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

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

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8

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 (β = 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

29

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

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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

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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

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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

139

140 *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.

145   - *<u>Disease and weed control strategy at field scale</u>*

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).

151
$$TFI = \sum_P \frac{\text{Dose\_sprayed}_p}{\text{Dose\_recommended}_p} \times \frac{\text{Area\_sprayed}_P}{\text{Area\_total}_P}$$

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 Agroequipement 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   mod1= lmer(X ~ Year * Winegrowing Region + (1+Year | 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

203   variables corresponding to the initial point values were named *Ini_<variable name>*. We calculated 9 variables in

204   all to depict the performance dynamics (see **Table 1**).
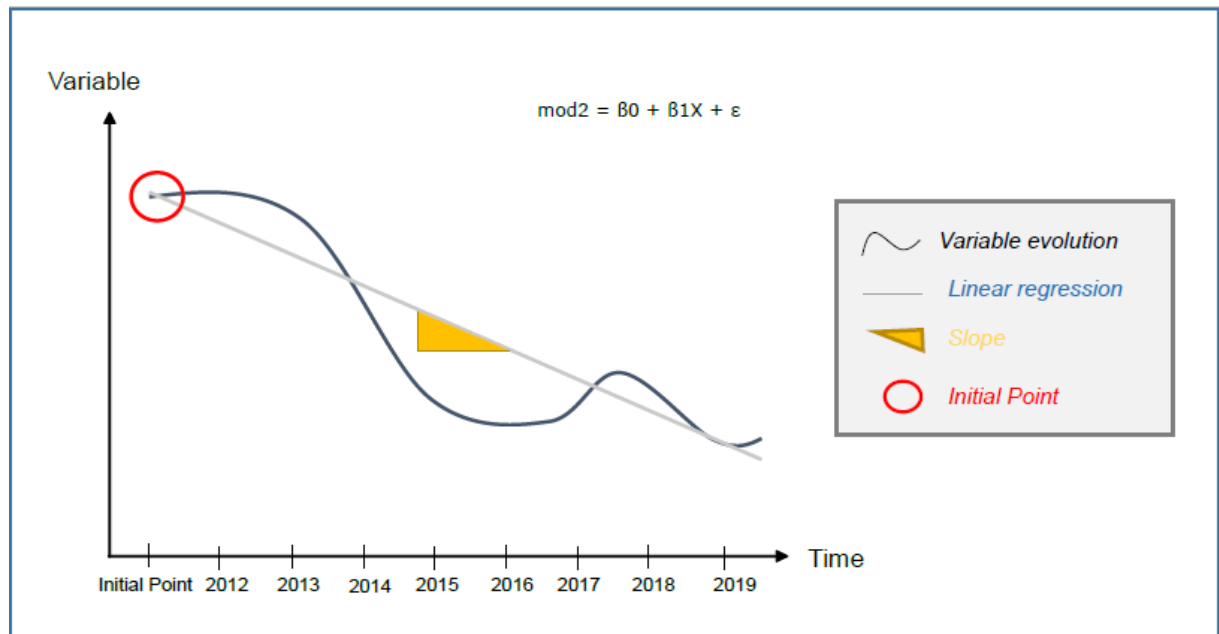
205

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, β1 the estimated slope, β0 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.

8

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.

Model construction

225

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*

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

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	Ø
Initial weed control strategy	Ini_TFI$_h$	TFI$_H$ at the initial point of the TFI$_h$	Ø
Change in disease control strategy	Evo_TFI$_h$	Extracted slope of the TFI$_f$ from Initial Point to 2019.	Ø
Change in weed control strategy	Evo_TFI$_h$	Extracted slope of the TFI$_h$ from Initial Point to 2019.	Ø
Change in productivity	Evo_Yield	Extracted slope of the yield from Initial Point to 2019.	hL ha^{-1}
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}
Change in costs	Evo_TractorCost	Extracted slope of the change in tractor labour cost from Initial Point to 2019.	€ ha^{-1}
	Evo_OperatingCost	Extracted slope of the change in operating cost from Initial Point to 2019.	€ ha^{-1}

266

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

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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: - 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. - 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. - 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)

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		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: - 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)

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13

269 We checked the loadings, i.e. the correlation between a latent variable and its manifest variables (Vinzi et al.,

270 2010). We verified that the shared variance between an MV and its LVs was larger than with other blocks using

271 cross loadings. Finally, the cross loadings were checked to ensure that the loadings (λ) between the MVs and their

272 respective LVs were higher than their loadings with the other LVs implemented in the model.

