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Diversity of pesticide use trajectories during agroecological transitions in vineyards: The case of the French DEPHY network

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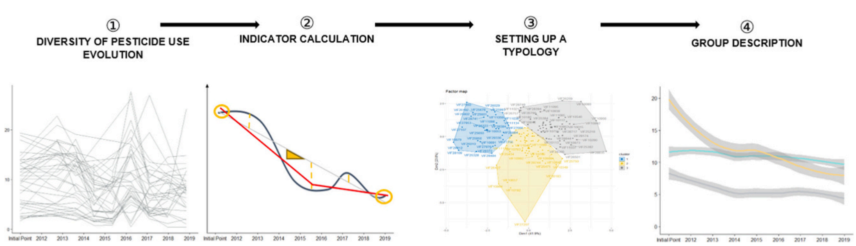
HIGHLIGHTS

- Differences in pesticide use changes at 161 French vineyards over a 10-year period were studied
- Indicators linked to the pesticide use trajectory were calculated, including the initial point, pathway taken and final point
- Three clusters were identified
- The three types differed in terms of technical changes implemented during the pesticide reduction transition

GRAPHICAL ABSTRACT



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ABSTRACT

CONTEXT: Winegrowers apply large quantities of pesticides to their vineyards to reduce high cryptogamic pressure. But these practices must change to lower pesticide use and improve viticulture sustainability. Different options for curbing pesticide use exist, and they can be progressively implemented following a specific temporal scheme in each production system. Some change trajectories can be more efficient than others in limiting pesticide applications. Combining trajectory studies and typology may be helpful in characterizing how farmers change their practices and in summarizing the various production system trajectories possible when transitioning towards pesticide use reduction.
OBJECTIVE: The aims of this study were i) to identify different types of pesticide use trajectories, and ii) to understand the options implemented by winegrowers to reduce their pesticide use.
METHODS: We analysed data from 161 farming systems in the DEPHY farm network in 12 French winegrowing regions over a 10-year period. Pesticide use was assessed with the treatment frequency index (TFI). We characterized the TFI trajectory of each farming system with six indicators and built a typology of TFI trajectories. We then analysed several indicators such as the use of biocontrol products and the dose sprayed to identify some of the management options chosen to achieve these pesticide use trajectories.
RESULTS AND CONCLUSIONS: Three clusters were identified and characterized in terms of pesticide use strategy. The first cluster represented farms with an initial point close to the regional average and which did not experience a significant TFI reduction (−13%). The second cluster comprised farms with a low TFI when entering the network that were able to further reduce their TFI over time (−48%). The last cluster represented farms with a high initial TFI and a high reduction (−63%). All clusters managed to reduce their pesticide use by combining several technical levers at different intensities. Some differences in the levers between clusters were observed.

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Cluster 2 farms are in the process of converting to organic farming and using the associated levers such as biocontrol and mechanical weeding.
SIGNIFICANCE: The changes implemented by cluster indicate a varying degree of progress in the transition towards pesticide use reduction. The initial point was identified as having a strong influence on the end result. The more intensively the technical levers were combined, the more difficult it was to reduce pesticide use. The DEPHY network supported winegrowers in their reduction of pesticides who managed to reduce their pesticide use by 13% to 63%.

1. Introduction

The dominant agricultural model is being challenged by the rise of societal debates on the environmental and health consequences of current intensive agricultural practices (Aubertot et al., 2005; Matson et al., 1997; Pretty et al., 2018; Wilson and Tisdell, 2001). To support and stimulate the transition towards low pesticide inputs, some countries have created public policies. In 2008 the French government launched its national ECOPHYTO plan with the aim of cutting pesticide use in half and ending the use of glyphosate by 2025 (Barzman and Dachbrodt-Saaydeh, 2011). Within the ECOPHYTO plan, a network of French demonstration farms, the DEPHY farm network, was created to promote and assess practices implemented to reduce pesticide use.

In 2008, the French government started up the ECOPHYTO national plan with the aim of a 50% decrease of the pesticide use and ending the use of glyphosate by 2018 (Barzman and Dachbrodt-Saaydeh, 2011). In 2015, the ECOPHYTO II plan was launched with new goals, the aim of supporting famers in the transition and find solutions to reduce pesticide use while maintaining a high productivity. Within the ECOPHYTO plan, a network of French demonstration farms, DEPHY-Farm network, was created to assess the implementation of practices to reduce the pesticide use. Technical changes can be complex and challenging for winegrowers particularly (Merot et al., 2019). The DEPHY-farm network is an interesting device to understand and characterize the way farmers perform the transition towards low pesticide use systems.

Lamine and Bellon (2009) have identified two different transition processes used by farms shifting to organic farming: i) an abrupt, direct and reversible transition or ii) a transition implemented through a progressive and continuous process of adaptation. These two transitions differ in the speed of change and the degree of modification to farm practices. Thus, the implementation of new practices is more or less gradual and can involve profound technical changes (Chantre and Cardona, 2014; Lamine, 2011; Padel et al., 2020; Toffolini et al., 2017).

During a transition towards pesticide use reduction, changes with various intensities can be implemented (Hill and MacRae, 1996; Sutherland et al., 2012). Change intensity can be characterized with the Efficiency, Substitution and Redesign framework (ESR) (Hill and MacRae, 1996). Thus, changes are associated to a gain of Efficiency (*e.g.* dose reduction), Substitution (*e.g.* use of biocontrol product) or Redesign process (*e.g.* conversion to organic farming). Changes linked to Efficiency or Substitution are associated with a progressive transition while changes associated to redesign are linked to a more abrupt and direct transition (Hill and MacRae, 1996; Lamine and Bellon, 2009; Merot et al., 2019). Wilson's transition theory (Wilson, 2008), conceptualized the path during a transition as a succession of linear periods. The linear period determines the possibility of a system to go in one direction but being interrupted by a nodal point.

Trajectory studies may help to characterize how farmers change as well as the factors and background of these changes (Cerf et al., 2010). Trajectory studies are carried out at different levels (organizational, technical, commercial, *etc.*) and can be linked to learning processes (Barbier and Lemery, 2000; Cerf et al., 2010). According to Ross et al. (2008), the transition process can be described according to three elements. The first element is the agent of change, *i.e.* what triggers change (public policies, psychosocial factors, *etc.*). The second element corresponds to the effect of change, *i.e.* the difference between the initial state and the final state. The last element is the mechanism of change, which corresponds to the path taken between states, *i.e.* the trajectory from one state to another. Trajectory is here considered to be the path followed by a system during its transition from an initial state to a final state through intermediate states (Merot et al., 2019). Thus, a transition can be characterized by the initial point, the effect of the transition (direction and intensity), and the trajectory.

Studying a vineyard or a production system trajectory involves the use of indicators. The selected indicators determine how the object of study is viewed. In the case of changes in practices, some studies have used the ESR framework established by Hill and MacRae (1996) to characterize the change implemented (Chantre et al., 2015; Merot et al., 2019) or calculated technical scores (Dupré et al., 2017). These indicators can be used to visualize the trajectory sequentially.

Transitions towards pesticide use reduction are distinct from farm to farm. Different solutions exist to implement change; for example, there are many levers to reduce pesticides in vineyards (use of biocontrol products, dose reduction or soil tillage to replace chemical weeding, *etc.*) (Jeuffroy et al., 2022). The chosen solutions can depend, for example, on the priority, the production mode and the specific farm context (Darnhofer et al., 2010). The technical changes made by farmers when transitioning towards a low-input system differed from one farm to another (Merot et al., 2019), even if different pathways can lead to the same final point (Deffontaines et al., 2020).

To understand and summarize farm diversity, as observed in the DEPHY-farm network, during an agroecological transition, the notion of farm typology is often used (Teixeira et al., 2018). Building a typology is a way to simplify and group a variety of farm cases into fewer types to better understand this diversity (Alvarez et al., 2018, Landais, 1998). Typology can condense and summarize a large, heterogeneous dataset to identify patterns and describe or even compare these patterns (Alvarez et al., 2018; Cortez-Arriola et al., 2015; Köbrich et al., 2003). Typologies are a first step to understand the transition process because they are used to assess and explain the differences between farming systems undergoing changes. In the literature, typologies built to analyse trajectories of practices mainly focus on the difference between initial and final points, sometimes taking an intermediate point and are based on qualitative data. Thus the trajectories, as a succession of phases building a specific path between the initial and final point are scarcely taken into account in typologies. When taken into account, trajectory studies are generally based on small samples of farms (ranging from a dozen to thirty farms) and the building of the typology does not involve quantitative methods to analyse dynamics. Such methods would become necessary when analysing large databases such as the DEPHY-Farm database.

