



HAL
open science

Lowering pesticide use in vineyards over a 10-year period did not reduce yield or work intensity

Esther Fouillet, Marie Gosme, Aurélie Metay, Bruno Rapidel, Clément Rigal,
Nathalie Smits, Anne Merot

► To cite this version:

Esther Fouillet, Marie Gosme, Aurélie Metay, Bruno Rapidel, Clément Rigal, et al.. Lowering pesticide use in vineyards over a 10-year period did not reduce yield or work intensity. *European Journal of Agronomy*, 2024, 158, pp.127199. 10.1016/j.eja.2024.127199 . hal-04575614

HAL Id: hal-04575614

<https://hal.inrae.fr/hal-04575614v1>

Submitted on 15 May 2024

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



Distributed under a Creative Commons Attribution - NonCommercial - NoDerivatives 4.0
International License

1 Lowering pesticide use in vineyards over a 10-year period did not reduce yield or work intensity

2 Esther Fouillet^{a,b}, Marie Gosme^a, Aurélie Metay^a, Bruno Rapidel^{a,c}, Clément Rigal^{a,c,d}, Nathalie Smits^a, and Anne Merot^a

3 ^a ABSys, Univ Montpellier, CIHEAM-IAMM, CIRAD, INRAE, Institut Agro, Montpellier, France

4 ^b Université Paris-Saclay, INRAE, AgroParisTech, UMR Agronomie, 91123, Palaiseau, France

5 ^c CIRAD, UMR ABSys, F-34398 Montpellier, France

6 ^d ICRAF, Vietnam office, Hanoi, Vietnam

7 corresponding author: esther.fouillet@inrae.fr

9 Abstract

10 Pesticides remain the most efficient way to control pest and disease pressure in vineyards and obtain satisfactory
11 yields in terms of quality and quantity. However, because of the harmful effects of pesticides on human health and
12 the environment, winegrowers have had to change their practices. To reduce pesticide use, winegrowers have a
13 range of levers at their disposal that are implemented at different spatial and temporal scales and with different
14 intensities of change. Beyond simply reducing pesticide use, these changes can also impact farms' economic and
15 social performances notably because vine is a perennial crop with inertia in the impacts of changes operated. In
16 this work, we assessed the covariation between various performances with time. We used the Agrosyst database,
17 which compiles data on the performances of French vineyard cropping systems engaged in a pesticide reduction
18 process for the past 10 years, implementing a reduction of 34%. Based on existing knowledge on transition
19 processes and pesticide reduction in vineyards, we used partial least squares path modelling (PLS-PM) to assess
20 the dynamic trade-offs between different performances during the pesticide use reduction process. We verified the
21 model we built (GoF = 0.44) and found no significant correlation between pesticide reduction, economic
22 performances (operating costs and fuel consumption), technical performance (mechanical work time) or
23 productivity (yield). Interestingly, we did not observe any effect from reducing fungicides on yield. We only
24 noticed a significant correlation between the initial weed control strategy and the change in weed control strategy
25 ($\beta = 0.18$). Furthermore, stopping herbicide use did not affect mechanical work time or costs. Our results are
26 encouraging in terms of maintaining both agronomic and economic performances when reducing pesticides in
27 vineyards.

28 **Keywords:** Dynamic; Pesticide use reduction; TFI, Treatment frequency index; Trade-off; Vineyard; Yield

1. Introduction

The negative effects of pesticides on the environment and human health is a public concern (Aulagnier and Goulet, 2017). To make agriculture more sustainable, reducing pesticide use is therefore a major priority. The agricultural industry must transition to low-input systems. Debates on pesticide use are all the more true for the wine sector, given that it is one of the most input-intensive agricultural sectors (Urruty et al., 2016) since grapevine (*Vitis vinifera*) crops face significant pest and disease pressure. In 2019, for example, the average treatment frequency index (TFI, Pingault et al., 2008) for French vineyards was 12.4, with fungicide treatments accounting for 81% of this TFI (Simonovici and Caray, 2021). By way of comparison, the average TFI for wheat (a major annual crop in France) was 4.9 in 2017 (Agreste, 2020). To date, pesticides are still the most efficient solution to obtain satisfactory yields in terms of quality and quantity (Fermaud et al., 2016), but winegrowers must change their practices to become less dependent on these products and reduce their negative environmental impacts.

To reduce pesticide use, winegrowers can choose from among several technical levers that have variable impacts on the farming system organisation (e.g. increased working time, more complex work). Hill and MacRae (1996) classified the intensity of implemented changes through a framework known as ESR (efficiency, substitution and redesign). The first step in reducing pesticide use is to increase input efficiency (E), i.e. reducing the total pesticide dose while achieving the same level of production (Hill and MacRae 1996). This can be achieved by optimising the dose and frequency of treatments (Fouillet et al., 2022). The second step is substitution (S), where chemical products are replaced with non-chemical pest control solutions or chemical treatment with a lower environmental impact. The last step, redesign (R), corresponds to more complex changes at the farming system level. For each of these three steps, a range of levers exists but none of them alone suffices to sustainably reduce pesticide use. Thus, because each of these technical levers is only partially effective, they must be combined to achieve a meaningful reduction in pesticide use (Jeuffroy et al., 2022).

Since technical levers are implemented at different spatial scales and intensities, they have different impacts in terms of the environment, agronomy, farm organisation and working time. For example, on an operational level, doses can be adapted for each treatment intervention to consider vine sensitivity and fungicidal pressure. Farmers can also choose to use copper or sulfur-based products in place of synthetic products on a single plot, several plots or the whole farm. This is a tactical decision that can potentially impact vineyard performances. In fact, copper and sulfur-based products are more leachable than synthetic products. Their use implies more

60 interventions per season and an increase in working time (Merot et al., 2019). From a more strategic angle,
61 replacing herbicides with mechanical weeding requires financial and time investments. New equipment is needed
62 for tilling, inter-weeding and mowing activities (Merot and Wery, 2017). The consequences of such changes are
63 therefore technical but also organisational and economic.

64
65 **To sustainably reduce their pesticide use, winegrowers need to change their practices while maintaining an**
66 **economically viable agricultural production throughout the transition process.** During the pesticide reduction
67 process, winegrowers must revise their objectives, which can no longer be focused on yield maximisation (Jacquet
68 et al., 2022). Multiple, conflicting environmental and economic objectives mean that compromises must be sought
69 (Klapwijk et al., 2014). Indeed, competition between activities can occur at the farming system level (Delecourt
70 et al., 2019). For example, increased working time and costs along with decreased productivity have been observed
71 after winegrowers implemented mechanical weeding to replace chemical weeding (Jacquet et al., 2019).

72 **To understand the pesticide reduction process and better support winegrowers during their transition,**
73 **knowledge is needed on the covariations between the agronomic, economic, social and environmental**
74 **performances.** To acquire such knowledge, researchers often design and assess the performances of low-input
75 cropping systems (Meynard et al., 2012), such as in the case of experimental plots designed with low pesticide use
76 within the experimental DEPHY network (Métral et al., 2018; Thiollet-Scholtus et al., 2019). The performances
77 of the newly designed systems are then assessed using tools and indicators (e.g. multi-criteria evaluation) and the
78 impacts of the new technical strategies on environmental, economic, technical and agronomic performances are
79 quantified (Métral et al., 2018; Thiollet-Scholtus et al., 2019). While the design and assessment of experimental
80 trials with low pesticide inputs produce important results, real production situations must also be considered within
81 a large set of production contexts, which can differ from experimental conditions (Jacquet et al., 2022).

82 Over the past two decades, numerous studies have proposed methods for multi-criteria evaluation of farming
83 system sustainability (Soulé et al., 2021). Two main types of methods can be distinguished: conventional methods
84 focusing on farming system assessment and production in the field (Repar et al., 2017), and life cycle assessments
85 (LCAs), which focus on the products and cover activities both in and outside the field (such as input manufacturing
86 and waste disposal). Both types of methods target high-yield farming systems to determine whether new technical
87 strategies are efficient (Aouadi et al., 2019). Moreover, to our knowledge, these methods do not propose a dynamic
88 view of farming systems during their transition towards systems using reduced amounts of pesticides nor do they
89 consider the potential trade-offs between agronomic, socio-economic and environmental performances over time

90 (Dardonville et al., 2021; Hodbod et al., 2016; Soulé et al., 2021). Thus, several authors have pointed out the need
91 to develop methods that integrate the dynamics of trade-offs.

92 **To contribute to this issue, this paper aims to characterise the effect of the dynamics of pesticide reduction**
93 **on productivity and socio-economic performances of farming systems over the long term (10 years).** We
94 used partial least squares path modelling that included dynamic indicators of these performances to explore the
95 potential trade-offs between agronomical, sociotechnical and economic performances over time. We hypothesised
96 that, during the transition process to reduce pesticide use, we would observe a decrease in yield and an increase in
97 manual labour and mechanical working time. The work was performed at the production system scale to take into
98 account the economic and labour evaluation.

99 **2. Materials and Methods**

100 *2.1. DEPHY network and Agrosyst database*

101 In France, the DEPHY network (Demonstration, Experimentation and Production of references on low-pesticide-
102 input systems) was created in 2010 to demonstrate the capacity of farmers to reduce their pesticide use within their
103 cropping systems. Farmers voluntarily participated in the network. A total of 280 cropping systems (i.e. several
104 plots that are grown with the same management strategy) were enlisted between 2010 and 2012 and another 270
105 vineyards joined in 2016. Vineyards were located across the 12 main French winegrowing regions (Alsace,
106 Bordeaux, Bouches-du-Rhône, Bugey-Savoie, Burgundy, Champagne, Charente, Côtes-du-Rhône, Gaillac,
107 Languedoc, Loire-Valley and Provence). Winegrowers were divided into groups managed by network advisors.
108 These advisors guided farmers during their progress towards pesticide reduction. Data describing cropping system
109 practices and performances, collected every year by the network advisors by survey, were gathered in the Agrosyst
110 database. This database provides information on pesticide use and agronomic indicators such as yield at the field
111 scale, with data available for each year starting from the year farmers joined the network. The Agrosyst team also
112 calculated various performance indicators (e.g. equipment use time, operating costs). In total and considering
113 missing data, we studied **161 cropping systems** for which we had at least 6 years of complete data for the studied
114 variables.

