **Overall score** | **Individual scores** | |
|---|---|---|
| | Yield loss | Other |
| **A (best)** | A | A |
| **A-** | A | ≥ B |
| **B** | B | B |
| **B-** | B | ≥ C |
| **C** | C | C |
| **C-** | C | ≥ D |
| **D** | D | D |
| **E (worst)** | E | E |

best possible value for definite scales (e.g. yield loss varies from 0 to 100%) or the best value observed in the database in the case of indefinite scales (e.g. bee food offer is nil or positive, without limitation). Class thresholds (e.g. > 95%) were chosen to discriminate the best performance. Less stringent thresholds can be used for secondary indicators.

If several weed impact indicators are used, the individual scores are combined into an overall score which equates the worst individual score. If one indicator is considered more important, this rule can be amended to partially upgrade the overall score if the dominant indicator scores better (e.g. the overall score is upgraded from C to B- if the dominant score scores B or better and the worst of the other indicators scores C) (see examples in Table 1.B). The choice of dominant vs other evaluation criteria was again based on surveys and interviews of farmers and advisors (Colas et al., 2015; Mézière et al., 2015b) but other scoring classes and combinations are possible if the objective is, for instance, to focus on trophic resources for pollinators.

### 2.2.5. *Build decision trees for overall performance (step I.4)*

Overall performance score was analysed depending on cultural practices, using classification and regression trees (CART, Breiman et al., 1984; Hothorn et al., 2006). These trees generate clusters (tree leaves) that are both homogeneous with respect to the response variable (here the overall score) and discriminated through sequences of binary splits (branches) on input variables (here cultural techniques). Decision trees were shown to overcome the complexity of numerous interactions between explanatory variables and non-linear relationships between explanatory and target variables (De'ath and Fabricius, 2000; Tittonell et al., 2008; Ferraro et al., 2009; Delmotte et al., 2011). We used the *ctree* function of the R party package, which estimates the distribution of the response variable in each tree leave, instead of the average value. The branches of the tree identified combinations of these descriptors and constituted management strategies that led to different performance scores. Instead of showing the most probable performance score for each management strategy, the tree leaves show the distribution of scores, i.e. the probabilities for achieving A, A-, …and E scores, respectively. This allows us to conclude not only whether a strategy A is better than a strategy B in average, but also whether this applies for instance in 90% of situations or only in 60%, which makes a huge difference to farmers. The best strategies were those with the lowest risk of an E score to take into account that most farmers focus on minimizing the risk of failure even at the cost lowering their average performance (Ridier et al., 2013).

Cultural practices were described by the same 31 synthetic cropping system descriptors as in a previous paper (Colbach et al., 2017a) (section B.4 online). These descriptors consisted of rotational variables (e.g. proportion of winter crops in the rotation) and average cultural practices during the simulation (e.g. mean number of tillage operations per year).

### 2.2.6. *Evaluate an existing cropping system (step II.1)*

A given cropping system can be evaluated with FlorSys, which can take several hours of simulation time but precisely calculates both the overall and individual performance probabilities. Evaluating the same cropping system with a multi-criteria decision tree (by finding the combination of practices characterizing the system in the tree and reading the corresponding performance in the leaf) only estimates the probabilities of the overall performance resulting from combining several weed impact indicators. There is also a loss of prediction quality. The decision tree allows an instantaneous evaluation but cannot predict the effects of small modifications in the cropping system because the cropping system descriptors used as explanatory variables in the tree are less detailed than the list of cropping operations introduced into FlorSys. For example, two cropping systems differing only in the brand of the applied herbicide, but with the same relative rate and the same mode of entry will have the same performance according to the decision tree whereas FlorSys will predict different performances if one brand is more efficient than the other. The decision tree can also affect a given cropping system to the wrong tree leaf.

### 2.2.7. *Identify inappropriate practices in the existing cropping system and pertinent changes to improve performance (step II.2)*

Comparing the branch with the analysed cropping system to the branches leading to the best results allows us to identify potential changes in cropping system characteristics that would improve the system's performance (e.g. spray more than 0.6 foliar-only herbicides per year). To translate these guidelines into operation dates and options (e.g. which herbicide products to apply at which rate and when), we analysed the operations of the best cropping systems answering to the guidelines. Moreover, some identified guidelines hide a more complex change that requires modifying several cropping system components (e.g. increasing the proportion of multiannuals in the rotation also requires tillage, sowing and herbicide strategies adapted to these crops). Looking at examples from the database is also helpful to understand and translate weird-looking guidelines that point to very particular systems.

### 2.2.8. *Propose and test prospective cropping systems (steps II.3 and II.4)*

Alternative cropping systems were built by modifying the inappropriate practices identified in step II.2, and simulated with FlorSys, using the same principles as in step I.1. The resulting individual and overall scores were compared to those of the initial system (step II.1).

A second design loop can be carried out (step II.4), for instance by combining the best options identified in step II.3. The final output will

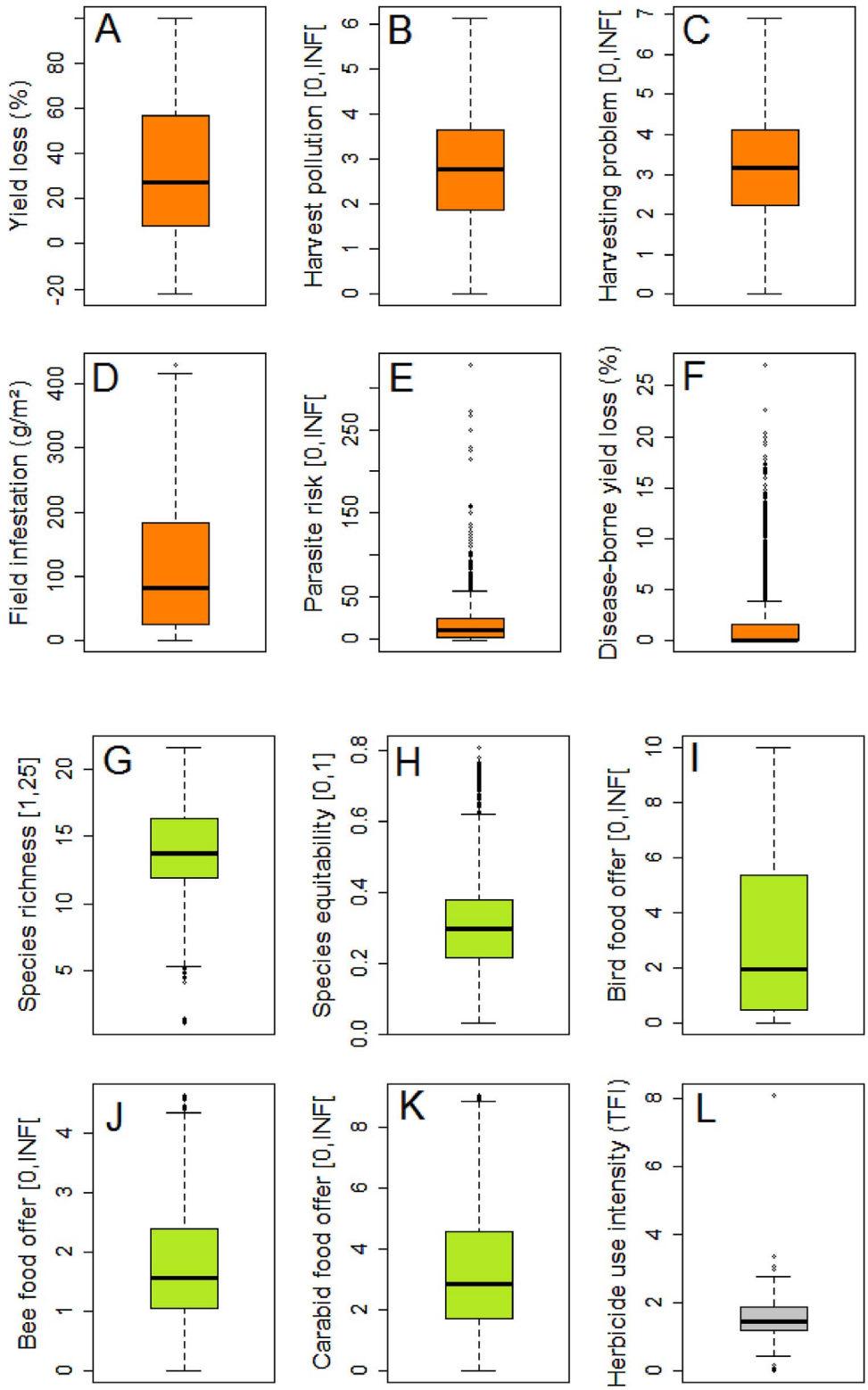


**Fig. 2.** Range of variation in indicator values averaged over 27 years of weed harmfulness for crop production (A-F), weed contribution to biodiversity (G-K) and herbicide use intensity (L) for the 255 cropping systems simulated with FlorSys. Whiskers and boxes show 5, 25, 50, 75 and 95 percentiles of the distribution; values outside the 5–95 percentile range are shown by dots. TFI is treatment frequency index, i.e. number of herbicide treatments at full dosage per year.

be one or several cropping systems that improve the multi-functional performance. To avoid changing and testing new cropping systems indefinitely, the user must define a stopping criterion based either on the number of steps (e.g. limit to two steps) or on the performance of the new systems (e.g. the risk of a bad score is below 10%). Here, the iteration was limited to two steps.

## 3. Results

### 3.1. Simulate weed impact indicators in cropping systems (step I.1)

The 255 simulated cropping systems resulted in a large range of variation in terms of weed impact indicators (Fig. 2). For instance, crop

yield loss averaged over the 27 simulated years ranged from −20% (i.e. a yield gain) to an extreme of loss of +90% (Fig. 2.A). The rare cases of yield gain correspond to systems where the weeds changed the soil climate, .e.g. a drier and colder soil delayed the emergence of spring crops and protected them from frost. Weed-borne parasite risk and yield loss caused by weed-borne disease were generally low but with frequent very extreme values (Fig. 2.E-F). Biodiversity indicators did not cover the whole possible range of variation. For instance, species richness was limited to a range of approximately 5–22 species, compared to a potential range of 0–25 species (Fig. 2.F). Herbicide use varied from 0 to 8 treatments at full dosage per year, with a median of 1.5 (Fig. 2.L).