We assumed that different strategies of pesticide use reduction exist but these strategies are difficult to identify given the diversity of production contexts among the different winegrowing regions. A major obstacle to the trajectories study is the need for a high amount of data over a long time. A method is needed to characterize the long-term dynamic of pesticide use so as go beyond regional effects. In fact, the method must overcome the diversity of the production contexts by identifying indicators derived from the individual trajectory and which are used to assess the dynamic. This paper aims to summarize and characterize the diversity of individual farms' pesticide use trajectories within the DEPHY network at a national scale (France) in a way that reflects the long-term dynamic of pesticide use reduction and goes beyond the regional effects.

To describe the diversity of transitions, we developed a typology to analyse pesticide use trajectory based on the calculation of indicators linked to the change in TFI. We consider these trajectories as mathematical trajectories (*i.e.* trajectory of quantitative data and numeric variables) to differentiate them from the mechanisms underlying the transition process (*i.e.* trajectory built on qualitative data and variables). We also described the different technical changes identified through performances evolution by Fouillet et al. (2022) with the Agrosyst database for each type of pesticide use trajectory to identify which levers can be implemented to reduce pesticide use.

2. Materials and methods

2.1. Vineyard system

Grapevine is a perennial plant, often planted in monoculture, which faces strong pest and disease pressures. Several threats can cause major damage, thus impacting the qualitative and quantitative characteristics of grapevine production (Fermaud et al., 2016). Pesticide applications remain the most effective way to control pest and diseases. In 2019, the average TFI for French vineyards was 12.4, with an average of 18 treatments per year (Simonovici and Caray, 2021), whereas the average TFI for wheat (a major annual crop in France) was 4.9 in 2017 (Agreste, 2020). Among pesticides, fungicides represent around 80% of pesticide use in vineyards. Most of these treatments aim to control downy mildew (*Plasmopara viticola*) and powdery mildew (*Erysiphe necator*). Insecticides account for <15% of pesticide treatments and are sprayed to control European grapevine moth (*Lobesia botrana*) and the leafhopper vector of Flavescence dorée (*Scaphoideus titanus*). Depending on the region and year, treatments to prevent Flavescence dorée can be compulsory by law. Herbicides represent the remaining 5% of pesticide use (Mailly et al., 2017) but are still applied on 72% of vineyards (Simonovici and Caray, 2021) on the inter-row or/and under the vine row. Pathogen development is highly correlated to the climatic conditions of the vineyard (humidity, rainfall and wind) (Mailly et al., 2017). This relationship leads to a range of practices between and within winegrowing regions.

2.2. The DEPHY network and the AGROSYST database

The DEPHY network was created in 2010 with the aim of demonstrating the capacity of farms voluntarily enrolled in the network to reduce their pesticide use. The DEPHY network includes >4000 farms and covers all French production sectors. The vineyard sector is represented by 280 farms that joined the network between 2010 and 2012 and an additional 270 farms that joined in 2016. Farms entering the network in 2016 join an existing group or form a new group depending on their location. The vineyards involved in the DEPHY network are divided into 49 groups across the main French winegrowing regions. Each group is composed of around a dozen winegrowers and is facilitated by a network engineer who supports the winegrowers in their efforts to reduce pesticide use with individual assistance and collective projects. The role of network engineer is essential in the motivation for change, in the choice of levers to implement and the dynamic of implementation. Engineers promote generic and well-known levers of pesticide reduction (dose reduction, frequency of treatment, choice of the products, equipment adjustments…), as well as tools to better schedule pesticide applications (*e.g.* decision support system for dose and date choice). When entering the network, winegrowers engaged part of their plots within the DEPHY-network named “cropping system” by the network.

The network engineer collects information on the phytosanitary strategy for each farm every year and enter the data into a database (AGROSYST Information System). Each phytosanitary intervention is recorded in the database with the dose and the name of the product.

To encourage data analysis and monitor pesticide use evolution, the AGROSYST database was created to compile information about the farming systems: farm context (*e.g.* agricultural area, farm equipment), phytosanitary strategy (all information on treatments: applied dose and product sprayed, *etc.*) and agronomic indicators such as yield. Other performance indicators available in the database (*e.g.* number of carcinogenic, mutagenic or toxic for reproduction (CMR) products used or the quantity of sulphur and copper applied) have been calculated using the raw data. When a farm joins the network, a diagnostic is performed with the farmer to collect information on its “initial point” based on the previous three years. Farming system details are then collected every year.

Data available for 373 vineyards (*i.e.* 89% of the network) between 2017 and 2019 reported the different levers mobilized in the DEPHY network. Among the levers most mobilized, the dose regulation (with or without DSS) (80%), mechanical weeding to replace herbicide product (76%) and the use of biocontrol products (*e.g.* sulphur products) (53%) were observed (internal communication). Few winegrowers mobilized levers based on prophylactic measures (18%). Therefore, we expect to see a decrease of the use synthetic products (fungicide and herbicide) linked to an increase and biocontrol products (Substitution strategy). Since most of the levers focus on the phytosanitary strategy, we should be able to capture the differences in phytosanitary strategy through the phytosanitary performances.

Only vineyards with >6 years of data were evaluated for this study. We selected a total of 161 farms entered between 2010 and 2011 in the network. These farms were distributed across 11 major French winegrowing regions: Alsace, Bordeaux, Bouches-du-Rhône, Bugey-Savoie, Champagne, Burgundy, Charente, Côtes-du-Rhône, Gaillac, Provence and Loire Valley.

2.3. TFI calculation

We assessed pesticide use by using the treatment frequency index (TFI, Pingault et al., 2008). TFI is the main indicator used within the DEPHY network to monitor pesticide use. TFI is the sum, for each pesticide product applied during the crop season, of the ratio between the applied dose and the full registered and recommended dose (Brunet et al., 2008; Fouillet et al., 2022). Different methods to calculate the TFI exist and differ regarding the full registered dose, either established by product or by targeted pest or disease. The TFI used in our study corresponds to the applied dose expressed as a fraction of the dose recommended to control specific targeted pests or diseases and by the proportion of sprayed area (see **Eq. 1**).

$$TFI = \sum_{P} \frac{\text{Dose\_sprayed}_p}{\text{Dose\_recommended}_p} \times \frac{\text{Area\_sprayed}_P}{\text{Area\_total}_P} \tag{1}$$

Eq.(1): Calculation of the TFI (Pingault et al., 2008) for a given year at the farming system scale. The dose sprayed per product corresponds to Dose_sprayed; the recommended dose for a product P for the target pest is Dose_recommended; Area_sprayed represents the surface area where the product was applied and Area_total is the total surface of the field where the treatment was sprayed (Pingault et al., 2008).

The recommended doses per product and per targeted pest/disease were extracted from the e-phy database published by the French Ministry of Agriculture (Ministère de l'Agriculture et de l'Alimentation, 2021). The e-phy database for 2020 was used for all 10 years of the study in order not to take into account the variations of the dose regulations during this period. The variables dose_sprayed, area_sprayed, area_total and the product name were directly available from the AGROSYST database.

For 3% of the treatments, we were not able to identify the product in the official database. As proposed in Fouillet et al. (2022), for these treatments we assigned a TFI of 1, which stands for a full dose applied to a given area. The TFI for a growing season corresponds to the sum of the TFI per treatment for all interventions performed during that growing season (see **Eq. 1**). We differentiated partial TFI depending on the target of the treatment: fungicide TFI (TFI_f), herbicide TFI (TFI_h) and insecticide/acaricide TFI (TFI_i). The TFI biocontrol was calculated separately following the principle of **Eq. 1** for the interventions based on the list of biocontrol products (sulphur, macroorganisms, microorganisms, natural substances, pheromones, elicitors).

All the variables used to calculate the TFI are summarized in Supplementary data 1.

2.4. Indicators used to build the typology

To characterize the type of pesticide use trajectories within the DEPHY network, six indicators were calculated using the TFI for each farm. These indicators can be used to describe the transition process. Some of the calculated indicators were adapted from the method of Martin et al. (2017) used by Bouttes et al. (2018) and Perrin et al. (2020). This method took into account the trends in farm performances: i) the slope of a linear model reveals the general trend (increase, decrease or stagnation), ii) the range of the residuals to evaluate the robustness and variability of the measurement and iii) the sum of squared deviations estimates the overall variability of the farming system. In total, the six indicators were calculated: the initial normalized TFI, the final TFI, the slope, the sum of square deviation, the maximum variation and the slope break (see Fig. 1).