115 **2.2. Knowledge gained previously about the DEPHY network and potential covariations for** 116 **performances**

117 The 161 selected cropping systems were already studied in a previous study (Fouillet et al., 2023, 2022). Previous
118 studies have shown an average pesticide reduction of 33% over 10 years within the DEPHY network based on TFI

119 analysis (Fouillet et al., 2022). Various TFI trajectories were observed and classified into three types (Fouillet et
120 al., 2023) which mainly differed by their TFI levels when farmers joined the DEPHY network (initial TFI).
121 Analysis of the trajectories showed that the higher the initial TFI, the greater the TFI reduction between 2010 and
122 2019. The TFI reduction was mainly explained by reduced fungicide use and, to a lesser extent, reduced herbicide
123 use during the 10-year study timeframe (Fouillet et al., 2022). Three key approaches to reducing fungicide use
124 were identified: reducing doses, decreasing the number of treatments, and partially or totally substituting copper-
125 and sulfur-based products and biocontrol for synthetic products. We assumed that reducing doses and the number
126 of treatments would directly reduce production costs. Fewer treatments would also presumably impact the
127 mechanical work and all related impacts (fuel consumption, mechanical costs, labour). Conversely, the use of
128 biocontrol and copper-based products could require an increased number of treatments. Because copper and sulfur
129 are more leachable and not systemic, their use requires more frequent interventions (every 8 days on average
130 instead of every 14 days for synthetic products) and more frequent interventions before and after rain (Merot et
131 al., 2019). If the treatments are not applied at the right time, berry damage and yield loss can occur (Merot et al.,
132 2020). The herbicide TFI reduction was associated with the cessation of herbicide use on part or all of the vineyard
133 (some inter-rows, all inter-rows, under the rows) (Fouillet et al., 2022). Chemical weeding could also be replaced
134 by mechanical weeding or mowing. Substituting mechanical techniques for chemical weeding involved the
135 acquisition of new equipment (e.g. undervine weeder, cover crop, mower) and more frequent interventions. As a
136 result, this change could increase fuel consumption, production costs and labour. Furthermore, an unsuitable weed
137 management strategy could lead to increased water and nitrogen competition and lower yields (Celette and Gary,
138 2013; Merot et al., 2022).

2.3. Individual performance analysis

2.3.1. Performance variables

141 Eight variables were selected to analyse farm performances to assess disease and weed control strategy, mechanical
142 work intensity, costs and productivity. The Agrosyst team calculated them based on the Agrosyst database. These
143 variables were used to characterise the changes in vineyards' disease and weed control strategy, productivity,
144 labour and costs over the 10 years of the study.

- Disease and weed control strategy at field scale

146 *Treatment frequency index:* The level of pesticide use was estimated by calculating the TFI. The TFI is the main
147 indicator used within the DEPHY network to assess changes in pesticide use. We calculated the TFI based on the

148 recommended dose established for each product for any targeted pest or disease. The TFI was calculated with the
149 applied dose expressed as a fraction of the dose recommended to control specific targeted pests or diseases and
150 according to the proportion of sprayed area (Eq(1), Fouillet et al., 2022; Pingault et al., 2008).

$$TFI = \sum_p \frac{Dose_sprayed_p}{Dose_recommended_p} \times \frac{Area_sprayed_p}{Area_total_p}$$

152 *Eq(1): Calculation of TFI (Pingault et al., 2008) for a given year at the cropping system scale. The TFI equals*
153 *the sum of the TFIs per treatment, where one treatment equals one product P sprayed and one date of*
154 *application. The dose sprayed per product corresponds to Dose_sprayed; the recommended dose for a product P*
155 *for the targeted pest is Dose_recommended; Area_sprayed represents the surface area where the product was*
156 *applied and Area_total is the total surface area of the field where the treatment was sprayed.*

157 We differentiated three partial TFIs: fungicide TFI (TFI_f), insecticide and acaricide TFI (TFI_i) and herbicide TFI
158 (TFI_h).

159 - Mechanical work intensity

160 *Mechanical working time (hour ha⁻¹):* This indicator is calculated for each mechanical operation, taking into
161 account the time spent using the equipment and the number of people required to carry out the operation.

162 *Mechanical working time* was calculated for the season (from the previous harvest to the harvest of the current
163 season).

164 *Fuel consumption (L ha⁻¹):* Fuel consumption is the amount of fuel used for all the interventions using a
165 combination of tools. It was calculated for each intervention based on references from the Bureau Commun du
166 Machinisme Agricole (BCMA). This professional organisation creates decision support tools (mutual aid scale)
167 and publishes documents to support agricultural equipment advisor networks, agricultural technicians and users.
168 The calculated fuel consumption accounts for part of the tractor labour costs.

169 - Costs

170 *Inputs costs (€ ha⁻¹):* This indicator corresponds to the expenses related to the purchase of inputs such as seeds and
171 plants, mineral and organic fertilisers, seed and plant treatments, irrigation and plant protection products, and
172 biological control products. To calculate these operational expenses, we used the prices of the inputs as indicated
173 by the users. When information on input prices was unavailable, the Agrosyst team used the default prices from
174 an Agrosyst reference framework for the relevant cropping season.

175 *Tractor labour costs (€ ha⁻¹):* The tractor labour cost was calculated from the time of use of the equipment, based
176 on a cost of 18 euro per one hour of work performed by a tractor operator (according to the Agroequipment Office
177 from the national Chamber of Agriculture). This value was determined by the Agrosyst team and do not vary over
178 time.

179 - *Productivity*

180 *Yield (hL ha⁻¹):* Reported yield was collected each year and expressed in hL of harvested grape juice per ha⁻¹.
181 Yield values were declared by winegrowers at the field scale.

182 2.3.2. *Statistical analysis*

183 Statistical analyses were performed using R software v. 3.6.2 (R Core Team, 2019) with the lme4 package (Bates
184 et al., 2015). The general change in each performance over time was assessed using linear mixed-effects models
185 (Eq(2)). The winegrowing regions were integrated as a fixed effect to collect the slope and intercept coefficients,
186 while the cropping systems followed over the studied period were integrated as a random effect.

187
$$\text{mod1} = \text{lmer}(X \sim \text{Year} * \text{Winegrowing Region} + (1 + \text{Year} | \text{cropping system}))$$

188 *Eq(2): Linear models used to visualise the change in a variable X over the 10-year study timeframe, taking into*
189 *account the winegrowing region effect, a categorical variable (Winegrowing Region). The cropping system effect*
190 *over time was integrated as a random effect. The equation was formulated using the R software lme4 package*
191 *language (Bates et al., 2015).*

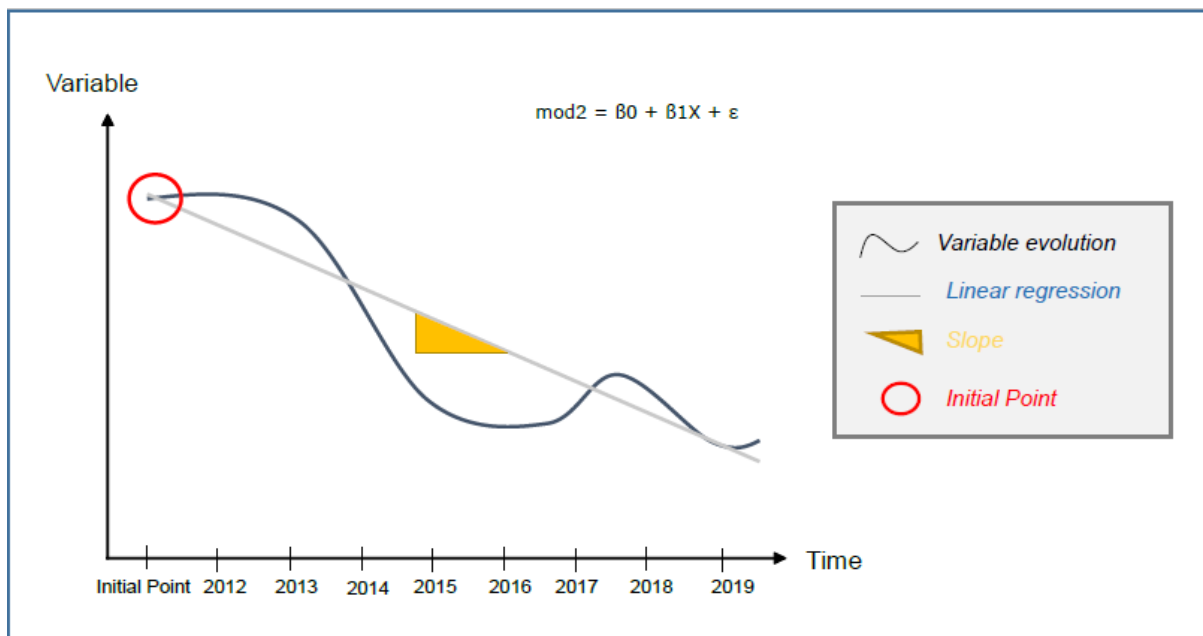
192 A t-test was performed to determine whether there was a significant difference in the variables between the
193 initial point (when the farm entered the DEPHY network) and the final point (2019).

194 2.4. Covariation analysis of the performance variables

195 2.4.1. *Variables to describe the performance dynamics*

196 To analyse the covariations between performances during the pesticide reduction process, we were not interested
197 in the individual raw variables presented above but rather in their initial value upon entry to the network as well
198 as their change in time. To assess the change in variables over time, we used dynamic indicators inspired by Martin
199 et al. (2017) and Fouillet et al.(2023). We extracted the slope of the linear model of each raw variable as a function
200 of time to reveal the overall change between the initial and final values (increase, decrease or stable) (see Fig.1.).
201 The value at the initial point was extracted for a set of variables listed below in Table 1. The new variables

202 corresponding to the slopes of linear regressions (figure 1, mod2) were named *Evo_<variable name>*. The new
 1
 2 203 variables corresponding to the initial point values were named *Ini_<variable name>*. We calculated 9 variables in
 3
 4 204 all to depict the performance dynamics (see [Table 1](#)).



205
 206
 207 **Fig. 1.** Indicators used to characterise the dynamic of the selected performances. The model linear model
 208 used with X the studied variable, β_1 the estimated slope, β_0 the estimated intercept and ϵ the residual

209 2.4.2. Covariation analysis: partial least squares path modelling (PLS-PM) method

210 *Method definition*

211 Partial least squares path modelling (PLS-PM) is a method used to explore the multiple relationships between
 212 various variables and to quantify the respective weights associated with these relationships (Tenenhaus et al.,
 213 2005). To date, PLS-PM has been mainly applied in the fields of social sciences and ecology. More recently, this
 214 method was also applied to agronomic studies (Quinio et al., 2017). Path models are built using unobservable
 215 variables, called construct variables or latent variables (LVs), and observable variables, also known as manifest
 216 variables (MVs). An LV is described using one or more MVs. PLS-PM is comprised of two sub-models: an inner
 217 model and an outer model (Sanchez, 2013). The inner model is the structural model that takes into account the
 218 relationships between LVs. The outer model, which corresponds to the measurement model, describes the
 219 relationships between the LV and a set of MVs. The group of MVs associated with an LV is defined as a block.