### 3.2. Choose optimization criteria (step I.2)

Five weed impact indicators were chosen for the optimization process, one for each of the impact types. Direct and sociological weed harmfulness were assessed via yield loss and field infestation. Parasite risk was included as an example of indirect weed harmfulness. Bee food offer was chosen as an example of weed contribution to biodiversity which interests both ecologists and farmers. The last optimization criterion was herbicide use intensity characterized via the treatment frequency index, as a proxy for herbicide impact on ground and surface water.

The Principal Component Analysis of the weed impact indicator values simulated for the 255 cropping systems showed that the three chosen harmfulness indicators were highly correlated, and that they were also correlated with weed-mediated bee food offer (Fig. 3). In other words, those systems with the best biodiversity service were also often those with the highest weed harmfulness, and vice-versa. Consequently, it would be difficult to find systems that reconciled harmfulness control and biodiversity promotion in the simulated database. Conversely, herbicide use intensity was located on an axis perpendicular to the other four indicators, i.e. it would be easier to identify systems that reconciled low herbicide use with low weed harmfulness.

### 3.3. Set-up a multi-criteria performance scale (step I.3)

To facilitate the comparison of cropping-system performance, the five weed impact indicators were first ranked into performance classes (individual scores) and then aggregated into a single score (overall

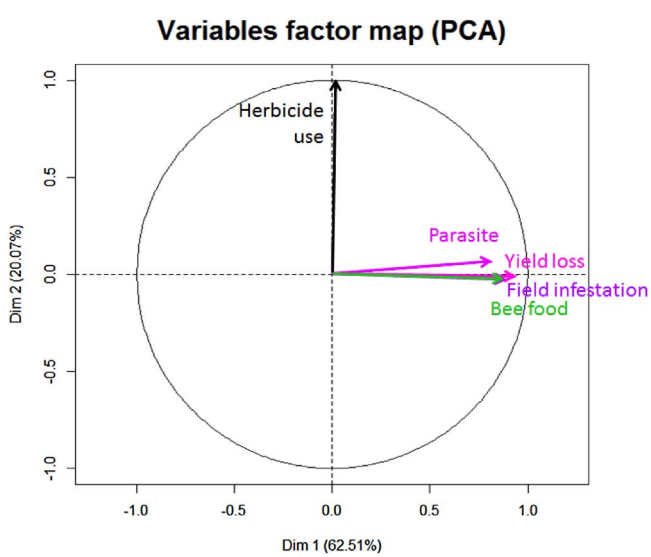


**Fig. 3.** Synergies and antagonisms between the chosen optimization criteria. Principal Component Analysis on weed impact indicator values per "cropping system x weather repetition", averaged over simulation for the 255 tested cropping systems. Weed benefits in green, harmfulness in purple, herbicide use intensity in black. Bee food hides field infestation (Nathalie Colbach © 2017). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

score). The same performance thresholds were used to score weed harmfulness and herbicide use (Table 1.A). Less stringent thresholds were used for biodiversity because this indicator is less important to farmers than most harmfulness indicators (Colas et al., 2015). When aggregating the individual scores into the overall performance score, crop yield loss was chosen as the dominant indicator which could partially compensate for lower performances of other indicators (Table 1.B). This criterion is the main concern for farmers, and thus makes the proposed weed management strategies more acceptable to farmers.

### 3.4. Build decision trees for overall performance (step I.4)

Decision trees were used to predict the probabilities of overall performance scores from combinations of cultural techniques. The decision tree identified ten management strategies resulting in ten performance patterns (leaves in Fig. 4) that differed in terms of herbicide use, weed harmfulness (reduced yield loss, field infestation, parasite risk) and biodiversity (bee food offer). Nine cropping system descriptors were necessary to discriminate them (variables in the nodes splitting the branches).

The best strategy (leaf n° 1) consisted of tillage during the first 198 days after crop harvest, with the last herbicide sprayed no later than 178 days before harvest, less than 60% of multi-annual crops in the rotation, mouldboard ploughing at least every 2 years, and foliar-only herbicides at least 2 years in 3. This combination ensured that the 30% maximum harmfulness and 50% minimum biodiversity targets (class D or better) were reached with a 63% probability though the 20% harmfulness/60% biodiversity target (class C-) was only reached in 3% of situations. The foliar herbicides were crucial: if their frequency was too low as in leaf n° 5 closest to leaf n° 1, targets were missed with a 90% probability (class E).

The second best strategy (leaf n° 2) presented a 50% risk of missing the lowest target and at best reached a C- score (yield loss < 20%, other harmfulness < 30% observed maximum, bee food > 60% observed maximum) with a 10% probability. It also included tillage during the first 198 days after crop harvest, but combined with spring/summer herbicide treatments, crop residue shredding at least every three years, and rolling prior or at crop sowing.

### 3.5. Evaluate an existing cropping system (step II.1)

As a reference cropping system to be improved step by step to reconcile weed harmfulness control, herbicide use reduction and biodiversity promotion, we chose a classical system from Burgundy, with an oilseed rape/wheat/barley rotation and yearly mouldboard ploughing (Table 3). The multi-criteria evaluation with FlorSys shows a high risk (90%) of a bad (E score) overall performance, with at best a 10% chance of a D-score performance (Fig. 5.A). The individual score greatly varied between weed impact indicators. Performance was worst for yield loss, with 90% risk of an E score (i.e. of at least 30% yield loss), and best for parasite risk, with only 30% of a C score or worse (i.e. more than 10% of maximum parasite level). The evaluation of the cropping system with the decision tree for harmfulness, herbicide use and biodiversity (Fig. 4) came roughly to the same conclusion for the overall performance score. It placed the system into the fifth best strategy out of 10, if strategies were ranked by increasing E-scores.

### 3.6. Identify inappropriate practices in the existing cropping system and pertinent changes to improve performance (step II.2)

The comparison of the system's descriptors with the descriptors of the best strategies identified those that did not meet the requirements for optimal management (Table 2). In total, six cropping system descriptors were identified that could be modified in the current system to potentially improve its performance, i.e. proportion of multiannual

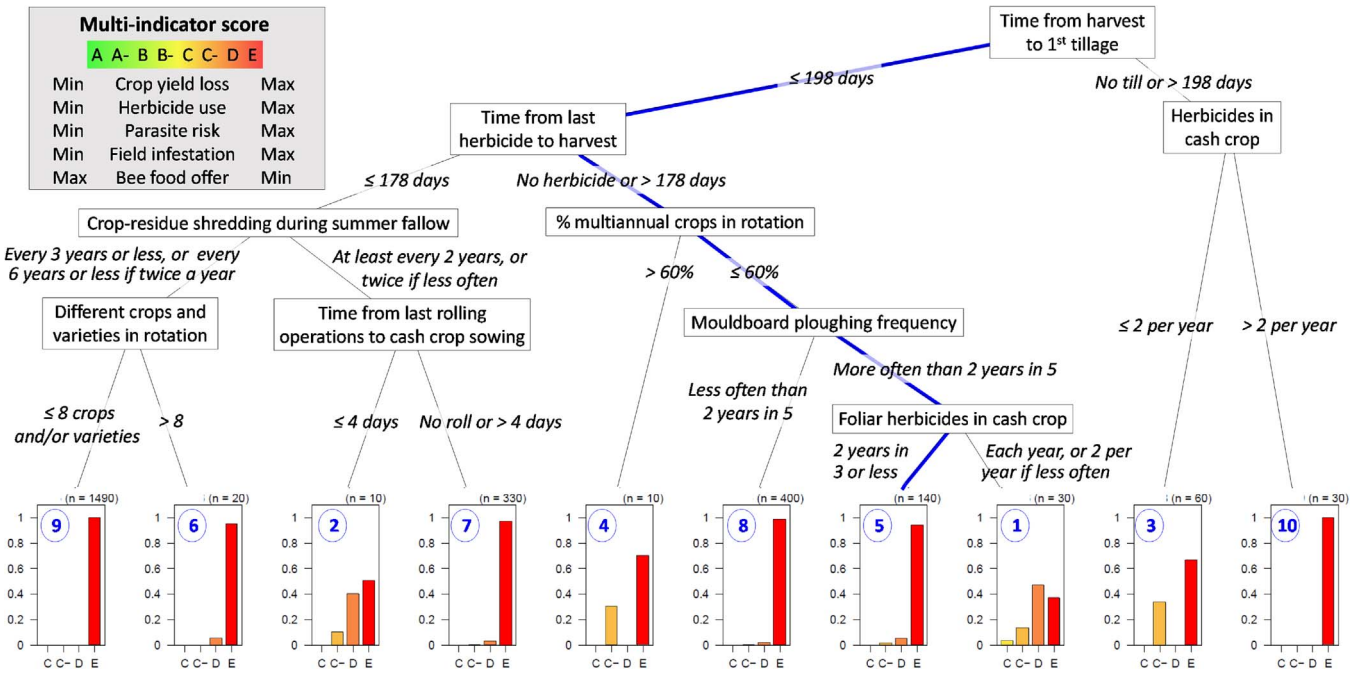


**Fig. 4.** Decision tree for identifying guidelines to reconcile herbicide use reduction, weed harmfulness control (crop yield loss, field infestation, parasite risk), and weed-mediated biodiversity (bee food offer) based on current farmers' practices. Terminal tree nodes show probabilities of weed impact scores (see Table 1) for each strategy, and are numbered with increasing E score probability. N indicates the number of "cropping system x weather" scenarios corresponding to each node. The blue bold pathway shows the performance of the cropping system of Table 3 (Nathalie Colbach © 2017). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

crops in the rotation, the timing of the first tillage, crop residue shredding and rolling frequency, herbicide types or numbers in cash crops and the timing of the last herbicide application during the cash crop.

