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Profiling farming management strategies with contrasting pesticide use in France

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ABSTRACT

Reducing pesticide use in agriculture is a major challenge to improve sustainability of cropping systems. It is critical to identify effective integrated farming strategies able to decrease substantially pesticide use. This study is based on a unique French national network of 1012 arable commercial farms involved in a pesticide reduction program. These farms displayed contrasting levels of pesticide use, and covered a large diversity of environmental characteristics and farming practices. Our objective was to identify profiles of management strategies showing contrasting pesticide use levels in France. Two categories of factors potentially related to pesticide use were considered successively, namely factors describing production situations and factors describing management strategies. Regression tree methods were applied to the dataset to identify combinations of factors associated with low vs. high pesticide use levels. Results showed that, among the factors describing production situations, the presence of livestock, climate conditions, and to a lesser extent soil characteristics were able to discriminate groups of farms with contrasting pesticide use levels. Among the factors describing management strategies, the crop sequence, the crop diversity, the pesticide spraying techniques, and soil tillage were frequently selected for discriminating farms characterised by low vs. high pesticide use levels, whereas specific factors such as mechanical weeding, crop cultivars and sowing dates were related with pesticide use in some production situations only. Across production situations, several contrasting strategies led to low levels of pesticide use. Besides, within each considered production situation, different strategies appeared associated with low levels of pesticide use. Our results reveal that a large diversity of strategies exists for controlling pests, weeds and diseases without high levels of pesticide use.

1. Introduction

A substantial reduction of pesticide use is required to make agriculture more sustainable (Matson et al., 1997). This objective will be achieved only if farming practices go through major changes in order to enhance the bio-physical regulation of pests (Wezel et al., 2014). In this context, the concept of Integrated Pest Management (IPM) emphasises the combination of a wide range of technical levers alternative to chemicals for pest management in order to achieve sustainable economic benefits with the lowest risk to human health and the environment (Glass, 1975; Barzman et al., 2015; Lamichhane et al., 2015). Many experiments based on IPM principles were carried out to assess potentialities of innovative approaches able to reduce pesticide use through the combination of alternative management options (e.g. Reganold et al., 2001; Deike et al., 2008; Chikowo et al., 2009). Innovative cropping systems tested in these experiments were based both on preventive (e.g. diversified crop rotation, soil tillage strategy including false seed bed techniques) and curative measures (e.g. biocontrol, mechanical weeding), with the objective to diversify perturbation factors of pests lifecycle (Barzman et al., 2015). However, economic, environmental and social performances of cropping systems are strongly influenced by bio-physical (e.g. climatic conditions, soil composition) and socio-economic (e.g. presence of livestock, outlets for industrial crops) local drivers (Bürger et al., 2012; Aouadi et al., 2015). These local drivers are not easy to control by farmers, and their combination defined a so-called concept of production situation (PS) (Aubertot and Robin, 2013). In classical experimental approaches, experimental outputs partly reflect the constraints and opportunities defined by the specific PS, and the generic value of conclusions may be questioned (Doré et al., 2011). Results from one experiment in one site might be valid only in those production contexts that are close to the experimental production context. The IPM-based management strategies that are likely to best reconcile the various aspects of agricultural sustainability might be different from one site to one another, but all combinations

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of management options cannot be tested experimentally in all types of PS. As a complementary approach, networks of commercial farms may create the opportunity to study real farms showing a diversity of farming managements in line with the constraints and opportunities coming from a wide range of PSs.

Launched in 2008, the French national plan Ecophyto has set a target of a 50% decrease in pesticide use, initially planned to be reached by the year 2018 (French Ministry of Agriculture and Fisheries, 2008). However, French agriculture is today far from achieving this goal, and the end of the initial plan was recently postponed to 2025. To guide farmers and help them to adopt more sustainable practices, one pillar of this plan relies on DEPHY, a national network of commercial demonstration farms. This network involves two thousand farms, committed since 2011 in a reduction of their pesticide reliance. It covers a large diversity of production systems, ranging from arable cropping to vineyards, orchards, vegetables, etc. DEPHY is based on 200 farm advisors, who both provide a local guidance to the farmers, and collect data. It produces a dataset for enhancing knowledge on the management measures that make it possible to reduce pesticide use. Each arable farm from the network is a based on a specific management strategy (MS) characterised by both the crop sequence and the sets of management techniques applied to the different crops.

Our hypotheses were: (i) MSs leading to low pesticide use are based on combinations of several management measures, (ii) those MSs are different across PSs, and (iii) low pesticide use levels could be reached through different MSs within a given PS. To test these hypotheses, we carried out a detailed analysis of pesticide use variability with the Classification and Regression Tree method (CART), able to handle complex interactions between explanatory variables. The method was previously used to study cropping systems. For example, it proved to be useful to understand how soil characteristics and crop management may explain variability in maize productivity in farms from western Kenya (Tittonell et al., 2008). Here we used biophysical, socio-economic, and management data collected over arable farms located in France. Regression trees were fitted to the dataset to identify combinations of factors discriminating farms according to their level of pesticide use, i.e. related to low vs. high pesticide use. This approach was first applied to pesticide use averaged at the farm level, and then separately to pesticide use for two major crops, namely winter wheat and maize, in order (i) to highlight indirect links between the composition of the crops sequence and pesticide use in wheat and maize, respectively, and (ii) to highlight further technical options related to pesticide use on these crops.

2. Material and methods

2.1. Data collected on the DEPHY demonstration farm network

In this study we focused on the 1012 non-organic arable farms of the DEPHY farm network, accounting for >66,000 ha of arable area. For each farm, the main MS was described in detail between 2009 and 2011. We collected data describing both the PS and the MS. A review of the scientific literature was performed to identify a set of variables which may potentially affect pesticide use intensity.

2.2. TFI

We used the Treatment Frequency Index (TFI) to quantify pesticide use in each farm. The TFI (OECD, 2001) estimates the number of reference doses applied, for each pesticide, per hectare and per crop season. TFI was expressed at the farm level by averaging the crop TFI according to the proportion of each crop in the crop sequence:

$$\mathrm{TFI} = \sum_{j=1}^{\mathrm{k}} \left(\sum_{i=1}^{n} \frac{\mathrm{D}_i \cdot S_i}{Dh_i \cdot S_t} \right) \cdot \omega_{\mathrm{j}}$$

where D_i, Dh_i, and S_i, $i = 1, \ldots,$ n are, respectively, the applied dose, the reference dose, and the treated surface area for the n spraying operations; S_t is the total plot area; and ω_j, $j = 1, \ldots,$ k are the proportions of each j crop in the crop sequence. The applied dose and the reference dose were both expressed for a given commercial product (that possibly contains several active ingredients). As recommended by the French Ministry of Agriculture for TFI computation, we selected the reference dose as the lowest of the different registered doses specified across the various possible targeted pests for each pesticide-crop combination. All registered doses came from the E-phy online database provided by the French Ministry of Agriculture (Ephy website, 2014). TFI is an indicator that summarizes dependence on pesticides, which should be distinguished from the environmental impact of pesticides.

2.3. Variables characterizing production situations

We identified 46 variables describing PSs. According to the literature, these variables could have some effects on crop development or pest pressure and therefore on pesticide use (details provided in Supplementary data Table S1). Some of these variables corresponded to bio-physical characteristics and described the effects of climate and soil or field characteristics at each site. Maximum yields achieved on winter wheat and maize during the previous years on each farm were used as a proxy for yield potentials, i.e., maximum yield values that could be obtained in a farm given its soil and climate characteristics. Climate variables were derived from the SAFRAN database (Quintana-Seguí et al., 2008) providing ten years (2002 − 2011) of daily national climatic data at the scale of 8×8 km spatial meshes. The other variables were related to the socio-economic background and described, for instance, the access to particular local market opportunities for agricultural outputs with high added-value (e.g. farms within the sugar beet catchment area of sugar factories, etc.), the combination of arable crops with livestock breeding in mixed farms, or the average field distance to the farm holding. Farms were considered to be associated with livestock as soon as the crop sequence included at least one self-consumed crop to feed livestock present on the farm.

2.4. Variables describing management strategies

278 variables were defined to describe the MSs (details provided in Supplementary data Table S1). These variables characterised crop rotation composition and diversity, soil tillage type and intensity, weed management strategy, pesticide spraying strategy and fertilisation rates. These variables were computed both separately for several crop species (e.g. winter wheat, maize, grassland, oilseed rape, sugar beet) and at the farm level using weighted average over the crop rotation, with weights equal to the frequencies of the crops in the crop sequence. Crop type diversity was assessed by measuring the frequency of cultivation of six different groups of species (Supplementary data Table S1). Sowing period diversity was described by measuring the frequency of occurrence of five different sowing periods over year.

2.5. Identification of combinations of variables discriminating low vs. high pesticide use

2.5.1. CART (Classification and Regression Tree)

We used a recursive partitioning approach based on the CART method (Breiman et al., 1984) to split our sample of 1012 TFI values using the PS and MS variables into sub-samples that build a regression tree explaining TFI variability. A split for a given node is a dichotomy leading to two lower nodes with contrasting TFI values. A split involves (i) the choice of the most discriminating variable among the set of explanatory variables, and (ii) the choice of the best dichotomy on the variable previously selected, so that it permits the highest reduction in the within node TFI variability. The final tree is composed of several branches, where each branch corresponds to a combination of successive splits between the root (i.e. the starting group) and a terminal node (i.e. a final group). This method does not need any assumption on the form of the relationship between the explanatory variables and the response variable. Another advantage is that this method handles missing values in the explanatory variables. In our dataset, missing data represented less than 3% of available data for the description of PSs and 0.3% of available data for the description of MSs.

CART was first applied to partition our sample of 1012 TFIs using the variables describing the PSs only. The terminal nodes of the resulting tree were used to define different categories of PSs showing contrasting TFI values. The minimum number of TFI values included in each terminal node was set to 100.

Then, CART was applied a second time to TFI values from each terminal node of the first tree (i.e. in each of the PS category). This second application of CART was performed using the variables characterizing MSs. One regression tree per PS category was generated, hence allowing the identification of profiles of MSs associated with contrasting values of TFI for each category of PS.

This second series of regression trees was built without restriction on the number of splits, i.e. on the length of branches, but were pruned by minimising the cross-validated mean squared error (Moisen, 2008) to avoid overfitting. This cost-complexity measure optimised the size of the tree to reduce the risk of tree instability.