220 MVs must be positively correlated to their LV (Vinzi et al., 2010). The correlation between LV and their MVs
221 was estimated by using the loading (λ) (Sanchez, 2013). The strength and direction of the relationships between
222 LVs and MVs was estimated with the path coefficient (β) obtained from regression. A negative β value indicated
223 a negative correlation, whereas a positive β value indicated a positive correlation. β was only considered when λ
224 indicated a significant correlation.

225 *Model construction*

226 We built our path model in a reflexive way, meaning we assumed that MVs were caused by their respective LVs
227 (Baxter, 2009). Partial least squares path modelling (PLS-PM) was used to model the relationships between the 9
228 manifest variables presented above and depict the change in performance. These variables comprised the set of
229 MVs in the model. The latent variables and the associated manifest variables are summarised in [Table 1](#).

230 We used our path model to test the hypothesis that reducing pesticide use impacted the other studied performances
231 of the farming system. The hypotheses used to construct the model were based on existing knowledge on pesticide
232 reduction processes in vineyard systems (see [Table 2](#) for a detailed description of these hypotheses). The
233 hypotheses used in the model also took into account existing knowledge on the transition pathway towards
234 pesticide use reduction (Chantre and Cardona, 2014; Martin et al., 2017; Merot et al., 2019a).

235 We chose to focus on the change in fungicide and herbicide use within the DEPHY network as these are the two
236 types of pesticides for which Fouillet et al. (2022) observed a significant decrease in use. Furthermore, insecticide
237 products only represent a small part of the total TFI (14%, Simonovici and Caray, 2021) and most insecticide
238 treatments are mandatory treatments against *Scaphoideus titanus*, the leafhopper vector of *Flavescence dorée*.
239 Fouillet et al. (2022) showed no significant decrease in the use of insecticide products within the DEPHY network
240 over 10 years.

241 We began building the model by setting up two latent variables representing the initial state of disease control
242 (cryptogamic diseases) and the initial state of weed control. This is because, during a pesticide reduction process,
243 the initial states of control indicate the potential for improvement that winegrowers may reach in terms of pesticide
244 use reduction (Fouillet et al., 2023; Merot et al., 2019b; Ross et al., 2008). Since regional effects have a strong
245 influence on pest and disease pressure (Fouillet et al., 2022; Mailly et al., 2017; Simonovici, 2019), we normalised
246 the TFI_f by using data provided by the French Ministry of Agriculture (Simonovici and Caray, 2021). TFI_h was
247 not normalised as it represents a small part of the TFI (4.8% in 2019, Fouillet et al., (2022) and consequently even
248 if there is a regional effect, it is limited on the TFI variation. (Mailly et al., 2017).

249 *Model quality assessment*

1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60
61
62
63
64
65

250 We assessed the quality of the constructed path model using a two-step process (Sanchez, 2013). First, we verified
251 the homogeneity and unidimensionality of the blocks and then the cross-loadings. The unidimensionality of each
252 block was verified since all MVs were positively correlated with their respective LVs (Sanchez, 2013). Blocks
253 were homogenous, meaning that we would be measuring the same unique underlying concept in each block (Vinzi
254 et al., 2010).

255

16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60
61
62
63
64
65

256 **Table 1.** Description of the latent variables and the associated manifest variables used in the PLS-PM model

Latent variable	Manifest variable	Manifest variable calculation	Unit of the converted variable
Initial disease control strategy	Ini_TFI _f	Normalised TFI _f at the initial point	∅ 258
Initial weed control strategy	Ini_TFI _h	TFI _H at the initial point of the TFI _h	∅ 259
Change in disease control strategy	Evo_TFI _h	Extracted slope of the TFI _f from Initial Point to 2019.	∅ 260
Change in weed control strategy	Evo_TFI _h	Extracted slope of the TFI _h from Initial Point to 2019.	∅ 261
Change in productivity	Evo_Yield	Extracted slope of the yield from Initial Point to 2019.	hL ha ⁻¹ 262
Change in mechanical work intensity	Evo_FuelConsumption	Extracted slope of the change in fuel consumption from Initial Point to 2019.	L ha ⁻¹
	Evo_MechanicalWork	Extracted slope of the change in mechanical work from Initial Point to 2019.	hour ha ⁻¹ 263
Change in costs	Evo_TractorCost	Extracted slope of the change in tractor labour cost from Initial Point to 2019.	€ ha ⁻¹ 264
	Evo_OperatingCost	Extracted slope of the change in operating cost from Initial Point to 2019.	€ ha ⁻¹ 265

266

267 **Table 2.** Hypotheses used to construct the PLS-PM model based on the existing knowledge on pesticide reduction processes in vineyard systems

16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60
61
62
63
64
65

Hypothesis number	Relationships between latent variables (LVs)	Hypothesis	References
(1)	Initial disease control strategy → Change in disease control strategy	The initial disease control strategy is related to the potential pesticide reduction. It is easier to significantly decrease pesticide use when the initial disease control strategy mainly relies on the use of systemic products rather than other products (copper/sulfur or biocontrol)	Fouillet et al. (2022)
(2)	Initial disease control strategy → Change in productivity	Productivity is highly dependent on disease control. Powdery and downy mildew can cause considerable yield losses in the absence of pesticide use or a suitable plant protection strategy. Depending on the initial disease control strategy, the change in productivity when pesticide use is reduced will vary: <ul style="list-style-type: none"> - With high disease pressure and a strong initial disease control strategy, productivity is expected to decline; - With high disease pressure and a minimal initial disease control strategy, productivity is expected to remain stable; - With low disease pressure and regardless of the initial disease control strategy, productivity is expected to remain stable. 	Fermaud et al. (2016) ; Merot and Smits (2020); Leroy et al. (2013)
(3)	Change in disease control strategy → Change in productivity	A better disease control strategy limits damages and substantial yield losses. When changing a disease control strategy, yields have been observed to fall after a decrease in pesticide use before returning to the initial level.	Merot and Smits (2020)
(4)	Change in disease control strategy → Change in mechanical work intensity	Disease control strategies depend on the type of products used, the dose per treatment and the frequency of applications. <ul style="list-style-type: none"> - If the dose per treatment is decreased without changes in the type of product used, no impact on mechanical work intensity is expected; - If the frequency of applications decreases without changes in the type of product used, the number of interventions is reduced and less mechanical work is expected; - A change in the type of products used has implications on the number of interventions and consequently on the mechanical work intensity. In particular, replacing synthetic pesticides with more leachable copper-based, sulfur-based or biocontrol products increases the frequency of treatments needed, especially in oceanic and northern winegrowing regions. 	Merot et al. (2019b); Rouault et al. (2016)
(5)	Change in disease control strategy → Change in costs	A change in disease control strategy can impact costs. <ul style="list-style-type: none"> - If the dose per treatment is decreased, costs are expected to fall; - If the frequency of applications decreases without changes in the type of product used, the number of interventions is reduced and costs are expected to fall; - A change in the type of products used has implications for the number of interventions and consequently for costs. As noted in hypothesis 4, replacing synthetic products with copper, sulfur or biocontrol products whose frequency of application is more dependent on rainfall can lead to an increase in the number of treatments, especially in oceanic and northern winegrowing 	Leroy et al. (2013); Merot et al. (2019b)

16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60
61
62
63
64
65

		regions. An increase in the number of treatments increases costs (fuel consumption, mechanical costs). Biocontrol products are also more expensive than synthetic products.	
(6)	Initial weed control strategy → Change in weed control strategy	The initial weed control strategy is related to the potential of herbicide use reduction. It is easier to significantly decrease herbicide use when the initial weed control strategy is highly dependent on the use of systemic products. In fact, the available levers to reduce herbicide use are limited to three options: <ul style="list-style-type: none"> - Replacing synthetic herbicides with biocontrol herbicides; - Replacing herbicides with mechanical weeding; - Replacing herbicides with cover crops mown. The implemented strategy can combine these options for the entire the plot or in the inter-rows.	Delpuech and Metay, (2018); Fouillet et al., (2022)
(7)	Initial weed control strategy → Change in productivity	The initial weed control strategy can impact the change in productivity. In fact, considering the major changes required to reduce herbicide use – namely changes in knowledge, equipment, and management and decision rules – there is a significant risk associated with leaving weeds to grow in spring after the changes are implemented. If vineyards are farmed without water and nitrogen restrictions, yields may fall before returning to their initial levels.	Jacquet et al. (2019) Merot and Smits (2020) Ripoche et al. (2011)
(8)	Change in weed control strategy → Change in productivity	Weed control strategies limit competition and substantial yield losses. As mentioned in hypothesis 7, when implementing levers to reduce herbicide use, allowing weeds to grow in spring, a critical stage for grapevine, comes with a significant risk. Competition for nitrogen and water from weeds can cause yields to decline before they return to initial levels.	Jacquet et al. (2019); Merot et al. (2022) Delpuech & Metay (2018), Celette & Gary (2013)
(9)	Change in weed control strategy → Change in mechanical work intensity	The change in weed control strategy related to the reduction of herbicides is expected to lead to an increase in mechanical work intensity because mechanical tillage is the most common alternative for herbicide reduction.	Jacquet et al. (2019) Merot et al. (2019)
(10)	Change in weed control strategy → Change in costs	The three potential options to reduce herbicide use cited in hypothesis 7 are all more expensive to implement than relying solely on synthetic herbicides. For example, an increase in the number of interventions will be more costly than herbicide interventions since the time required for mechanical weeding is higher than applying herbicides. Reducing expenses related to synthetic herbicides does not offset the increase in costs related to mechanical work intensity.	Jacquet et al. (2019) Merot et al. (2019)
(11)	Change in mechanical work intensity → Change in costs	An increase in mechanical workload can lead to the hiring of new employees and therefore to an increase in costs.	Merot et al. (2019)

268

269 We checked the loadings, i.e. the correlation between a latent variable and its manifest variables (Vinzi et al.,
1 270 2010). We verified that the shared variance between an MV and its LVs was larger than with other blocks using
2
3
4 271 cross loadings. Finally, the cross loadings were checked to ensure that the loadings (λ) between the MVs and their
5
6 272 respective LVs were higher than their loadings with the other LVs implemented in the model.
7