To translate the broad guidelines into precise operation dates and options, the cropping systems from the database answering to the required management rules were analysed. For instance, the decision tree advised to introduce crop residue shredding and late rolling. To determine in which crops and at which dates to do this, there were several ways to exploit the database: (1) to identify the cropping systems that were included in the corresponding tree branch (here n° 2) to check whether they apply the required techniques to the crops of the system to be improved (here oilseed rape, wheat and barley), (2) to rank, by decreasing E-score probability, the cropping systems including the required crops and techniques, and copy their strategy. In the present example, branch n°2 did not include any of the required crops, so we looked at the whole database to identify the best system with crop residue shredding before cereals and to fix the date of shredding (usually 4–10 days after previous crop harvest).

### 3.7. Propose and test prospective cropping systems (steps II.3 and II.4)

The reference system includes herbicides that were withdrawn from the market since the system was identified in farm surveys. Before using the guidelines of Fig. 4 to improve the system, the herbicide programmes were modified to use only authorized products (details in section B.5.2 online). The decision tree of Fig. 4 indicates that the performance remains unchanged as spraying dates, relative rates and herbicide entry modes did not change. As the new products have a slightly different efficacy spectrum, FlorSys simulations though showed a slight improvement in overall performance and yield loss. Conversely, parasite risk and field infestation deteriorated (Fig. 5.B vs. A).

Based on the analysis of step II.2, four alternative cropping systems were tested (Fig. 5.C-E) to reconcile weed harmfulness control, herbicide use reduction and biodiversity promotion, corresponding to the changes required by the best three strategies of the decision tree. Replacing either the root-entering herbicide (alternative A1) or the root + pseudo-root herbicide (entering both via roots and shoot tips) in barley by a spring foliar herbicide entering via leaves (alternative A1') improved overall performance (Fig. 5.C and D). The second option produced the best results, improving all indicators, except herbicide use (Fig. 5.D). Among the two other alternatives, crop residue shredding before cereals combined with rolling the soil at crop sowing (Fig. 5.G) the most reduced the risk of E score performance. None of the alternatives notably reduced herbicide use or improved bee food.

A further option was tested which combined the two best individual alternatives, i.e. A1' (replacing a pseudo-root + root herbicide in barley by a foliar one) and A2 (introducing crop residue shredding before cereals and rolling on sowing day). The risk of bad performance (E score, 40%) was nearly as low as for the best individual strategy (30%, A1') whereas the best possible performance was better (10% C score, instead of 30% C- in A1') (Fig. 5.G).

The performance of the best alternatives (A1', A2) was better than the best performance among the initial 255 systems in the database whose probability of bad performance was 50% and of best performance was 10% C score (section D.1 online).

### 3.8. Effect of evaluation and optimization criteria

The decision trees, the best existing systems in the database, and the proposed alternatives greatly depended on the chosen optimization criteria. If only the four indicators of weed harmfulness and herbicide use were considered, the decision tree used 20 descriptors and resulted into 40 different strategies, among which many with quite good results (Appendix A). The best strategy resulted in 100% of A- score and consisted of rotations of spring and/or winter crops sown before 1 Oct, with the last tillage during the three weeks before cash crop sowing, using multi-entry herbicides only, with less than 2.6 applications on cash crops per year. This strategy differed from the best strategy identified for reconciling all five optimization criteria. If the number of criteria was further reduced to only crop yield loss and herbicide use, there was little change in the guidelines of the decision tree (Appendix A). This is due to the high correlation among the harmfulness indicators (section 3.1).

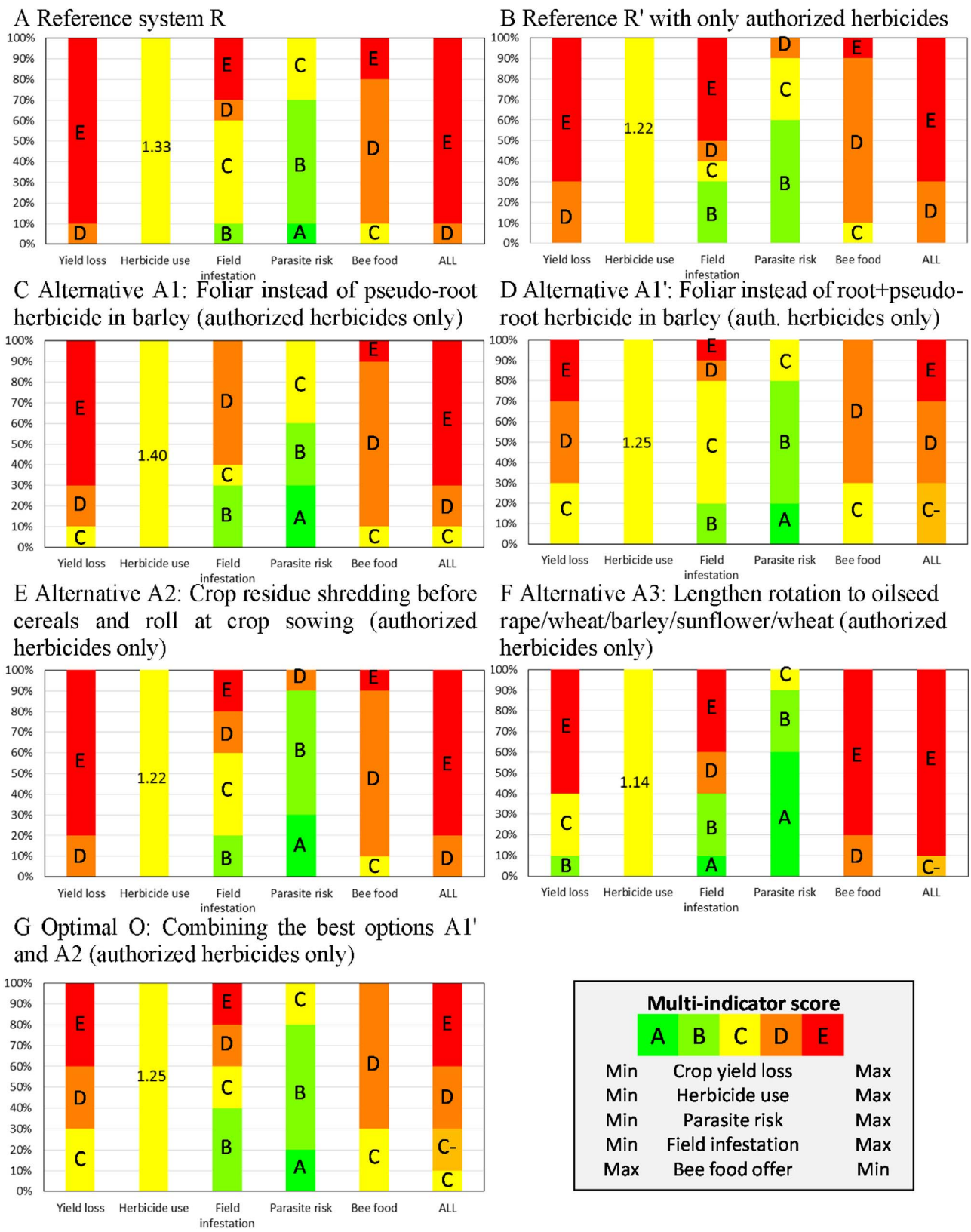


**Fig. 5.** Multi-criteria evaluation with FlorSys simulations of the existing Burgundy cropping system of Table 3 (A), the same but updating the herbicide programme to currently authorized products (B), and six alternative systems using authorized herbicides and based on the guidelines of the decision tree of Fig. 4 for reconciling weed harmfulness control, herbicide use reduction (with frequency treatment index on graph) and biodiversity promotion (C-G). For determination of weed impact scores, see Table 1 (Nathalie Colbach © 2017).

**Table 2**
Management strategies for reconciling multiple weed impact objectives identified from a decision tree and ranked by increasing probability of E score. Each line corresponds to a terminal leaf node, and the strategy descriptors describe the tree branches. Example of reduced herbicide use, reduced weed harmfulness (crop yield loss, field infestation, parasite risk) and improved biodiversity (bee food offer). For weed impact scores, see Table 1. Strategy 5 (bold) corresponds to the cropping system of Table 3 that was improved in steps II.2-II.4); italics in strategies 1–4 (i.e. better than strategy 5) refer to practices that are not implemented in strategy 5 and that potentially improve the performance of this cropping system.

| Strategy | Overall performance (probability) | | | | Strategy descriptors (average over rotation) | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | C | C- | D | E | Rotation | Mouldboard ploughing | First tillage (relative to previous harvest) | Crop residue shredding during fallow | Timing of rolling | Herbicides on cash crops | |
| | | | | | | | | | | Number | Timing of last spraying |
| 1 | 0.03 | 0.13 | 0.47 | 0.37 | ≤ 60% multiannuals | More than 2 years in 5 | During the first 198 days | | | *> 0.67 foliar herbicides per year*[$] | Earlier than 178 days before harvest (or no herbicide) |
| 2 | 0.00 | 0.10 | 0.40 | 0.50 | | | During the first 198 days | *> 0.33 per years*[§] | *During the last 4 days before sowing* | | *During the last 178 days before harvest* |
| 3 | 0.00 | 0.33 | 0.00 | 0.67 | | | *Later than 198 days after harvest (or no till)* | | | *≤ 2 herbicides per year* | |
| 4 | 0.00 | 0.30 | 0.00 | 0.70 | *> 60% multiannuals* | | During the first 198 days | | | | Earlier than 178 days before harvest (or no herbicide) |
| **5** | **0.00** | **0.01** | **0.05** | **0.94** | **≤ 60% multiannuals** | **More than 2 years in 5** | **During the first 198 days** | | | **≤ 0.67 foliar herbicides per year** | **Earlier than 178 days before harvest (or no herbicide)** |
| 6 | 0.00 | 0.00 | 0.05 | 0.95 | > 8 crops or varieties | | During the first 198 days | ≤ 0.33 per years | | | During the last 178 days before harvest |
| 7 | 0.00 | 0.00 | 0.03 | 0.97 | | | During the first 198 days | > 0.33 per years | No roll or earlier than 4 days before sowing | | During the last 178 days before harvest |
| 8 | 0.00 | 0.00 | 0.02 | 0.98 | ≤ 60% multiannuals | Less than 2 years in 5 | During the first 198 days | | | | Earlier than 178 days before harvest (or no herbicide) |
| 9 | 0.00 | 0.00 | 0.00 | 1.00 | ≤ 8 crops or varieties | | During the first 198 days | ≤ 0.33 per years | | | During the last 178 days before harvest |
| 10 | 0.00 | 0.00 | 0.00 | 1.00 | | | Later than 198 days after harvest (or no till) | | | > 2 herbicides per year | |

[§] either more often than once every three years, or more often than twice every six years, etc.[$] Either, more than one foliar herbicides in 2 years in 3, or two foliar herbicides every 3 years.