The recursive partitioning method was implemented on TFI calculated at the farm level, but also on TFI values calculated for winter wheat and maize separately. These two crops were the most cultivated in the farm network (respectively 86% and 61% of farms included winter wheat and maize).

2.5.2. Random Forest

Although the CART method is a powerful tool to analyse complex relationships among a large set of variables, the instability of regression trees remains one of the main limits of this approach (Marshall and Kitsantas, 2012). Here, we used the Random Forest method to prioritise explanatory variables according to their discriminatory power and their importance in the splitting process quality. The ranking of variables generated by this method provides insights on the quality of the trees built with the CART method.

The Random Forest method is a Machine-learning classification method based on a high number of decision trees (Breiman, 2001). The algorithm was implemented to generate randomly 1000 subsamples (with replacement) from the full TFI sample and to build a decision tree for each subsample. The resulting set of 1000 trees (the forest) was then used to calculate two criteria, namely (i) the average contribution of each explanatory variable to reduce the impurity of terminal nodes, and (ii) the risk of misclassification associated with the permutation of values for each explanatory variable. These two criteria were used to rank the explanatory variables according to their ability to increase nodes purity or to their importance for discriminating low vs. high TFI values. The resulting ranking was used to identify variables with robust discriminative power.

2.5.3. Description of PS categories and MS profiles

Explanatory variables might be correlated, so the selection of variables by the CART method might hide the effects of combined variables that are not selected. Multiple comparisons between PS categories and MS profiles were therefore performed using all explanatory variables by multiple rank comparisons with the Benjamini & Hochberg correction on p-value (Benjamini and Hochberg, 1995) to get additional information that were not directly visible on the trees. This was useful to identify all the combined variables that significantly discriminated the terminal nodes previously produced by the CART method. All the explanatory variables presented below in the 'Results' section to discriminate PS and MS profiles reflected significant differences between clusters (see Supplementary data Table S4). Statistical significance was based on type 1 error rate of 5%.

2.6. Softwares and procedures

Databases were handled with SAS 9.4 ®. Statistical analyses were carried out with the software R version 3.1.2 (R Development Core Team, 2014). Regression trees and Random Forest were built respectively with the *rpart* (Therneau and Atkinson, 1997) and *Random Forest* (Liaw and Wiener, 2002) packages. Multiple comparisons were performed using the 'Kruskal' function from the *agricolae* package (Conover, 1999).

3. Results

3.1. Analysing TFI at the farm level

3.1.1. First partitioning: identification of PS categories

Over the network, average TFI at the farm level was 3.3. The most important variables describing the PS that were identified with the Random Forest method were (i) the combination of arable crops with livestock breeding, (ii) the local market opportunities for industrial crop outlets (e.g. sugar beet, potato, seed maize), and (iii) climatic variables such as solar radiation, potential evapotranspiration (PET), precipitations, relative air humidity, and wind speed (Supplementary data Table S2).

The variables selected by the CART method (Supplementary data Fig. S3) were those with high rankings according to the Random Forest method, and this revealed that the CART outputs were robust. Other variables were identified by multiple comparison methods, and therefore could be used to complement the description of the output PS categories (Supplementary data Table S4). The six categories of PS identified from the CART regression tree were characterised by average TFI values ranging from 1.7 to 5.5 (Table 1). The variability of TFI within each PS was large (Fig. 1). For example, in PS6, the TFI values varied from 0.8 to 16.7. The first splitting variable selected by CART was the combination with livestock or not. The categories PS1 to PS3 were associated with livestock, enabling the cultivation of forage crops, whereas PS4 to PS6 corresponded to farms based on cash crops only. The next variables selected by CART were related to the climate. Decreasing average annual temperatures, global annual radiation and annual PET were observed from PS1 to PS3 (average annual temperature varying from 12.0 °C in PS1 to 10.5 °C in PS3, global annual radiation from 470 $kJ \cdot cm^{-2}$ to 419 $kJ \cdot cm^{-2}$, and annual PET from 757 mm in PS1 to 632 mm in PS3), and from PS4 to PS6 (average annual temperature ranging from 12.7 °C in PS4 to 10.9 °C in PS6, global annual radiation from 459 $kJ \cdot cm^{-2}$ to 403 $kJ \cdot cm^{-2}$, and annual PET from 781 mm to 626 mm). The opposite trend was identified for relative air humidity, increasing from PS1 to PS3 (respectively from 78% to 82%) and from PS4 to PS6 (respectively from 76% to 82%). In addition, averaged annual precipitation appeared to be higher in PS3 than in PS1 (880 mm vs. 837 mm) and higher in PS6 than in PS4 and PS5 (827 mm vs. 776 and 749 respectively). The access to irrigation was more frequent in PS1 and PS4 than in the other PS categories (26% of farms with access to irrigation in PS1, 39% in PS4 vs. a range from 3% to 9% in other categories of PS). Fields with high yield potential were more frequent in PSs without livestock than in others (+11%), along with a lower frequency of sandy soils (−10%) and a significantly higher pH (average pH ranging from 7.2 to 7.4 in PS4, PS5 and PS6 vs. ranging from 6.4 to 6.8 in PS1, PS2, PS3).

Not surprisingly (considering the weight of climatic variables in discriminating PS categories), the six categories of PS were geographically not evenly distributed across the national territory (Fig. 2). PSs corresponding to sites with livestock and mixed farming were distributed over a central region around Paris, and PSs corresponding to high TFIs tended to be located in the northern part of the country. However, sites located in the same county could be classified in different PS categories, and then different PS categories could be represented in a given county.

Table 1
Details of production situations identified with the recursive partitioning of TFI at the farm level.
The variable 'presence of livestock' is the proportion of farms associated with livestock within the PS. For average TFI, significant differences between PS are given with significance letters resulting from the multiple rank comparisons.

Production situation	Average TFI	Main locations	Presence of livestock	Climate conditions	Main crops
PS1	1.7 a	Central-southern France	100%	High temperatures and dry climate	Straw cereals, grassland, maize
PS2	2.3 b	North-western France	100%	Medium temperatures	Straw cereals, maize, grassland
PS3	3.3 c	Northern France	100%	Low temperatures and wet climate	Straw cereals, maize, oilseed rape
PS4	3.2 c	Central and southern France	0%	High temperatures and dry climate	Straw cereals, maize, sunflower
PS5	4.2 d	Central and northern France	0%	Medium temperatures	Straw cereals, oilseed rape
PS6	5.5 e	Northern France	0%	Low temperatures and wet climate	Straw cereals, oilseed rape, sugarbeet & potato

In PSs associated with livestock, the proportion of temporary grasslands in the cultivated area decreased from PS1 to PS3 (27% of cropped area in PS1, 15% in PS2 and 8% in PS3), and the opposite trend was noted for winter wheat (35% in PS3, 28% in PS2 and 20% for PS1), with also more oilseed rape in PS3 (13% in PS3 vs. 4% in PS1 and PS2). In PSs without livestock, maize was mostly grown in PS4 (29% of cropped area in PS4 vs. 8% in PS5 and 4% in PS6) and straw cereals and oilseed rape were mainly associated with PS5 and PS6 (58% and 53% of straw cereals in PS5 and PS6 respectively vs. 41% in PS4; 20% and 13% of oilseed rape in PS5 and PS6 vs. 8% in PS4). Sugar beet, potato, and field vegetable were mostly grown in PS6, a PS category predominantly located in northern France and characterised by deep silt soils with high yield potential. Focusing on technical management, inversion tillage was more frequent in farms associated with livestock (between 77% and 78% of farms with livestock included inversion tillage vs. 64% to 68% in farms where livestock was absent). Conversely, the frequency of tillage operations was higher in farms without livestock (ranging from 2.2 to 2.4 tillage operations vs. from 1.5 to 1.9 tillage operations in farms with livestock). Pesticide application strategies in PS1 and PS4 were more frequently based on full dose applications on straw cereals than in other PS categories (full dose pesticide applications represented 50% of pesticide applications on straw cereals in PS1 and 44% in PS4 vs. they varied from 31% to 35% in other PSs). N fertilisation rates in winter wheat also varied across PS categories, with more N inputs in PS3 to PS6 (from 176 to 179 kg $N \cdot ha^{-1} \cdot year^{-1}$) as compared to PS1 and PS2 (146 kg $N \cdot ha^{-1} \cdot year^{-1}$), consistently with higher yield potential in PSs without livestock breeding.

3.1.2. Second data partitioning: identification of profiles of MSs in each category of production situation

Over the six previously identified PS categories, we identified 54 profiles of MSs (Fig. 3). Across all PS, results of Random Forest showed that several variables describing the crop sequence (proportions of grassland, straw cereal, oilseed rape, potato and seed maize) had strong influence on TFI. Variables describing the spraying strategy (proportion of reduced doses), the fertilisation rates and the tillage strategy also frequently appeared at the top of the Random Forest ranking (see Supplementary data Table S2).

Two MS were identified in PS1 (Fig. 3a; Supplementary data Fig. S3, Supplementary data Table S4), MS1 (average TFI = 1.0, $N = 54$) and MS2 (average TFI = 2.3, $N = 71$). Farms from MS1 were associated with (i) a higher proportion of temporary grassland than in farms from MS2 (57% vs. 5% respectively on average), (ii) a higher crop type diversity (2.8 types of crops on average vs. 2.5 respectively), (iii) a higher diversity in sowing periods (on average 2.6 different periods for the profile MS1 vs. 2.4 for MS2). Although the frequency of tillage

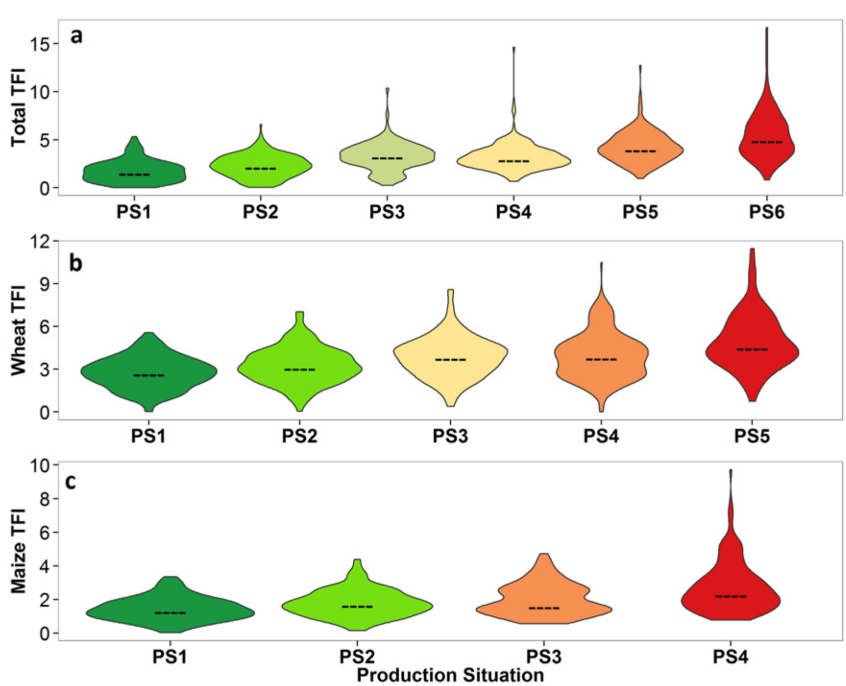

Fig. 1. Violin plots representing the distribution of the Treatment Frequency Index within each PS. Dashed lines indicate the median TFI. a. TFI computed at the farm level b. Wheat TFI. c. Maize TFI.