8 273 *Model validation*

10
11 274 The model robustness was validated using the goodness of fit (GoF) index and a bootstrapping procedure (1000
12
13 275 times). A GoF threshold value of 0.4 was considered acceptable to verify the model (see Grace et al., 2016; Puech
14
15 276 et al., 2015; Quinio et al., 2017). The PLS-PM was performed with R software v. 3.6.2 (R Core Team, 2019) using
16
17 277 the *plspm* package (Sanchez et al., 2015).
18
19

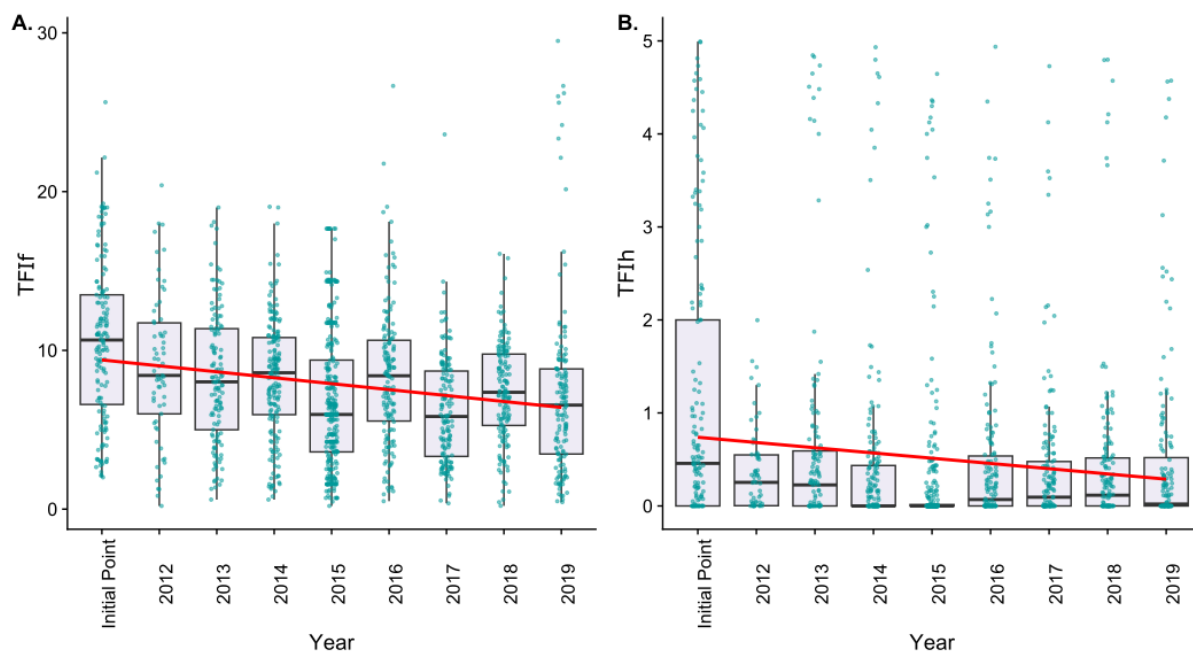
20 278 **3. Results**

22 279 *3.1. Change in environmental, economic and technical performances over the 10-year study timeframe*

24
25 280 Both fungicide and herbicide uses were significantly reduced over the 10-year study period according to the linear
26
27 281 model ($p < 0.05$, [Fig. 2, supplementary data 1](#)). Concerning fungicide use, the TFI_f decreased from 10.6 ± 4.9 to
28
29 282 7 ± 5.4 between the initial year and 2019, corresponding to a 34% mean reduction with a high inter- and intra-
30
31 283 annual variability As for herbicide use, the TFI_h decreased from 1.2 ± 1.5 to 0.5 ± 0.9 between the initial year and
32
33 284 2019, corresponding to a 58% mean reduction. In all, 27% of the cropping systems used herbicides in 2019,
34
35 285 compared to 43% at the initial point.
36
37

38 286

41 287



288

289 **Fig. 2.** Change in pesticide use over the 10 years of the study. (A.) Change in TFI_f. and (B.) change in TFI_h.

290 Outliers are not represented. Whiskers display the 5th and 95th percentiles. Horizontal bars indicate the first
 291 quartile, median and third quartile.

292 The linear model showed a significant decrease in operational costs (p value<0.01, **Fig. 3D**). The operational costs
 293 decreased from 648.2±402.7 € ha⁻¹ to 349.9±707 € ha⁻¹ between the initial year and 2019, corresponding to a 46%
 294 mean reduction.

295 No significant change in the mechanical working time, fuel consumption or tractor labour costs was observed over
 296 the study period. The mechanical working time ranged between 26.6±17.3 and 21.6±28 hour ha⁻¹ between the
 297 initial point and 2019 (Fig. 3A). The fuel consumption varied between 247±132 L ha⁻¹ and 286±288 L ha⁻¹ between
 298 the initial point and 2019 (Fig. 3B). The tractor labour cost varied between 427.2±311.8 € ha⁻¹ and
 299 347.3±445.8 € ha⁻¹ between the initial point and 2019 (Fig. 3C). The yield varied from 63.4±22.3 hL ha⁻¹ and
 300 65.7±23.9 hL ha⁻¹ (Fig. 4).

301

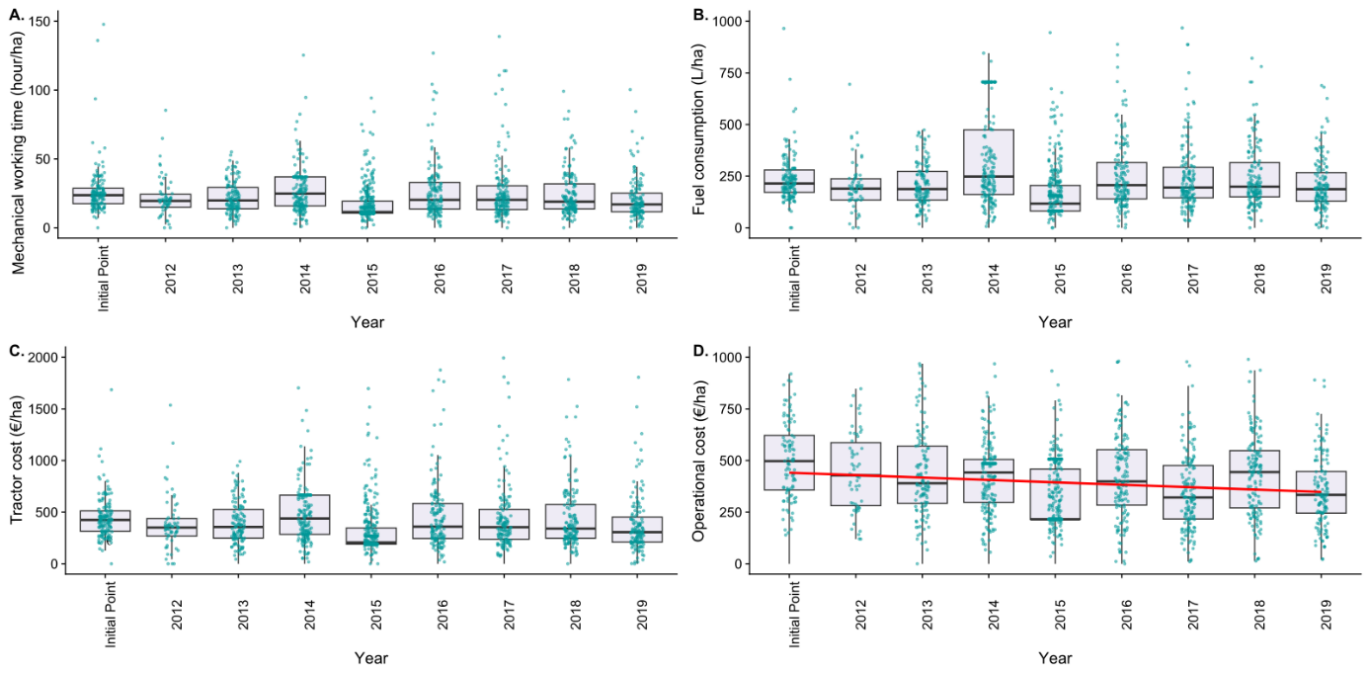


Fig. 3. Change in the economic and working time performances over the 10 years of the study. (A.) Change in mechanical working time (hour ha^{-1}). (B.) Change in the fuel consumption (L ha^{-1}). (C.) Change in the tractor labour cost (€ ha^{-1}). (D.) Change in the operational cost (€ ha^{-1}).

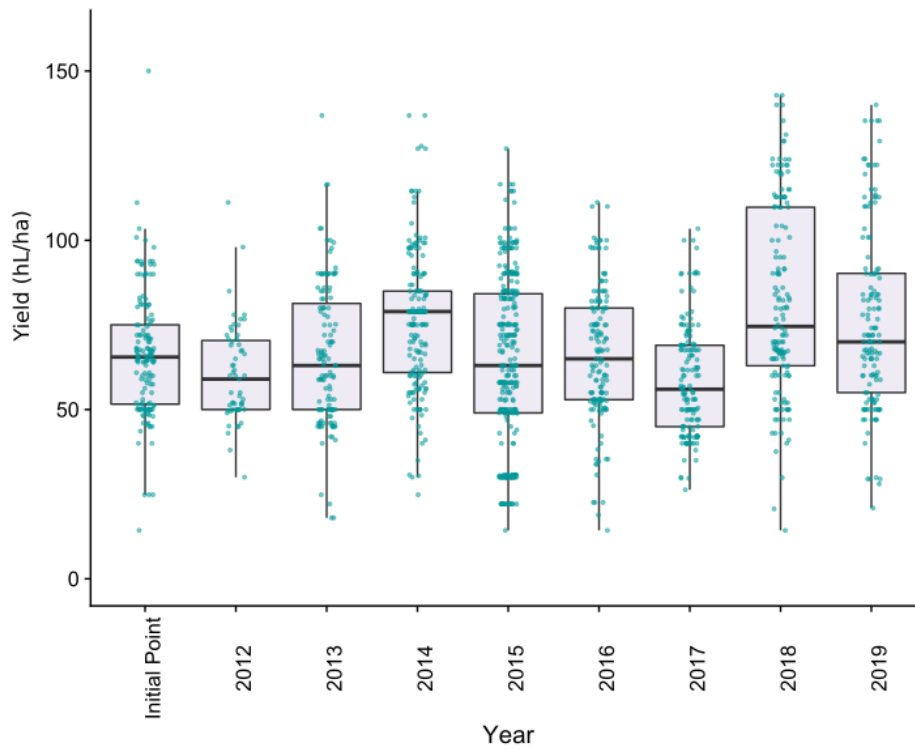


Fig. 4. Change in the yield (hL/ha) from the initial point to 2019.