273 *Model validation*

274 The model robustness was validated using the goodness of fit (GoF) index and a bootstrapping procedure (1000

275 times). A GoF threshold value of 0.4 was considered acceptable to verify the model (see Grace et al., 2016; Puech

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

277 the *plspm* package (Sanchez et al., 2015).

3. Results

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

280 Both fungicide and herbicide uses were significantly reduced over the 10-year study period according to the linear

281 model (p<0.05, **Fig. 2, supplementary data 1**). Concerning fungicide use, the TFI_f decreased from 10.6±4.9 to

282 7±5.4 between the initial year and 2019, corresponding to a 34% mean reduction with a high inter- and intra-

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

284 2019, corresponding to a 58% mean reduction. In all, 27% of the cropping systems used herbicides in 2019,

285 compared to 43% at the initial point.

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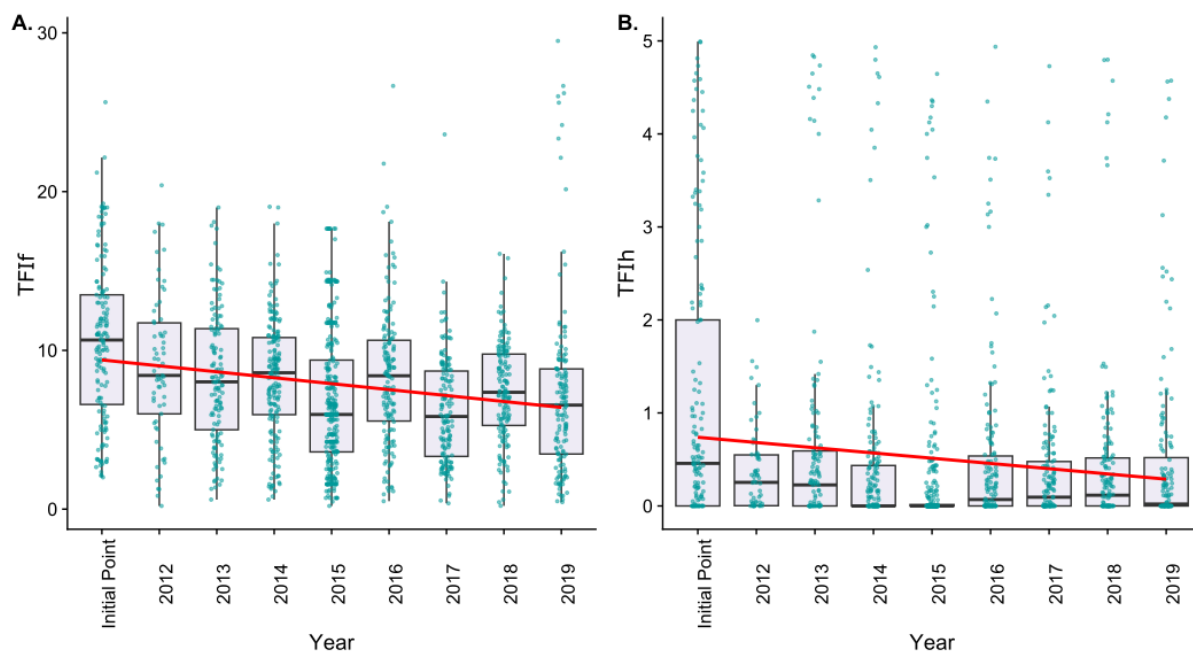
289 **Fig. 2.** Change in pesticide use over the 10 years of the study. (A.) Change in TFI_f. and (B.) change in TFI_h.

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).