**Table 3**
Cultural operations in a classical Burgundy cropping system an oilseed rape/wheat/barley rotation, based on statistics from the Biovigilance-Flore network (Fried et al., 2008; Colbach et al., 2016).

| Management technique | Oilseed rape | Wheat | Barley |
|---|---|---|---|
| Tillage | Plough[§] (14 July)<br>Discs (2 x 31 July)<br>Power harrow[%] (14 Aug)<br>Spring tine (26 Aug) | Discs[$] (14 Aug)<br>Plough (14 Sept)<br>Power harrow (9 Oct) | Discs (31 July)<br>Plough (20 Aug)<br>Spring tine[%] (9 Spet)<br>Power harrow (7 Oct) |
| Sowing date | 26 Aug | 9 Oct | 7 Oct |
| Sowing density | 56 seeds/m² | 344 seeds/m² | 330 seeds/m² |
| Interrow width | 13 cm | 12 cm | 12 cm |
| Herbicides[∞] | Trifluraline[&] 2L/ha (25 Aug)<br>Napropamide[#] 1.9 L/ha (25 Aug)<br>Quizalofopethyl P[♣] 0.75 L/ha (4 Oct) | Flupyrsulfuron-methyle + metsulfuronmethyle[○] 0.03 kg/ha (15 March) | Imazamethabenz-methyl[♦] 1.5L/ha (6 Nov)<br>Isoproturon[●] 1.5 L/ha (6 Nov) |
| Fertilization | 43 m³/ha manure (14 July)<br>75 kg N/ha (16 Feb)<br>75 kg N/ha (15 March) | 65 kg N/ha (16 Feb)<br>92 kg N/ha (15 March)<br>33 kg N/ha (16 April) | 55 kg N/ha (16 Feb)<br>65 kg N/ha (15 March) |
| Harvest date | 11 July | 17 July | 1 July |

[§] With an 14-inch mouldboard plough equipped with a skim-coulter, 25 cm deep. [$] 10 cm deep. [%] 5 cm deep
[∞] Herbicides can enter plants via leaves ("foliar"), shoot tips during emergence ("pseudo-root") or roots ("root"). Multiple entry modes are possible. Foliar herbicides only kill weeds on the day of spraying, the other herbicides persist and act over several days and weeks. Systemic herbicides circulate inside the target plant and their efficiency depends less on dosage.
[&] Pseudo-root, regulatory rate = 2.5 L/ha, withdrawn
[#] Pseudo-root, regulatory rate = 9 L/ha, withdrawn
[♣] Foliar, systemic, regulatory rate = 1.2 L/ha
[○] Foliar, systemic, regulatory rate = 0.03 kg/ha
[♦] Root, foliar, systemic, regulatory rate = 2 L/ha, withdrawn
[●] Root, systemic, regulatory rate = 2.4 L/ha

The existing cropping system that we aimed to improve corresponded to the worst of 38 strategies in terms of two-indicator (crop yield loss and herbicide use) performance (data not shown). There were thus considerably more cropping system descriptors whose modifications would potentially improve the system's performance, particularly as the two-indicator decision tree was also built with twice the number of descriptors as the five-indicator decisions tree of Fig. 4. Eight descriptors could potentially be changed to achieve the six best

**Table 4**
Multi-criteria performance simulated by FlorSys for existing reference cropping systems (R) and alternative systems (A, O) aiming to reconcile weed harmfulness control and reduced herbicide use. For weed impact scores, see Table 1.

| Strategy | Necessary changes according to decision tree | Best systems in database include | Modifications applied to analysed cropping system | | Multi-criteria performance score | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | A | A- | B | B- | C | C- | D | E |
| R | | | Reference (Table 3) | | 0 | 0 | 0 | 0 | 0 | 0.0 | 0.1 | 0.9 |
| R' | | | Replace withdrawn herbicides by authorized herbicides | | 0 | 0 | 0 | 0 | 0 | 0.0 | 0.3 | 0.7 |
| A1 | ≤0.26 pseudo-root[&] herbicides per year[∞] and > 0.99 multi-entry herbicides per year[$] | Spring crops or 3-year lucerne | Replace one pseudo-root by one multi-entry herbicide<br>Introduce sunflower | | 0 | 0 | 0 | 0.1 | 0.1 | 0.0 | 0.6 | 0.2 |
| A2 | Winter-crop sowing date after 1 Oct<br>Harvest crops other than spring crops before 24 April | 3-year lucerne | Delete oilseed rape<br>Introduce lucerne | Replace oilseed rape by lucerne | 0 | 0 | 0 | 0 | 0 | 0.0 | 0 | 1.0 |
| A3 | ≤ 2 crop species or varieties in rotation<br>≤ 0.99 in-crop herbicides per year<br>≤ 0.26 pseudo-root only herbicides per year | | Delete one crop. Must keep OSR[§] to ensure early winter crop sowing date<br>Delete barley which has two herbicides<br>Delete barley with its pseudo-root only herbicide | OSR/wheat, delete one herbicide in OSR, adapted tillage date before OSR to later harvest of wheat (vs. barley) | 0 | 0 | 0 | 0.1 | 0.3 | 0.0 | 0.1 | 0.5 |
| A3' | | Mechanical weeding in OSR | Same as A3 with mechanical weeding in winter oilseed rape | | 0 | 0 | 0 | 0 | 0.4 | 0.0 | 0 | 0.6 |
| A4 | ≤ 0.26 pseudo-root only herbicides per year<br>> 2.59 in-crop herbicides per year<br>More than 104 days between ploughing to cash crop sowing | | Replace one pseudo-root by one multi-entry herbicide<br>PRE herbicides in OSR closer to sowing to be included in in-crop herbicides, additional herbicide in barley<br>Replace plough by discs because of short fallow periods | | 0 | 0 | 0 | 0.4 | 0.2 | 0.0 | 0.1 | 0.3 |
| A5 | ≤ 0.26 pseudo-root only herbicides per year<br>Winter-crop harvest date after 12 July | Spring crops in rotation | Add spring pea<br>Wheat instead of barley | OSR/wheat/pea/wheat | 0 | 0 | 0 | 0.3 | 0.1 | 0.0 | 0.1 | 0.5 |
| A6 | ≤ 0.26 pseudo-root only herbicides per year<br>> 1.79 in-crop herbicides<br>Last herbicide during the 124 days before harvest | Spring foliar herbicides | Foliar herbicide instead of pseudoroot in barley<br>PRE OSR herbicide closer to sowing to be included in in-crop herbicides<br>Spring foliar instead of autumn foliar herbicide in OSR<br>Spring foliar instead of autumn pseudo-root in barley | | 0 | 0 | 0 | 0 | 0 | 0.0 | 0.3 | 0.7 |
| O | Combine best options | | A5 + mechanical weeding in OSR (A3') + PRE herbicide closer to OSR sowing (A4, A6) | | 0 | 0 | 0 | 0.2 | 0.2 | 0.0 | 0.3 | 0.3 |

[&] See section 2.1.1 for type and effects of herbicides. [∞] Either, less than one herbicide every 3-4 years, or less than two herbicides every 7-8 years, etc. [$] Either, more than one herbicide every year, or more than two herbicides every two years etc. [§] OSR = winter oilseed rape

performances. These differed from those identified in the five-indicator tree of Fig. 4, and in several cases required to have a look at the best systems in the database to get pointers on how to respect the guidelines of the decision tree. For instance, the guideline requiring to harvest crops other than spring crops before 24 April (Appendix A) corresponded to systems including a 3-year lucerne (for fodder production) that was followed by a spring crop.

Seven alternatives were designed to reconcile reduced yield loss and reduced herbicide use (Table 4). The alternative replacing oilseed rape by lucerne (A2) deteriorated performance, the one resulting from the sixth best strategy (A6) changed nothing, and the five remaining alternatives reduced the risk of an E score, to 60% or less (A3, shortened rotation replacing one herbicide by mechanical weeding) and, at best, to 20% (A1, lengthened rotation, replacing one pseudo-root by one multi-entry herbicide). While the reference systems at best produced a D score, some alternative systems had a probability of at least 30% of a B- score (A4, A5).

The most efficient changes were not always those expected. For instance, the system that most lengthens and diversifies the rotation (A2) produced the worst result; the one that simplified tillage and added a further herbicide in barley (while also replacing one pseudo-root by one multi-entry herbicide, shifting PRE herbicides in OSR closer to sowing) was the best alternative (A4). The ranking of the alternatives did not necessarily follow that of the decision tree strategies, e.g. alternative A2 based on the second-best strategy performed worst.

Similarly, the O system changed the rotation to oilseed rape/wheat/spring pea/wheat, replaced one herbicide in oilseed rape by mechanical weeding, delayed tillage before rape and applied the PRE herbicide before oilseed rape closer to sowing. It combined several individual alternatives to reconcile reduced harmfulness and herbicide use (Table 4) but did not perform better than the best alternative used to design system O (A4) though with a lower herbicide use (0.95 instead of 1.4 for A4). It also scored better than the worst of the O-inspiring alternatives (A3', A5, A6). According to the decision tree, it should though have performed much better, with a 0% risk of an E score and 83% chance of a B- score (strategy 5 in Appendix A).

In conclusion, the decision trees and optimizing guidelines depended on the optimizing criteria, and the more antagonistic the weed impact indicators were, the worse the multi-criteria performance was and the fewer optimizing strategies were identified. Changing individual techniques according to the decision tree guidelines in an existing cropping system did not always lead to the expect performance, pointing to an important interaction among techniques. Similarly, combining individually interesting techniques could result in a worse performance than each individual change.