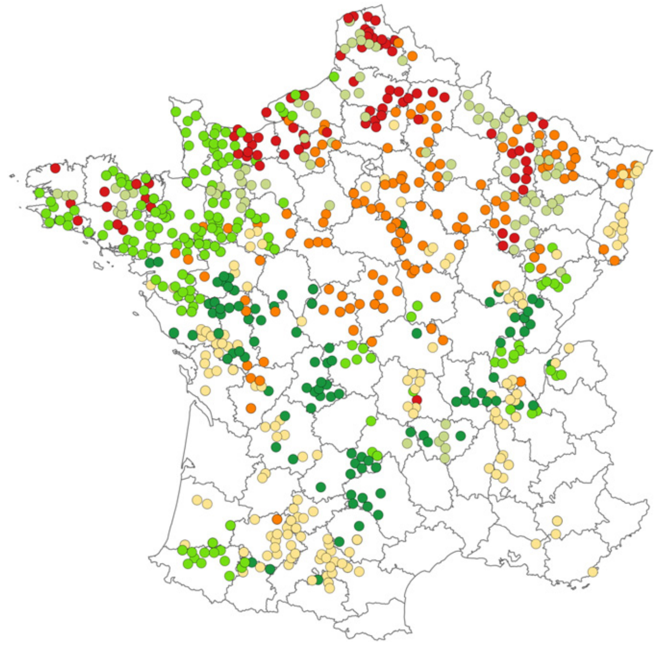

Fig. 2. Map of sites in the DEPHY network, coloured according to their PS category identified with the recursive partitioning of TFI at the farm level. ●: PS1; ●: PS2; ●: PS3; ●: PS4; ●: PS5; ●: PS6. Counties (French 'departments') are delimited with the grey lines.

operations was higher in MS2 (1.9 tillage operations/year^{-1}) than in MS1 (1.0), inversion tillage was more represented in MS1 (85% of farms included inversion tillage at least once over the crop rotation) than in MS2 (73% of farms). The proportion of farms implementing occasional inversion tillage (i.e. inversion tillage less frequent than every two years) was higher in MS1 (54%) than in MS2 (14%). The N fertilisation level appeared significantly lower in farms from MS1 (131 kg N·ha^{-1} on average) than in MS2 (169 kg N·ha^{-1}), but K fertilisation rates were higher in MS1 (105 kg K·ha^{-1} vs. 84 kg K·ha^{-1} in MS2).

In PS2, we identified 21 profiles of MS (Fig. 3b; Supplementary data Fig. S3, Supplementary data Table S4), with average TFI ranging from 0.3 (MS1, $N = 16$) to 6.6 (MS21, N = 1). MS21 displayed only one farm that was discriminated from the others because of a substantially higher proportion of field vegetables (38% of cropped area). The presence of temporary grasslands was higher in MS1–MS4 (from 41% to 73%) than in other MS (from 0% to 3.3%, excluding MS21), with more sugar beets and field vegetables in more pesticide-reliant profiles. As visible on the regression tree, mechanical weeding appeared more frequent in MS5 and MS6 (0.7 operation·ha^{-1}·year^{-1}) than in most other MSs (from 0 to 0.2 operation·ha^{-1}·year^{-1}), and it was coupled with the absence of pesticide application at full dose in MS5. Straw cereals were significantly less cultivated in MS7 than in MS8–MS12 (25% vs. 53% to 56% respectively), MS7 being characterised by a high proportion of maize (69% of cropped area on average). Pesticide use was significantly lower in MS7 than in MS9–MS12, but not than MS8. MS8 displayed a high frequency of pesticide application at low doses, which was particularly visible on wheat, representing 99% of pesticide applications. MS1–MS4 tended to display a lower frequency of tillage operations (ranging from 0.9 to 1.5 tillage operations/year^{-1}) compared to other profile of MS (ranging from1.6 to 2.7 tillage operations/year), but they were also associated with a high proportion of farms resorting to inversion tillage (between 79% and 91% of farms using inversion tillage).

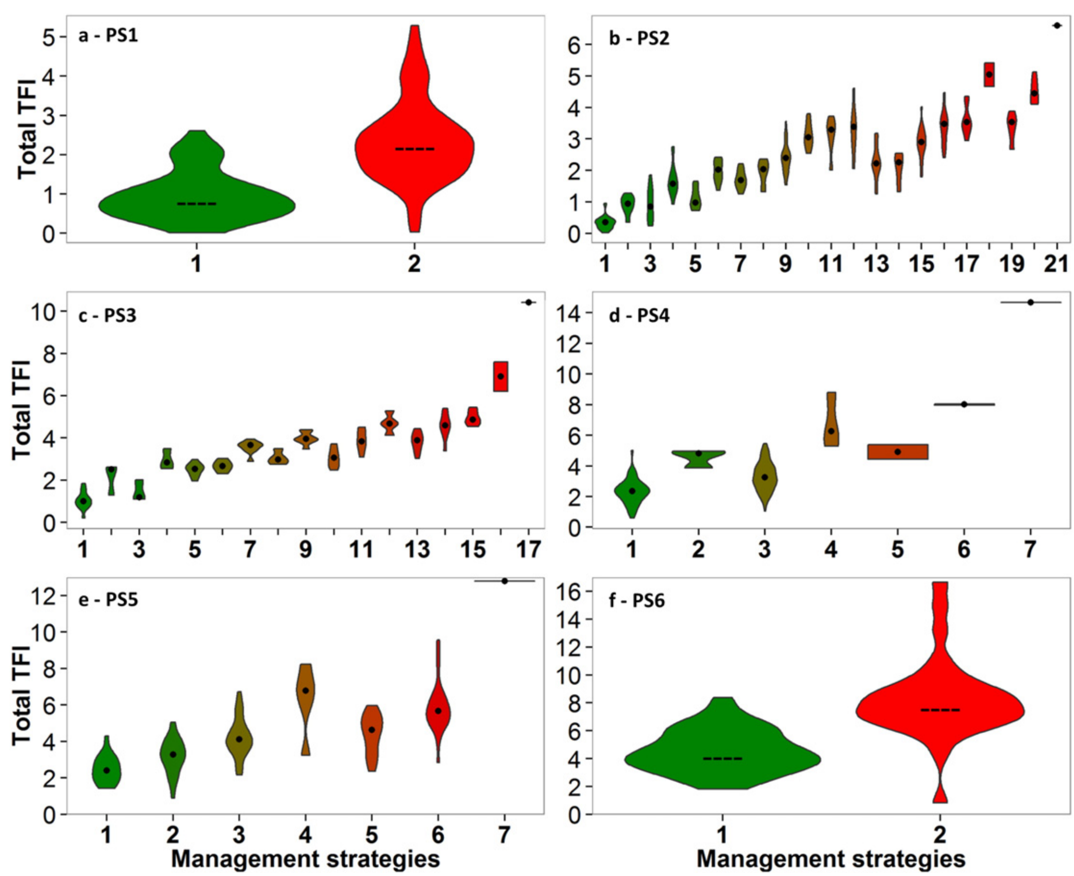

Fig. 3. Distribution of the TFIs within the profiles of MS identified with CART in each category of PS (violin plots). a. PS1 b. PS2 c. PS3 d. PS4 e. PS5 f. PS6. Dashed lines or dots indicate the median TFI.

In PS3, we identified 17 profiles of MS (Fig. 3c; Supplementary data Fig. S3, Supplementary data Table S4), with average TFI ranging from 1.0 (MS1, $N = 14$) to 10.4 (MS17, N = 1). Profiles MS16 and MS17 displayed high proportions of potato and sugar beet (representing together >33% of cropped area), associated with field vegetables in the case of MS17 (22% of cropped area). Temporary grasslands were significantly more cultivated in MS1 and MS2 than in other MSs (50% and 35% vs. from 0% to 6.5% respectively). As visible on the regression tree (Supplementary data Fig. S3), MS3–MS9 were distinguished from MS10–MS15 because all farms from MS3–MS9 and MS10–MS15 applied respectively less and >30% of total pesticides at full dose. Interestingly, MS3 and MS5 were both distinguished from adjacent MS profiles by a lower frequency of inter-season cover crops.

In PS4, we identified 7 profiles of MS (Fig. 3d; Supplementary data Fig. S3, Supplementary data Table S4), with average TFI ranging from 2.3 (MS1, $N = 58$) to 15 (MS7, $N = 1$). Once again, the only farm from the profile MS7 was discriminated due to a very high proportion of field vegetables (50%). Other profiles of MS composed with few farms were created because they displayed a high proportion of seed maize (72% in MS2 and 81% in MS4). Farms from MS3 had significantly more straw cereals and oilseed rape than farms from MS1 (respectively, straw cereals: 47% vs. 26%; oilseed rape: 10% vs. 1.6%), MS1 being essentially composed of farms with a high proportion of maize (57%). The crop type and sowing period diversity were also significantly higher in MS3 than in MS1 (respectively 2.7 vs. 1.7 different types of crop, 2.8 vs. 1.7 different sowing periods). The share of farms resorting to inversion tillage was higher in MS1 than in MS3 (78% of farms in MS1 and 65% in MS3).

