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## Identifying pesticide cocktails at country-wide scale

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## ABSTRACT

1 Wild organisms are exposed to complex cocktails of pesticides owing to the  
2 considerable diversity of substances and agricultural practices. The study of pesticide  
3 cocktails is essential because of potentially strong synergistic effects, making cocktails  
4 effects not predictable from the effects of single compounds. In addition, little is known  
5 about the exposure of organisms to pesticide cocktails *in natura*.

6 We aimed to identify the number and composition of pesticide cocktails potentially  
7 occurring in French farmland, using a database of pesticide purchases listed at the  
8 postcode level. We developed a statistical method based on a mixture model to cluster  
9 postcodes according to the identity, purchase probability and quantity of 279 active  
10 substances.

11 We found that the 5,631 French postcodes can be clustered into 18 postcode  
12 groups characterized by a specific pattern of pesticide purchases, that is a particular  
13 pesticide cocktail. Substances defining cocktails can be sorted into “core” substances  
14 highly probable in most postcode groups and “discriminating” substances are specific  
15 to and highly probable in some postcode groups only, thus playing a key role in the  
16 identity of pesticide cocktails. We found 13 core substances: two insecticides  
17 (deltamethrin and lambda-cyhalothrin), seven herbicides (glyphosate, diflufenican,  
18 fluroxypyr, MCPA, 2,4-d, triclopyr, pendimethalin) and four fungicides (fludioxonil,  
19 tebuconazole, difenoconazole, thiram). The number of discriminating substances per  
20 postcodes group ranged from 2 to 80. These differences in substance purchases  
21 seemed related to differences in crop composition but also potentially to regional  
22 effects.

23 Overall, our analyses return (1) sets of molecules that are likely to be part of the  
24 same pesticide cocktails, for which synergetic effects should be investigated further  
25 and (2) areas within which biodiversity might be exposed to similar cocktail  
26 composition. This information will hopefully be of interest for future ecotoxicological  
27 studies to characterise the actual impact of pesticide cocktails on biodiversity in the  
28 field.

29 **Keywords:** Active Substances, Cluster, mixture model, expectation-maximization  
30 algorithm, risk assessment

## INTRODUCTION

31           Since the mid-20<sup>th</sup> century, pesticides have become of common use in agriculture  
32 and their effects on both the environment and human health are now a concern. For  
33 example, systemic pesticides are known to affect a broad range of organisms, from  
34 invertebrates, both terrestrial and aquatic, to amphibians or birds (Humann-Guillemint  
35 et al., 2019; Mahmood et al., 2016; Yang et al., 2008), thereby questioning the  
36 sustainability of agroecosystem functioning and related services (Deguines et al.,  
37 2014; Dudley et al., 2017; Furlan et al., 2018; Geiger et al., 2010). Pesticides are also  
38 identified as a concern for human health, with numerous pesticide poisonings reported  
39 across developing countries (Boedeker et al., 2020) and recent evidence of  
40 relationships between diseases such as Parkinson's or cancers and exposure to  
41 organophosphate insecticides (Sheahan et al., 2017; Tassin de Montaigu and  
42 Goulson, 2020).

43           Pesticides effects on biodiversity are usually demonstrated with a focus on a  
44 single substance or a limited set of substances in general (e.g. thiamethoxam,  
45 clothianidin, imidacloprid, thiacloprid or glyphosate; (Botías et al., 2015; Busse et al.,  
46 2001; Rundlöf et al., 2015; Van Bruggen et al., 2018). Yet, wild organisms are exposed  
47 to complex cocktails (Dudley et al., 2017), owing to the diversity of substances  
48 available and used in farmlands. Hence, studying substance cocktails is considered a  
49 central task for environmental risk assessment (Lydy et al., 2004a), notably because  
50 the effects of pesticide cocktails can strongly exceed the additive effects of single  
51 compounds (Bopp et al., 2016; Junghans et al., 2006). Laboratory experiments  
52 demonstrate synergetic interactions among substances within cocktails, affecting the  
53 effect of the cocktail in non-additive ways (Cedergreen, 2014; Hernández et al., 2017;  
54 Heys et al., 2016). While the importance of studying the effects of cocktails beyond  
55 those of single substances was highlighted as soon as the late sixties (Keplinger and  
56 Deichmann, 1967), and their evaluation is mandatory in the European Union since  
57 2009 (EC No 1107/2009), few attempts to do so exist outside laboratories (Gibbons et  
58 al., 2015).