## 4. Discussion

### 4.1. Novel method for cropping system design

We developed a simulation-based method for multi-objective cropping system design, combining multi-criteria evaluation of a large set of cropping systems, decision rules based on decision trees and simulations of prospective cropping systems with a "virtual field" model. This work benefits from a set of indicators developed in previous studies which translate weed outputs of a cropping system model into indicators for assessing weed-related harmfulness and biodiversity (M & zière et al., 2015b; Colbach et al., 2017a), and used the combination of these indicators with the virtual-field model FlorSys to identify cropping system strategies for reaching single (Colbach et al., 2017a) or combined biodiversity and production objectives (Mézière et al., 2015a). Compared to Mézière et al's (2015a) study, our decision trees are more complete and more robust, as they are based on more and more contrasting cropping systems and regions. The comprehensive multi-criteria score used here is the result of a logical combination of performance classes that ensures that a well performing indicator cannot compensate the bad performance of another indicator. This made it easier to rank the management strategies and to identify those answering best to our requirements. The conclusions drawn in the present study depend, of course, on the domain of validity and the prediction quality of the FlorSys model. For a discussion of the limits inherent to FlorSys (e.g. missing weed types or biophysical processes),

see our previous simulation study (Mézière et al., 2015a) as well as the recent evaluation of the model (Colbach et al., 2016).

Our method was based on a simulation of biophysical processes responsible for effects of cultural techniques. Other models use expert knowledge to evaluate the advantages and disadvantages of the technique to optimize (e.g. crop rotation, Dogliotti et al., 2003; Schönhart et al., 2011), resulting in simpler models that allow to investigate all possible options (Dogliotti et al., 2003) and/or to determine the optimal solution via mathematical or numerical optimization (deVoil et al., 2006; Schönhart et al., 2011). This approach is difficult to adapt to the particular case of weed dynamics and their impacts on crop production and biodiversity, because of the multi-annual scale needed to assess weed impacts and the high number of interacting cultural techniques that affect these weed impacts. This explains why most weed studies are limited to an assessment of weed management strategies existing in fields or proposed by experts (SELOMA, Stigliani and Cosimo, 1993; WeedSOFT, Neeser et al., 2004) whereas we were able to go further and propose new cropping systems from our simulations.

To our knowledge, this is the first simulation-based method going beyond the evaluation of weed management strategies by designing innovative strategies. Moreover, the method aims to reconcile multiple objectives and not simply to control weed infestation. There are a few decision tools for weed management that evaluate crop yield loss and the economic return of the scenarios proposed by the user but these mostly consider a single weed species, focus on herbicides and are based on a very simplistic relationship between weed density and crop yield loss (e.g. RIM, Pannell et al., 2004).

There are several models for multi-criteria evaluation and design of crop management strategies for other aims. For instance, BETHA (Loyce et al., 2002b, 2002a) automatically generates crop management plans from an agronomic model which includes simple relationships that predict crop production quantity and quality from the crop management plan and the pedoclimate, and then performs a multi-criteria evaluation to rank the proposed crop management plans. Applying this approach to our case would be difficult because of the multiannual scale of cultural practices and weed impacts to consider.

SIMBA takes BETHA's approach to the multiannual scale (Tixier et al., 2008). It combines a decision-rule model with a multiannual process-based cropping system model for banana crops, evaluates systems with a series of economic and environmental indicators. However, because of the number of management inputs, only individual decision rules can be optimized, using a mean climatic year. This shows that automatic optimization algorithms would be difficult to use in our case, where management inputs are even more numerous, with considerable interactions among themselves and with pedoclimatic conditions.

Though it is slow and manual, our approach accounts for interaction among techniques and with pedoclimate. Our method moreover identifies the major cultural practices and combinations, and makes them visible to users. This is essential for workshops co-designing cropping systems with farmers and advisors, and is major pedagogic asset to make cropping practices evolve. More importantly, our method not only considers average effects, but also includes probabilities of success or disaster. The latter is particularly important as farmers are often more interested in reducing the risk of bad results or the variability in production, rather than in increasing average production or income over the years (Ridier et al., 2013).

### 4.2. Implications for reconciling multiple objectives

Our method made it possible to improve existing cropping systems with changes that would very probably not have been proposed by experts in workshops for designing cropping systems. Indeed, most of the changes operated in the cropping systems (e.g. introduce rolling at crop sowing, change the timing of ploughing) do not belong to the strategies known for controlling weeds (Van Acker, 2009; Lutman et al., 2013). Moreover, experts are certainly very efficient in designing cropping systems aiming to introduce a small number of techniques (e.g. Reckling et al., 2016) or at a single objective (e.g. reduce disease incidence, Hossard et al., 2013) while accounting for famers' production context (i.e. physical, chemcial and biological components of the field other than the crop and the socio-economical context that influence the farmer's decisions, Aubertot and Robin, 2013). But it is considerably more difficult to optimize combinations of techniques and to propose systems aiming to optimize several objectives as we did here, particularly when needing to consider multi-annual effects as in weed control. Consequently, expert-based multi-objective design is rare (Colnenne-David and Dore, 2015).

Our method made it possible to improve cropping system performance in terms of multiple objectives, particularly when focusing on weed harmfulness control and reduced herbicide use only. But even though the tested alternatives outperformed the best systems of the database on which the decision was based, none of the improved systems succeeded in reconciling weed harmfulness control, reduced herbicide use and biodiversity promotion. A previous study was already unsuccessful in identifying current farmers' practices that reconciled these three objectives (Mézière et al., 2015a). Here, we arrived at the same conclusion, despite analyzing ten times the number of cropping systems and including four new regions as well as prospective cropping systems (direct sowing, cover crops, Colbach et al., 2014d; glyphosate-tolerant maize, Bürger et al., 2015). One solution is to investigate more and different systems. Another is to include production situations in our decision trees, as farmers adapt their strategies to the production context, and a strategy efficient in a given context can be deficient in another (Lechenet et al., 2016).

The present method was more successful to propose systems that reconcile less antagonistic objectives, e.g. weed harmfulness control and reduced herbicide use, moving from an existing system with a 90% risk of inacceptable performance to a system with only 30% risk. But even this easier objective showed the difficulty to design multi-performant systems. Indeed, combining individually good strategies into a new strategy did not necessarily result in a better performance, because of the many implicated processes and the strong interactions between practices. These interactions also explain why FlorSys and the decision tree predicted similar performances for systems that were included in the database but could differ in their assessment of novel combinations of cultural techniques. Moreover, we only tested a small number of possible alternatives for each decision rule (e.g. different shredding dates, introducing different spring crops, different management options for lucerne). It was also often difficult to know which changes were best, as the cropping system descriptors used in the guidelines averaged practices over the years and often over different crops. For instance, “apply one herbicide per year in average” can mean both “apply two herbicides every two years” or “apply one herbicide every year”. It is thus quite probable that we missed better alternatives.

Here, we chose to minimize the risk of unacceptable performance when designing the new cropping systems, assuming that farmers are risk adverse (Ridier et al., 2013). If we had decided to maximise the probability of the best performance instead, the decision rules and practice changes would have been different. For instance, we would have introduced multi-annuals or switched to no till in order to improve the chance of a good performance while accepting a higher risk of inacceptable performance, instead of changing herbicide programmes and introducing rolling and crop residue shredding.

### 4.3. Where to go from here?

The previous analysis concluded that the present method must still be improved. The cropping-system database should be enlarged by increasing the diversity of the cropping systems and practices. This diversity can be increased by including innovative practices. For

instance, site-specific weed management only sprays herbicides on weed patches which reduces pesticide use while still controlling weeds (Berge et al., 2013). Similarly, our database included few systems with multi-specific crop canopies which exploit resources better, in particular when chemical input are reduced (Liebman and Dyck, 1993; Corre-Hellou et al., 2011). It is also mostly limited to French pedo-climatic conditions; to be applicable outside France and correctly assess interactions between cropping systems and pedo-climate, further regions and cropping system types must be included (e.g. no till organic systems, permanent crop cover, crop mixtures).

The diversity of the database can also be increased by including random combinations of practices. But FlorSys can require more than 100 variables to describe a cropping system and simulations are time-consuming, which limits the range of exploration. A feasible alternative would be to run a broad sensitivity analysis on a reasonable number of random cropping system. This would not only add new management practices to the database and the decision trees, but also point to the practices and practice combinations to investigate in depth.

A more diverse database would also decrease the correlation between cultural practices that occur in farming practices. We tried to remedy to this problem by a careful selection of cropping system descriptors and by the use of decision trees which can handle correlated predictors. The results of the trees can still be difficult to interpret, as some influential predictors can be hidden by others, and the selected variables are not always the ones that are the easiest to interpret. One solution is to look at surrogate splits, i.e. alternative variables that would have produced a similar partition in the tree, and use these to guide cropping system improvement. Here, we tried another approach when we analysed the cropping systems found in the target leaf to identify practices that were generally associated to the practice identified by the target leaf.

The decision trees can be improved further, by increasing the number and precision of the cropping system descriptors in the decision tree, and by including production situations. A solution would be to build separate trees for each production situation (Lechenet et al., 2016). This would help to adapt strategies to farmers' constraints and objectives, and thus facilitate the adoption of the innovative strategies.

To leave room for manoeuvre to farmers, methods for optimizing cropping systems must result in a set of optimal strategies instead of proposing a single solution (Ould-Sidi and Lescourret, 2011; Groot et al., 2012). The optimization step faces two major problems: (1) how to explore a large space of search, and (2) how to integrate multi-criteria evaluation (Bergez et al., 2010; Groot et al., 2010; Grechi et al., 2012). In future, we could increase the range and speed of exploration by developing new optimization algorithms that emulate our manual approach, i.e. by including search strategies based on decision trees to overcome the constraints due to the number of inputs and outputs to be optimized and the length of the simulations.