In our case study, we first characterized for each vineyard the initial and "final" state of the transition and extracted the two following indicators to characterize changes:

- the **initial normalized TFI** (*normalized_TFI*) corresponds to the ratio between the initial TFI in a vineyard and the regional TFI provided by the French Ministerial Statistical Service for Agriculture data. The normalization let to eliminate the winegrowing region effect. In fact, the indicator *initial normalized_TFI* reflects the intensity of pesticide reduction compared to other vineyards in the same winegrowing region. The database from the French Ministerial Statistical Service for Agriculture is representative of the cropping practices in the different French winegrowing regions. The surveys are conducted every three years at the field scale on a representative sample of 4000 farms. For farms which entered the DEPHY network in 2010, the initial TFI was calculated using the data from 2008, 2009 and 2010. For the farms which entered in 2011, the calculation was made using the 2009, 2010 and 2011 data. The normalization was performed with the 2010 regional TFI. A normalized TFI under 1 indicates that the winegrower is using less pesticide than the regional average.
- the **final TFI** (*final_TFI*) corresponds to the mean TFI for the last three years (2017, 2018, 2019)to be consistent with the initial point calculation and to limit the year effect. The final TFI is an unnormalized value.

These first two indicators were completed by indicators of the trajectory. We used a linear model to characterize the pesticide use trajectory based on TFI evolution (data not normalized) over the 10-year period. For each production system, several indicators were extracted:

- the **slope** (*slope*) was used to characterize the path taken from the initial TFI to TFI in 2019;
- the **sum of squared deviations** (*SSD*) was calculated to characterize the variability around the slope
- the **maximum variation** (*max_variability*) corresponds to the maximum residuals having the largest absolute value were extracted to indicate the variability of the TFI over the 10-year study period.

Trajectories are not necessarily linear and regular, and ruptures can occur (Wilson, 2007).

- the **slope break** (*slope_break*) was used to characterized ruptures during the trajectory. In order to qualify these ruptures, two-piecewise continuous linear regressions were conducted for each farm. Two-piecewise linear models are a common nonlinear model which assume the existence of a breakpoint at the junction of two-line segments. The location of the breakpoint was considered as a model parameter and the most relevant value was found by maximum likelihood. The slopes of the lines before and after the "best" hypothetic breakpoint were compared. The slope change is used to evaluate if the farming system was experiencing a break during the pesticide reduction process. We hypothesized that only one main rupture happened during the transition. We also hypothesized that a rupture could happen during the re-engagement of farms in 2016.

2.5. Indicators describing the phytosanitary strategies and used to explain the types of TFI trajectories

To identify changes in the phytosanitary strategy that were implemented to reduce pesticide use, we looked at the management practices used by the DEPHY farmers highlighted in the study by (Fouillet et al.,

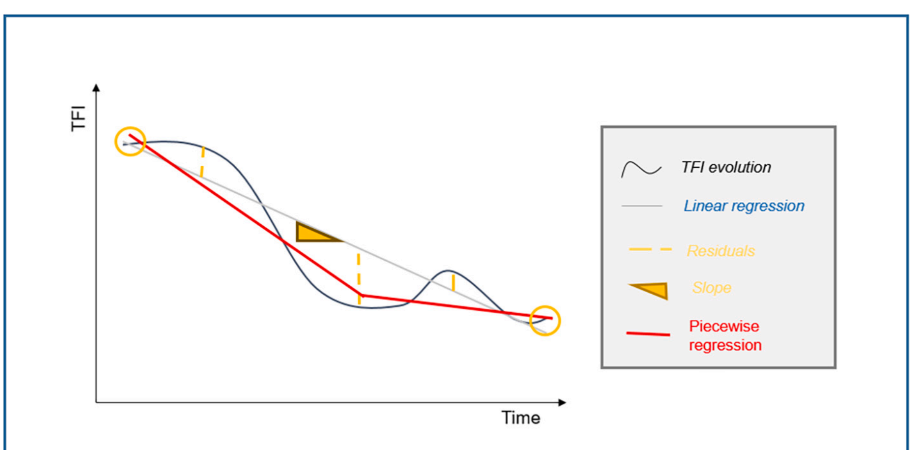

Fig. 1. Overview of the indicators calculated to set up the pesticide use trajectory typology inspired by the methodology from Martin et al. (2017). The slope was obtained with the linear regression over time based on the raw measurement, and the maximal residual of the regression was extracted. The piecewise regression was used to identify the existence of a transitional rupture. The initial TFI and final TFI were also extracted.

2022). The list of the data we used for the study are summarized in the Supplementary data 2. All the indicators used to characterize changes in the phytosanitary practices are available in the AGROSYST database. The different management practices studied were: the type of product used, the applied dose per treatment, the use of chemical herbicide and the production mode.

We described changes in the type of product used, the applied dose per treatment, use of chemical herbicide and production mode by us the Efficiency, Substitution, Redesign (ESR) framework (Hill and MacRae, 1996; Pretty et al., 2018). The ESR framework distinguishes three different changes: the first type of changes (E, efficiency) mainly seeks to resources optimisation, the second type of changes (S, substitution) is mostly based on the substitution of one or more elements (*i.e.* products, equipment…) and the third changes (R, redesign) generally focused on reorganizing the production system. The redesign strategy is associated with both technical levers and the production mode (organic farming).

Type of product used.

First, we focused on the use of biocontrol products. The list of biocontrol products authorized by the Ministry of Agriculture includes 4 categories: macroorganisms (insects, mites, *etc.*), microorganisms (bacteria, viruses), chemical mediators (pheromones and elicitors) and natural substances (biocontrol products are composed of substances present in the natural environment and can be of plant, animal or mineral origin). These new compounds in the products are more leachable and the frequency of application is more dependent on rainfalls. (Rouault et al., 2016). A change of product was characterized as a substitution. The substitution of chemical products with biocontrol involves a different reasoning of the treatments (increase of the number of treatments). To characterize the use of biocontrol products, we used several indicators:

- Whether or not a biocontrol product was used
- The biocontrol share ($TFI_{biocontrol}$ over total TFI)
- The sulphur quantity applied. Sulphur products are considered by French regulations as biocontrol products. In organic vineyards, sulphur is mostly used to control powdery mildew.
- The use of mating disruption (biocontrol product) against the leafhopper vector of *Flavescence dorée*.

Then, we focused on the use of copper products. Copper products are not considered to be a biocontrol product but are authorized and mostly used in organic farming against downy mildew. Similar as the sulphur product, copper products are more leachable. Indicators used to characterize copper products used were:

- Whether or not a copper product was used
- The quantity of copper sprayed

The number of carcinogenic, mutagenic or toxic for reproduction (CMR) products sprayed was also characterized.

Applied dose per treatment (fungicides, herbicides, insecticides). The dose sprayed indicates if a dose was adapted to the current situation with a more or less complex decision-making process (for fungicide and insecticides products). Decision Support System or dose adaptation depending on climate and phenological stage are tools highly implemented by the winegrowers in the DEPHY-Network (internal communication). In 2019, 80% of the farms were using these levers to reduce their pesticide use. The DSS are nowadays well known (DECItrait or Optidose) and are often proposed to the winegrowers when they are joining the DEPHY network. Pesticide use can be reduced by 30–50% in vineyard systems by using decision support system (Thiollet-Scholtus et al., 2019).

An herbicide dose reduction indicates a change in the weeded strip under the row or the stopping of the weeding in the inter-row. Dose reduction was qualified as gain of efficiency.

Use of chemical herbicides. Even if herbicide represents a small part of the TFI, stopping the use of herbicide product implies organizational change (*e.g.* increase in work time, increase of the cost (Jacquet et al., 2019). If the TFI_h was zero, we considered that the winegrowers were implementing mechanical weeding under the row (Fouillet et al., 2022). Replacing the use of herbicide product by mechanical weeding was qualified as redesign (Merot et al., 2019).

The production mode (conventional farming, organic farming or farming system in conversion) was also available in the database. The conversion to organic farming implies the implementation of several levers (the stopping of systemic product and herbicide product) (Merot et al., 2019). Hill and MacRae (1996) qualified the conversion towards organic farming as redesign.

Data on behavioral levers (*e.g.* use of decision support systems) are not available in the database; the indicators used are mainly quantitative indicators linked to the use of phytosanitary treatments.

2.6. *Statistical analysis and data processing*

The data were processed with R software v. 3.6.2 (R Core Team, 2019) and Rstudio v. 1.3.1093 (RStudio Team, 2020) with the Tidyverse package (Wickham et al., 2019) and the broom package (Robinson and Hayes, 2020). The graphics were made using the ggplot2 package (Wickham, 2016).

2.6.1. *Statistical method used to build the typology*

The typology was based on the indicators presented in section 2.4. A principal component analysis (PCA) followed by a hierarchical cluster analysis (HCA) were performed using FactoMineR (Lê et al., 2008).

We performed the PCA with the six indicators to identify the relationships between the variables. The missing values represented only 0.6% of the data, which is why the missing values were replaced by the mean of the variable.

The farm trajectory typology was then produced using an HCA on the coordinates on the PCA axes with an eigenvalue >1 (Kaiser criterion). We used the Euclidean distance computed on the factorial coordinate of the individuals. We identified the optimum number of clusters based on the largest relative loss of inertia using Ward's method.