59           Studies examining the effects of substance cocktails use two approaches:  
60 bottom-up or top-down (Altenburger et al., 2013; Hernández et al., 2017; Relyea,

61 2009). The bottom-up approach aims at testing all possible cocktail compositions,  
62 starting from pairs of substances to more complex combinations. This method makes  
63 it challenging to consider more than a handful of substances. For example, ten  
64 substances represent 45 possible pairs and over a thousand possible combinations of  
65 three or more substances (Lydy et al., 2004a). Moreover, such approach might be  
66 more suited to experiments in controlled rather than natural environments, as the latter  
67 are recognized as strongly contaminated (Tang et al., 2021), making the control of  
68 cocktail composition difficult. The top-down approach proposes to compare the effect  
69 of cocktails, starting from potentially frequent cocktails including a high number of  
70 substances but at the cost of not testing all combinations. In addition, the few existing  
71 field studies generally focused on the effects of pesticide cocktails composed of a  
72 restricted number of substances, on specific crops or on restricted spatial extent,  
73 thereby limiting a broad understanding of cocktail effects. (e.g. Brittain et al., 2010;  
74 Hallmann et al., 2014; Millot et al., 2017, but see Schreiner et al., 2016 & (Fritsch et  
75 al., 2022). The top-down approach makes it critical to identify relevant cocktail  
76 compositions, i.e. those actually occurring in the fields. The number of actual cocktails  
77 encountered in agroecosystems should be much lower than the number of possible  
78 combinations of substances because each substance is intended for a limited set of  
79 crops only and because agricultural production is regionally specialised on particular  
80 crops. Such regional specialisation implies that existing cocktails are likely to be  
81 spatially structured. However, we still miss an overall picture of the cocktail composition  
82 and spatial structure over large spatial extents.

83 Here, we introduce a new statistical method to identify relevant pesticide  
84 cocktails, i.e. actual combinations of substances potentially co-occurring in  
85 agroecosystems across Metropolitan France. We overcame the general problem of  
86 limited availability of data on temporal and spatial use of pesticides (Navarro et al.,  
87 2021) by taking advantage of the recent publication of an up-to-date database on  
88 pesticide purchase in France, the French national bank of pesticide sales database.  
89 This database has registered mandatory declarations of quantities of active substance  
90 purchased in France since 2013 (law n°2006-1772) at a relatively fine spatial grain  
91 (postcode of the buyer). France is also the seventh largest users of pesticides in the  
92 world (FAO 2020) and has a wide range of agricultural types (Urruty et al., 2016), which  
93 makes it a well-suited case country to try and identify pesticide cocktails encountered

94 in the field by wild organisms, as well as their spatial variation. Applying an  
95 Expectation/Maximization algorithm to a mixture model, we obtained a clustering of  
96 French postcodes on the basis of the composition of active substances purchased. We  
97 show that the number of clusters, i.e. groups of postcodes with a similar composition  
98 of purchased pesticides, is reasonably low and that this clustering is spatially coherent  
99 and related to crop planting, as expected with regional specialisation. We show how  
100 such clustering can be used to identify potentially important pesticide substances and  
101 cocktails deserving further investigation.

## METHODS

### 102 **1.1 Pesticide data**

103 Data on active substances were obtained from the French national bank of  
104 pesticide sales (BNV-d; <https://bnvd.ineris.fr>). The BNV-d database registers  
105 mandatory declarations of active substances sold in France. For each active substance  
106 sale, the seller indicates the amount and the postcode of the buyer in the database.  
107 This database thus indicates the quantity of active substances purchased at the spatial  
108 resolution of the postcode of the buyer. Substances are identified with their generic  
109 name and a unique identifier, the Chemical Abstracts Service number. We modified  
110 generic names when synonyms were found. We only retained substances with a  
111 license fee (i.e. under compulsory declaration) because we can expect thorough  
112 reporting for these.