The way to upscale from individual criteria to a multi-criteria evaluation is crucial (Crespo et al., 2010; Ould-Sidi and Lescourret, 2011; Dury et al., 2012). There are many procedures for aggregating scores, depending on how indicators compensate each other: weighted sums, weighted products, or hierarchical decomposition through the Analytic Hierarchy Process approach (Saaty, 1990). Our performance score has the advantage to weight optimization criteria (e.g. crop yield loss is the most and bee food offer the least important) without allowing compensation between indicators (e.g. a high bee food offer does not cancel out a high yield loss). However, the score masks individual performances (e.g. a bad overall performance can be due to either yield loss or bee food). Conversely, multivariate decision trees identify clusters of cropping systems that show similar performance profiles with respect to the whole set of indicators, but comparing strategies is more difficult.

There is a complete different avenue of improvement, which consists in integrating innovative management techniques and associated biophysical processes into FlorSys. For instance, the model version used here assumes that weed populations are all sensitive to herbicides, which is a highly optimistic point of view. As a consequence, we recently included herbicide resistance in the model, starting with resistance to glyphosate (Colbach et al., 2017b; Colbach et al., 2017c) which is used over large acreage and often associated with simplified tillage or direct sowing, two practices attempting to reduce environmental impacts of agriculture (e.g. Holland, 2004). Including perennial weeds in FlorSys would also be needed to correctly assess the effect of these practices.

## 5. Conclusion

The present work developed an innovative method for multi-objective cropping system design, combining a cropping-system database, decision trees and a "virtual field" model. Thanks to the complementarity of data and methods, we were able to design multi-performant cropping systems, without using complex and time-consuming optimization methods. To be truly multi-performant, the method must still be improved by exploring more diverse cropping systems to build decision trees thar are more detailed in terms of cropping practices, with a better prediction of averages and probabilities of the multiple performance criteria. The method must also be adapted to be usable as a decision-aid tool by non-modellers and, particularly, extension services and farmers. To this end, future users have to be involved to understand their needs and have a practical use of the tool (Prost et al., 2012), e.g. via survey or workshops, to identify the positive and negative points to improve (Colas et al., 2016). The decision tree and method for improving cropping systems step by step are also a valuable tool for workshops co-designing cropping systems with farmers and advisors. Finally, we focused on multi-criteria evaluation of weed impacts, but cropping systems must also be evaluated for other economic, social and environmental effects (Pelzer et al., 2012).

## Acknowledgements

This project was supported by INRA, the French project CoSAC (ANR-15-CI.18-0007) and the research programme "Assessing and reducing environmental risks from plant protection products" funded by the French Ministries in charge of Ecology and Agriculture.

**Appendix A. Management strategies for reconciling multiple weed impact objectives identified from a decision tree and ranked by increasing probability of E-score. Each line corresponds to a terminal leaf node, and the strategy descriptors describe the tree branches. For determination of weed impact scores, see Table 1. Only scenarios with less than 5% of E scores are listed. Scenarios were ranked by decreasing A-, B etc scores. Sowing and harvesting dates refer to cash crops. Red italics show conditions that are not fulfilled by the existing cropping system of Table 3 which does not belong to the strategies listed here.**

A. Reduced herbicide use and reduced crop yield loss.

| | A- | B | B- | C | C- | D | E | Rotation, sowing and harvest dates | Tillage | Herbicides |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | Winter crops sown before 1 Oct or no winter crops | | ≤ 2.6 herbicides per year, among which > *1 multi-entry herbicide/year*, and ≤ *0.26 pseudo-root herbicides per year* |
| 2 | 0.60 | 0.30 | 0.00 | 0.10 | 0.00 | 0.00 | 0.00 | *Crops other than spring crops harvested before 24 April* | | |
| 3 | 0.00 | 0.00 | 0.98 | 0.00 | 0.00 | 0.00 | 0.03 | < *2 crops and/or varieties in rotation*, winter crops before 1 Oct | Max depth > 10 cm, till last during the 2 weeks before sowing | ≤ *1 herbicide per year*, among which ≤ 1 multi-entry herbicide/year and ≤ *0.26 pseudo-root herbicides per year* |
| 4 | 0.00 | 0.00 | 0.90 | 0.10 | 0.00 | 0.00 | 0.00 | Winter crops sown before 1 Oct or no winter crops | | > 1.8 herbicides/year, among which > *2 multi-entry herbicides/year* and ≤ *0.26 pseudo-root herbicides per year* |
| 5 | 0.00 | 0.00 | 0.83 | 0.17 | 0.00 | 0.00 | 0.00 | > 2 crops and/or varieties in rotation, winter crops sown before 1 Oct and *harvested after 12 July*, or no winter crops | Max depth > 10 cm, till last during the 2 weeks before sowing | ≤ 2.6 herbicides per year, among which ≤ 1 multi-entry herbicide/year and ≤ *0.26 pseudo-root herbicides per year* |
| 6 | 0.00 | 0.00 | 0.80 | 0.15 | 0.00 | 0.00 | 0.05 | No multi-annual crops, winter crops before 1 Oct | Max depth > 10 cm and *mean depth > 11 cm*, till last during the 2 weeks before sowing | 1.8-2.6 herbicides per year, among which ≤ 1 multi-entry herbicide/year and ≤ *0.26 pseudo-root herbicides per year*; *spray during the 125 days before harvest* |
| 7 | 0.00 | 0.00 | 0.55 | 0.28 | 0.00 | 0.11 | 0.05 | No multi-annual crops, winter crops before 1 Oct | Max depth > 10 cm, last till during the 2 weeks before sowing, plough at least occasionally | 1.8-2.6 herbicides per year, among which ≤ 1 multi-entry herbicide/year and ≤ *0.26 pseudo-root herbicides per year*; *spray during the 125 days before harvest* |
| 8 | 0.00 | 0.00 | 0.37 | 0.34 | 0.15 | 0.14 | 0.01 | No multi-annual crops, winter crops before 1 Oct | Max depth > 10 cm, till last during the 2 weeks before sowing, never plough | 1.8-2.6 herbicides per year among which ≤ 1 multi-entry herbicide/year and ≤ *0.26 pseudo-root herbicides per year*; spray last > 125 days before harvest |
| 9 | 0.00 | 0.00 | 0.10 | 0.50 | 0.00 | 0.40 | 0.00 | Winter crops sown before 1 Oct or no winter crops | | > *2.6 herbicides per year*, among which 0.3-3 multi-entry herbicides/year and ≤ *0.26 pseudo-root herbicides per year*; spray first 58-84 days after cash crop sowing |
| 10 | 0.00 | 0.00 | 0.06 | 0.17 | 0.56 | 0.20 | 0.01 | Winter crops sown before 1 Oct or no winter crops | | > *2.6 herbicides per year*, among which 0.3-3 multi-entry herbicides/year and ≤ *0.26 pseudo-root herbicides per year*; *spray during the 58 days after sowing*, do not spray during the 168 days before harvest |
| 11 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 | 0.00 | 0.00 | Winter crops sown before 1 Oct or no winter crops | *Max depth ≤ 10 cm*, till at least occasionally | ≤ 2.6 herbicides per year among which ≤ 1 multi-entry herbicide/year and ≤ *0.26 pseudo-root herbicides per year* |
| 12 | 0.00 | 0.00 | 0.00 | 0.00 | 0.99 | 0.00 | 0.01 | Winter crops sown before 1 Oct or no winter crops | Till first during the first 171 days after harvest | ≤ 2.6 herbicides per year among which 0.3-2 multi-entry herbicide/year, ≤ *0.26 pseudo-root herbicides per year* and *no foliar herbicides*; *spray during the 58 days after sowing*; *spray during the 168 days before harvest* |