2.6.2. *Characterization of the different clusters of pesticide use trajectory*

In order to compare the indicators used to set up the typology between clusters, we used a one-way ANOVA and Tukey test for numeric and continuous indicators with normal distribution of the errors. A non-parametric test (Kruskall-Wallis) and Wilcoxon test were used for non-normal distribution.

We assessed changes in the phytosanitary strategy indicators by comparing the initial point (un-normalized) and final points between and within clusters. For indicators computed as proportions, we used a **Pearson's chi-squared test** to test the change in indicators between the initial and final point between and within clusters. To test the evolution of numeric indicators between the initial and final points, we used a ***t*-test**. *P*-values are mentioned throughout the results section.

3. Results

3.1. *Typology of pesticide use trajectory*

3.1.1. *Classification quality*

The dataset used for the classification contained 161 farms. The first two components of the PCA combined 67.9% of the variance. The first PCA component, which accounts for 40.8% of the total variance, expresses the strong positive correlation between the normalized TFI upon entry in the network and the SSD. The variable slope and the slope change are also associated with this component. The second component, which explains 27.1% of the variance, is associated with three variables: *final_TFI*, *max_variability* and *slope change*. The HCA was based on the first 2 components of the PCA.

3.1.2. Typology

Three clusters of 75, 53 and 33 farms were identified. All indicators were significantly related to each cluster (Supplementary data 3). The three types are present in almost every winegrowing region and every group (see Supplementary data 4 and 5) but in different proportions. Farms belonging to cluster 2 were dominant in the Bouches-du-Rhône, Provence and Alsace. In Charente and Côtes-du-Rhône, there were no farms in cluster 3. Farms belonging to cluster 1 were mainly in the Loire Valley, Charente and Côtes-du-Rhône.

The three different types of pesticide use trajectories are differentiated (Fig. 2.1). The first type, cluster 1, corresponds to farms with lower pesticide use than cluster 3 when entering the DEPHY network and which did not decrease their TFI. The second type, cluster 2, also corresponds to farms with lower initial pesticide use upon entering the network than cluster 3 and which decreased their TFI over the 10-year period. The last type, cluster 3, corresponds to farms with the highest level of pesticide use at the initial point among the three clusters and which achieved a substantial pesticide reduction over the 10-year period.

When looking at TFI changes according to winegrowing regions, the same trends were observed visually even in different regions (see supplementary 6). For example, for Bordeaux and Champagne (Fig. 2.2 and 2.3), the mean trajectories show similar trends but some differences are still observed. More inter-annual variability is observed for each cluster in Champagne (*e.g.* TFI pikes in 2012).

3.1.3. Characteristics of the six TFI trajectory indicators for the three clusters

Cluster 1 farms presented a mean normalized TFI that was similar to the national standards (0.89). The mean TFI at the initial point was 11.6 and the mean final TFI was 9.7, which corresponds to a decrease of 1.9 TFI points. Farms in this cluster had the smallest TFI reduction (−16.4%). The mean slope is −0.23 TFI points per year. The farming systems in cluster 1 had the smallest maximum variability (0.37) and a mean SSD of 14.47. A total of 30.6% of farms in this cluster experienced a break in their trajectories. The median year of TFI slope change for these farms was 2015, with a positive mean increase of 0.68. This increase indicates a slowdown in the TFI decrease process.

Cluster 2 farms were characterized by the smallest normalized initial TFI (0.52), meaning that before entering in the network, these farms were already applying around half the quantity of pesticides than other farms in the region. In the network, these farms still reduced their TFI by 48.7% with an initial TFI of 8.2 and a final TFI of 4.2, which corresponds to a decrease of 4 TFI points. The mean slope is −0.32. The cluster 2 farms also had the highest variability (0.86) but a low SSD (17.8). A total of 24% of these farms experienced a break in their trajectories during the 10-year period. The mean slope change was −1, indicating an acceleration in the process of pesticide use reduction. The median year of TFI slope change was 2013.

Cluster 3 farms had the highest initial TFI, higher than the national trends (1.53). The mean TFI at the initial point was 20.8 and the mean final TFI was 7.7, which corresponds to a decrease of 13.1 TFI points. The farms in this cluster had the highest TFI reduction rate (−63%) and the highest slope (−1.38). A large variability was observed: the SSD was highest for cluster 3 with a mean of 113 and the mean maximum of variability was 0.42. A total of 30% of the farms in cluster 3 experienced a break in their trajectories. A mean slope change of −1.7 was observed, indicating an acceleration in the process of pesticide use reduction. The median year of the slope change was 2014.

The initial normalized TFI, slope change and SSD were not significantly different for clusters 1 and 2 (Fig. 3). No significant difference was identified for the slope break for clusters 2 and 3 (p-value >0.05).

No significant difference was identified for the maximum variability for clusters 1 and 3. The final point distribution was significantly different among the three clusters.

3.2. Levers implemented within clusters identified with pesticide use evolution

3.2.1. Disease control

The *t*-test showed a significant difference between the TFI at the initialand final pointsfor the three clusters (t-test, $p < 0.001$, Table 2). The percentage of decrease, calculated between the initial point and the final point, was −16.4% for cluster 1, −49.7% for cluster 2 and − 63% for cluster 3. The same trends are observed for the TFI_f as all clusters significantly reduced their fungicide use from the initial to the final point (t-test, $p < 0.05$, Table 2). The reduction of the fungicide dose applied per treatment was significantly different between the initial and

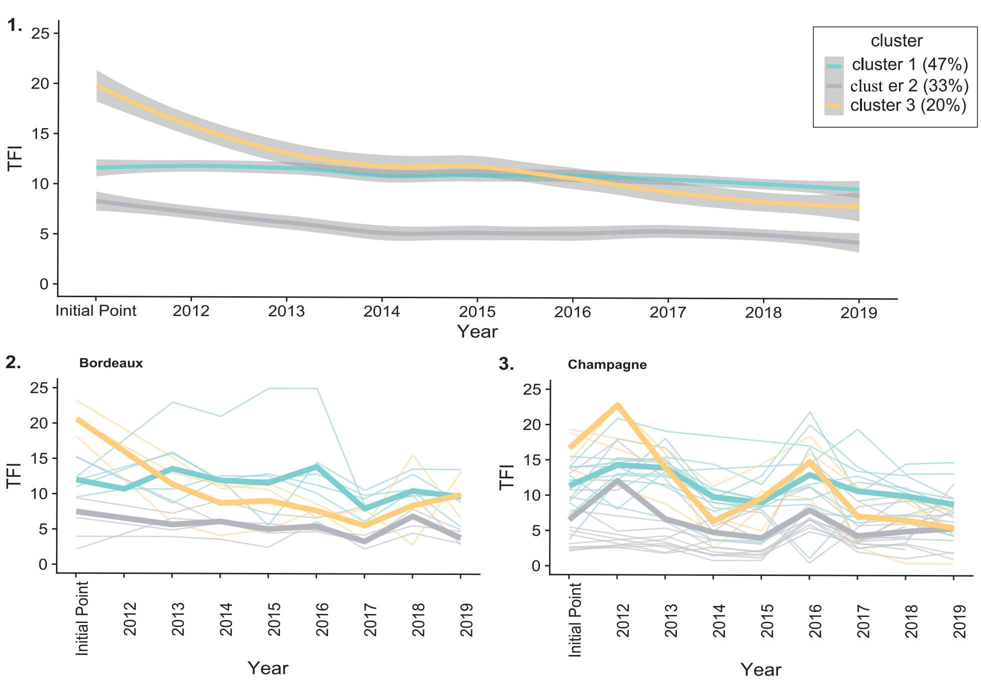

Fig. 2. Change in the TFI per cluster (1.) Mean pesticide use trajectory per cluster. (2.) Change in the TFI per cluster in Bordeaux. The bold lines correspond to the average trajectories by type. The thin lines correspond to the individual trajectories. (3.) Change in the TFI per cluster in Champagne. The bold lines correspond to the average trajectories by type. The thin lines correspond to the individual trajectories. The changes in the TFI for the other winegrowing regions are available in Supplementary data 6. Cluster 1 is represented by the blue line, cluster 2 by the grey line and cluster 3 by the yellow line. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