113 The years registered in the database ranged from 2013 to 2020. We discarded  
114 the year 2013 because of incomplete data during the first reporting year, and the two  
115 last years of the time series (2019 and 2020) because additions and changes in the  
116 database are allowed for two years after a declaration. Also, note that the legislation  
117 has kept changing until 2016, with consequences for the mandatory nature of  
118 declaration for some substances or treatments. In particular, until 2016 the  
119 geographical information associated with seed coating substances was that of the  
120 seed coating company, not of the buyer. Hence, 2017 can be considered the most  
121 accurate and thorough year within the period 2013-2020.

122 The data provides the total mass (in g) bought per substance with mandatory  
123 declaration, of which in 2017 there were 279. We studied the data at the postcode  
124 scale, assuming that substances purchased in a given postcode would be used within

125 the same postcode. In metropolitan France, postcode areas range from 0.17 km<sup>2</sup> to  
126 614.39 km<sup>2</sup> (median = 62.79 km<sup>2</sup>, Q1 = 19.59 km<sup>2</sup>, Q3=140.36 km<sup>2</sup>). Using specific  
127 postcodes (CEDEX) that enable the identification of private companies, we discarded  
128 the data related to the national railroad company (SNCF): SNCF is a major buyer with  
129 central purchasing bodies that do not use the substances within the postcode of  
130 purchase. We converted all remaining CEDEX codes to their corresponding regular  
131 postcode. We were thus left with 5,631 postcodes with information about the quantities  
132 (in g) of 279 active substances purchased in 2017. We classified these substances  
133 into fungicides, herbicides, insecticides following the Pesticide Properties Data Base  
134 (PPDB) (Lewis et al., 2016) and the European commission pesticide database  
135 (ec.europa.eu/food/plant/pesticides/eu-pesticides-database/active-substances).  
136 There were also substances belonging to other categories (32 other target groups;  
137 Table S2 for a complete list) that we classified as “other”.

138 To relate the use of active substances to the area of arable land in postcodes, we  
139 extracted the total area of cropland from the 2016 French Land Parcel Identification  
140 System (LPIS, [Agence de Services et de Paiements, 2015](#)). This database is a  
141 geographic information system developed under the European Council Regulation No  
142 153/2000, for which the farmers provide annual information about their fields and crop  
143 rotation. We grouped the 16 categories of cropland types used in LPIS into 11 sub-  
144 groups (Figure S9) (Cantelaube and Carles, 2010; Levavasseur et al., 2016). We  
145 summed the area of all types of cropland but meadows to obtain the total crop area  
146 per postcode.

## 147 **1.2 Mixture model**

### 148 **1.2.1 Input data**

149 As described above, the dataset consisted of  $n$  (=5,361) postcodes and  $p$  (=279)  
150 substances. For each postcode  $i$  ( $1 \leq i \leq n$ ) and substance  $j$  ( $1 \leq j \leq p$ ), we denoted  
151 by  $X_{ij}$  the presence/absence variable, which is 1 if substance  $j$  is bought in postcode  
152  $i$  and 0 otherwise, and by  $Y_{ij}$  the log of the quantity of substance  $j$  bought in postcode  
153  $i$  (when used) normalized with the cropland area of postcode  $i$ :

$$154 \quad Y_{ij} = \log \left( \frac{\text{quantity of substance } j \text{ bought in postcode } i}{\text{cropland area of postcode } i} \right)$$

155 ( $Y_{ij}$  is NA when substance  $j$  is not bought in postcode  $i$ ).

## 156 **1.2.2 Model**

157 We aimed to provide a clustering of the postcodes according to the quantity of  
158 the various substances bought. Mixture models (McLahan and Peel, 2000) provide a  
159 classical framework to achieve such a clustering. The model we consider assume that  
160 the  $n$  postcodes are spread into  $K$  groups and that their respective use of the different  
161 substances depends on the group they belong to. Mixture models precisely aim at  
162 recovering this unobserved group structure from the observed data.