B. Reduced herbicide use and reduced weed harmfulness (crop yield loss, field infestation, parasite risk).

| | A- | B | B- | C | C- | D | E | Rotation, sowing and harvest dates | Tillage | Herbicides |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | Winter crops sown before 1 Oct or no winter crops | Till last during the 3 weeks before sowing | ≤ 2.6 herbicides per year among which > *1 multi-entry herbicide/year* and ≤ *0.26 pseudo-root herbicides per year* |
| 2 | 0.60 | 0.10 | 0.20 | 0.10 | 0.00 | 0.00 | 0.00 | Winter crops sown after 1 Oct, > *60% multiannual crops* | | |
| 3 | 0.00 | 0.00 | 0.98 | 0.00 | 0.00 | 0.00 | 0.03 | ≤ *2 crops and/or varieties in 30 years*, winter crops sown before 1 Oct or no winter crops | Max depth > 10 cm, till during the 3 weeks before sowing | ≤ 2.6 herbicides per year among which ≤ 1 multi-entry herbicide/year and ≤ *0.26 pseudo-root herbicides per year* |
| 4 | 0.00 | 0.00 | 0.90 | 0.10 | 0.00 | 0.00 | 0.00 | Winter crops sown before 1 Oct or no winter crops | *No plough or plough earlier than 105 days before sowing* | > *2.6 herbicides per year* among which root herbicides less than every year and ≤ *0.26 pseudo-root herbicides per year* |
| 5 | 0.00 | 0.00 | 0.83 | 0.16 | 0.01 | 0.00 | 0.00 | > 2 crops and/or varieties in 30 years; winter crops sown before 1 Oct and *harvested after 12 July*, or no winter crops | Max depth > 10 cm, till during the 3 weeks before sowing | ≤ *1.8 herbicides per year* among which ≤ 1 multi-entry herbicide/year and ≤ *0.26 pseudo-root herbicides per year* |
| 6 | 0.00 | 0.00 | 0.80 | 0.15 | 0.00 | 0.00 | 0.05 | No multi-annual crops, winter crops sown before 1 Oct or no winter crops | Max depth > 10 cm and *mean depth > 11 cm*, till during the 3 weeks before sowing | > 1.8 herbicides per year among which ≤ 1 multi-entry herbicide/year and ≤ *0.26 pseudo-root herbicides per year*; *spray during the 124 days before harvest* |
| 7 | 0.00 | 0.00 | 0.37 | 0.34 | 0.15 | 0.14 | 0.01 | No multi-annual crops, winter crops sown before 1 Oct or no winter crops | Max depth > 10 cm, till during the 3 weeks before sowing, no plough | 1.9-2.6 herbicides per year among which ≤ 1 multi-entry herbicide/year and ≤ *0.26 pseudo-root herbicides per year*; spray last > 124 days before harvest |
| 8 | 0.00 | 0.00 | 0.15 | 0.50 | 0.00 | 0.35 | 0.00 | Includes winter crops, with winter crops sown 20 Sept-1 Oct | Max depth > 12 cm and mean depth < 10 cm, till during the 3 weeks before sowing, plough during the 105 before sowing | > *2.6 herbicides per year* among which root herbicides less than every year and ≤ *0.26 pseudo-root herbicides per year* |
| 9 | 0.00 | 0.00 | 0.07 | 0.23 | 0.57 | 0.13 | 0.00 | *Winter crops sown before 20 Sept or no winter crops* | mean depth < 10 cm; *till first during the 13 days after harvest*, till during the 3 weeks before sowing; plough during the 105 days before sowing | > *2.6 herbicides per year* among which root herbicides less than every year and ≤ *0.26 pseudo-root herbicides per year* |
| 10 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 | 0.00 | 0.00 | Winter crops sown before 1 Oct or no winter crops | *Max depth ≤ 10 cm*; till during the 3 weeks before sowing | ≤ 2.6 herbicides per year among which ≤ 1 multi-entry herbicide/year and ≤ *0.26 pseudo-root herbicides per year* |
| 11 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 | 0.00 | 0.00 | *Winter crops sown before 20 Sept. or no winter crops* | Mean depth < 10 cm; till first later than 13 days after harvest, till during the 3 weeks before sowing; plough during the 105 days before sowing | > *2.6 herbicides per year* among which < 1 root herbicide per year and ≤ *0.26 pseudo-root herbicides per year* |
| 12 | 0.00 | 0.00 | 0.00 | 0.00 | 0.70 | 0.30 | 0.00 | Includes winter crops, with winter crops sown 20 Sept-1 Oct | *Max depth ≤ 12 cm*, mean depth < 10 cm; till during the 3 weeks before sowing; plough during the 105 days before sowing | > *2.6 herbicides per year* among which < 1 root herbicide per year and ≤ *0.26 pseudo-root herbicides per year* |
| 13 | 0.00 | 0.00 | 0.00 | 0.00 | 0.99 | 0.00 | 0.01 | Winter crops sown before 1 Oct or no winter crops | Till first during the 171 days after harvest, till during the 3 weeks before sowing | > *2.6 herbicides per year* among which ≥ 1 root herbicides/year and ≤ *0.26 pseudo-root herbicides per year*; *spray during the 124 before harvest* |

## Appendix B. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.eja.2017.04.005.

## References


Aubertot, J.N., Robin, M.H., 2013. Injury profile SIMulator, a qualitative aggregative modelling framework to predict crop injury profile as a function of cropping practices, and the abiotic and biotic environment. I. conceptual bases. PLoS One 8.

Bürger, J., Granger, S., Guyot, S.H.M., Messéan, A., Colbach, N., 2015. Simulation study of the impact of changed cropping practices in conventional and GM maize on weeds and associated biodiversity. Agric. Syst. 137, 51–63.

Barbash, J.E., Thelin, G.P., Kolpin, D.W., Gilliom, R.J., 2001. Major herbicides in ground water: results from the National Water-Quality Assessment. J. Environ. Qual. 30, 831–845.

Berge, T.W., Goldberg, S., Kaspersen, K., Netland, J., 2013. Towards machine vision based site-specific weed management in cereals. Comput. Electron. Agric. 81, 79–86.

Bergez, J.E., Colbach, N., Crespo, O., Garcia, F., Jeuffroy, M.H., Justes, E., Loyce, C., Munier-Jolain, N., Sadok, W., 2010. Designing crop management systems by simulation. Eur. J. Agron. 32, 3–9.

Breiman, L., Friedman, J.H., Olshen, R.A., Stone, C.J., 1984. Classification and Regression Trees. Chapman and Hall (Wadswoth, Inc.), New York, USA 254 p.

Chicouene, D., 2007. Mechanical destruction of weeds: a review. Agron. Sustainable Dev. 27, 19–27.

Chikowo, R., Faloya, V., Petit, S., Munier-Jolain, N., 2009. Integrated Weed Management systems allow reduced reliance on herbicides and long term weed control. Agric. Ecosyst. Environ. 132, 237–242.

Colas, F., Cordeau, S., Jeuffroy, M.-H., Villerd, J., Colbach, N., 2015. Which decision-support system for sustainable weed management: needs and constraints of crop advisors. In: 17th European Weed Research Society Symposium: "Weed management in changing environments". Montpellier, France.

Colbach, N., Biju-Duval, L., Gardarin, A., Granger, S., Guyot, S.H.M., Mézière, D., Munier-Jolain, N.M., Petit, S., 2014a. The role of models for multicriteria evaluation and multiobjective design of cropping systems for managing weeds. Weed Res. 54, 541–555.

Colbach, N., Busset, H., Roger-Estrade, J., Caneill, J., 2014b. Predictive modelling of weed seed movement in response to superficial tillage tools. Soil Tillage Res. 138, 1–8.

Colbach, N., Collard, A., Guyot, S.H.M., Mézière, D., Munier-Jolain, N.M., 2014c. Assessing innovative sowing patterns for integrated weed management with a 3D crop:weed competition model. Eur. J. Agron. 53, 74–89.

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. Agric. Ecosyst. Environ. 183, 197–204.

Colbach, N., Bertrand, M., Busset, H., Colas, F., Dugué, F., Farcy, P., Fried, G., Granger, S., Meunier, D., Munier-Jolain, N.M., Noilhan, C., Strbik, F., Gardarin, A., 2016. Uncertainty analysis and evaluation of a complex: multi-specific weed dynamics model with diverse and incomplete data sets. Environ. Modell. Softw. 86, 184–203.

Colbach, N., Bockstaller, C., Colas, F., Gibot-Leclerc, S., Moreau, D., Pointurier, O., Villerd, J., 2017a. Assessing broomrape risk due to weeds in cropping systems with an indicator based on a simulation model. Ecol. Indic.

Colbach, N., Darmency, H., Fernier, A., Granger, S., Le Corre, V., Messéan, A., 2017b. Simulating changes in cropping practices in conventional and glyphosate-resistant maize. II. Effect on weed impacts on crop production and biodiversity. Environ. Sci. Pollut. Res. 24, 13121–13135.

Colbach, N., Fernier, A., Le Corre, V., Messéan, A., Darmency, H., 2017c. Simulating changes in cropping practices in conventional and glyphosate-resistant maize: I. Effects on weeds. Environ. Sci. Pollut. Res. 24, 11582–11600.

Colbach, N., 2010. Modelling cropping system effects on crop pest dynamics: how to compromise between process analysis and decision aid. Plant Sci. 179, 1–13.

Colnenne-David, C., Dore, T., 2015. Designing innovative productive cropping systems with quantified and ambitious environmental goals. Renewable Agric. Food Syst 30, 487–502.

Corre-Hellou, G., Dibet, A., Hauggaard-Nielsen, H., Crozat, Y., Gooding, M., Ambus, P., Dahlmann, C., von Fragstein, P., Pristeri, A., Monti, M., Jensen, E.S., 2011. The competitive ability of pea-barley intercrops against weeds and the interactions with crop productivity and soil N availability. Field Crops Res. 122, 264–272.

Crespo, O., Bergez, J.E., Garcia, F., 2010. Multiobjective optimization subject to uncertainty: application to irrigation strategy management. Comput. Electron. Agric. 74, 145–154.

Davis, A.S., Hill, J.D., Chase, C.A., Johanns, A.M., Liebman, M., 2012. Increasing cropping system diversity balances poroductivity, profitability and environmental health. PLoS One 7, e247149.

De'ath, G., Fabricius, K.E., 2000. Classification and regression trees: a powerful yet simple technique for ecological data analysis. Ecology 81, 3178–3192.

Delmotte, S., Tittonell, P., Mouret, J.C., Hammond, R., Lopez-Ridaura, S., 2011. On farm assessment of rice yield variability and productivity gaps between organic and conventional cropping systems under Mediterranean climate. Eur. J. Agron. 35, 223–236.

Dogliotti, S., Rossing, W.A.H., Ittersum, M. K.v., 2003. ROTAT, a tool for systematically generating crop rotations. Eur. J. Agron. 19, 239–250.

Dury, J., Schaller, N., Garcia, F., Reynaud, A., Bergez, J.E., 2012. Models to support cropping plan and crop rotation decisions: a review. Agron. Sustainable Dev. 32, 567–580.

Eurostat, 2016. Agri-environmental indicator – consumption of pesticides. Available at. http://ec.europa.eu/eurostat/statistics-explained/index.php/Agri-environmental_indicator_-_consumption_of_pesticides.

Ferraro, D.O., Rivero, D.E., Ghersa, C.M., 2009. An analysis of the factors that influence sugarcane yield in Northern Argentina using classification and regression trees. Field Crops Res. 112, 149–157.

Fried, G., Norton, L.R., Reboud, X., 2008. Environmental and management factors determining weed species composition and diversity in France. Agric. Ecosyst. Environ. 128, 68–76.

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

Gerowitt, B., 2003. Development and control of weeds in arable farming systems. Agric. Ecosyst. Environ. 98, 247–254.

Gibot-Leclerc, S., Brault, M., Pinochet, X., Sallé, G., 2003. Rôle potentiel des plantes adventices du colza d'hiver dans l'extension de l'orobanche rameuse en Poitou-Charentes. Comptes Rendus de Biologie 326, 645–658.

Grechi, I., Ould-Sidi, M.-M., Hilgert, N., Senoussi, R., Sauphanor, B., Lescourret, F., 2012. Designing integrated management scenarios using simulation-based and multi-objective optimization: application to the peach tree-Myzus persicae aphid system. Ecol. Modell. 246, 47–59.

Groot, J.C.J., Rossing, W.A.H., 2011. Model-aided learning for adaptive management of natural resources: an evolutionary design perspective: model-aided learning for adaptive NRM. Methods Ecol. Evol. 2, 643–650.