3.2. Path model: covariation of environmental, economic and technical performances over the 10-year study period

The path model (Fig. 5) was verified since blocks were unidimensional and by cross-loading validation (see supplementary data2). Furthermore, the goodness of fit was acceptable (GoF = 0.44). The bootstrap procedure indicated that only 2 of the 11 path coefficients (β) were significant (Fig. 5): i) the link between initial herbicide use and the change in herbicide use and ii) the link between the change in work intensity and the change in costs.

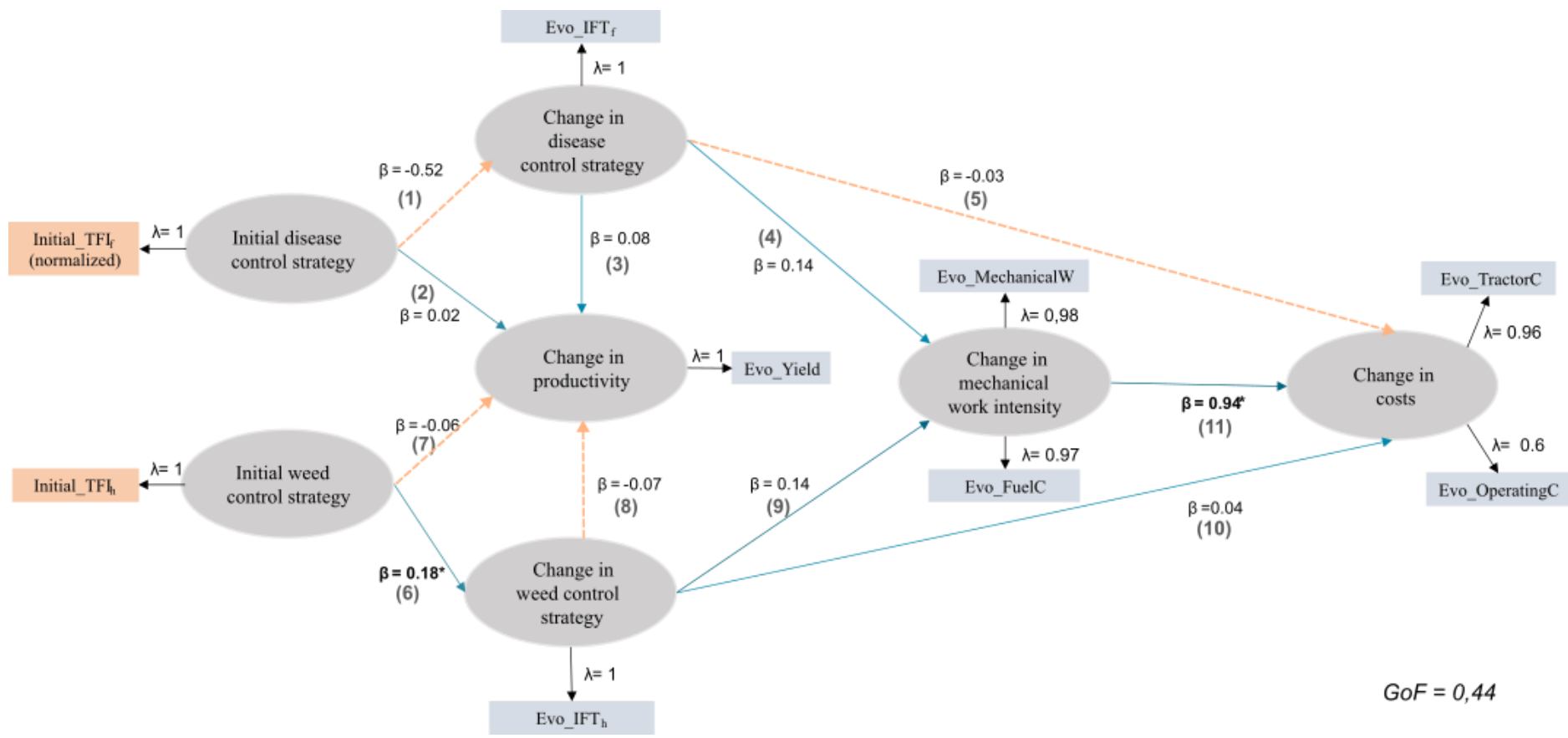
Among the variables describing plant health control strategies, we only observed a low positive effect of the initial weed control strategy on the change in weed control ($\beta = 0.18$, pvalue = 0.025). The impact of the initial disease control strategy on the change in disease strategy was negative but non-significant ($\beta = -0.52$, pvalue > 0.05). No significant impact of the weed control strategy or disease control strategy was observed on productivity. The initial weed control strategy and the change in weed control strategy had a non-significant negative impact on productivity ($\beta = -0.06$ and $\beta = -0.07$, pvalue < 0.01). Our hypothesis of a yield reduction due to a decrease in or cessation of herbicide use was not validated. The same finding was observed for the initial disease control strategy

329 and the change in disease control strategy, as the impacts of both on productivity was non-significant. Therefore,
1
2 330 our hypothesis of a yield decrease due to a fungicide reduction was not verified.
3

4 331 A strong and positive relationship between the change in work intensity and the change in the costs was observed
5
6 332 ($\beta = 0.94$, $p \text{ value} < 0.05$). Our hypothesis of a mechanical work increase due to a change in weed control strategy
7
8 333 was not validated since the correlation, although positive, was found to be non-significant ($\beta = 0.14$, $p \text{ value} > 0.05$).
9
10 334 The same finding was observed for the change in disease control strategy with regard to the change in mechanical
11
12 335 work intensity. There were non-significant correlations between the change in costs and changes in the disease
13
14 336 control strategy ($\beta = 0.04$, $p \text{ value} > 0.05$) and in the weed control strategy ($\beta = -0.03$, $p \text{ value} > 0.05$).
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60
61
62
63
64
65

16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60
61
62
63
64
65

337



338

339 **Fig. 5.** The complete path model with latent variables (LVs, grey ovals) and manifest variables (MVs, blue rectangles). Path coefficients (β) were computed from regressions; they represent the
 340 strength and direction (orange arrow, dotted line = negative; blue arrow, full line = positive) of relationships between the LVs. Loading (λ) represents the correlation between an MV and its
 341 respective LV. Asterisks indicate that the path coefficients (β) were significantly different from 0 based on 95% percentile confidence intervals calculated using 1000 bootstrap samples.
 342 Meanings of the variables are detailed in [Table 1](#) and the numbers in parentheses correspond to the model construction hypotheses described in [Table 2](#).

15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60
61
62
63
64
65

343

344 **4. Discussion**

1
2 345 **4.1. This article aimed to characterise the covariations between the performances of different vineyard**

3
4 346 **cropping systems as winegrowers were transitioning to lower pesticide use.** We used the French

5
6 347 national Agrosyst database, which provides comprehensive information over a long time period (10

7
8 348 years). We built and verified a statistical method (PLS-PM), considering the dynamic of the pesticide

9
10 349 reduction process, and showed that pesticide use reduction was not significantly related to the evolution

11
12 350 of productivity (yield), economic (operating costs and fuel consumption) and technical performances,

13
14 351 technical performance (mechanical work time). **Change in performances over time**

15
16
17 352 Analysis of the individual performances indicated that nearly all of them remained stable over the 10-year study

18
19 353 timeframe, despite a 34% decrease in TFI_f and 58% decrease in TFI_h , with only the input costs experiencing a 46%

20
21 354 decrease. All the other performances – mechanical work time, tractor labour costs, fuel consumption and yield –

22
23 355 showed no significant change over time.

24
25 356 Performances result from multiple processes. Thus, the lack of change observed here can be partly explained by

26
27 357 the context and characteristics of grapevine production systems. First, the vineyard crop management sequence

28
29 358 requires numerous manual and mechanical interventions that must be carried out every year, regardless of the

30
31 359 pesticide use strategy (e.g. pruning, harvesting). This elucidates why there is minimal variation in the proportion

32
33 360 of work time (both manual and mechanical) and operational costs across different years for each vineyard

34
35 361 recorded in the database. Even if pesticide use was reduced, harvest costs or winter pruning costs do not vary every

36
37 362 year. This regular share of performances can make it difficult to identify an impact due to pesticide reduction for

38
39 363 each individual vineyard. Second, regarding changes in yield, in most vineyards, yield is regulated by protected

40
41 364 designation of origin (PDO) and protected geographical indication (PDI) schemes (Stranieri and Tedeschi, 2019).

42
43 365 Winegrowers voluntarily control the productive potential in their vineyards during winter pruning to meet PDO

44
45 366 and PDI requirements. Lastly, a high variability between individual vineyards in the database was observed for

46
47 367 each performance each year. Part of this variability can be traced back to the regional effect and its impact on pest

48
49 368 and disease pressure, as well as to the specific features of each winegrowing region (in particular yield objectives)

50
51 369 (Fouillet et al., 2022; Mailly et al., 2017). For example, some practices, such as the type of pruning or the width

52
53 370 between the rows – just like the yield restrictions mentioned above – are imposed by the specifications of the

54
55 371 geographical indication schemes.