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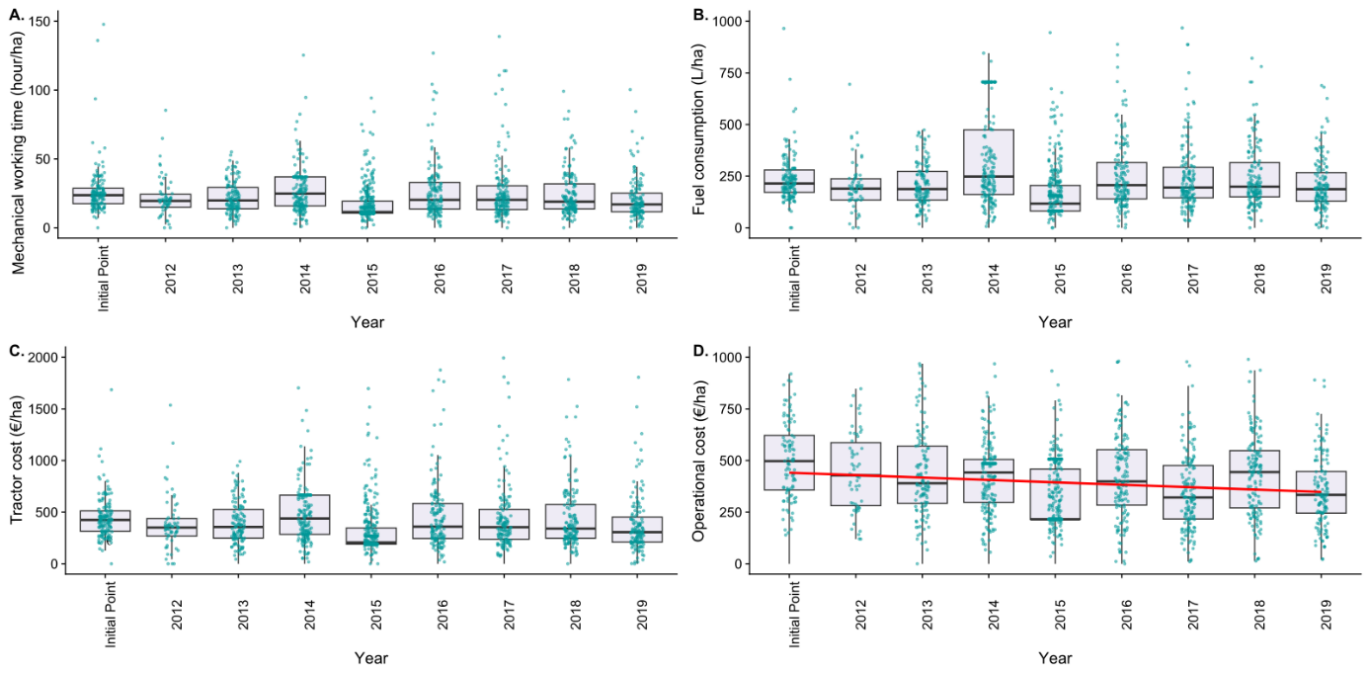
Fig. 3. Change in the economic and working time performances over the 10 years of the study. (A.) Change in mechanical working time (hour ha^{-1}). (B.) Change in the fuel consumption (L ha^{-1}). (C.) Change in the tractor labour cost (€ ha^{-1}). (D.) Change in the operational cost (€ ha^{-1}).
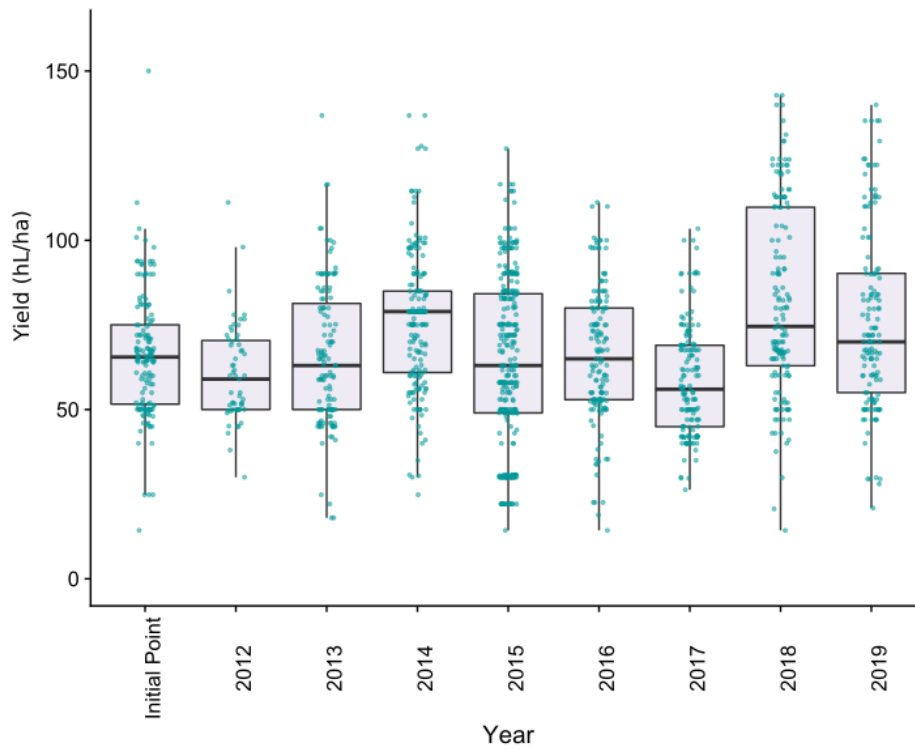
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Fig. 4. Change in the yield (hL/ha) from the initial point to 2019.