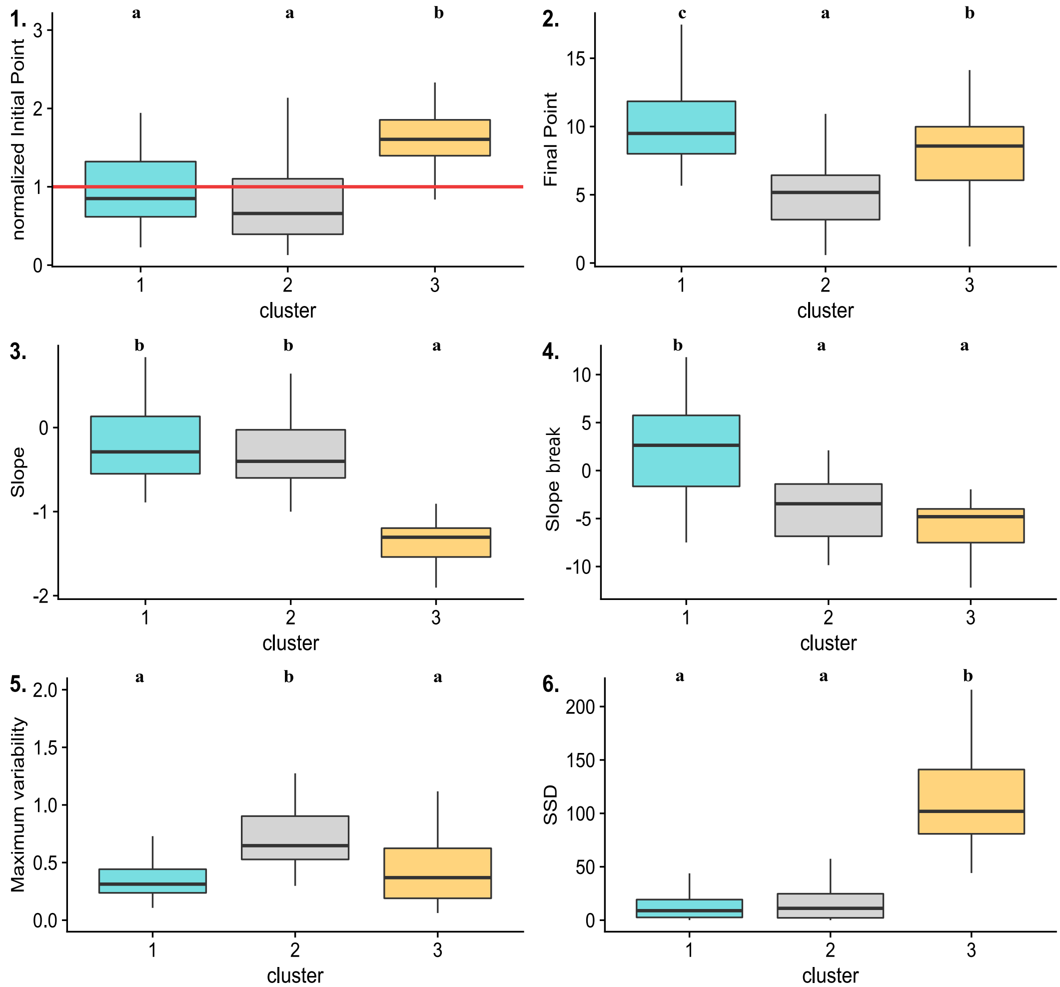

Fig. 3. Distribution of the calculated indicators per cluster. (1.) Initial point normalized the red line represent the mean level of pesticide use at the national scale (2.) Final point, (3.) Slope, (4.) Slope break, (5.) Maximum variability, (6.) Sum square deviation (SSD). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)
The horizontal black lines across the boxes represent the median. The end of the boxes represents the first and third quartiles; the whiskers indicate the minimum and maximum values. For a given indicator, distributions per cluster are significantly different if associated with a different letter (Wilcoxon test, p < 0.05 or Tukey test, p-value < 0.05).

final points within the 3 clusters (*t*-test, $p < 0.001$, Fig. 5B). A significant fungicide dose reduction from 11.6% from the initial point to 2019 was observed within cluster 1, −42.8% for cluster 2 and − 43.6% for cluster 3.

At the initial point, the proportion of farms using biocontrol products was significantly different among the clusters (Pearson's chi-squared test, $p < 0.05$, Table 1). Cluster 2 had the highest proportion of farming systems using biocontrol products at the initial point (79.3%). An average 80% of the farms in the three clusters used biocontrol products at the final point (Fig. 5A). The $TFI_{biocontrol}$ product increased significantly for cluster 2 over the 10-year period (*t*-test, $p < 0.01$). The percentage of farms using biocontrol increased over the 10-year period for clusters 1 and 3 (Pearson's chi-squared test, $p < 0.05$). The biocontrol rate increased significantly over the 10-year period (t-test, $p < 0.05$): +74.5% in cluster 2 and + 115% for cluster 3. The change in cluster 1 (+32.3%) was not significant.

The proportion of farms using copper and sulphur products was not significantly different between clusters at the initial point or at the final point (Pearson's chi-squared test, $p > 0.05$). Additionally, the change in the number of farms using copper and sulphur was similar between the initial and final points for the three clusters (Pearson's chi-squared test, $p > 0.05$). The quantity of copper products was stable over the 10 years for the 3 clusters (*t*-test, $p > 0.05$). The quantity of sulphur applied increased for cluster 2 between initial and final point (*t*-test, $p < 0.01$, Fig. 5F).

The proportion of farms using CMR products was significantly different among clusters both at the initial point and when tested at the final point (Pearson's chi-squared test, $p < 0.01$ for the initial and final points, Table 2). Regarding the change between the initial and final points, the highest rate of decrease of CMR product use was for the cluster 2 farms: at the final point, only 13% of the farms were using CMR products (Fig. 5E). Cluster 3 had the highest proportion of farms using CMR products at the initial and final points. The mean number of CMR products used decreased significantly over the 10-year period for all 3 clusters (t-test, $p < 0.001$). Cluster 3 farms had the highest number of CMR products used at the initial point (10.4). At the final point, cluster 3 farms had the highest number of CMR products used (3.1), similar to cluster 1 (2.9).

3.2.2. *Weed control*

The change in the TFI_h between the initial and final points was significantly different for clusters 2 and 3, indicating a significant reduction in the use of herbicidal products (t-test, $p < 0.05$, Table 2). The change between the initial and final points in the proportion of farms using herbicides was significantly different within the three clusters (Pearson's chi-squared test, $p < 0.05$, Table 1, Fig. 5C). The proportion of

Table 1
Change in the technical levers between initial and final points. Pearson's chi-squared test was conducted between the initial and final points within and between clusters.

		Cluster 1 (n = 75)			*Cluster 2 (n = 53)*			*Cluster 3 (n = 33)*			*Comparison between clusters (Chi2)*	
		Initial Point	*Final Point*	*Chi2*	*Initial Point*	*Final Point*	*Chi2*	*Initial Point*	*Final Point*	*Chi2*	*IP*	*FP*
Type of farming system	% of farms in conventional farming	100%	98.5%		59.2%	44.4%		100%	90.6%			
	% of farms in conversion	0%	1.49	*NS*	4.1%	4.44%	*NS*	0%	3.1%	*NS*	***	***
	% of farms in organic farming	0%	0%		36.7%	55.16%		0%	6.3%			
Phytosanitary strategy – Fungal pressure	% of farms using biocontrol products	65.33%	81.33%	**	79.25%	83.02%	*NS*	63.64%	75.79%	*	*	*NS*
	% of farms using sulphur products	60%	70.67%	*NS*	77.36%	81.13%	*NS*	66.67%	72.73%	*NS*	*NS*	*NS*
	% of farms using copper products	74.7%	77.3%	*NS*	90.6%	86.8%	*NS*	81.8%	87.9%	*NS*	*NS*	*NS*
	% of farms using CMR products	86.7%	52%	***	58.5%	13%	***	97%	54.5%	***	***	***
Phytosanitary strategy – Insect pressure	% of systems using insecticides products	44%	48%	*NS*	35.84%	24.53%	*NS*	63.64%	51.52%	*NS*	*	**
	% of farms using mating disruption	4%	34.67%	***	7.55%	77.36%	***	6.1%	45.45%	***	*NS*	***
Phytosanitary strategy – Weed pressure	% of farms using herbicides	81.33%	64%	*	54.72%	16.98%	***	87.88%	72.2%	**	***	*NS*

NS: $p > 0.05$; *: $p < 0.\ 1$; **: $p < 0.01$; ***: $p < 0.001$.

Table 2
Change in the technical levers over time. T-tests were conducted to assess whether the reduction was significant.