56
57
58
59 372 **4.2. Lowering TFI is not related to reductions in yield, costs or mechanical work**

373 **4.2.1. Changes in yield and pesticide reduction**

1
2 374 We observed that the 34% mean pesticide reduction was not related to an evolution in productivity. In particular,
3
4 375 we did not observe any impact of the fungicide reduction on yield, regardless of the initial yield when entering the
5
6 376 network. We can therefore assume that fungal diseases have been sufficiently controlled despite lower fungicide
7
8 377 use regardless of the level of initial fungicide use. This finding is a validation of a winegrower's choice to undertake
9
10 378 the transition to reduce pesticide use. Data analysis was performed at the national scale (see [supplementary data](#)
11
12 379 [3](#)). To investigate further, it could be interesting to consider local yield objectives because yields in vineyard
13
14 380 systems are highly variable at inter- and intra-region scales (Fouillet et al., 2022; Mailly et al., 2017; Merot et al.,
15
16 381 2022). With the yield objective, another indicator such as the yield achievement ratio (ratio between the reported
17
18 382 yield and the target yield, which was unavailable in the Agrosyst database; Merot et al. (2022)) could have been
19
20 383 used to explicitly integrate the production target and avoid the strong winegrowing region effect.
21
22

23 384 **4.2.2. Costs, change in work time and pesticide reduction**

24
25
26 385 Interestingly, no impact of the pesticide reduction was observed on economic (costs) or sociotechnical (work time)
27
28 386 performances. This result invalidates our hypothesis of an increase in costs due to substituting mechanical weeding
29
30 387 for herbicide inputs, such as what was observed by Jacquet et al. (2021) in vineyards. Similarly, Lechenet et al.
31
32 388 (2014, 2017), using the Agrosyst database on arable crops, showed that farmers could reduce their pesticide use
33
34 389 by an average of 42% without negatively impacting their profitability or productivity (Lechenet et al., 2017, 2014).
35
36 390 The 2017 study by Lechenet et al. was based on a single datapoint per farm (when farmers entered the network)
37
38 391 and used a regression model to assess the effect of TFI on productivity and profitability. In our study, which was
39
40 392 based on a longer time scale (10 years), we integrated the slope as an evolution of indicators. Indeed, since pesticide
41
42 393 use is mainly reduced due to gains in efficiency (e.g. dose reduction) and substitution (e.g. use of biocontrol
43
44 394 products) (Aulagnier and Goulet, 2017; Fouillet et al., 2022), it does not involve any change in equipment or
45
46 395 number of operations (Román et al., 2022). Studies showed that only a few farmers redesigned their farming
47
48 396 systems within the DEPHY network (Aulagnier and Goulet, 2017), therefore avoiding levers such as preventive
49
50 397 treatments, or even the more involved process of converting to organic farming, both of which are known to
51
52 398 significantly impact the way the vineyard is managed (increase in work time and changes in equipment, etc.).
53
54
55 399 Moreover, some technical operations that are expensive in terms of costs and work time, such as pruning or
56
57 400 harvesting, are not affected by reduced pesticide use and can mask the impact of other changes in practices (e.g.
58
59 401 change from herbicide use to mechanical weeding) (Strub et al., 2021). In their study on the impact of conversion
60
61
62
63
64
65

402 to organic farming in terms of the technical and economic performances of vineyard systems, Merot et al. (2019)
1
2 403 separated grape-growing and harvesting costs because switching from mechanical to manual harvesting (or vice
3
4 404 versa) significantly impacts production costs. Analysing grape-growing and harvesting costs separately would
5
6 405 make it possible to better identify the impact of technical changes when reducing pesticide use.
7

8
9 406 The economic performance was assessed using production cost while most studies assess economic performance
10
11 407 through net or gross margins (Delord et al., 2015). Net margin is calculated as total fixed revenue minus input
12
13 408 costs, mechanisation costs and labour costs (Aouadi et al., 2019). In the Agrosyst database, economic data such as
14
15 409 gross and net margins were not available for vineyard systems. . We used other economic indicators and integrated
16
17 410 more social indicators by considering the work involved (mechanical and manual work time) (Sgroi and
18
19 411 Sciancalepore, 2022). Furthermore, total revenues in viticulture systems are highly variable due to the diversity of
20
21 412 marketing strategies and the high yield variability on a spatial and temporal scale (Aouadi et al., 2019)..
22

23 413 **4.3. Methodology used to study the covariation between performances**

24 414 **4.3.1. *Characterising temporal variations of practices and performances***

25
26
27
28 415 The Agrosyst database provided a large quantity of information on vineyards and their economic, sociotechnical
29
30 416 and economic performances over 10 years at the French national scale. Change can be seen as a multistep process
31
32 417 that includes periods of learning and experimentation (Catalogna, 2018; Chantre and Cardona, 2014), and studying
33
34 418 the dynamics of these changes is necessary to take into account the fact that farmers implement and adapt their
35
36 419 practices over a long time. Yet, there are still methodological issues to address when assessing these cropping
37
38 420 system performances to integrate their dynamics. In this study, we adapted the PLS-PM method by integrating
39
40 421 dynamic indicators to characterise the change in performances. The dynamic was considered by extracting slopes
41
42 422 from linear models. The small number of methods integrating dynamics with mathematical indicators raises the
43
44 423 question of how to consider temporal evolutions. We chose to describe the evolution by integrating the slope and
45
46 424 the initial point in the PLS-PM model. Dardonville et al. (2022) describe the dynamics of agricultural performances
47
48 425 with four different criteria over 8 years: the level of performance calculated with the mean, the stability or
49
50 426 variability calculated with the standard deviation or the coefficient of variation, the trend calculated with the slope
51
52 427 coefficient of a mixed linear regression; and finally, the resistance calculated by subtracting the average
53
54 428 performance before and after the break (high and rapid evolution).
55
56

57 429 **4.3.2. *Possible sensitivity indicator to pesticide reduction***

58
59
60
61
62
63
64
65

430 In our model, the environmental impact of pesticide use was assessed using the TFI, which is the main indicator
1
2 431 used within the French ECOPHYTO plan to assess pesticide use in farming systems (Guichard et al., 2017).
3
4 432 Pesticide use can also be assessed with other indicators such as the number of unit doses (NUD) or the quantity of
5
6 433 active ingredients (QAI). More recent indicators include the toxicity risk indicator (IRT, Mghirbi et al., 2015) or
7
8 434 the pesticide load (Kudsk et al., 2018), which both take into account the ecotoxicity of the sprayed products. All
9
10 435 of the above indicators, including TFI, can highlight changes in plant protection strategies. However, none of these
11
12 436 indicators can assess the changes in practices that lead to this reduction, such as prophylactic measures or cover
13
14 437 crops (Jacquet et al., 2022) or change in spraying equipment (Michael et al., 2021).

15
16 438 We assumed that a model that takes into account finer variables (e.g. risk to the operator depending on product
17
18 439 toxicity, working conditions and safety issues) could identify potential trade-offs, especially in terms of health,
19
20 440 labour and costs. Delecourt et al. (2019) and Duval et al. (2021) highlighted a change in work organization during
21
22 441 agroecological transitions, in terms of working time and human resources (workforce and skills), work
23
24 442 organisation (competition between activities at the farming system scale) and work safety. Overall, indicators of
25
26 443 working conditions, such as greater meaningfulness of the work performed (Duval et al., 2021) or the satisfaction
27
28 444 of livestock farmers (Perrin and Martin, 2021), improved when farms were converting to organic farming. These
29
30 445 findings on work-related variables highlight the need to better account for socio-economic indicators such as net
31
32 446 margin or number of workers. Yet, such socio-economic data are difficult to obtain from existing databases, and
33
34 447 acquiring it requires in-depth surveys

35
36
37 448 Furthermore, the implementation of new practices depends on the farmer's attitude towards and perception of risk
38
39 449 (e.g. yield loss acceptability). Bonke et al. (2021) showed that some farmers were willing to accept potential yield
40
41 450 losses and forego profits by diversifying their crops depending on the farm's economic strategy. One of the
42
43 451 limitations of big data analysis is gaining access to these more specific variables as used in multi-criteria evaluation
44
45 452 that are not available in the AGROSYST database. For example, DEPXiPM-grapevine (Gary et al., 2015) is a
46
47 453 multi-criteria model for assessing the sustainability of vineyard systems. The description of environmental
48
49 454 durability is exhaustive and the socio-economic evaluation is based on expert knowledge.

50 455 **Conclusion**

51
52 456 This study aimed to characterise the covariation between the different performances of vineyard cropping systems,
53
54
55 457 involved in a pesticide reduction process over 10 years. The study focused on vineyard, a perennial crop with a
56
57 458 high change inertia. First, the evolution of pesticides use (fungicide and herbicide), economic and technical
58
59
60
61
62
63
64
65

459 performances were characterized. Over the ten years, a reduction of pesticide (fungicide and herbicide) and
1 operational cost was observed while the other performances remained stable. e built and verified a model to study
2 460 the correlations between performances and changes in practices, which is necessary when studying change
3
4 461 processes. We did not identify any relation between initial pesticide use (fungicide and herbicide) on agronomic
5
6 462 and sociotechnical performances.
7
8 463

9
10 464 The DEPHY network seems to offer relevant support to help winegrowers reduce their pesticide use given that no
11
12 465 covariation between performances was observed during the pesticide reduction process. The observed reduction
13
14 466 in TFI had no impact on changes in yield nor work intensity or costs. We suggest that a similar model should be
15
16 467 adapted for the vineyard cropping system with indicators to give greater weight to socio-economic indicators, such
17
18 468 as work organisation or farmers' objectives and satisfaction during the pesticide reduction process, all of these
19
20 469 being key elements of a successful transition to low-input systems.
21
22

23 470 **Acknowledgements**

24
25
26 471 We would like to thank the winegrowers and farm advisors from the DEPHY network. This research is part of a
27
28 472 PhD project funded by the Région Occitanie (France) and ECOPHYTO Plan (ARPHY - OFB N° 4147). The
29
30 473 authors acknowledge the support of the French National Research Agency (ANR) under the grant 20-PCPA-0010
31
32 474 (VITAE). The authors also thank Teri Jones-Villeneuve for the English language review. We are very grateful to
33
34 475 two reviewers whose comments contributed to improve the quality of the initial manuscript.
35
36

37 476

38 477 **References**

- 39
40 478 Agreste, 2020. Pratiques culturales en grandes cultures 2017.
41
42 479 Aouadi, N., Macary, F., Ugaglia, A.A., 2019. Evaluation des performances socio-
43 480 économiques et environnementales de systèmes viticoles en bordelais par une méthode
44 481 multicritère d'aide à la décision, in: Journées de recherches en sciences sociales.
45 482 Presented at the Journées de recherches en sciences sociales, Bordeaux, France.
46 483 Aulagnier, A., Goulet, F., 2017. Des technologies controversées et de leurs alternatives. Le
47 484 cas des pesticides agricoles en France. *Sociol. Trav.* 59.
48 485 <https://doi.org/10.4000/sdt.840>
49 486 Bates, D., Mächler, M., Bolker, B., Walker, S., 2015. Fitting Linear Mixed-Effects Models
50 487 Using lme4. *J. Stat. Softw.* 67, 1–48. <https://doi.org/10.18637/jss.v067.i01>.
51 488 Baxter, R., 2009. Reflective and formative metrics of relationship value: A commentary
52 489 essay. *J. Bus. Res.* 62, 1370–1377. <https://doi.org/10.1016/j.jbusres.2008.12.004>
53 490 Bonke, V., Michels, M., Musshoff, O., 2021. Will Farmers Accept Lower Gross Margins for
54 491 the Sustainable Cultivation Method of Mixed Cropping? First Insights from Germany.
55 492 *Sustainability* 13, 1631. <https://doi.org/10.3390/su13041631>
56
57
58
59
60
61
62
63
64
65