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 (β = 0.18, pvalue = 0.025). The impact of the initial disease

control strategy on the change in disease strategy was negative but non-significant (β = –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 (β = −0.06 and β = −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

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329   and the change in disease control strategy, as the impacts of both on productivity was non-significant. Therefore,

330   our hypothesis of a yield decrease due to a fungicide reduction was not verified.

331   A strong and positive relationship between the change in work intensity and the change in the costs was observed

332   ($\beta = 0.94$, p value<0.05). Our hypothesis of a mechanical work increase due to a change in weed control strategy

333   was not validated since the correlation, although positive, was found to be non-significant ($\beta = 0.14$, p value>0.05).

334   The same finding was observed for the change in disease control strategy with regard to the change in mechanical

335   work intensity. There were non-significant correlations between the change in costs and changes in the disease

336   control strategy ($\beta = 0.04$, p value>0.05) and in the weed control strategy ($\beta = -0.03$, p value>0.05).
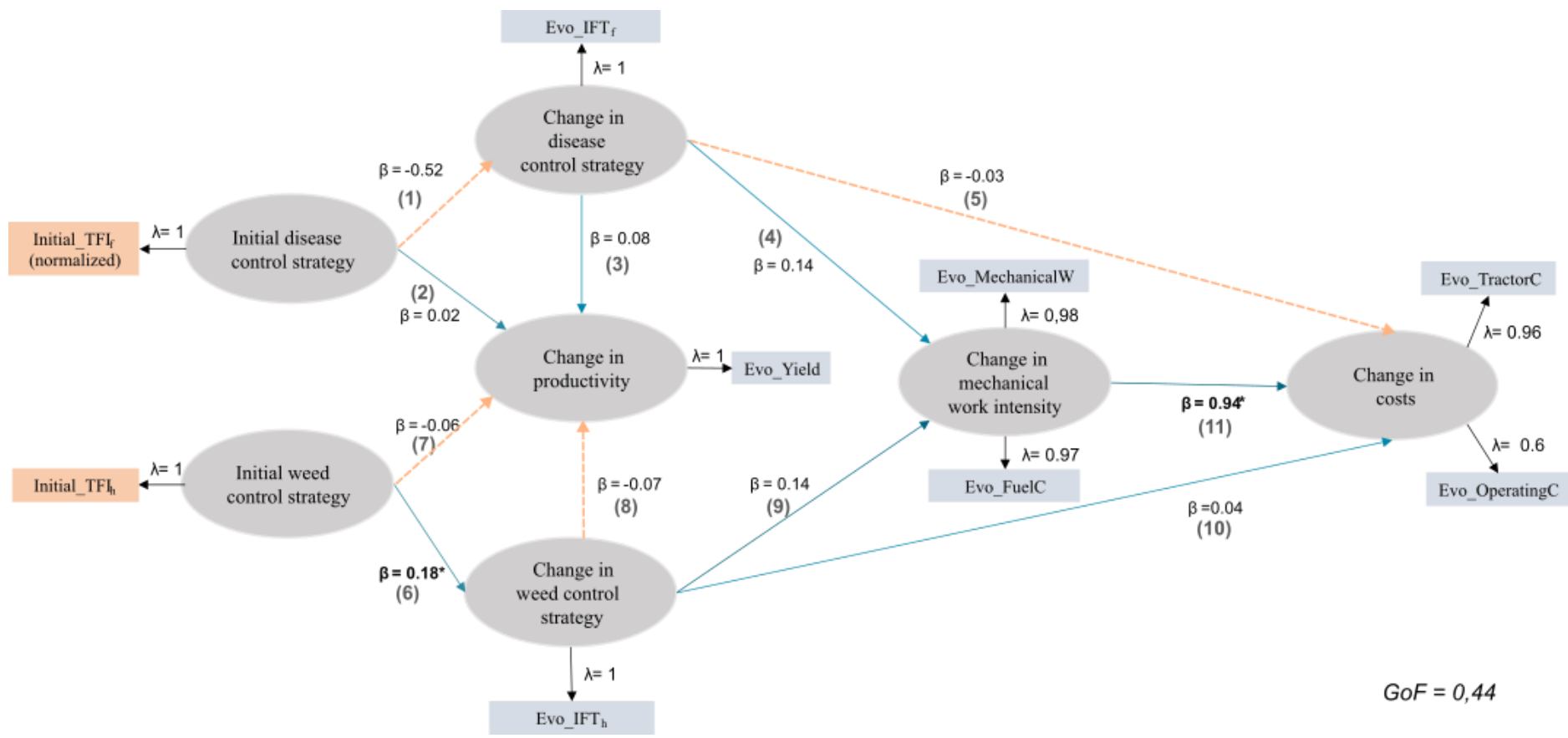
Fig. 5. The complete path model with latent variables (LVs, grey ovals) and manifest variables (MVs, blue rectangles). Path coefficients (β) were computed from regressions; they represent the

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

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.

Meanings of the variables are detailed in Table 1 and the numbers in parentheses correspond to the model construction hypotheses described in Table 2.

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4. Discussion

4.1. This article aimed to characterise the covariations between the performances of different vineyard cropping systems as winegrowers were transitioning to lower pesticide use. We used the French national Agrosyst database, which provides comprehensive information over a long time period (10 years). We built and verified a statistical method (PLS-PM), considering the dynamic of the pesticide reduction process, and showed that pesticide use reduction was not significantly related to the evolution of productivity (yield), economic (operating costs and fuel consumption) and technical performances, technical performance (mechanical work time). **Change in performances over time**