		Cluster 1 (n =75)		Cluster 2 (n= 53)		Cluster 3 (n= 33)	
Pesticide strategy	Change in the mean TFI	−14.7%	***	−40.7%	***	−60.1%	***
	Change in the $TFI_{biocontrol}$	+4%	*NS*	+46.6	**	−7%	*NS*
	Change in the biocontrol share	+ 32.3%	*NS*	+74.5	***	+115%	***
	Change in the number of CMR products	−65.8%	***	−90.2%	***	−70.2%	***
Pesticide strategy – Fungicidal pressure	Change in the sulphur quantity sprayed	+26.4%	*NS*	+59.5%	**	+77.6%	*NS*
	Change in the copper quantity sprayed	+15.05%	*NS*	+52.56%	*NS*	−13.8%	*NS*
	Change in the TFI_f	−7.3%	**	−44.4%	**	−57.7%	*
	Change in the fungicide dose applied per treatment	−23.8%	***	−42.8%	***	−43.6%	***
Pesticide strategy –Insecticidal pressure	Change in the TFI_i	−21%	*NS*	−2.5%	*NS*	−10%	*NS*
	Change in the insecticidal dose applied per treatment	−11.6 %	*	+10%	*NS*	−13.6%	**
Pesticide strategy – Herbicidal pressure	Change in the TFI_h (including TFI = 0)	−24%	*NS*	−0.77%	**	−80%	***
	Change in the herbicide dose applied per treatment	−20.6%	*	+7.4%	*NS*	−55.7%	***

NS: $p > 0.05$; *: $p < 0.\ 1$; **: $p < 0.01$; ***: $p < 0.001$.

farms among clusters using herbicides was similar at the initial point (Pearson's chi-squared test, p-value = 0.12) but significantly different at the final point (Pearson's chi-squared test, p-value <0.001). A significant decrease in the applied dose was observed for the three clusters between the initial and final points (t-test, $p < 0.01$, Table 2). Farms from cluster 1 managed to reduce their dose applications by 70%, from a mean dose of 0.61 to a mean dose of 0.19.

3.2.3. *Pest control*

Regarding the change in insecticidal management, a non-significant decrease in the TFI_i was observed in all clusters (t-test, $p > 0.05$, Table 2). However, a significant decrease in the TFI_i per treatment was observed for cluster 1 and cluster 3 (t-test, $p < 0.05$). The proportion of farms using insecticidal products was significantly different among clusters at both the initial and final points (Pearson's chi-squared test, $p < 0.05$, Table 1, Fig. 5D). The proportion of farms from clusters 1 and 2 using insecticidal products decreased by 19% and 46.8%, respectively. The proportion of farms using mating disruption significantly increased over the 10-year period in all three clusters (Pearson's chi-squared test, $p < 0.001$). In 2010, the proportion of farms using mating disruption was similar among clusters (Pearson's chi-squared test, $p = 0.12$) but was significantly different at the final point (Pearson's chi-squared test, $p < 0.001$).

3.2.4. *Production modes*

The proportion of production modes (conventional farming, organic farming or in conversion) between clusters was significantly different at the initial and final points (Pearson's chi-squared test, $p < 0.001$, Table 1, Fig. 4). At the initial point, 100% of the farms in clusters 1 and 3 had a conventional farming system. At the final point, a large majority of the farms had conventional farming systems in cluster 3 (90.6%) and cluster 1 (98.5%). For the cluster 2 farms, a higher proportion of farms had an organic farming system (36.7% at the initial point) compared to clusters 1 and 3 (0% for both). In cluster 2, farming systems in conversion to organic farming appeared as soon as they entered the network. For cluster 3, conversions towards organic farming started in 2016 and represented 6.3% of the cluster. The proportion of farming systems in conversion to organic farming in 2019 at the final point was 1.5% for cluster 1 and 3.1% for cluster 3. Cluster 1 did not include any farms with organic farming systems at the final point. However, the proportion of farms depending on the production mode were similar between the initial and final points within each cluster (Table 1).

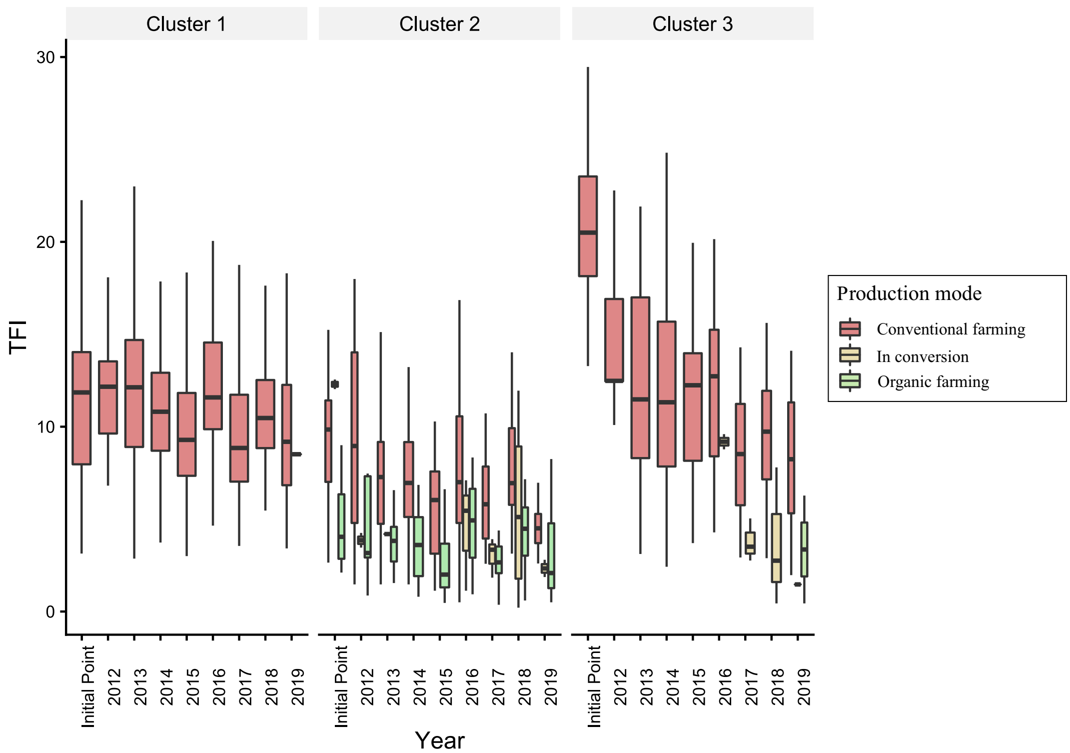

Fig. 4. Change in the TFI by cluster and production mode. Outliers are not represented. Whiskers display the 5th and 95th percentiles. Horizontal bars indicate the first quartile, median and third quartile.

3.3. Change intensity

Looking at each type, we observed that cluster 1 corresponded to farms that were already using pesticides efficiently when they entered the network: their normalized initial TFI was lower than 1 at the initial point. It seems that these farms did not implement new levers, and a large majority of them continued using CMR products and herbicides (Fig. 4). However, a progressive transition towards reducing herbicide, insecticide and fungicide doses was observed. These farms moved towards greater efficiency and substitution.

When we looked at cluster 2 farms, we noticed that they were already well advanced in terms of efficient pesticide use (Fig. 5). In all, 36.7% of farms were engaged in organic farming at the initial point and 55.2% at the final point. A few farms were already using CMR and herbicidal products (58.5%). A high dose reduction of TFI_f was observed and associated with an increase in efficiency. The reduction in the sprayed fungicide dose with no decrease in the quantity of copper products used demonstrated efficiency-based strategies. At the final point, a large majority of the farms were using mating disruption and biocontrol products. These changes were related to the large of the farms in organic farming or in conversion to organic farming. The technical levers associated with this mode of production were the use of copper and sulphur, the cessation of systemic products and the implementation of soil tillage when farms stopped using herbicides.

Cluster 3 farms entered the DEPHY network with a high consumption of pesticide products and experienced the highest TFI decrease (Fig. 5). Looking at the changes occurring over the 10-year study period, we observed a high dose reduction affecting all phytosanitary treatments (insecticides, fungicides and herbicides). The reduction of the TFI_h and the slight reduction of the number of farms using herbicides indicated a decrease in the weeded strip (only under the row) rather than a total cessation of herbicide use as observed in cluster 2. The biocontrol rate over the global TFI increased while the TFI biocontrol remained stable. These changes indicate a reduction of the TFI without substituting biocontrol products. All these elements indicate substantial efficiency gains and substitution in these farms.

In summary, based on the ESR framework from Hill and MacRae (1996) the pesticide reduction strategies for cluster 1 and cluster 3 were mainly based on efficiency and substitution and differed in their initial levels of pesticide use when entering the network (Fig. 6). Cluster 2 farms undertook deeper changes, moving towards more redesign-based changes (Fig. 6).

4. Discussion

This paper aimed to characterize and understand the various pesticide use trajectories within the DEPHY network. The method used allowed us to identify three types of pesticide use trajectories. The three types were significantly differentiated by their initial TFI, the path taken (slope, decrease, variability, and rupture) and their final TFI. The farms were categorized into the different types and are found across all winegrowing regions. The typology developed was both robust and exceeded the winegrowing region effect, a factor that can impact pesticide use intensity (Fouillet et al., 2022). This means that the three types of trajectories identified were the result of the winegrowers' own strategies rather than the consequences of the particularities of the winegrowing region even if some minor differences in term of inter-annual variability was observed as in 2015–2019 for clusters 1 and 3.

All three trajectory types showed a significant reduction in pesticide use, but the reduction differed in intensity. The farming systems in cluster 1 experienced the smallest TFI decrease (−14.7%). Farming systems from cluster 2 managed to reduce their TFI by 40.7%, while the cluster 3 farming systems experienced the highest TFI decrease of 68.8%.