In PS5, we identified 7 profiles of MS (Fig. 3e; Supplementary data Fig. S3, Supplementary data Table S4), with average TFI ranging from 2.5 (MS1, $N = 18$) to 13 (MS7, N = 1). MS7 displayed a higher proportion of potato than other MSs (20% vs. from 0% to 1% in other MSs), along with a high proportion of sugar beet (10%). Profiles MS1–MS4 displayed lower proportions of winter crops, particularly oilseed rape, than MS5–MS6 (ranging from 10% to 16% in MS1–MS4 whereas it reached 35% in MS5–MS6). Comparing MS1–MS3 to MS5–MS6, (i) the proportion of summer crops were higher in MS1–MS3 (from 12% to 22% vs. close to 1% in MS5–MS6), and (ii) the diversity of crop types and sowing periods was higher in MS1–MS3 (crop type: from 2.7 to 2.9 different crop types vs. 2 in MS5–MS6; sowing date: from 3 to 3.1 different sowing periods vs. 2.3 in MS5–MS6). Mechanical weeding was significantly more frequent in MS1 than in other profiles (0.2 in MS1 vs. from 0 to 0.1 in other MSs), and it was coupled with a higher frequency of low dose pesticide applications (71% vs. from 37% to 55% respectively). Winter wheat cultivar diversity was higher in MS1 than in MS5 (2.7 varieties vs. 1.3 respectively) and wheat disease resistance was higher in MS1 than in MS5–MS6 (resistance mark value: 5.2 vs. 4.7 respectively). The frequency of tillage operations was higher in MS4 (3.0 tillage operations/year^{-1}) than in MS2–MS3 (2.2), MS6 (2.1) and MS7 (1.7), along with a higher resort to inversion tillage (80% of farms resorted to inversion tillage in MS4 vs. from 57% to 67% in MS1–MS3 and MS5–MS6).

Two profiles of MS were identified in PS6 (Fig. 3f; Supplementary data Fig. S3, Supplementary data Table S4), MS1 (average TFI = 4.5, $N = 85$) and MS2 (average TFI = 8.2, $N = 31$). Compared to MS1, MS2 was characterised by a higher proportion of field vegetables (4% in MS1 vs. 14% in MS2), potato (0% in MS1 vs. 20% in MS2) and sugar beet (5% in MS1 vs. 13% in MS2), but a lower proportion of straw cereals (57% in MS1 vs 42% in MS2), oilseed rape (17% in MS1 vs. 2% in MS2) and grain legumes (5% in MS1 vs. 1% in MS2). Crop type diversity was higher in MS1 than in MS2 (2.7 vs. 2.1 types of crop respectively). In line with the high presence of row crops, mechanical weeding was more frequent in MS2 than in MS1 (0.1 operation$\cdot$ha$^{-1}\cdot$year^{-1} in MS1 vs. 0.4 in MS2), but pesticide applications at low doses were more associated with MS1 (50% of pesticide applications) than MS2 (42% of pesticide applications). N fertilisation rates were lower in MS1 (154 vs. 183 kg N$\cdot$ha^{-1} in MS1 and MS2 respectively). We also detected a significant difference of irrigation level between the two profiles of MS (120 mm$\cdot$year^{-1} in MS1 vs. 257 mm$\cdot$year^{-1} in MS2). 60% of farms from MS1 performed inversion tillage whereas it reached 84% in MS2. We noticed however that the proportion of farms implementing occasional inversion tillage (frequency under 0.5) was higher in MS1 (22% of farms in MS1 vs. 10% in MS2).

3.2. Analysing TFI on winter wheat

3.2.1. First partitioning: identification of production situations

Winter wheat was cultivated in 873 out of the 1012 farms of the national network, with TFI = 3.7 on average on this crop. The Random Forest method identified the variables 'surface area of the cropping system', climatic variables such as 'solar radiation', 'potential evapotranspiration' and 'relative air humidity', and 'association with livestock' as the main discriminating variables for wheat TFI (Supplementary data Table S2).

We discriminated five productions situations with average TFI ranging from 2.7 to 4.9 and increasing from PS1 to PS5 (Table 2), except between PS3 and PS4, where pesticide reliance was not significantly different (Fig. 1; Supplementary data Fig. S3, Supplementary data Table S4). Association with livestock was less represented in PS1 and PS5 (<35% of farms) whereas the distribution was more equitable in other categories of PS (between 50% and 60% of farms with livestock in PS2, PS3 and PS4). Averaged temperatures were high in PS1–PS2 (12.7 °C), intermediate in PS3 (T = 11.4 °C) and low in PS4–PS5 (T = 11 °C), in line with the geographic distribution of the PS (Fig. 4) from southern to northern France. In the same way, PET was gradually decreasing from PS1 to PS5, with PS4 not significantly different from PS5, along with a decrease in annual global radiation. Logically, the relative air humidity followed the opposite pattern and increased from PS1 to PS5 (see Supplementary data Table S4).

A higher risk of drought stress coming from high temperatures, lower precipitations and an uneven distribution of precipitation (frequency of rainy days per year) was noticed in PS1. The access to irrigation systems was however more represented in PS1 (31% of farms with access to irrigation in PS1 vs. from 4% to 13% in PS2 to PS5). Soil pH was lower in PS2 and PS3 than in other categories (6.7 in both PSs vs 7.0 to 7.3 in other PSs). The average surface area of the cropping system was related to the size of the farm, and was higher in PS5 than in other PSs (large-scale farms specialised on grain production). The proportion of farms associated with a high yield potential was higher in PS4 (58% of farms) and PS5 (64% of farms) than in other categories (ranging from 38% to 45%), and the available water capacity was significantly lower in PS2 than in PS3–PS5 (100 mm in PS2 vs. 123, 150 and 146 mm in PS3, PS4 and PS5 respectively).

Sugar beet was more cultivated in northern arable land from PS4 and PS5 (respectively 4.6% and 4.8% of cropping area vs. between 0 and 1.1% in other PSs). The proportions of straw cereals, mainly winter wheat and barley, and of oilseed rape decreased progressively from PS5 to PS1 (proportions of straw cereal varied from 57% in PS5 to 45–46% in PS1 and PS2, proportions of oilseed rape varied from 18% in PS5 to 8% in PS1 and PS2). The proportions of summer crops, such as maize and sunflower, exceeded 30% in PS1 and PS2, whereas it ranged from 12% to 22% in other PSs. The cropping area devoted to temporary grasslands also tended to be higher in PS1 (9%) and PS2 (12%) than in PS4 (4%) and PS5 (1%). The proportion of farms using inversion tillage ranged from 64% to 74% across all PSs. The frequency of soil tillage operations at the farm level was similar among PS categories. Full dose pesticide applications were significantly more frequent in PS1 than in other PSs, representing 49% of pesticide applications at the farm level.

3.2.2. Second partitioning: identification of profiles of MSs in each category of production situation

Over the five PSs previously identified, we discriminated 13 profiles of MSs (Fig. 5). The Random Forest method selected pesticide dose reduction and variables linked to the fertilisation strategy, particularly

Table 2
Details of production situations identified with the recursive partitioning of TFI on winter wheat.
The variable 'presence of livestock' is the proportion of farms associated with livestock within the PS. For average TFI, significant differences between PS are given with significance letters resulting from the multiple rank comparisons.

Production situation	Average wheat TFI	Main locations of farms	Presence of livestock	Climate conditions	Main crops
PS1	2.7 a	Southern France	35%	High temperatures and dry climate	Straw cereals, maize, sunflower
PS2	3.3 b	Central eastern France	59%	High temperatures and dry climate	Straw cereals, maize, grassland
PS3	3.9 c	Central northern France	55%	Medium temperatures	Straw cereals, maize, oilseed rape
PS4	3.9 c	Northern France	52%	Low temperatures and wet climate	Straw cereals, maize, oilseed rape
PS5	4.9 d	Northern France	27%	Low temperatures and wet climate	Straw cereals, oilseed rape

the amount of nitrogen fertilizers, as the main discriminatory variables across the PSs. Variables related to the crop sequence as well as variables describing wheat management (cultivar disease resistance and sowing date) also discriminated wheat TFI according to the Random Forest method (Supplementary data Table S2).

In PS1, we identified two profiles of MS (Fig. 5a; Supplementary data Fig. S3, Supplementary data Table S4), namely MS1 (average wheat TFI = 1.3, $N = 11$) and MS2 (average wheat TFI = 2.9, $N = 133$). Compared to MS2, MS1 displayed significantly (i) lower proportions of straw cereal, particularly winter wheat (20% in MS1 vs. 34% in MS2), and oilseed rape (2% in MS1 vs. 8% in MS2), (ii) higher proportion of temporary grassland (35% in MS1 vs. 7% in MS2), and (iii) higher proportion of maize (28% in MS1 vs. 17% in MS2). Early sowing of winter crops tended to be more represented in MS1 than in MS2 (respectively 29% vs. 6% of winter crop area). Inversion tillage was more represented in farms from MS1 (91% of farms resorting to inversion tillage) than from MS2 (67%), but soil tillage operations were more frequent in MS2 than in MS1 (on average 2.1 tillage operations in MS2 vs. 1.4 in MS1). N fertilisation rates on wheat were close in both MSs (171–173 kg N$\cdot$ha^{-1}).

In PS2, we highlighted three profiles of MS (Fig. 5b; Supplementary data Fig. S3, Supplementary data Table S4), with average wheat TFI ranging from 2.3 (MS1, $N = 34$) to 4.2 (MS3, $N = 45$). Farms from MS1 included significantly (i) less straw cereals than MS2 and MS3 (respectively 21% in MS1 and 52% in MS2–MS3), particularly less winter wheat (respectively 17%, 39% and 34%), (ii) less oilseed rape (1%, 11% and 8% respectively), (iii) but more temporary grassland (45% in MS1, 2% in MS2 and 4% in MS3). Crop type diversity was higher in MS1 than in MS2–MS3 (respectively 2.9, 2.7 and 2.5). Compared to MS1 and MS3, the profile MS2 was characterised by a higher frequency of pesticides applied at low doses on winter wheat (65% of pesticides applied on wheat in MS2 vs. 47% in MS1 and 28% in MS3). Tillage frequency before winter wheat was lower in MS1 than in other MSs (1.1 tillage operations$\cdot$ha^{-1} in MS1 vs 1.6 in MS2 and MS3), but farms with inversion tillage were slightly more frequent in MS1 than in MS2–MS3 (76% of farms with inversion tillage in MS1 vs. 69% in MS2–MS3). N fertilisation inputs on wheat were lower in MS1 than in MS2-MS3 (respectively 143 kg N$\cdot$ha^{-1} in MS1 vs. 164–165 in MS2–MS3).