Groot, J.C.J., Jellema, A., Rossing, W.A.H., 2010. Designing a hedgerow network in a multifunctional agricultural landscape: balancing trade-offs among ecological quality, landscape character and implementation costs. Eur. J. Agron. 32, 112–119.

Groot, J.C.J., Oomen, G.J.M., Rossing, W.A.H., 2012. Multi-objective optimization and design of farming systems. Agric. Syst. 110, 63–77.

Heap, I., 2016. The international survey of herbicide resistant weeds. Available www.weedscience.com. Internet.

Holland, J.M., 2004. The environmental consequences of adopting conservation tillage in Europe: reviewing the evidence. Agric. Ecosyst. Environ. 103, 1–25.

Hossard, L., Jeuffroy, M.H., Pelzer, E., Pinochet, X., Souchere, V., 2013. A participatory approach to design spatial scenarios of cropping systems and assess their effects on phoma stem canker management at a regional scale. Environ. Modell. Softw. 48, 17–26.

Hothorn, T., Hornik, K., Zeileis, A., 2006. Unbiased recursive partitioning: a conditional inference framework. J. Comput. Graph. Stat. 15, 651–674.

Lechenet, M., Bretagnolle, V., Bockstaller, C., Boissinot, F., Petit, M.S., Petit, S., Munier-Jolain, N.M., 2014. Reconciling pesticide reduction with economic and environmental sustainability in arable farming. PLoS One 9.

Lechenet, M., Makowski, D., Py, G., Munier-Jolain, N., 2016. Profiling farming management strategies with contrasting pesticide use in France. Agric. Syst. 40–53.

Liebman, M., Dyck, E., 1993. Crop rotation and intercropping strategies for weed managment. Ecol. Appl. 3, 92–122.

Liebman, M., Gallandt, E.R., 1997. 9 − many little hammers: ecological management of crop-Weed interactions. In: Jackson, L.E. (Ed.), Ecology in Agriculture. Academic Press.

Lopez, B., Ollivier, P., Togola, A., Baran, N., Ghestem, J.-P., 2015. Screening of French groundwater for regulated and emerging contaminants. Sci. Total Environ. 518, 562–573.

Loyce, C., Wéry, J., 2006. Les outils des agronomes pour l'évaluation et la conception des systèmes de culture. In: Doré, T., Le Bail, M., Martin, P., Ney, B., Roger-Estrade, J. (Eds.), L'agronomie Aujourd'hui. QUAE Éditions.

Loyce, C., Rellier, J., Meynard, J.M., 2002a. Management planning for winter wheat with multiple objectives (1): the BETHA system. Agric. Syst. 72, 9–31.

Loyce, C., Rellier, J., Meynard, J.M., 2002b. Management planning for winter wheat with multiple objectives (2): ethanol-wheat production. Agric. Syst. 72, 33–57.

Lutman, P.J.W., Moss, S.R., Cook, S., Welham, S.J., 2013. A review of the effects of crop agronomy on the management of Alopecurus myosuroides. Weed Res. 53, 299–313.

Mézière, D., Colbach, N., Dessaint, F., Granger, S., 2015a. Which cropping systems to reconcile weed-related biodiversity and crop production in arable crops? An approach with simulation-based indicators. Eur. J. Agron. 68, 22–37.

Mézière, D., Petit, S., Granger, S., Biju-Duval, L., Colbach, N., 2015b. Developing a set of simulation-based indicators to assess harmfulness and contribution to biodiversity of weed communities in cropping systems. Ecol. Indic. 48, 157–170.

Marshall, E.J.P., Brown, V.K., Boatman, N.D., Lutman, P.J.W., Squire, G.R., Ward, L.K., 2003. The role of weeds in supporting biological diversity within crop fields. Weed Res. 43, 77–89.

Munier-Jolain, N.M., Guyot, S.H.M., Colbach, N., 2013. A 3D model for light interception in heterogeneous crop:weed canopies: model structure and evaluation. Ecol. Modell. 250, 101–110.

Munier-Jolain, N.M., Collard, A., Busset, H., Guyot, S.H.M., Colbach, N., 2014. Modelling the morphological plasticity of weeds in multi-specific canopies. Field Crops Res. 155, 90–98.

Naudin, K., Husson, O., Scopel, E., Auzoux, S., Giner, S., Giller, K., 2015. PRACT (Prototyping Rotation and Association with Cover crop and no Till) − a tool for designing conservation agriculture systems. Eur. J. Agron. 69, 21–31.

Neeser, C., Dille, J.A., Krishnan, G., David, A.M., Rawlinson, J.T., Martin, A.R., Bills, L.B., 2004. WeedSOFT: a weed management decision support system. Weed Sci. 52, 115–122.

Oerke, E., 2006. Crop losses to pests. J. Agric. Sci. 144, 31–43.

Ould-Sidi, M.M., Lescourret, F., 2011. Model-based design of integrated production systems: a review. Agron. Sustainable Dev. 31, 571–588.

Pannell, D.J., Stewart, V., Bennett, A., Monjardino, M., Schmidt, C., Powles, S.B., 2004. RIM: a bioeconomic model for integrated weed management of Lolium rigidum in Western Australia. Agric. Syst. 79, 305–325.

Pelzer, E., Fortino, G., Bockstaller, C., Angevin, F., Lamine, C., Moonen, C., Vasileiadis, V., Guérin, D., Guichard, L., Reau, R., Messéan, A., 2012. Assessing innovative cropping systems with DEXiPM, a qualitative multi-criteria assessment tool derived from DEXi. Ecol. Indic. 18, 171–182.

Petit, S., Boursault, A., Le Guilloux, M., Munier-Jolain, N., Reboud, X., 2011. Weeds in agricultural landscapes: a review. Agron. Sustainable Dev. 31, 309–317.
Pillet, E., Cavallaro, P., Chartier, N., Silveira, T.D., Debandt, M., Deliere, L., Devillers, O., Eckert, C., Emonet, E., Garcin, A., Houdin, A., Munier-Jolain, N., Omon, B., Sagnes, J.-L., Ardavansoleymani, Tresch, P., Blondel, L., Bouille, D., Combier, M., Cortel, S., Daudin, T., Descoureaux, D., Dumas-Lattaque, L., Laudinot, V., Molinier, P., Merot, E., Minette, S., Montagnon, J.-M., Pambou, I., Pottiez, B., Vandewalle, A., Lechenet, M., Abiven, F., 2014. DEPHY-Ferme: Premiers résultats à l'échelle Nationale. 50 p.
Prost, L., Cerf, M., Jeuffroy, M.H., 2012. Lack of consideration for end-users during the design of agronomic models: a review. Agron. Sustainable Dev. 32, 581–594.
Reckling, M., Hecker, J.M., Bergkvist, G., Watson, C.A., Zander, P., Schlafke, N., Stoddard, F.L., Eory, V., Topp, C.F.E., Maire, J., Bachinger, J., 2016. A cropping system assessment framework-Evaluating effects of introducing legumes into crop rotations. Eur. J. Agron. 76, 186–197.
Ricou, C., Schneller, C., Amiaud, B., Plantureux, S., Bockstaller, C., 2014. A vegetation-based indicator to assess the pollination value of field margin flora. Ecol. Indic. 45, 320–331.
Ridier, A., Ghali, M.B.E., Nguyen, G., Kephaliacos, C., 2013. The role of risk aversion and labor constraints in the adoption of low input practices supported by the CAP green payments in cash crop farms. Revue d'Études en Agriculture et Environnement 94, 195–219.
Saaty, T.L., 1990. How to make a decision: the analytic hierarchy process. Eur. J. Oper. Res. 48, 9–26.
Schönhart, M., Schmid, E., Schneider, U.A., 2011. Crop Rota − A crop rotation model to support integrated land use assessments. Eur. J. Agron. 34, 263–277.
Stigliani, L., Cosimo, R., 1993. SELOMA: expert system for weed management in herbicide-Intensive crops. Weed Technol. 7, 550–559.
Storkey, J., Cussans, J.W., 2007. Reconciling the conservation of in-field biodiversity with crop production using a simulation model of weed growth and competition. Agric. Ecosyst. Environ. 122, 173–182.
Swinton, S.M., Buhler, D.D., Forcella, F., Gunsolus, J.L., King, R.P., 1994. Estimation of crop yield loss due to interference by multiple weed species. Weed Sci. 42, 103–109.
Tittonell, P., Sheperd, K.D., Vanlauwe, B., Giller, K.E., 2008. Unravelling the effects of soil and crop management on maize productivity in smallholder agricultural systems of western Kenya − An applcation of classification regression tree analysis. Agric. Ecosyst. Environ. 123, 137–150.
Tixier, P., Malezieux, E., Dorel, M., Wery, J., 2008. SIMBA, a model for designing sustainable banana-based cropping systems. Agric. Syst. 97, 139–150.
Ulrich, U., Kruger, C., Hormann, G., Fohrer, N., 2015. Pesticide contamination of German small water bodies: a status report. Hydrol. Wasserbewirtsch. 59, 227–238.
Van Acker, R.C., 2009. Weed biology serves practical weed management. Weed Res. 49, 1–5.
Vinson, F., Merhi, M., Baldi, I., Raynal, H., Gamet-Payrastre, L., 2011. Exposure to pesticides and risk of childhood cancer: a meta-analysis of recent epidemiological studies. Occup. Environ. Med. 68, 694–702.
Waggoner, J.K., Henneberger, P.K., Kullman, G.J., Umbach, D.M., Kamel, F., Beane Freeman, L.E., Alavanja, M.C.R., Sandler, D.P., Hoppin, J.A., 2013. Pesticide use and fatal injury among farmers in the Agricultural Health Study. Int. Arch. Occup. Environ. Health 86, 177–187.
Wisler, G.C., Norris, R.F., 2005. Interactions between weeds and cultivated plants as related to management of plant pathogens. Weed Sci. 53, 914–917.
deVoil, P., Rossing, W.A.H., Hammer, G.L., 2006. Exploring profit—sustainability trade-offs in cropping systems using evolutionary algorithms. Environ. Modell. Softw. 21, 1368–1374.