Analysis of the individual performances indicated that nearly all of them remained stable over the 10-year study timeframe, despite a 34% decrease in TFI_f and 58% decrease in TFI_h, with only the input costs experiencing a 46% decrease. All the other performances – mechanical work time, tractor labour costs, fuel consumption and yield – showed no significant change over time.

Performances result from multiple processes. Thus, the lack of change observed here can be partly explained by the context and characteristics of grapevine production systems. First, the vineyard crop management sequence requires numerous manual and mechanical interventions that must be carried out every year, regardless of the pesticide use strategy (e.g. pruning, harvesting). This elucidates why there is minimal variation in the proportion of work time (both manual and mechanical) and operational costs across different years for each vineyard recorded in the database.Even if pesticide use was reduced, harvest costs or winter pruning costs do not vary every year. This regular share of performances can make it difficult to identify an impact due to pesticide reduction for each individual vineyard. Second, regarding changes in yield, in most vineyards, yield is regulated by protected designation of origin (PDO) and protected geographical indication (PDI) schemes (Stranieri and Tedeschi, 2019). Winegrowers voluntarily control the productive potential in their vineyards during winter pruning to meet PDO and PDI requirements. Lastly, a high variability between individual vineyards in the database was observed for each performance each year. Part of this variability can be traced back to the regional effect and its impact on pest and disease pressure, as well as to the specific features of each winegrowing region (in particular yield objectives) (Fouillet et al., 2022; Mailly et al., 2017). For example, some practices, such as the type of pruning or the width between the rows – just like the yield restrictions mentioned above – are imposed by the specifications of the geographical indication schemes.