### 163 **1.2.2.1.1 Groups definition**

164 We denoted by  $Z_i$  the group to which postcode  $i$  belongs. We assumed the  $Z_i$  are  
165 all independent and that each postcode  $i$  belongs to group  $k$  ( $1 \leq k \leq K$ ) with  
166 respective proportions  $\pi_k$ :

$$167 \quad \pi_k = \Pr\{Z_i = k\}. \quad (1)$$

168 Note that the  $\pi_k$  consists of only  $K - 1$  independent parameters, as they have to sum  
169 to one ( $\sum_{k=1}^K \pi_k = 1$ ).

### 170 **1.2.2.1.2 Emission distribution**

171 The model then describes the distribution of the observed data conditional on the  
172 group to which each postcode belongs. The distribution of the presence/quantity pair  
173  $(X_{ij}, Y_{ij})$  is built in two stages: first, if postcode  $i$  belongs to group  $k$ , substance  $j$  is used  
174 in the postcode with probability  $\gamma_{kj}$ :

$$175 \quad \gamma_{kj} = \Pr\{X_{ij} = 1 | Z_i = k\}, \quad (2)$$

176 then, if substance  $j$  is used in postcode  $i$ , its log-quantity is assumed to have a  
177 Gaussian distribution:

$$178 \quad (Y_{ij} | X_{ij} = 1, Z_i = k) \sim \mathcal{N}(\mu_{kj}, \sigma_{kj}^2). \quad (3)$$

179 with  $\mu_{kj}$  and  $\sigma_{kj}^2$  the mean and variance of the log-quantity of substance  $j$  used in a  
180 postcode from group  $k$ , provided that the substance is bought in the postcode. In  
181 addition to the  $(K - 1)$  proportions  $\pi_k$  and the  $K \times p$  probabilities  $\gamma_{jk}$ , this model  
182 involves  $K \times p$  mean parameters  $\mu_{kj}$  and as many variance parameters  $\sigma_{kj}^2$ . This  
183 makes a total of  $K - 1 + 3Kp$  parameters to be estimated.

184 Combining Equations (2) and (3), we defined the conditional distribution  $f_{jk}$  for  
185 substance  $j$  in a postcode from group  $k$ :

$$186 \quad f_{jk}(x_{ij}, y_{ij}) = x_{ij}\gamma_{kj}\phi(y_{ij}; \mu_{kj}, \sigma_{kj}^2) + (1 - x_{ij})(1 - \gamma_{kj})$$

187 denoting by  $\phi(\cdot; \mu, \sigma^2)$  the probability density function of the Gaussian distribution  
188  $\mathcal{N}(\mu, \sigma^2)$ .

189 To avoid over-parametrization, we also considered models with constrained variance,  
190 assuming either that the variance depends on the substance but not on the group:  
191  $\sigma_{kj}^2 \equiv \sigma_j^2$ , or that the variance is the same for all substances in all groups:  $\sigma_{kj}^2 \equiv \sigma^2$ .

### 192 **1.2.3 Inference**

193 Mixture models belong to incomplete-data models, i.e. they can deal with  
194 situations where part of the relevant information is missing. For the sake of brevity, we  
195 denoted by  $Y$  the set of observed variables (i.e. all the  $(X_{ij}, Y_{ij})$ ) and by  $Z$  the set of  
196 unobserved variables (i.e. the  $Z_i$ ). We further denoted by  $\theta$  the whole set of parameters  
197 to be estimated:  $\theta = (\{\pi_k\}, \{\gamma_{kj}\}, \{\mu_{kj}\}, \{\sigma_{kj}^2\})$ .

198 A classical way to estimate the set of parameters  $\theta$  is to maximize the log-  
199 likelihood of the data  $\log p(Y; \theta)$  with respect to the parameters. An important feature  
200 of incomplete-data models is that this log-likelihood is not easy to compute, and even  
201 harder to maximize, as its calculation requires integrating over the unobserved variable  
202  $Z$ . However, the so-called 'complete' log-likelihood, which involves both the observed  
203  $Y$  and the unobserved  $Z$ ,  $\log p(Y, Z; \theta)$  is often tractable.