The differences in TFI reductions between clusters can be explained by the potential for improvement expressed at the initial point. Indeed, the farming systems from the three clusters differed in terms of the initial point. We observed that cluster 3 farms entered the DEPHY network with a high normalized TFI, indicating pesticide use that exceeded the national average. Cluster 1 and 2 farming systems both

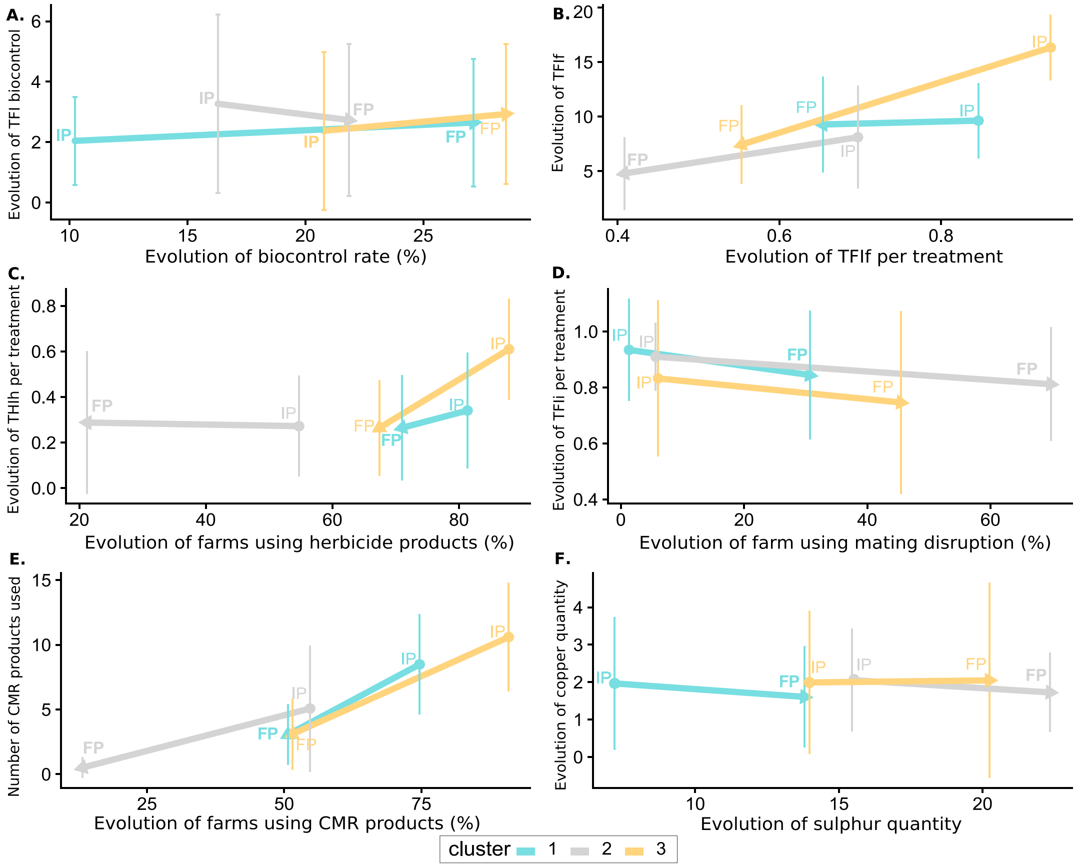

Fig. 5. (A.) Change in the biocontrol rate based on the $TFI_{biocontrol}$ between the initial point (IP) and final point (FP) for each cluster. (B). Change in the fungicide dose based on the TFI_f change between the IP and FP for each cluster (C.) Change in the TFI_h and the percentage of farms using herbicide products between the IP and FP for each cluster. (D.) Change in the percentage of farms using mating disruption depending on the mean TFI_i per treatment between the IP and FP for each cluster. (E.) Change in the percentage of farms using carcinogenic, mutagenic, or toxic for reproduction (CMR) products based on the number of CMRs used between the IP and FP for each cluster. (F.) Change in the applied sulphur quantity based on the applied copper quantity between the IP and FP for each cluster.

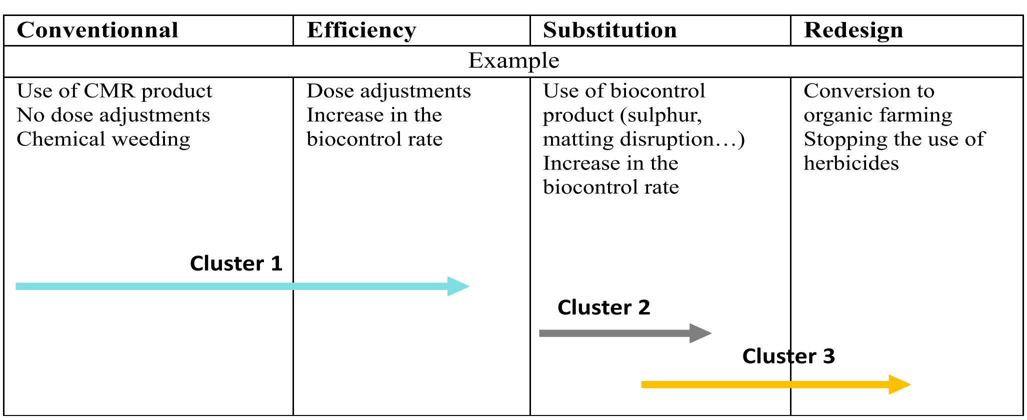

Fig. 6. Summary of changes observed between the initial point (IP) and final point (FP) for each cluster based on the Efficiency, Substitution, Redesign (ESR) framework (Hill and MacRae, 1996). The phytosanitary strategies of each cluster are positioned on an ESR gradient, which also includes conventional (corresponding to an absence of phytosanitary strategy reasoning). Practices corresponding to each strategy were associated with each letter (conventional, E, S, R). Cluster 1 is represented by the blue arrow, cluster 2 with the grey arrow and cluster 3 with the yellow arrow. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

started with a lower initial TFI compared to the national average TFI value. However, their pesticide use reduction was different. Thus, the initial point appears to be a key point of the transition towards a low-input farming system. Ross et al. (2008) formalized that the path taken strongly depends on the initial state. Merot et al. (2020) showed by using a typology of technical changes for vineyards in conversion to organic farming that the path taken by farms was also highly dependent on the initial state. Our results suggest that it is easier for systems starting with a high TFI to reduce their TFI than for those starting with a low TFI to achieve further decreases. For winegrowers with an overuse of pesticide (Cluster 3), the modification of the phytosanitary strategy (dose reduction, change of product) is based on simple levers but with a high impact on the TFI. As the winegrowers from the cluster 3 had a use of pesticide product higher than the national average, it is therefore easier to reduce the pesticide use compared to those who are not overusing pesticide (cluster 1 and cluster 2). Also, slope breaks, reflecting a change in slope (increase or decrease) in the TFI trajectory, were observed in farms from all clusters rapidly after engaging in the network.

The slope break may also indicate a slowdown in the TFI decrease (*i.e.* abrupt decrease followed by a stagnation). For all clusters, the mean year of rupture takes place before 2014.

The three clusters were also characterized by the variability around the slope, which provided information about the specific farming system's sensitivity and adaptation to abiotic and biotic hazards over time (Martin et al., 2017). These variabilities were partly linked to the adaptation of treatments to pest and disease pressure. The year effect on pesticide use was substantial (Mailly et al., 2017). An increase in the TFI was observed in 2016 and again in 2018 when winegrowers contended with severe infestations of downy mildew (Fouillet et al., 2022). Differences in climatic conditions also lead to variability in practices over time and space (Mailly et al., 2017). The highest variability around the slope was observed for cluster 2 farms. Cluster 1 corresponded to the farms with the smallest maximal variability and SSD. For clusters 2 and 3, we observed a high dose reduction of fungicide treatments indicating that winegrowers in these clusters adapted their pesticide treatments depending on the period or pest and disease pressure (Fouillet et al., 2022). Thus, looking at the difference in term of variability between clusters, we can assume that winegrowers who adapted their pesticide treatment according to pest and disease pressure experienced a higher variability of pesticide use. The more the winegrowers reduced their pesticide use the more the TFI varied within cluster: TFI increases were higher in years with high pressure, while TFI decreases were greater in years with low pressure. Unlike cluster 1 farms, the cluster 2 farms managed to adapt their phytosanitary practices according to the climatic conditions and pest and disease pressures.