- 493 Catalogna, M., 2018. Expérimentations de pratiques agroécologiques réalisées par des
1 494 agriculteurs: proposition d'un cadre d'analyse à partir du cas des grandes cultures et
2 495 du maraîchage diversifié dans le département de la Drôme. Université d'Avignon.
- 3 496 Celette, F., Gary, C., 2013. Dynamics of water and nitrogen stress along the grapevine cycle
4 497 as affected by cover cropping. *Eur. J. Agron.* 45, 142–152.
5 498 <https://doi.org/10.1016/j.eja.2012.10.001>
- 6 499 Chantre, E., Cardona, A., 2014. Trajectories of French Field Crop Farmers Moving Toward
7 500 Sustainable Farming Practices: Change, Learning, and Links with the Advisory
8 501 Services. *Agroecol. Sustain. Food Syst.* 38, 573–602.
9 502 <https://doi.org/10.1080/21683565.2013.876483>
- 10 503 Dardonville, M., Bockstaller, C., Therond, O., 2021. Review of quantitative evaluations of the
11 504 resilience, vulnerability, robustness and adaptive capacity of temperate agricultural
12 505 systems. *J. Clean. Prod.* 125456. <https://doi.org/10.1016/j.jclepro.2020.125456>
- 13 506 Dardonville, M., Bockstaller, C., Villerd, J., Therond, O., 2022. Resilience of agricultural
14 507 systems: biodiversity-based systems are stable, while intensified ones are resistant and
15 508 high-yielding. *Agric. Syst.* 197, 103365. <https://doi.org/10.1016/j.agry.2022.103365>
- 16 509 Delecourt, E., Joannon, A., Meynard, J.-M., 2019. Work-related information needed by
17 510 farmers for changing to sustainable cropping practices. *Agron. Sustain. Dev.* 39, 28.
18 511 <https://doi.org/10.1007/s13593-019-0571-5>
- 19 512 Delord, B., Montaigne, É., Coelho, A., 2015. Vine planting rights, farm size and economic
20 513 performance: Do economies of scale matter in the French viticulture sector? *Wine*
21 514 *Econ. Policy* 4, 22–34. <https://doi.org/10.1016/j.wep.2015.03.001>
- 22 515 Delpuech, X., Metay, A., 2018. Adapting cover crop soil coverage to soil depth to limit
23 516 competition for water in a Mediterranean vineyard. *Eur. J. Agron.* 97, 60–69.
24 517 <https://doi.org/10.1016/j.eja.2018.04.013>
- 25 518 Duval, J.E., Blanchonnet, A., Hostiou, N., 2021. How agroecological farming practices
26 519 reshape cattle farmers' working conditions. *Agroecol. Sustain. Food Syst.* 45, 1480–
27 520 1499. <https://doi.org/10.1080/21683565.2021.1957062>
- 28 521 Fermaud, M., Smits, N., Merot, A., Roudet, J., Thiéry, D., Wery, J., Delbac, L., 2016. New
29 522 multipest damage indicator to assess protection strategies in grapevine cropping
30 523 systems: An indicator of multipest damage in grapevine. *Aust. J. Grape Wine Res.* 22,
31 524 450–461. <https://doi.org/10.1111/ajgw.12238>
- 32 525 Fouillet, E., Delière, L., Chartier, N., Munier-Jolain, N., Cortel, S., Rapidel, B., Merot, A.,
33 526 2022. Reducing pesticide use in vineyards. Evidence from the analysis of the French
34 527 DEPHY network. *Eur. J. Agron.* 136, 126503.
35 528 <https://doi.org/10.1016/j.eja.2022.126503>
- 36 529 Fouillet, E., Delière, L., Flori, A., Rapidel, B., Merot, A., 2023. Diversity of pesticide use
37 530 trajectories during agroecological transitions in vineyards: The case of the French
38 531 DEPHY network. *Agric. Syst.* 210, 103725.
39 532 <https://doi.org/10.1016/j.agry.2023.103725>
- 40 533 Gary, C., Dubuc, M., Metral, R., Fortino, G., 2015. DEXiPM Grapevine® (version 1.0), a tool
41 534 for analysing the sustainability of grapevine cropping systems. DEXiPM Grapevine®
42 535 data input manual.
- 43 536 Grace, J.B., Anderson, T.M., Seabloom, E.W., Borer, E.T., Adler, P.B., Harpole, W.S.,
44 537 Hautier, Y., Hillebrand, H., Lind, E.M., Pärtel, M., Bakker, J.D., Buckley, Y.M.,
45 538 Crawley, M.J., Damschen, E.I., Davies, K.F., Fay, P.A., Firn, J., Gruner, D.S., Hector,
46 539 A., Knops, J.M.H., MacDougall, A.S., Melbourne, B.A., Morgan, J.W., Orrock, J.L.,
47 540 Prober, S.M., Smith, M.D., 2016. Integrative modelling reveals mechanisms linking
48 541 productivity and plant species richness. *Nature* 529, 390–393.
49 542 <https://doi.org/10.1038/nature16524>
- 50
51
52
53
54
55
56
57
58
59
60
61
62
63
64
65

- 543 Guichard, L., Dedieu, F., Jeuffroy, M.-H., Meynard, J.-M., Reau, R., Savini, I., 2017. Le plan
1 544 Ecophyto de réduction d'usage des pesticides en France : décryptage d'un échec et
2 545 raisons d'espérer. *Cah. Agric.* 26, 14002. <https://doi.org/10.1051/cagri/2017004>
- 3 546 Hill, S.B., MacRae, R.J., 1996. Conceptual Framework for the Transition from Conventional
4 547 to Sustainable Agriculture. *J. Sustain. Agric.* 7, 81–87.
5 548 https://doi.org/10.1300/J064v07n01_07
- 6 549 Hodbod, J., Barreteau, O., Allen, C., Magda, D., 2016. Managing adaptively for
7 550 multifunctionality in agricultural systems. *J. Environ. Manage.* 183, 379–388.
8 551 <https://doi.org/10.1016/j.jenvman.2016.05.064>
- 9 552 Jacquet, F., Delame, N., Vita, J.L., Huyghe, C., Reboud, X., 2021. The micro-economic
10 553 impacts of a ban on glyphosate and its replacement with mechanical weeding in
11 554 French vineyards. *Crop Prot.* 150, 105778.
12 555 <https://doi.org/10.1016/j.cropro.2021.105778>
- 13 556 Jacquet, F., Delame, N., Vita, J.L., Reboud, X., Huyghe, C., 2019. Alternatives au glyphosate
14 557 en viticulture. Evaluation économique des pratiques de désherbage (Expertise).
15 558 INRAE.
- 16 559 Jacquet, F., Jeuffroy, M.-H., Jouan, J., Le Cadre, E., Litrico, I., Malausa, T., Reboud, X.,
17 560 Huyghe, C., 2022. Pesticide-free agriculture as a new paradigm for research. *Agron.*
18 561 *Sustain. Dev.* 42, 8. <https://doi.org/10.1007/s13593-021-00742-8>
- 19 562 Jeuffroy, M.-H., Ballot, R., Mérot, A., Meynard, J.M., Simon, S., 2022. Des systèmes de
20 563 culture agroécologiques pour diminuer l'usage des pesticides. Chapitre 3., in: *Zéro*
21 564 *Pesticide : Un Nouveau Paradigme de Recherche Pour Une Agriculture Durable*,
22 565 *Synthèses*. Edition Quae, Versailles Cedex.
- 23 566 Klapwijk, C., van Wijk, M., Rosenstock, T., van Asten, P., Thornton, P., Giller, K., 2014.
24 567 Analysis of trade-offs in agricultural systems: current status and way forward. *Curr.*
25 568 *Opin. Environ. Sustain.* 6, 110–115. <https://doi.org/10.1016/j.cosust.2013.11.012>
- 26 569 Kudsk, P., Jørgensen, L.N., Ørum, J.E., 2018. Pesticide Load—A new Danish pesticide risk
27 570 indicator with multiple applications. *Land Use Policy* 70, 384–393.
28 571 <https://doi.org/10.1016/j.landusepol.2017.11.010>
- 29 572 Lechenet, M., Bretagnolle, V., Bockstaller, C., Boissinot, F., Petit, M.-S., Petit, S., Munier-
30 573 Jolain, N.M., 2014. Reconciling Pesticide Reduction with Economic and
31 574 Environmental Sustainability in Arable Farming. *PLoS ONE* 9, e97922.
32 575 <https://doi.org/10.1371/journal.pone.0097922>
- 33 576 Lechenet, M., Dessaint, F., Py, G., Makowski, D., Munier-Jolain, N., 2017. Reducing
34 577 pesticide use while preserving crop productivity and profitability on arable farms. *Nat.*
35 578 *Plants* 3, 17008. <https://doi.org/10.1038/nplants.2017.8>
- 36 579 Leroy, P., Smits, N., Cartolaro, P., Delière, L., Goutouly, J.-P., Raynal, M., Alonso Ugaglia,
37 580 A., 2013. A bioeconomic model of downy mildew damage on grapevine for evaluation
38 581 of control strategies. *Crop Prot.* 53, 58–71.
39 582 <https://doi.org/10.1016/j.cropro.2013.05.024>
- 40 583 Mailly, F., Hossard, L., Barbier, J.-M., Thiollet-Scholtus, M., Gary, C., 2017. Quantifying the
41 584 impact of crop protection practices on pesticide use in wine-growing systems. *Eur. J.*
42 585 *Agron.* 84, 23–34. <https://doi.org/10.1016/j.eja.2016.12.005>
- 43 586 Martin, G., Magne, M.-A., Cristobal, M.S., 2017. An Integrated Method to Analyze Farm
44 587 Vulnerability to Climatic and Economic Variability According to Farm Configurations
45 588 and Farmers' Adaptations. *Front. Plant Sci.* 8, 1483.
46 589 <https://doi.org/10.3389/fpls.2017.01483>
- 47 590 Merot, A., Alonso Ugaglia, A., Barbier, J.-M., Del'homme, B., 2019a. Diversity of
48 591 conversion strategies for organic vineyards. *Agron. Sustain. Dev.* 39, 16.
49 592 <https://doi.org/10.1007/s13593-019-0560-8>
- 50
51
52
53
54
55
56
57
58
59
60
61
62
63
64
65