#### 204 **1.2.3.1.1 Expectation-Maximization algorithm**

205 The Expectation-maximization (EM) algorithm (Dempster;A.P et al., 1977) resorts  
206 to the complete log-likelihood to achieve maximum-likelihood inference for the  
207 parameters. More specifically, because  $\log p(Y, Z; \theta)$  can not be evaluated (as  $Z$  is not  
208 observed), EM uses the conditional expectation of the complete likelihood given the  
209 observed data, namely  $\mathbb{E}[\log p(Y, Z; \theta)|Y; \theta]$ , as an objective function, to be maximized  
210 with respect to  $\theta$ .

211 The EM algorithm alternates the steps 'E' (for expectation) and 'M' (for  
212 maximization) until convergence. It can be shown that the likelihood of the data

213  $\log p(Y; \theta)$  increases after each EM step. The reader may refer to Dempster et al.  
 214 (1977) or McLahan and Peel (2000) for a formal justification of the procedure.

### 215 **1.2.3.1.2 E step**

216 This step aimed at recovering the relevant information to evaluate the objective  
 217 function. In the case of mixture models, the E steps only amounts to evaluating the  
 218 conditional probability  $\tau_{ik}$  for the postcode  $i$  to belong to group  $k$  given the data  
 219 observed for the postcode and the estimate of the parameter  $\theta_{ik}$  after iteration  $h - 1$ :

$$220 \quad \tau_{ik}^{(h-1)} = \Pr\{Z_i = k | \{(X_{ij}, Y_{ij})\}_{1 \leq j \leq p}; \theta^{(h-1)}\}$$

221 The calculation of  $\tau_{ik}$  simply resorts to Bayes formula. In the following, we drop the  
 222 iteration superscript ( $h$ ) for the sake of clarity, and we use the notation  $\hat{\theta}$  to indicate  
 223 the current estimate. Because the substance are assumed to be independent, we get

$$224 \quad \hat{\tau}_{ik} = \hat{\pi}_k \prod_{j=1}^p \hat{f}_{jk}(x_{ij}, y_{ij}) / \left( \sum_{\ell=1}^K \hat{\pi}_\ell \prod_{j=1}^p \hat{f}_{j\ell}(x_{ij}, y_{ij}) \right).$$

### 225 **1.2.3.1.3 M step**

226 The M step updates the parameter estimate by maximizing  
 227  $\mathbb{E}[\log p(Y, Z; \theta) | Y; \theta^{(h-1)}]$  with respect to  $\theta$ . The objective function can be calculated  
 228 using the conditional probabilities  $\tau_{ik}$ s

$$229 \quad \mathbb{E}[\log p(Y, Z; \theta) | Y; \theta^{(h)}] = \sum_{i=1}^n \sum_{k=1}^K \hat{\tau}_{ik} (\log \pi_k + \sum_{j=1}^p \log f_{kj}(x_{ij}, y_{ij})).$$

230 The maximization of this function yields in close-form update formulas for all  
 231 parameters. All estimates can be viewed as weighted versions of intuitive proportions,  
 232 means or variance. Let us first define

$$233 \quad \hat{N}_k = \sum_{i=1}^n \hat{\tau}_{ik}, \hat{M}_{kj} = \sum_{i=1}^n \hat{\tau}_{ik} x_{ij}.$$

234  $\hat{N}_k$  is the current estimate of the number of entities belonging to group  $k$ ;  $\hat{M}_{kj}$  is the  
 235 current estimate of the number of entities from group  $k$  where substance  $j$  is bought.  
 236 For the proportions and probability of use, we get the following updates:

$$237 \quad \hat{\pi}_k = \hat{N}_k / n, \hat{\gamma}_{kj} = \hat{M}_{kj} / \hat{N}_k.$$

238 For the quantitative part of the model, we get additionally:

$$239 \quad \hat{\mu}_{kj} = \frac{1}{\hat{M}_{jk}} \sum_{i=1}^n \hat{\tau}_{ik} x_{ij} y_{ij} \hat{\sigma}_{kj}^2 = \left( \frac{1}{\hat{M}_{jk}} \sum_{i=1}^n \hat{\tau}_{ik} x_{ij} y_{ij}^2 \right) - (\hat{\mu}_{kj})^2.$$

240 Similar estimates of  $\sigma_j^2$  and  $\sigma^2$  can be derived for the models with constrained  
 241 variances.