4.2. Lowering TFI is not related to reductions in yield, costs or mechanical work

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4.2.1. *Changes in yield and pesticide reduction*

We observed that the 34% mean pesticide reduction was not related to an evolution in productivity. In particular, we did not observe any impact of the fungicide reduction on yield, regardless of the initial yield when entering the network. We can therefore assume that fungal diseases have been sufficiently controlled despite lower fungicide use regardless of the level of initial fungicide use. This finding is a validation of a winegrower's choice to undertake the transition to reduce pesticide use. Data analysis was performed at the national scale (see **supplementary data 3**). To investigate further, it could be interesting to consider local yield objectives because yields in vineyard systems are highly variable at inter- and intra-region scales (Fouillet et al., 2022; Mailly et al., 2017; Merot et al., 2022). With the yield objective, another indicator such as the yield achievement ratio (ratio between the reported yield and the target yield, which was unavailable in the Agrosyst database; Merot et al. (2022)) could have been used to explicitly integrate the production target and avoid the strong winegrowing region effect.

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

Interestingly, no impact of the pesticide reduction was observed on economic (costs) or sociotechnical (work time) performances. This result invalidates our hypothesis of an increase in costs due to substituting mechanical weeding for herbicide inputs, such as what was observed by Jacquet et al. (2021) in vineyards. Similarly, Lechenet et al. (2014, 2017), using the Agrosyst database on arable crops, showed that farmers could reduce their pesticide use by an average of 42% without negatively impacting their profitability or productivity (Lechenet et al., 2017, 2014). The 2017 study by Lechenet et al. was based on a single datapoint per farm (when farmers entered the network) and used a regression model to assess the effect of TFI on productivity and profitability. In our study, which was based on a longer time scale (10 years), we integrated the slope as an evolution of indicators. Indeed, since pesticide use is mainly reduced due to gains in efficiency (e.g. dose reduction) and substitution (e.g. use of biocontrol products) (Aulagnier and Goulet, 2017; Fouillet et al., 2022), it does not involve any change in equipment or number of operations (Román et al., 2022). Studies showed that only a few farmers redesigned their farming systems within the DEPHY network (Aulagnier and Goulet, 2017), therefore avoiding levers such as preventive treatments, or even the more involved process of converting to organic farming, both of which are known to significantly impact the way the vineyard is managed (increase in work time and changes in equipment, etc.).

Moreover, some technical operations that are expensive in terms of costs and work time, such as pruning or harvesting, are not affected by reduced pesticide use and can mask the impact of other changes in practices (e.g. change from herbicide use to mechanical weeding) (Strub et al., 2021). In their study on the impact of conversion

402 to organic farming in terms of the technical and economic performances of vineyard systems, Merot et al. (2019)

403 separated grape-growing and harvesting costs because switching from mechanical to manual harvesting (or vice

404 versa) significantly impacts production costs. Analysing grape-growing and harvesting costs separately would

405 make it possible to better identify the impact of technical changes when reducing pesticide use.

406 The economic performance was assessed using production cost while most studies assess economic performance

407 through net or gross margins (Delord et al., 2015). Net margin is calculated as total fixed revenue minus input

408 costs, mechanisation costs and labour costs (Aouadi et al., 2019). In the Agrosyst database, economic data such as

409 gross and net margins were not available for vineyard systems. . We used other economic indicators and integrated

410 more social indicators by considering the work involved (mechanical and manual work time) (Sgroi and

411 Sciancalepore, 2022). Furthermore, total revenues in viticulture systems are highly variable due to the diversity of

412 marketing strategies and the high yield variability on a spatial and temporal scale (Aouadi et al., 2019)..