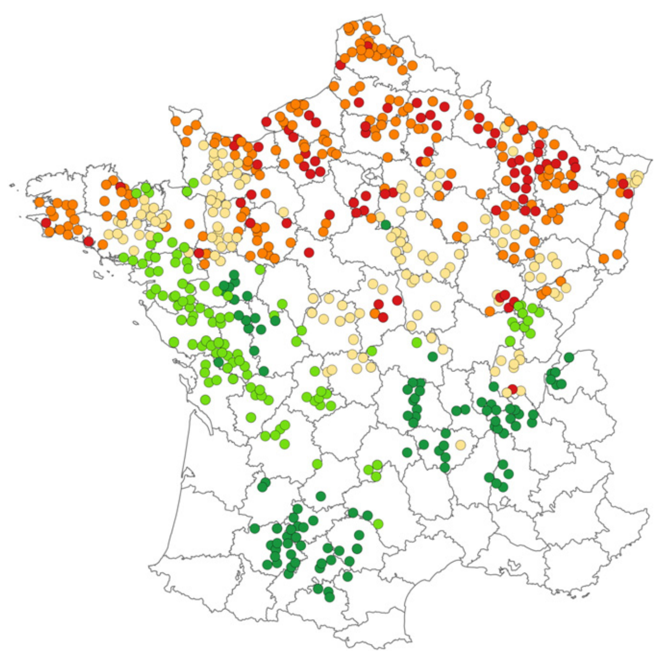

Fig. 4. Map of sites in the DEPHY network, coloured according to their PS category defined from the segmentation of TFI in wheat (●: PS1; ●: PS2; ●: PS3; ●: PS4; ●: PS5). Counties (French 'departments') are delimited with the grey lines.

In PS3, we identified two profiles of MS (Fig. 5c; Supplementary data Fig. S3, Supplementary data Table S4), MS1 (average wheat TFI = 3, $N = 45$) and MS2 (average wheat TFI = 4.1, $N = 156$). Although no significant difference appeared on the proportions of the different crops cultivated in farms from these MSs, we highlighted a significantly higher crop type diversity as well as sowing period diversity in MS1 than in MS2 (crop type diversity: 2.9 types of crop in MS1 vs. 2.6 types of crop in MS2; sowing period diversity: 2.9 different sowing periods in MS1 vs 2.7 in MS2). Low pesticide doses on wheat were also more frequent in MS1 (74% of pesticide applications on wheat) than in MS2 (43% of pesticide applications). No significant difference appeared between both profiles concerning N fertilisation on wheat, but P fertilisation rates on wheat were higher in MS2 than in MS1 (25 kg P$\cdot$ha^{-1} in MS2 vs. 12 kg P$\cdot$ha^{-1} in MS1).

In PS4, we discriminated three profiles of MS (Fig. 5d; Supplementary data Fig. S3, Supplementary data Table S4), with average wheat TFI ranging from 2.3 (MS1, $N = 41$) to 5.4 (MS3, $N = 31$). In farms from MS1, the proportions of straw cereal and oilseed rape were significantly lower than in farms from MS2 (straw cereal: 48% of cropped area and 53% respectively; oilseed rape: 8% of cropped area and 14% respectively). In addition, the proportion of winter wheat appeared lower in MS1 (34%) than in MS3 (41%). The proportion of maize was higher in MS1 and MS2 than in MS3 (18–19% in MS1–MS2 vs. 3% in MS3). Farms from MS3 were however more associated with high added value crops such as potato, sugar beet, or field vegetables (e.g. potato: 19% in MS3 vs. 1% in MS1 and 0% in MS2). When focusing on wheat, we highlighted significantly higher cultivar diversity in farms from MS1 than in MS3 (respectively 2.4 varieties and 1.7 varieties). Although wheat tolerance to lodging appeared higher in MS3 compared to MS1–MS2 (lodging tolerance mark = 6.7 in MS3 vs 6.2 in MS1 and 6.3 in MS2), average wheat disease resistance was higher in MS1–MS2 (average disease resistance mark = 5 in MS1, 4.9 in MS2 and 4.7 in MS3). Pesticides were more frequently applied at low doses on wheat in MS1 than in MS2–MS3 (83% of pesticide applications in MS1 vs. 47% in MS2 and 55% in MS3). We detected higher N fertilisation inputs on wheat in MS3 than in MS1 and MS2 (respectively 182, 154 and 169 kg N$\cdot$ha^{-1}). Although we found no significant difference between MSs for tillage strategy before wheat, the proportion of farms resorting to inversion tillage at least once over the crop sequence increased from MS1 to MS3 (respectively 66%, 74%, 84%).

In PS5, we identified three profiles of MS (Fig. 5e; Supplementary data Fig. S3, Supplementary data Table S4), with average wheat TFI ranging from 4.1 (MS1, $N = 49$) to 7.7 (MS3, $N = 11$). Although the proportion of winter wheat was significantly higher in farms from MS1 than from MS2 and MS3 (respectively 40%, 37% and 30% of cropped

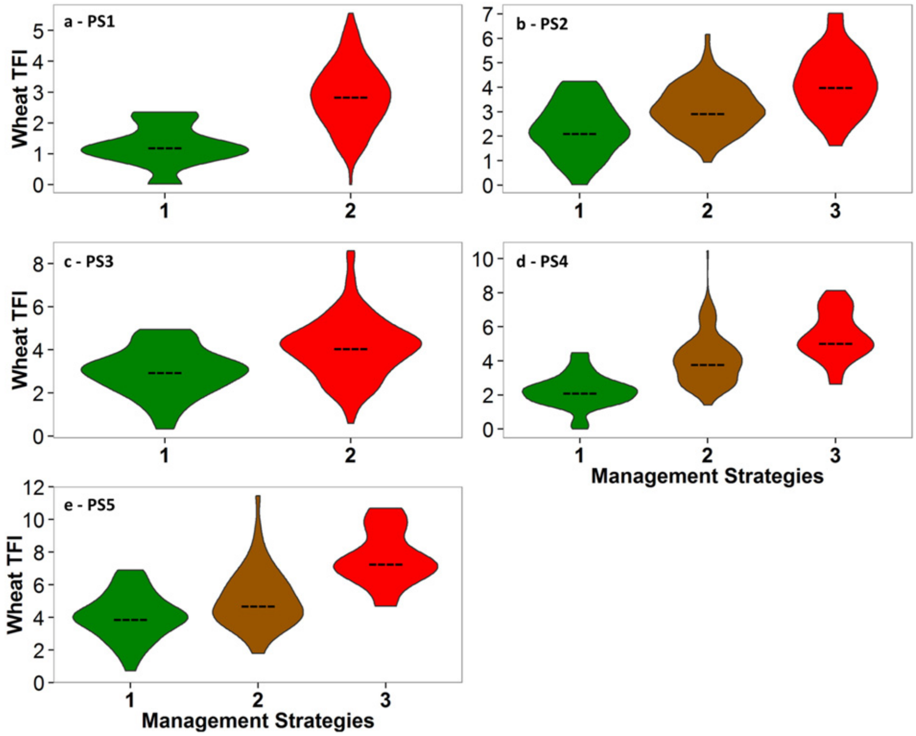

Fig. 5. Distribution of the wheat TFIs within the profiles of MS identified with CART in each category of PS (violin plots). a. PS1 b. PS2 c. PS3 d. PS4 e. PS5. Dashed lines or dots indicate the median TFI.

area), the proportion of straw cereal was lower in MS1 than in MS2 and MS3 (respectively 52%, 59% and 70%). Winter barley was more cultivated in MS3 and MS2 than in MS1 (respectively 25%, 14% and 6%), and oilseed rape was also more represented in MS3 (27% of cropped area in MS3 vs. 18% in MS2 and 15% in MS1). Summer crops represented on average 12% to 14% of cropped area in MS1–MS2, while they were absent in MS3. Grain legumes accounted for 8% of cropped area in MS1, while they represented only 1% in MS2–MS3. Crop type diversity and sowing period diversity were significantly higher in farms from MS1 than from MS2 and MS3 (crop type diversity: 3.2 crop types in MS1 vs. 2 in MS2–MS3; sowing period diversity: 3.2 different sowing periods in MS1 vs. 2.7 in MS2–MS3). Wheat cultivar diversity appeared higher in MS1 and MS2 than in MS3 (2 varieties in MS1, 1.7 in MS2 and 1 in MS3), but wheat tolerance to lodging was higher in farms from MS3 (lodging tolerance mark = 6.9 in MS3 vs. 6.4 in MS1 and MS2). Tillage frequency computed either at the farm level or before wheat was higher in MS3 than in MS1 and MS2 (on average 3.5 tillage operations on wheat vs. 1.8 in MS1–MS2)·The frequency of tillage operations was higher in MS3 than in other profiles of MS, which was particularly visible on winter wheat (on average 3.5 tillage operations in MS3 vs. 1.8 in MS1–MS2). However, the proportion of farms with at least one inversion tillage over the crop sequence was substantially higher in MS1 and MS2 than in MS3 (respectively 71%, 65% and 27% of farms). N fertilisation on wheat was significantly higher in MS3 than in MS1 (respectively 190 kg $N \cdot ha^{-1}$ and 171 kg $N \cdot ha^{-1}$).

3.3. Analysing TFI on maize

3.3.1. First partitioning: Identification of production situations

Maize was cultivated in 613 out of 1012 farms from the demonstration farm network, with TFI = 1.9 on average on this crop. The Random Forest method highlighted average annual temperature, average annual PET, annual precipitations and the number of rainy days as the most discriminating variables for pesticide reliance on maize. The access to outlets for high added value crops such as seed maize was also a discriminative factor of TFI (Supplementary data Table S2).

We discriminated four categories of PSs with average TFI on maize ranging from 1.4 to 2.7 (Table 3). Intermediate situations PS2 and PS3 were not significantly different on their average pesticide reliance (Fig. 1; Supplementary data Fig. S3, Supplementary data Table S4). Herbicide TFI on maize was lower in PS1 than in other PSs (1.4 in PS1 vs. 1.6–1.7 in other PSs).

PS1 and PS2 only included mixed farms that were associated with livestock, whereas PS3 encompassed only grain farms and PS4 a mix of both (41% of crop-livestock farms). Yield potential tended to be higher in PS3 (76% of sites with high yield potential) and PS4 (69%)

Table 3
The variable ‘presence of livestock’ is the proportion of farms associated with livestock within the PS. For average TFI, significant differences between PS are given with significance letters resulting from the multiple rank comparisons.