#### 242 **1.2.4 Model selection**

243 To select the number of groups  $K$  and to choose between the models with  
244 unconstrained and constrained variances, we used the Bayesian Information Criterion  
245 (BIC, Schwarz, 1978). We adopted the same form as in Fraley and Raftery [1999], that  
246 is:

$$247 \quad BIC = \log p(Y; \hat{\theta}) - \frac{n}{2} \log(\# \text{independent parameters}).$$

248 As indicated above, the number of independent parameters is:

- 249 •  $K - 1 + 3Kp$  with unconstrained variances  $\sigma_{jk}^2$ ,
- 250 •  $K - 1 + 2Kp + p$  with constant variance for each substance  $\sigma_{jk}^2 \equiv \sigma_j^2$ ,
- 251 •  $K + 2Kp$  with constant variance  $\sigma_{jk}^2 \equiv \sigma^2$ .

#### 252 **1.2.5 Estimated parameters**

253 The output of the mixture model yielded  $K$  groups with their corresponding  
254 estimated parameters, that is  $\hat{t}_{ik}, \hat{\gamma}_{kj}, \hat{\mu}_{kj}, \hat{\sigma}_{kj}^2$ , with  $k$  one of the  $K$  groups obtained,  $j$   
255 an active substance and  $i$  a postcode. These estimated parameters gave information  
256 on groups of postcodes and substances bought per group.

257  $\hat{t}_{ik}$  was the conditional probability that a postcode  $i$  belong to each group  $k$  given the  
258 quantities of substances bought in the postcode. We used this probability to associate  
259 each postcode to its most probable group.

260  $\hat{\gamma}_{kj}$  was the probability of a substance  $j$  to be used in a postcode of group  $k$ . We used  
261 this probability to study the composition of active substances in each group  $k$ .

262  $\hat{\mu}_{kj}$  and  $\hat{\sigma}_{kj}^2$  were the estimated mean and variance of the log-quantity of substance  $j$   
263 per square meter of cropland purchased in a postcode from group  $k$ . These quantities  
264 were used to refine our understanding of the substance composition of postcode  
265 groups.

### 266 **1.3 Analyses on estimated parameters**

#### 267 **1.3.1 Spatial structure of the groups**

268 To characterise the spatial structure of postcode groups, we quantified the spatial  
269 spread of postcodes belonging to a same group via the area of the convex hull of the  
270 group. The convex hull of a group is the smallest convex set that contains all postcodes  
271 of the group.

272 Regardless of their spatial aggregation, most groups contain a few scattered  
273 postcodes, such that the convex area of all groups generally contains most of France,  
274 making comparisons of the area irrelevant. To circumvent this difficulty, we merged all  
275 contiguous postcodes within a group into single polygons and retained only the largest  
276 polygons, representing 80% of the total area of a group. This eliminated the scattered  
277 postcodes outside the main core of postcodes within a group.

278 We also characterized the similarity among the  $K$  groups in terms of substance  
279 use via hierarchical clustering on distances between groups. To obtain a matrix of  
280 between-group distances, we used results from the mixture model and calculated a  
281 maximum-likelihood inference when two randomly chosen groups were merged (see  
282 method in 1.2). We repeated this step for each possible group pair. We thus obtained  
283 a matrix of between-group distances, characterized as differences in likelihood  
284 between mixture models. Using this matrix, we computed an agglomerative nesting  
285 clustering, using Ward criterion, implemented in the R package *cluster* (Maechler et  
286 al.,2019, R Core Team 2021).

### 287 **1.3.2 Searching for the drivers of the substance composition of groups**

288 We tried to identify some of the possible drivers of the substance composition of  
289 groups using two complementary approaches. First, we tested whether the groups  
290 obtained with the mixture model, which by construction differ in terms of active  
291 substances purchased, also differed in terms of crop composition. To compare the  
292 proportion of area covered with different crops among groups, we performed a log-  
293 ratio analysis (LRA). This approach was implemented in the R package *easyCODA*  
294 (Greenacre, 2019, R Core Team 2021). Second, we used Mantel tests (Mantel &  
295 Valand 1970) to estimate the correlations between three distance matrices among  
296 postcode groups: distances in the composition of substances purchased in the group  
297 (see above), distances in crop composition, and geographic distances. We used a  
298 spearman method and used 9999 permutations, computed with the *vegan* package  
299 (Oksanen and Simpson, 2022)