4.3. Methodology used to study the covariation between performances

4.3.1. *Characterising temporal variations of practices and performances*

415 The Agrosyst database provided a large quantity of information on vineyards and their economic, sociotechnical

416 and economic performances over 10 years at the French national scale. Change can be seen as a multistep process

417 that includes periods of learning and experimentation (Catalogna, 2018; Chantre and Cardona, 2014), and studying

418 the dynamics of these changes is necessary to take into account the fact that farmers implement and adapt their

419 practices over a long time. Yet, there are still methodological issues to address when assessing these cropping

420 system performances to integrate their dynamics. In this study, we adapted the PLS-PM method by integrating

421 dynamic indicators to characterise the change in performances. The dynamic was considered by extracting slopes

422 from linear models. The small number of methods integrating dynamics with mathematical indicators raises the

423 question of how to consider temporal evolutions. We chose to describe the evolution by integrating the slope and

424 the initial point in the PLS-PM model. Dardonville et al. (2022) describe the dynamics of agricultural performances

425 with four different criteria over 8 years: the level of performance calculated with the mean, the stability or

426 variability calculated with the standard deviation or the coefficient of variation, the trend calculated with the slope

427 coefficient of a mixed linear regression; and finally, the resistance calculated by subtracting the average

428 performance before and after the break (high and rapid evolution).

4.3.2. *Possible sensitivity indicator to pesticide reduction*

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

We assumed that a model that takes into account finer variables (e.g. risk to the operator depending on product toxicity, working conditions and safety issues) could identify potential trade-offs, especially in terms of health, labour and costs. Delecourt et al. (2019) and Duval et al. (2021) highlighted a change in work organization during agroecological transitions, in terms of working time and human resources (workforce and skills), work organisation (competition between activities at the farming system scale) and work safety. Overall, indicators of working conditions, such as greater meaningfulness of the work performed (Duval et al., 2021) or the satisfaction of livestock farmers (Perrin and Martin, 2021), improved when farms were converting to organic farming.These findings on work-related variables highlight the need to better account for socio-economic indicators such as net margin or number of workers. Yet, such socio-economic data are difficult to obtain from existing databases, and acquiring it requires in-depth surveys

Furthermore, the implementation of new practices depends on the farmer's attitude towards and perception of risk (e.g. yield loss acceptability). Bonke et al. (2021) showed that some farmers were willing to accept potential yield losses and forego profits by diversifying their crops depending on the farm's economic strategy. One of the limitations of big data analysis is gaining access to these more specific variables as used in multi-criteria evaluation that are not avalaible in the AGROSYST database. For example, DEPXiPM-grapevine (Gary et al., 2015) is a multi-criteria model for assessing the sustainability of vineyard systems. The description of environmental durability is exhaustive and the socio-economic evaluation is based on expert knowledge.

Conclusion

This study aimed to characterise the covariation between the different performances of vineyard cropping systems, involved in a pesticide reduction process over 10 years. The study focused on vineyard, a perennial crop with a high change inertia. First, the evolution of pesticides use (fungicide and herbicide), economic and technical

459 performances were characterized. Over the ten years, a reduction of pesticide (fungicide and herbicide) and

460 operational cost was observed while the other performances remained stable. e built and verified a model to study

461 the correlations between performances and changes in practices, which is necessary when studying change

462 processes. We did not identify any relation between initial pesticide use (fungicide and herbicide) on agronomic

463 and sociotechnical performances.

464 The DEPHY network seems to offer relevant support to help winegrowers reduce their pesticide use given that no

465 covariation between performances was observed during the pesticide reduction process. The observed reduction

466 in TFI had no impact on changes in yield nor work intensity or costs. We suggest that a similar model should be

467 adapted for the vineyard cropping system with indicators to give greater weight to socio-economic indicators, such

468 as work organisation or farmers' objectives and satisfaction during the pesticide reduction process, all of these

469 being key elements of a successful transition to low-input systems.

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