Production Situation	Average maize TFI	Main Locations of farms	Presence of livestock	Climate conditions	Main crops
PS1	1.4 a	North western France	100%	Low summer temperatures	Straw cereals, maize, grassland
PS2	1.8 b	Central and northern France	100%	Low summer temperatures and wet climate	Straw cereals, maize, grassland
PS3	2.0 b	Northern France	0%	Medium summer temperatures	Straw cereals, maize
PS4	2.7 c	Southern France	41%	High summer temperatures and dry climate	Maize, straw cereal

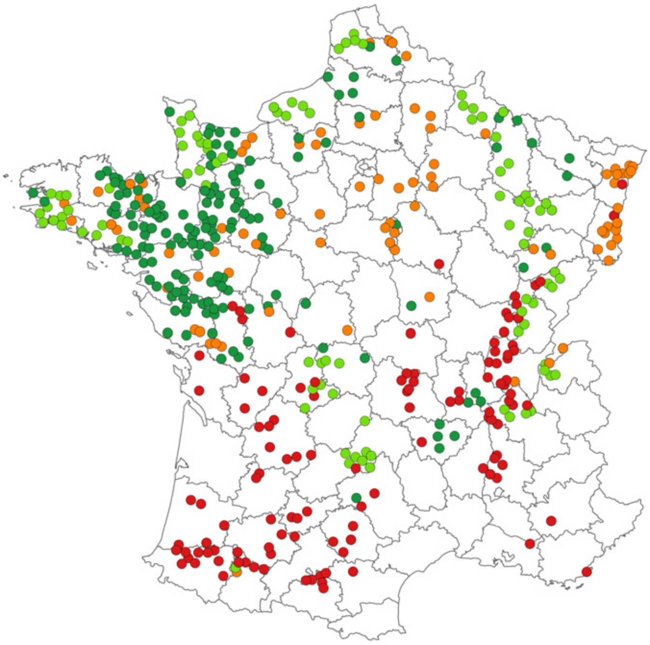

Fig. 6. Map of sites in the DEPHY network, coloured according to their PS category identified with the recursive partitioning of maize TFI. (●: PS1; ●: PS2; ●: PS3; ●: PS4). Counties (French 'departments') are delimited with the grey lines.

compared with PS2 (53%) and PS1 (48%). Climatic variables discriminated PSs, that were therefore geographically distributed (Fig. 6). Summer temperatures were higher in PS3 (16.3 °C) and PS4 (17.8 °C) as compared with PS1 (15.9 °C) and PS2 (15.5 °C), and both annual solar radiation and potential evapotranspiration were higher in PS4 than in other PSs. The number of days with average temperature exceeding 30 °C was substantially higher in PS4 (15 days/year^{-1}) than in PS1 (5 days/year^{-1}), PS2 (4 days/year^{-1}) and PS3 (7 days/year^{-1}). Total precipitations were the highest in PS2 with 1033 mm per year on average. Although the amount of precipitations was significantly higher in PS4 (862 mm) than in PS3 (779 mm) and PS1 (782 mm), the distribution of precipitations over the year was more uneven in PS4 (118 rainy days per year in PS4 vs. 129 and 128 in PS1 and PS3 respectively), which was offset by a higher frequency of irrigation (58% of farms including irrigation system in PS4 vs. 19% in PS3, 3% in PS2 and 8% in PS1). The soil pH was significantly lower in PS1 and PS2 (6.4 and 6.5 respectively vs. 7.1 in PS3 and 6.9 in PS4), but they displayed higher rates of soil organic matter (3.1% in PS1 and 4% in PS2 vs. 2.9 and 2.4 in PS3 and PS4 respectively).

Winter crops were more represented in PS1, PS2 and PS3 than in PS4, with higher proportions of straw cereals, particularly winter wheat (respectively 31%, 26%, 34% and 19% of winter wheat in the crop sequence on average) and winter barley in PS2 (11%). Oilseed rape was also more cultivated in PS2 (7%) and PS3 (8%) than in PS4 (3%). Crop type diversity was significantly lower in PS4, with a higher proportion of summer crops, with maize as a preponderant crop (53% in PS4 while respectively 32%, 30% and 36% in PS1, PS2 and PS3), particularly seed maize (on average 6% of cropped area). Temporary grasslands were more cultivated in PS1 and PS2 (16% and 17% of cropped area respectively vs. 0% in PS3 and 4% in PS4). The frequency of inversion tillage was comparable between PSs (from 74% to 77% of farms resorting to inversion tillage), except for PS2, where this frequency was higher (88% of farms). The frequency of tillage operations before maize was lower in PS2 (2.3 tillage operations.ha^{-1}·year^{-1}) than in PS1 (2.8) and PS3 (3.0). In line with a high proportion of summer row crops, the frequency of mechanical weeding at the farm level tended to be higher in PS4, but when considering this frequency on maize, this difference was no longer significant.

Pesticide spraying strategies were more frequently based on full doses applications in PS4 (47% of total TFI) than in PS1 (29% of total TFI), PS2 and PS3 being intermediate (39% and 37%, respectively).

At the farm level, averaged N fertilisation rates were significantly higher in PS2 (176 kg N·ha^{-1}) and PS4 (184 kg N·ha^{-1}) than in PS1 (154 kg N·ha^{-1}). On maize, averaged N fertilisation rates were higher in PS2 (240 kg N·ha^{-1}) and PS4 (213 kg N·ha^{-1}) than in PS3 (184 kg N·ha^{-1}). For K, fertilisation rates were higher in PS1 and PS2 than in PS3 and PS4 at the farm level (respectively 95 kg K·ha^{-1} and 101 kg K·ha^{-1} vs. 56 kg K·ha^{-1} and 71 kg K·ha^{-1}). Organic fertilizers represented an important part of N fertilisers applied in PS1 and PS2 (51% and 43% respectively vs. 17%–18% in PS3 and PS4).

3.3.2. Second partitioning: identification of profiles of MSs in each category of production situation

Across the four categories of PS, we discriminated 15 profiles of MS with contrasting levels of pesticide use on maize (Fig. 7). The Random Forest method allowed to identify the main variables discriminating maize TFIs (Supplementary data Table S2), namely the pesticide dose reduction, the proportion of pre-emergence herbicide applications, the proportion of maize and seed maize in the crop sequence, the frequency of mechanical weeding, tillage operations and inversion tillage, as well as variables related to the fertilisation strategy, particularly the proportion of organic fertilizers.

In PS1, we discriminated five profiles of MS (Fig. 7a; Supplementary data Fig. S3, Supplementary data Table S4), with average maize TFI ranging from 0.67 (MS1, $N = 39$) to 2 (MS5, $N = 82$). Farms from MS1 and MS2 displayed a high frequency of low dose pesticide applications on maize (on average 99–100% of pesticide applications) compared with MS3–MS5 (between 18% and 44% of pesticide applications, see Supplementary data Fig. S3). The frequency of mechanical weeding on maize discriminated farms from MS1 and MS3 compared to MS2, MS4 and MS5 (1.4 operations·ha^{-1} in MS1, 1.5 in MS3, between 0 and 0.2 in MS2, MS4 and MS5). Groups of MSs did not contrast with each other on the type of crops they cultivated, except a higher proportion of summer crops in MS3 (45% vs. from 26% to 32% in other MS), a higher proportion of temporary grasslands in MS1 than in MS2 and MS4 (respectively 27%, 13% and 14%), and a lower proportion of maize in MS1 (25% vs. from 32% to 38% in other profiles of MS). Fertilisation rates on maize tended to be higher in MS4 than in other MSs (e.g. for N fertilisation, 238 kg N·ha^{-1} in MS4 vs. from 170 to 197 in MS1–MS3). Inversion tillage before maize was less frequent in MS2 than in MS1, MS3 and MS5 (on average 0.45 inversion tillage operations·year^{-1} in MS2 vs. between 0.67 and 0.75 in MS1, MS3 and MS5). At the farm level, tillage operations were more frequent in MS3 than in other profiles of MS, except MS5 (2.3 operations per year in MS3 vs. 1.8 in MS1, MS2 and MS4).

Two profiles of MS were identified in PS2 (Fig. 7b; Supplementary data Fig. S3, Supplementary data Table S4), MS1 ($N = 63$, average maize TFI = 1.5) and MS2 ($N = 49$, average maize TFI = 2.2). Compared to farms from MS2, farms from MS1 were characterised by lower proportions of grassland (10% in MS1 and 26% in MS2), higher proportions of straw cereals, particularly winter wheat (30% in MS1 and 21% in MS2), and higher proportions of oilseed rape (10% in MS1 and 4% in MS2). Pesticide application strategies on maize were more frequently based on low doses in MS1 than in MS2 (respectively 73% and 27% of pesticide applications), along with a lower occurrence of pre-emergence herbicides on maize (34% of herbicide applications in MS1, 47% in MS2). The frequency of tillage operations was significantly higher in MS1 (1.8 operations/year^{-1}) than in MS2 (1.5), with a high proportion of farms with at least one inversion tillage operation during the crop rotation in both cases (89% of farms with inversion tillage in MS1, and 86% in MS2).