### 300 **1.3.3 Test of the temporal robustness of the mixture model**

301 To test robustness of the results of the mixture model based on the pesticide  
302 purchase data from the year 2017, we also run the mixture model on BNV-d data over  
303 the period 2015 to 2018. To do so, we aggregated all purchase data from 2015 to 2018  
304 and analysed these data in the same way as those from 2017. In the following, the  
305 groups obtained with the mixture model applied on the 2017 data (respectively 2015-  
306 2018 data) are referred to as the “2017 groups” (respectively the “2015-2018 groups”).

307 We used postcode probabilities to be in group  $k$  (i.e.  $\hat{\tau}_{ik}$ ) to compare results from  
308 the two mixture models, with the 2017 groups as a reference. We compared each 2017  
309 group with all 2015-2018 groups by calculating the proportion of postcodes in each  
310 2017 group that belong to each 2015-2018 group. We thus obtained a matrix with the  
311 percentage of postcodes from 2017 groups that were found in the various 2015-2018  
312 groups (Gelbard et al., 2007).

## RESULTS

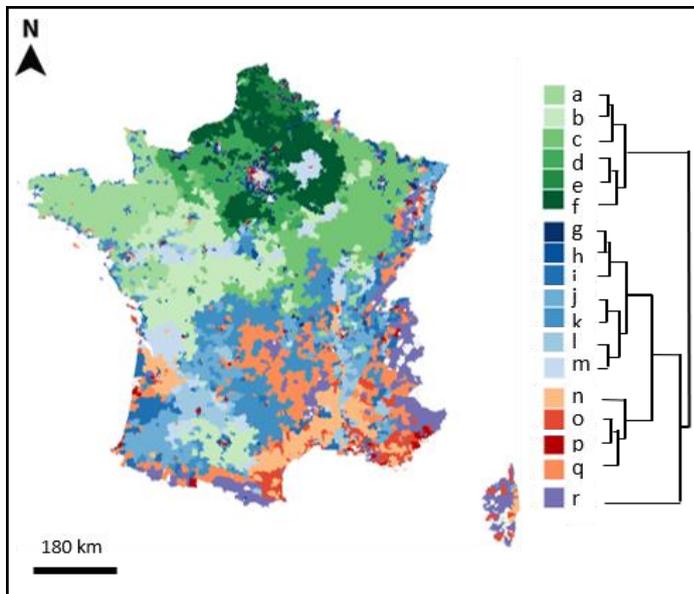
### 313 **1.4 The mixture model yields a small number of groups of postcodes**

314 The mixture model with unconstrained variances had the highest BIC and  
315 classified the 5,631 postcodes into 18 groups on the basis of 2017 purchase data for  
316 279 active substances (Figure S2). Most postcodes were unambiguously attributed to  
317 a single of these groups, as shown by the bimodal distribution of the probability for a  
318 postcode  $i$  to belong to group  $k$ , with most values close to 0 or 1 (Figure S3). Only 17  
319 out of 5,631 postcodes had a maximum probability to be in a group lower than 0.7.

320 Most groups of postcodes identified by the mixture model were spatially  
321 aggregated, albeit of contrasting sizes (Figure 1). The number of postcodes per group  
322 ranged from 159 to 585 (median = 294, Q1 = 239, Q3= 362), which translated into a  
323 cropland area per group ranging from 81.45 km<sup>2</sup> to 30858.86 km<sup>2</sup> (median = 4372.32  
324 km<sup>2</sup>, Q1 = 1761.08 km<sup>2</sup>, Q3= 12863.21 km<sup>2</sup>). The cropland area of groups was  
325 negatively related to the area of the convex envelop encompassing it, such that groups  
326 with the largest cropland area tended to be the most spatially clustered (Figure 2).  
327 Such a spatial clustering of postcodes purchasing similar pesticide substances was

328 expected as agricultural practices are spatially structured (see below) but keep in mind  
329 that the mixture model did not incorporate spatial information.