- 593 Merot, A., Alonso Ugaglia, A., Barbier, J.-M., Del'homme, B., 2019b. Diversity of
1 594 conversion strategies for organic vineyards. *Agron. Sustain. Dev.* 39, 16.
2 595 <https://doi.org/10.1007/s13593-019-0560-8>
- 3 596 Merot, A., Metay, A., Smits, N., Thiollet-Scholtus, M., 2022. Adaptation of the regional
4 597 agronomic diagnosis for grapevine yield analysis. *OENO One* 56, 87–99.
5 598 <https://doi.org/10.20870/oeno-one.2022.56.1.4568>
- 7 599 Merot, A., Smits, N., 2020. Does Conversion to Organic Farming Impact Vineyards Yield? A
8 600 Diachronic Study in Southeastern France. *Agronomy* 10, 1626.
9 601 <https://doi.org/10.3390/agronomy10111626>
- 11 602 Merot, A., Wery, J., 2017. Converting to organic viticulture increases cropping system
12 603 structure and management complexity. *Agron. Sustain. Dev.* 37, 19.
13 604 <https://doi.org/10.1007/s13593-017-0427-9>
- 14 605 Métral, R., Chevrier, C., Bals, N., Bouisson, Y., Didier, V., Enard, C., Fremond, N., Garin, P.,
15 606 Gauthier, T., Genevet, B., Goma-Fortin, N., Guillios, F., Ohl, B., Thierry, J., 2018.
16 607 DEPHY EXPE EcoViti Arc Méditerranéen : synthèse des résultats 2012-2017. *Innov.*
17 608 *Agron.* 3–20.
- 19 609 Meynard, J.-M., Dedieu, Benoit, Bos, A.P., 2012. Re-design and co-design of farming
20 610 systems. An overview of methods and practices, in: Darnhofer, I., Gibbon, D., Dedieu,
21 611 Benoît (Eds.), *Farming Systems Research into the 21st Century: The New Dynamic.*
22 612 Springer Netherlands, Dordrecht, pp. 405–429. [https://doi.org/10.1007/978-94-007-](https://doi.org/10.1007/978-94-007-4503-2_18)
23 613 [4503-2_18](https://doi.org/10.1007/978-94-007-4503-2_18)
- 25 614 Mghirbi, O., Kamel, E., Philippe, L.G., Elisabeth, M., Jacques, F., Habiba, A., Jean-Paul, B.,
26 615 2015. Assessing plant protection practices using pressure indicator and toxicity risk
27 616 indicators: analysis of the relationship between these indicators for improved risk
28 617 management, application in viticulture. *Environ. Sci. Pollut. Res.* 22, 8058–8074.
29 618 <https://doi.org/10.1007/s11356-014-3736-4>
- 31 619 Michael, C., Gil, E., Gallart, M., Stavrinides, M.C., 2021. Evaluation of the Effects of Spray
32 620 Technology and Volume Rate on the Control of Grape Berry Moth in Mountain
33 621 Viticulture. *Agriculture* 11, 178. <https://doi.org/10.3390/agriculture11020178>
- 35 622 Perrin, A., Martin, G., 2021. Driving factors behind subjective resilience on organic dairy
36 623 sheep farms. *Ecol. Soc.* 26, art13. <https://doi.org/10.5751/ES-12583-260313>
- 37 624 Pingault, N., Pleyber, É., Champeaux, C., Guichard, L., Omon, B., 2008. Produits
38 625 phytosanitaires et protection intégrée des cultures : l'indicateur de fréquence de
39 626 traitement (IFT). *Notes et études socio-économiques* 61–94.
- 41 627 Puech, C., Poggi, S., Baudry, J., Aviron, S., 2015. Do farming practices affect natural enemies
42 628 at the landscape scale? *Landsc. Ecol.* 16.
- 43 629 Quinio, M., De Waele, M., Dessaint, F., Biju-Duval, L., Buthiot, M., Cadet, E., Bybee-Finley,
44 630 A.K., Guillemain, J.-P., Cordeau, S., 2017. Separating the confounding effects of
45 631 farming practices on weeds and winter wheat production using path modelling. *Eur. J.*
46 632 *Agron.* 82, 134–143. <https://doi.org/10.1016/j.eja.2016.10.011>
- 48 633 R Core Team, 2019. R: A language and environment for statistical computing. R Foundation
49 634 for Statistical Computing, Vienna, Austria.
- 51 635 Repar, N., Jan, P., Dux, D., Nemecek, T., Doluschitz, R., 2017. Implementing farm-level
52 636 environmental sustainability in environmental performance indicators: A combined
53 637 global-local approach. *J. Clean. Prod.* 140, 692–704.
54 638 <https://doi.org/10.1016/j.jclepro.2016.07.022>
- 56 639 Ripoché, A., Rellier, J.-P., Martin-Clouaire, R., Paré, N., Biarnès, A., Gary, C., 2011.
57 640 Modelling adaptive management of intercropping in vineyards to satisfy agronomic
58 641 and environmental performances under Mediterranean climate. *Environ. Model.*
59 642 *Softw.* 26, 1467–1480. <https://doi.org/10.1016/j.envsoft.2011.08.003>

- 643 Román, C., Peris, M., Esteve, J., Tejerina, M., Cambray, J., Vilardell, P., Planas, S., 2022.
 1 644 Pesticide dose adjustment in fruit and grapevine orchards by DOSA3D: Fundamentals
 2 645 of the system and on-farm validation. *Sci. Total Environ.* 808, 152158.
 3 646 <https://doi.org/10.1016/j.scitotenv.2021.152158>
 4 647 Ross, A.M., Rhodes, D.H., Hastings, D.E., 2008. Defining changeability: Reconciling
 5 648 flexibility, adaptability, scalability, modifiability, and robustness for maintaining
 6 649 system lifecycle value. *Syst. Eng.* 11, 246–262. <https://doi.org/10.1002/sys.20098>
 7 650 Rouault, A., Beauchet, S., Renaud-Gentie, C., Jourjon, F., 2016. Life Cycle Assessment of
 8 651 viticultural technical management routes (TMRs): comparison between an organic and
 9 652 an integrated management route. *OENO One* 50. [https://doi.org/10.20870/oeno-](https://doi.org/10.20870/oeno-one.2016.50.2.783)
 10 653 [one.2016.50.2.783](https://doi.org/10.20870/oeno-one.2016.50.2.783)
 11 654 Sanchez, G., 2013. PLS path modeling with R. Trowchez Editions, Berkeley.
 12 655 Sanchez, G., Trinchera, L., Russolillo, G., 2015. plspm: Tools for Partial Least Squares Path
 13 656 Modeling (PLS-PM). R package version 0.4.9. <https://github.com/gastonstat/plspm>.
 14 657 Sgroi, F., Sciancalepore, V.D., 2022. Climate change and risk management policies in
 15 658 viticulture. *J. Agric. Food Res.* 10, 100363. <https://doi.org/10.1016/j.jafr.2022.100363>
 16 659 Simonovici, M., 2019. Enquête Pratiques phytosanitaires en viticulture en 2016. Nombre de
 17 660 traitements et indicateurs de fréquence de traitement. ECOPHYTO - Ministère de la
 18 661 transition écologique et solidaire.
 19 662 Simonovici, M., Caray, J., 2021. Enquête Pratiques culturelles en viticulture en 2019 - IFT et
 20 663 nombre de traitements, Chiffres & Données. ECOPHYTO - Ministère de la transition
 21 664 écologique.
 22 665 Soulé, E., Michonneau, P., Michel, N., Bockstaller, C., 2021. Environmental sustainability
 23 666 assessment in agricultural systems: A conceptual and methodological review. *J. Clean.*
 24 667 *Prod.* 325, 129291. <https://doi.org/10.1016/j.jclepro.2021.129291>
 25 668 Stranieri, S., Tedeschi, P., 2019. The Role of Quality in Wine Production and Market:
 26 669 European Rules, CAP and New Technology, in: Conca Messina, S.A., Le Bras, S.,
 27 670 Tedeschi, P., Vaquero Piñeiro, M. (Eds.), *A History of Wine in Europe, 19th to 20th*
 28 671 *Centuries, Volume II, Palgrave Studies in Economic History.* Springer International
 29 672 Publishing, Cham, pp. 255–274. https://doi.org/10.1007/978-3-030-27794-9_11
 30 673 Strub, L., Kurth, A., Loose, S.M., 2021. Effects of Viticultural Mechanization on Working
 31 674 Time Requirements and Production Costs. *Am. J. Enol. Vitic.* 72, 46–55.
 32 675 <https://doi.org/10.5344/ajev.2020.20027>
 33 676 Tenenhaus, M., Vinzi, V.E., Chatelin, Y.-M., Lauro, C., 2005. PLS path modeling. *Comput.*
 34 677 *Stat. Data Anal.* 48, 159–205. <https://doi.org/10.1016/j.csda.2004.03.005>
 35 678 Thiollet-Scholtus, M., Muller, A., Abidon, C., Audema, P., Bailly, C., Chaumonnot, S.,
 36 679 Grignon, J., Keichinger, O., Klein, C., Langenfeld, A., Ley, L., Lemarquis, G., Nassr,
 37 680 N., Nibaudeau, R., Rabolin-Meinrad, C., Ribeiro, S., Schneider, C., Weissbart, J.,
 38 681 2019. Performances multicritères de systèmes viticoles à réduction drastique d'intrants
 39 682 dans le vignoble alsacien (PEPSVI). *Innov. Agron.* 76 (1), 219–236.
 40 683 Urruty, N., Deveaud, T., Guyomard, H., Boiffin, J., 2016. Impacts of agricultural land use
 41 684 changes on pesticide use in French agriculture. *Eur. J. Agron.* 80, 113–123.
 42 685 <https://doi.org/10.1016/j.eja.2016.07.004>
 43 686 Vinzi, V.E., Trinchera, L., Amato, S., 2010. PLS Path Modeling: From Foundations to Recent
 44 687 Developments and Open Issues for Model Assessment and Improvement, in: Esposito
 45 688 Vinzi, V., Chin, W.W., Henseler, J., Wang, H. (Eds.), *Handbook of Partial Least*
 46 689 *Squares.* Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 47–82.
 47 690 https://doi.org/10.1007/978-3-540-32827-8_3
 48 691