In PS3, we identified three profiles of MS (Fig. 7c; Supplementary data Fig. S3, Supplementary data Table S4), with average maize TFI ranging from 1.5 (MS1, $N = 59$) to 3.1 (MS3, $N = 25$). Compared to farms

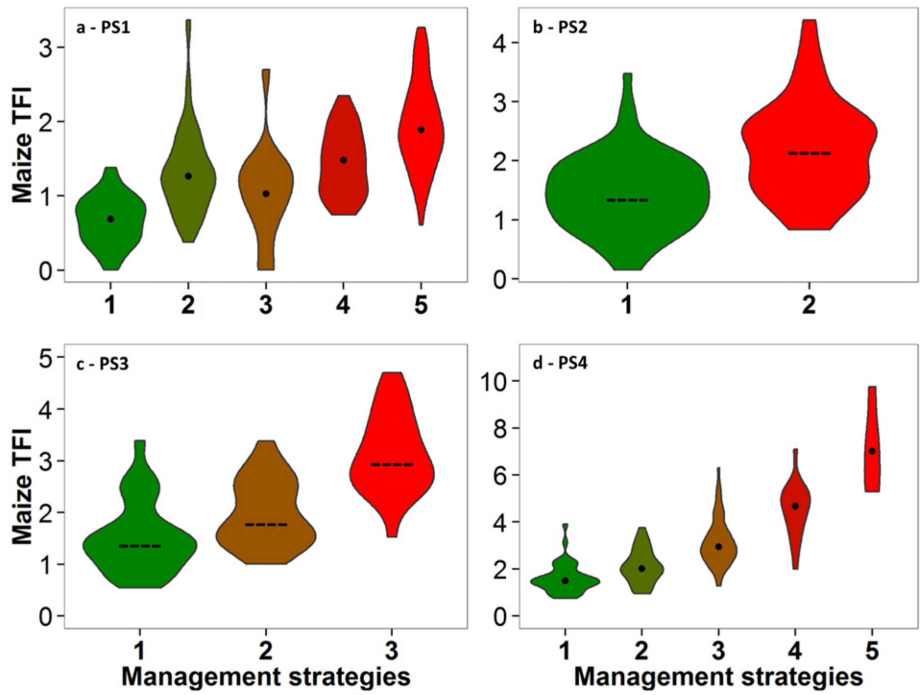

Fig. 7. Distribution of the maize TFIs within the profiles of MS identified with CART in each category of PS (violin plots). a. PS1 b. PS2 c. PS3 d. PS4. Dashed lines or dots indicate the median TFI.

from MS1 and MS2, farms from MS3 displayed higher proportions of summer crops, particularly maize (62% vs. 28% in MS1 and MS2), lower proportions of straw cereals (27% vs. 47–49% in MS1 and MS2), and more particularly winter wheat (22% in MS3, 36% in MS1 and 41% in MS2), lower proportions of grain legumes (0% in MS3 vs. 5–6% in MS1–MS2). Crop type diversity and sowing period diversity were also lower in MS3 than in MS1 and MS2 (crop type diversity: 2.1 different types of crop in MS3, 2.8 in MS1 and 2.9 in MS2; sowing period diversity: 2.2 different sowing periods in MS3, 3.1 in MS1 and 3.2 in MS2). Low doses of pesticide applications on maize were more frequent in farms from MS1 than in other profiles of MS (77% of pesticide applications in MS1, 39% in MS2, 28% in MS3). Organic fertilisation was frequent in MS1 and MS2 (20% of total N fertilisation in MS1, 27% in MS2 and no organic fertilisation in MS3). Irrigation on maize was higher in MS3 than in MS1 and MS2 (on average 56 mm in MS3, 17 mm in MS1 and 9 mm in MS2). Although inversion tillage before maize was less frequent in MS2 than in MS3, the proportion of farms with at least one inversion tillage during the crop rotation was actually higher in MS2 (91%) than in MS3 (84%) and MS1 (69%).

In PS4, we discriminated five profiles of MS (Fig. 7d; Supplementary data Fig. S3, Supplementary data Table S4), with average maize TFI ranging from 1.6 (MS1, $N = 40$) to 7.1 (MS5, $N = 5$). MS4 and MS5 displayed high proportions of seed maize (Supplementary data Fig. S3) as compared to other profiles of MS (37% in MS4, 64% in MS5, and close to 0% in MS1–MS3). In addition, mechanical weeding and tillage operation frequency on maize were higher in MS4–MS5 than in MS1–MS3 (mechanical weeding: on average 1 operation·year^{-1} in MS4, 0.9 in MS5, and between 0.3 and 0.4 in MS1–MS3; tillage frequency: 3.4 operations·year^{-1} in MS4, 5.1 in MS5, and between 2.0 and 2.4 in MS1–MS3). Irrigation on maize was also higher in MS4–MS5, with on average 221 mm in MS4, 301 mm in MS5, vs. from 66 mm to 101 mm in MS1–MS3. Grain legumes were more represented in MS4 (4% of cropped area) than in MS5 (0%). The frequency of pesticide applications with low doses on maize decreased from MS1 to MS3 (70% of pesticide applications on maize in MS1, 34% in MS2, 23% in MS3). Compared to other profiles of MS, the proportion of farms with inversion tillage was lower in MS1 (55% of farms with inversion tillage) than in other profiles (from 76% of farms with inversion tillage in MS3 to 89% in MS4).

4. Discussion

Our analysis of the great diversity of farms in the DEPHY network showed that low levels of pesticide use were related with combinations of management options, that we called management strategies. This is consistent with a previous study showing that a significant part of pesticide use variability was explained by crop management (Bürger et al., 2012). We validated our first hypothesis, as we found that MSs associated with low pesticide use actually varied as a function of the agricultural context, that we could classified in a range of PS categories. As an example in the case of TFI analysis at the farm level in the context of farms with livestock in the warm central-southern regions (PS1), MSs from the profile with the lowest pesticide use (MS1, 59% lower pesticide use than MS2) resulted from the combination of high proportions of grasslands, a high diversity in crop types and sowing periods, low rates of N fertilisation, occasional inversion tillage and a low frequency of tillage operations, both in line with the multiannual nature of temporary grassland. Conversely in the context of farms widely cultivating maize in warm regions from central and southern France (PS4), MSs from the profile with the lowest pesticide use (MS1, 30% lower pesticide use than MS3) resulted from the combination of poorly diversified crop sequences, but a high resort to soil tillage operations such as inversion tillage, shallow tillage, or mechanical weeding. Table 4 presents the main management details of two farms from these contrasting profiles of strategy.

We also validated our second hypothesis: we found that, within a given category of PS, not one but several profiles of MS may be associated with a low pesticide use. For instance, the case of maize in farms associated with livestock in western France was illustrative (PS1). Two profiles of MS associated with more than 20% lower pesticide use than the mean TFI in the PS were identified (MS1 and MS3, Supplementary data Fig. S3). Both were associated with a significantly higher resort to mechanical weeding, but the first one (MS1) was associated with a

Table 4
Management details of two contrasting farms, both with low pesticide use.
PS1: Context of farms with livestock in the warm regions from central-southern France.
PS4: Context of farms widely cultivating maize in warm regions from central and southern France.
Crop type diversity measures the number of crop types (over 6 crop types) that are each cultivated on more than 10% of cropped area. Sowing period diversity measures the number of sowing periods for crops (over 5 sowing periods) that each represented on more than 10% of cropped area.

Production situation	PS1	PS4
Management strategy	MS1	MS1
Location	Central eastern France	South-western France
TFI	0.8	2.0
Herbicide TFI	0.6	1.5
Biocontrol TFI	0.3	0.0
Crop sequence	Silage maize-winter wheat-alfalfa (3 years)-silage maize	Grain maize (monoculture)
Length of the crop sequence (years)	6	1
Crop type diversity	3	1
Sowing period diversity	3	1
Tillage strategy	Frequent inversion tillage ($0.5 < \text{frequency} < 1$)	Annual inversion tillage ($\text{frequency} = 1$)
Mechanical weeding (Annual frequency)	0	1
Reduced dose (Proportion of pesticide applications)	77	32
Nitrogen inputs ($\text{kg N} \cdot \text{ha}^{-1}$)	120	153
Irrigation (mm)	0	160

higher frequency of reduced dose, a lower proportion of summer crops, particularly maize, and a lower frequency of tillage operations than the second strategy (MS3).

These results suggest that reducing pesticide use and associated environmental impacts would probably rely on various solutions, reflecting the diversity in production situations to which management strategies must be adapted. However, despite the great diversity of strategies associated with reduced reliance on pesticide, some factors and management options were identified as recurrent factors related to pesticide use, factors that should be further considered when addressing the issue of the reduction of pesticide use. The potential explanatory power of these factors on pesticide use will be discussed in the following sections.

4.1. Climate and soil

Climate and soil variables appeared as key factors discriminating PSs based on pesticide use. For TFI analysed at farm level and on winter wheat, warmer climates were associated with PSs showing lower average pesticide use, whereas we found the opposite trend on maize. The direct influence of climate on pest pressure was already studied (Rotem, 2012), and may explain a part of TFI variability we observed between wheat PSs (e.g. some wheat diseases are favoured by mild and humid climates). Pesticide use could also be directly influenced by soil characteristics (soil type, available water capacity, pH, organic matter content), which varied from a PS category to another (Garbeva et al., 2004). In addition of having a direct effect on pest pressure, pedoclimatic factors also determine the type of crops that are grown and affect therefore indirectly the level of pesticide use, some crops being typically highly reliant on pesticides while other, in particular more rustic crops, are easily grown with lower amounts of pesticides.

4.2. Mixed farming, a major discriminative factor of pesticide reliance

We highlighted that farms with livestock were less reliant on pesticide than others. The presence of livestock provides extra outlets for forage crops, and farms mixing crops and livestock have thus more opportunities to diversify crop sequences with forage crops (including forage maize, temporary grasslands, triticale and other 'rustic' cereals). Forage crops usually require little amounts of pesticides (Clark, 2004; Lemaire et al., 2014; see also Supplementary data Fig. S5), and might have other agronomical value, such as contributing to weed control at the cropping system level (Meiss et al., 2010).

Our results hence support the potential role of mixed farming and livestock in a re-greening agriculture (Janzen, 2011; Asai et al., 2014), and we encourage further debate around (i) the energy efficiency and land use efficiency associated with livestock breeding (Pimentel and Pimentel, 2003; Smith et al., 2010; Wilkinson, 2011), and (ii) the complementarity between crop cultivation and livestock in mixed crop-livestock systems as a way to increase farm robustness (Herrero et al., 2010).

4.3. Crop sequence

Over most MSs, we found that the type of crop cultivated was a strong discriminative factor of pesticide reliance. Of course, high proportions of crops typically associated with low TFIs, such as temporary grasslands (most often in connection with local livestock, see the discussion above), maize and sunflower (Supplementary data Fig. S5), were associated with the least pesticide-reliant profiles of MSs, whereas oilseed rape, sugar beet, potato and field vegetables were more frequent in profiles of MSs with the highest pesticide reliance. Pesticide use at the farm level is consequently directly influenced by the proportion of crops with low vs. high intrinsic pesticide reliance. This direct effect of the crop sequence composition on farm TFI is very strong and partly masked the effects of the crop sequence on pest pressure in each crop, although it might influence the need for pesticide applications. This is precisely the reason why, after identifying the main major effects of management strategies on TFI computed at the farm level, we refined the analysis by performing recursive partitioning of TFI computed for the two major crops separately (wheat and maize), using both variables describing the wheat and maize management and variables describing the strategy at the farm level. Those supplementary analyses succeeded in identifying more precise combinations of management options associated with low vs. high pesticide use in wheat or maize. Interestingly, these identified strategies combined aspects of wheat/maize management and aspects of cropping system management, reflecting the multiannual and cumulative effects of crop sequence and management on pest pressure (see the discussion thereafter).