In our study, we considered an initial TFI (the year of entry into the network) and final TFI. The initial and final TFI are arbitrary because farmers may have started to reduce their pesticide use before entering the network and continued to implement technical levers after the final point. Unlike the conversion to organic farming, the reduction of pesticide use does not have a specific legal compliance period (Lamine et al., 2009). The speed and intensity of change was therefore different for each farmer. Practices can more easily be readjusted from one year to the next, such as when they are adapted to disease risks. Based on the example of the cluster 1 farms for which we did not observe redesign change, changes were mainly based on efficiency and substitution. Thus, change at a slow speed and low intensity was observed on farms already using pesticides efficiently before entering the DEPHY network. At the initial point, it seems that cluster 1 and 2 farms had already begun transitioning towards reducing their pesticide use based on their initial TFI and management strategies. Meanwhile, cluster 3 farms started with a high initial TFI, and the analysis of their pesticide strategies at the initial point indicated limited adjustments of phytosanitary treatments. The high TFI decrease indicated that entering the DEPHY network was associated with a trigger event (Sutherland et al., 2012) for the cluster 3 winegrowers. Entering the network seemed to have less impact for farms in cluster 1, while farms in clusters 2 and 3 managed to quickly reduce their TFI. However, cluster 1 winegrowers maintained a low TFI throughout the 10-year period when entering the DEPHY network. However, farms that were already in organic farming when entering the network had lower pesticide use than conventional farms.

Furthermore, the typology allowed us to characterize differences in technical changes that were implemented. In fact, clusters of TFI trajectories differed in terms of technical lever implementation and the intensity of change (Fig. 4 and 5). Winegrowers managed to reduce their pesticide use by combining these different technical levers. The difference in terms of TFI reduction between clusters can be explained by the initial point as discussed previously as well as by the intensity of the changes implemented. The levers mobilized by all farms – dose reduction and use of non-CMR products – constituted a first step in reducing pesticides. These changes mostly centred on efficiency and substitution. Other levers were, however, mobilized in clusters 2 and 3, such as mating disruption. Other levers, such as stopping herbicidal product applications, were distinctive for cluster 2, which saw the lowest pesticide use at the final point. The implementation of mechanical weeding indicated a higher intensity of change: the more herbicides were stopped, the more the TFI decreased. Implementation of mechanical weeding was the sign of changes on all cultural practices that contributed to pesticide use. Within cluster 2, a majority of farms had a production method associated with organic agriculture whose control of cryptogammic diseases relied mainly on the use of copper and sulphur. While organic farming practices in vineyards are seen as a way of reducing pesticide use, they lead to an increase in the application of other products such as copper and sulphur (Merot and Wery, 2017). However, the intensive use of these substances can be controversial (*e.g.* there is some debate on the ecotoxicity of copper). A study by Karimi et al. (2020) showed that the maximum authorized yearly dose of copper in France (6 kg/ha) had no significant impact on the soil quality function. Regardless, reducing the use of these products requires the implementation of deeper change such as preventive measures (Jeuffroy et al., 2022). We found that the main levers implemented by the winegrowers were not disruptive practices. We observed that the more intensively these levers were implemented and combined, the more the TFI decreased. And the more these levers were implemented and combined, the more difficult it was to reduce TFI.

Looking at the difference of initial point, the change intensity and the final point, we can assume that there was a kind of continuity between the TFI trajectories. By starting with a high pesticide use and experiencing a high TFI decrease by implementing changes of low intensity (cluster 3 TFI trajectory), winegrowers had two possible pathways: i) a low pesticide use reduction linked to the implementation and adaptation of technical levers mainly based on efficiency and substitution (cluster 1 TFI trajectory) or ii) achieving a greater pesticide use reduction by implementing levers associated to redesign strategy (cluster 2). We also hypothesized that the trajectory from cluster 2 could even be the continuity of cluster 1 trajectory. While it was easy to reduce the TFI by implementing simple levers such as dose reduction or the use of biocontrol, to reduce the TFI sustainably, clusters 1 and 3 had to implement deeper changes.

The three types of trajectories showed a connection to knowledge and learning. Trajectories of changes are not simply due to a willingness to adopt a new practice – they also depend on farmers' knowledge and efforts to learn (Sutherland et al., 2012). In terms of implementation, several studies showed that knowledge of change was acquired progressively in connection with a learning process (Chantre, 2014; Chantre et al., 2015; Coquil et al., 2014). Some practices require special equipment, new skills and specific knowledge (Blesh and Wolf, 2014; Salembier et al., 2020). For example, mechanical weeding is more complex than chemical weeding. This practice requires new knowledge about the state of the soil, vegetation and suitable equipment (Garcia et al., 2018). In terms of risks taken, mechanical weeding increases the costs of production and labour time (Jacquet et al., 2019). Changes in management strategy combined with technical changes increase the complexity of the farming operations (Aouadi et al., 2021). Obstacles related to the farm context (*e.g.* farm size, commercialization mode) also impact the technical changes. Thus farmers need support from advisors or a peer group when implementing new practices and a system redesign aimed at pesticide reduction (Darré, 1985; Guichard et al., 2017). Advisory services provided by the network engineer in the DEPHY farm network played a key role in reducing TFI. Advisors supported and organized the learning process and knowledge capitalization (de Tourdonnet et al., 2015).

Finally, we showed that the normalized initial point indicated a potential of improvement available to winegrowers. To help winegrowers reduce their pesticide use, qualifying their initial point is a necessary step. Doing so can allow advisors to better guide winegrowers towards the levers they need to implement by identifying the levers they are already using and the levers which can be intensified. Whatever the trajectory type considered, this study showed that a deep redesign is complex to implement and implies taking risks that impact all performances (*e.g.* yield loss) and the organization of farm operations (Aouadi et al., 2021; Jacquet et al., 2022). The implementation process is a key issue to support farmers in their change process. For farms wishing to engage in an agroecological transition, our results show that the support offered within the framework of the DEPHY network allowed farms to either reduce their TFI or maintain a lower TFI than the average. Nevertheless, these results show that the levers implemented and the changes made do not permit farmers to completely stop using pesticides. Other changes and innovations seem necessary to achieve this objective.

Our study was based on the evolution of performances to identify the potential changes of practices. Agrosyst database, is a good tool to assess the evolution of performances and monitor the pesticide use evolution at the DEPHY-scale. This database has generated “big data” on farms moving towards pesticide use reduction, and the information it gathers makes it a unique source worldwide (Lamichhane et al., 2019). The typology used in this study allowed us to go beyond winegrowing region specificities and to gain knowledge in terms of genericity. This method makes it possible to see the general pesticide use trajectory of farms to better support farmers in their transition process. According to Perrot and Landais (1993), the methodological decisions will determine the typology depending on the objectives, the nature of data and the sample. Our method can be completed with: (i) the use of Partial Least Square to explain the diversity (Martin et al., 2017, Perrin et al., 2020); (ii) the use of linear mixed model with a selection of explanatory variable. There are only few approaches that take dynamics and trajectory into account. Dardonville et al. (2022) identified other methods to explore: the KLM method, a longitudinal data clustering algorithm to identify different type of trajectories or the KmlShape method, which groups time series into trajectories according to their shape and the intensity of variations, taking into account the time lag between variations in different series. However, these methods still need further development. The data provided by the Agrosyst database give users information to study the impact of pesticide use reduction on other performances (*i.e.* yield, net margin…).

The use of other performances could be interesting to understand the diversity of the trajectory of other performances linked to the pesticide use reduction but also to identify the lock-ins link to agro-ecological transition such as organizational (Merot et al., 2019), economical (Chèze et al., 2020) or behavioral lock-ins (Dessart et al., 2019). However, this information is important to fully understand the process of change but are still missing in the database. The drivers of these changes are not observable in the database, for example information on the behavior (*e.g.* decision rules) and behavioral triggers (*e.g.* impact of the advisors on the change implementation). The database allows to work on a large scale and on data of 10 years which allows to gain in genericity by working on a large number of production systems but does not contain important information to understand some changes and the farmer's motivations to implement these changes. To guide policy design a better knowledge of the drivers influencing practices is necessary (Dessart et al., 2019; Finger and Möhring, 2022). This important information has to be accessed through survey instead, on a reduced sample.

5. Conclusion

The method constructed in this study allowed us to identify three pesticide use trajectories by integrating the dynamics in a large diversity of production contexts. The trajectories differed in terms of the types and intensity of changes implemented during the vineyard transition towards production systems with low pesticide use. We observed that levers used by farmers resulting in a pesticide use reduction were mainly based on efficiency (*e.g.* reducing fungicide dose) and substitution (use of biocontrol products). The same levers that were implemented in all types but with differences in terms of intensity explain the difference of pesticide use reduction. We found that the lower the TFI and the more intensively these levers were combined, the more the pesticide reduction was slow. The pesticide use reduction depended on the initial point and the levers implemented. These indicators should be take into account by advisors when supporting winegrowers in their pesticide use reduction. The types identified provide a solid foundation for further in-depth studies of the transition away from pesticide-intensive production systems to more precisely identify the levers implemented and their implementation over time.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.agsy.2023.103725.

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