In winter wheat, fungicide and herbicide applications represented respectively 39% and 43% of total wheat TFI. MSs with low pesticide reliance were frequently associated with (i) high proportions of temporary grasslands and/or summer crops (such as maize), (ii) low proportions of winter crops and straw cereals, (iii) a high diversity in crop types and/or sowing periods. These characteristics are all related to a higher disruption of pest biological cycle. In situations with mild climate in central western France (PS2), farms from MS1 displayed the lowest pesticide use and also the highest proportion of temporary grassland. In this PS, the proportion of temporary grassland in the crop sequence appeared indeed negatively correlated to wheat total TFI, herbicide and fungicide TFI, suggesting the potential of this multiannual crop for an improved control of pathogens and weeds in winter wheat. On maize, contrary to wheat, the diversification of the crop sequence was not as frequently related to pesticide use. The situations without livestock from northern France (PS3) were the only category of PS where a higher crop type and sowing period diversity discriminated strategies with low pesticide use. Even more illustrative in situations with livestock from central northern France (PS2), a relatively high proportion of temporary grassland was associated with the most pesticide reliant profile of MS.

Our study therefore suggests that the strategy of diversifying crops to reduce pesticide use might have contrasting efficiency as a function of the PS and farm characteristics. Nevertheless, beyond these restrictive comments, we also showed that crop diversification was frequently associated with farms displaying low pesticide use, and may constitute a promising lever to further reduce pesticide reliance over many situations. The necessity of relocating agricultural productions to increase farm and regional biodiversity is today considered as a critical step for the agroecological transition (Duru et al., 2015). Since the 50s, the progressive regional specialization was probably the source of an increase in the production efficiency of farms in line with possible economies of scale (e.g. collection and storage of harvested crops) or technical simplifications. Conversely, this specialization entailed the geographical concentration of certain crops (Dessaint et al., 2014), sometime known as highly pesticide-reliant, as it is already observed in France for sugar beet or potato, consequently increasing pesticide pressure on a narrow cropping area. In addition, by reducing crop diversity and the frequency of the same crop, it boosted a unique selective pressure on pests, hence an increase in potential damages on crops caused by pest and a more frequent need for curative measures such as pesticide for controlling pests. Distributing more evenly the commercial crops would not only (i) contribute to the reduction of pesticide reliance (see also Lechenet et al., 2014), but moreover (ii) increase farm robustness for productivity and profitability (Davis et al., 2012). However, it would also make farm management and supply chains organisation more complex compared with the current situation, a critical point already source of lock-in hampering the crop diversification process (Meynard et al., 2013).

4.4. Soil tillage

Inversion tillage is often reported in the literature to affect weeds and pathogens dynamics by deep burial of weed seeds (Ball, 1992; Cardina et al., 2002) and crop residues (Bockus and Shroyer, 1998) respectively. In our study, we showed that the relation between tillage strategy and pesticide use depended on the PS, and may be positively or negatively related to the level of pesticide use from one context to another. For example in the analysis of TFI at the farm level, we found that low pesticide reliant strategies were more associated with inversion tillage than other MSs in mixed farms with livestock in western and southern France (PS1 and PS2), whereas the opposite was highlighted in farms of northern France without livestock but producing industrial crops with high added value (PS6). However, both in PS1 and PS6, we found, among farms with inversion tillage, a higher proportion of farms with occasional inversion tillage in low pesticide reliant MSs. In addition, we highlighted that MS with low pesticide use in wheat in southern France (PS1 and PS2) were associated with a higher proportion of farms including inversion tillage at least once over the crop rotation, although no significant difference appeared between MS on the frequency of inversion tillage just before winter wheat. This result underlines the necessity to consider the effects of inversion tillage at the cropping system level rather than at the single crop management level. The interactions between the crop sequence and the frequency of ploughing at the cropping system level has been addressed previously for weed management, and it might be useful to make use of such synergies when designing strategies able to reduce the germinating potential of the weed seed bank (Munier-Jolain et al., 2005).

4.5. Low doses for pesticide applications

Reduced doses for pesticide applications were often part of strategies associated with low pesticide use. In winter wheat in central-northern France (PS3 and PS4), pesticide applications at low dose represented more than 70% of total pesticide applications in the two profiles of MS with the lowest pesticide use. In maize in western France (PS1), all pesticide applications were performed at reduced dose in the profile of MS with the lowest level of pesticide use on maize, along with a high frequency of mechanical weeding. The complementarity between low application doses of herbicide and mechanical weeding was already reported as an efficient strategy for weed control in maize, with a decrease in herbicide use that may reach 75% compared with a fully herbicide based system (Mulder and Doll, 1993). Herbicide dose reduction is still often reported as increasing the risk of rapid evolution of weed resistance, therefore questioning the sustainability of this strategy. This issue was particularly addressed in recent studies, highlighting a higher risk to select phenotypic resistance at low herbicide use rates, due to non-target-site mechanism (Neve and Powles, 2005). However, to our knowledge, little is known about the risk for selecting resistance when low doses are consistently associated with various other management measures for pest and weed perturbation, as implemented by numerous farmers from our network, and also already suggested for the design of innovative IPM strategies (Barzman et al., 2015). Further studies are needed to investigate the efficacy of long term pest control when low doses of pesticides are applied in combination with diversified crop sequence as well as a range of prophylactic and curative measures for pest control that are alternative to pesticide use.

4.6. Additional discriminative factors of pesticide use identified in particular PSs

Over the range of situations in our network, other technical aspects discriminated punctually MSs with low pesticide use. In maize of western France (PS1), mechanical weeding was a major feature of strategies with the lowest pesticide use. In this PS, the correlation was strongly negative between herbicide TFI on maize and the frequency of mechanical weeding operations. Conversely, in maize of southern France, mechanical weeding was mostly associated with MSs displaying the highest pesticide use and the highest proportion of seed maize, and no correlation appeared between herbicide TFI on maize and mechanical weeding. Such a discrepancy of results confirmed the necessity to distinguish PSs and to analyse each technique as part of a strategical combination of technical options.

In wheat, the cultivar disease resistance emerged, in certain PSs, as a factor related to the level of pesticide reliance. In northern France, fungicide use was negatively correlated with the disease resistance mark of cultivars (PS4), and wheat cultivar diversity also appeared higher in systems with low pesticide use (PS4 and PS5). Increasing cultivar diversity was already reported as contributing to the dilution of selection pressure on pathogens (Hajjar et al., 2008) as well as a promising way to improve weed control (Pakeman et al., 2015).

4.7. Residual variability in pesticide reliance

The iterative regression trees defining PSs and MSs accounted for 73%, 36% and 63% of the total variability in farm TFI, wheat TFI and maize TFI respectively, showing that a significant share of pesticide use remained uncaught by our models. It suggested that explanatory variables we used did not describe all the differences in PSs and MSs with enough accuracy. In particular, we lacked additional socio-economic data to better characterise the constraints and opportunities defined by the PS. For instance, the proximity of the farm to advisory services would provide interesting information on the possibility for a farmer to benefit from management advice. Further information about farm characteristics (e.g. available workforce) may also contribute to explain further differences in pesticide use level. Concerning MSs, precise data on the farmer's decision-making would be very helpful to get a more accurate description of the farmer strategy. For instance, some farmers might accept a number of weeds or a few minor pest symptoms supposed to have negligible economic impacts, while others target weed-free fields and the best possible crop health status. This variability in decision-makers' perception facing a similar situation is known to be a significant driver of the variability observed in crop protection strategies, which may affect directly the level of pesticide use (Norton, 1976; Mumford, 1981). However, data characterising decision are often subjective and then hard to be collected or described rigorously at the scale of such a large farm network. We currently work on a new information system able to collect data on decisional aspects in each farm from the network. This would improve the characterisation of pest control objectives in line with risk aversion, and would make it possible to quantify the relative weight of tactical decision making for pesticide treatments on the level of pesticide use, as compared to prophylactic strategical measures for pest management.

4.8. Conclusion and outlook

In this study, we benefited from a unique dataset collected at the scale of the national territory, covering a wide diversity of production situations and offering a large sample of farms with contrasting management strategies. Using partitioning methods, we first identified several types of production situation associated with a first level of variability in pesticide use. Using once again partitioning methods, we secondly identified, in each production situation, various profiles of managements strategies associated with low vs. high pesticide use, i.e. explaining a second level of variability in pesticide use. We showed that MSs with low pesticide use were different from a production situation to another, confirming the importance to consider the production context when addressing the question of drivers to reduce pesticide reliance. In a given production situation, we found that several profiles of management strategies displayed low levels of pesticide use, suggesting that there is not only one but several ways to be low reliant on pesticides. Although we highlighted the diversity of strategical options as a function of the situation, some management measures, such as the crop diversification, the soil tillage strategy and the pesticide dose reduction appeared as rather transverse discriminative factors, i.e., they were associated with low pesticide use across diverse situations. Mechanical weeding, wheat cultivar and sowing date were conversely more punctual discriminative factors as they contributed to discriminate strategies with high vs. low TFI in only one or two of our categories of production situation. The analysis of TFI variability could still be refined by collecting additional variables to better characterise factors from production situation and management strategy, in particular by getting information on farmer's decision-making.

The objective of this paper was not to provide ready-made recipes for pesticide reduction fitting each situation, but we hope we provided a generic overview of the main combinations of factors associated with low vs. high pesticide use. As compared to previous IPM experiments, this study (i) considers management strategies that are surely adoptable by the farmers in the real life (as they were indeed observed in the real life), (ii) considers the diversity of management strategies that are possible within the IPM paradigm, and (iii) considers the diversity of production contexts that might influence the management strategies. This work may be useful for policy makers to help them to adapt local regulations and incentives targeting the development of IPM and the reduction of pesticide use, taking into account the specificities of the local agricultural context. For instance, policies supporting crop diversification might be crucial in some areas specialised in cereals and oilseed rape production, while the promotion of mechanical weeding appears a major lever in areas where maize is the main crop.

This study identified management strategies with limited reliance on pesticide. The further important question to address is the question of the economic and environmental performances of these cropping systems with low pesticide use. Do they tend to show lower vs. higher economic profitability than systems with high pesticide reliance? Do they tend to have lower vs. higher energy efficiency? Do they tend to reduce the pollution by pesticide residues and the associated toxicity as expected? Do they require a higher workload at the farm level? Do the relationships between TFI and the various components of agricultural sustainability vary as a function of the production context? Those questions will be addressed in a suite of articles based on the same network of demonstration farms.

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