330



331

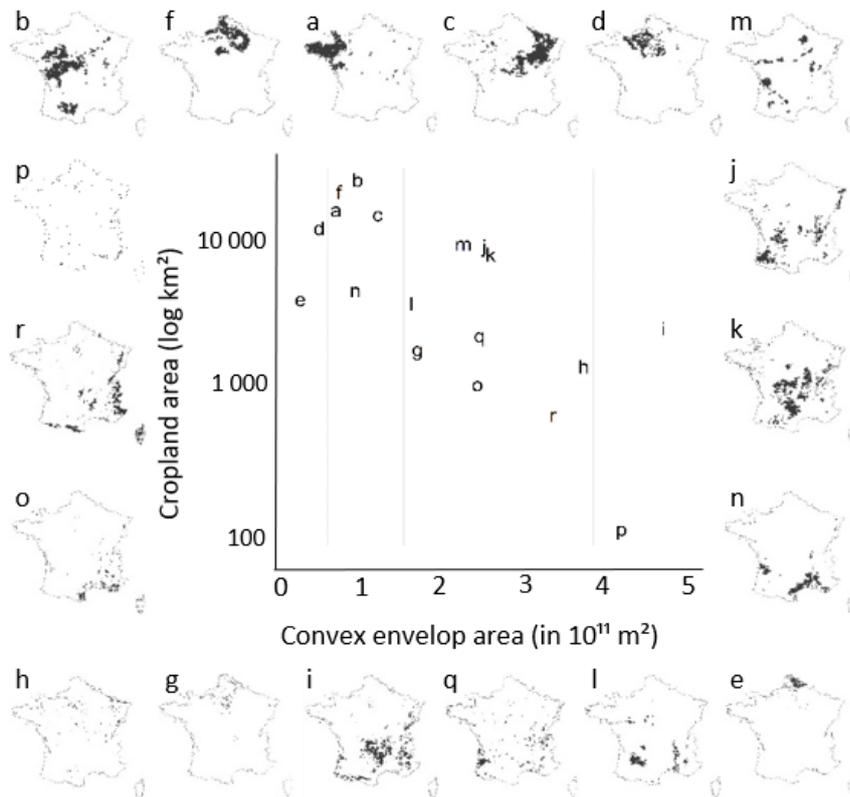
332 *Figure 1: Map of France split into postcode groups obtained from the mixture model on the basis*  
333 *of active substances purchased in postcodes. Postcodes within a group share the same colour.*  
334 *The dendrogram was obtained using an agglomerative hierarchical*

335

336 Postcode groups corresponded to specific geographical and/or agricultural  
337 regions. For example, group a corresponded mostly to Brittany (the western peninsula)  
338 and group c was predominantly located in North-eastern France. Groups m and o were  
339 more scattered across the country but overlapped almost perfectly with wine regions  
340 (*Figure 2*). Note that a few groups were composed of a limited number of postcodes  
341 spatially scattered across France (e.g. groups i, h, and p, *Figure 2*). In particular, group  
342 p represented less than 2 km<sup>2</sup> of cropland and is generally discarded in the following.

343 The groups identified by the mixture model were relatively robust to a change in  
344 the temporal range of the data, as shown by the results of the mixture model on the  
345 2015-2018 data (*Figure S7*). This second clustering yielded 24 groups and the  
346 percentage of shared postcodes between the 2017 groups and their most similar 2015-  
347 2018 groups varied between 38% and 83% (median= 64%, Q1=54%, Q3= 74%). For  
348 example, groups corresponding to Northern France (group e vs. group 6) or the  
349 Champagne region (group c vs. 2) were stable over time (*Figure S7*). The higher  
350 number of groups obtained with the 2015-2018 mixture model (24 vs. 18) was often  
351 due to the split of some 2017 groups into two 2015-2018 groups. For example, for 2017

352 group *r*, there was 48% similarity with 2015-2018 group 21 and 44% similarity with  
 353 group 23. Similarly, Brittany was covered by 2017 group *a* vs. 2015-2018 groups 16  
 354 and 20 (*Figure S7*). Because of this temporal consistency in the clustering, we only  
 355 present in the following the analyses on the 2017 dataset, which is thought to be more  
 356 accurate (see 1.1).

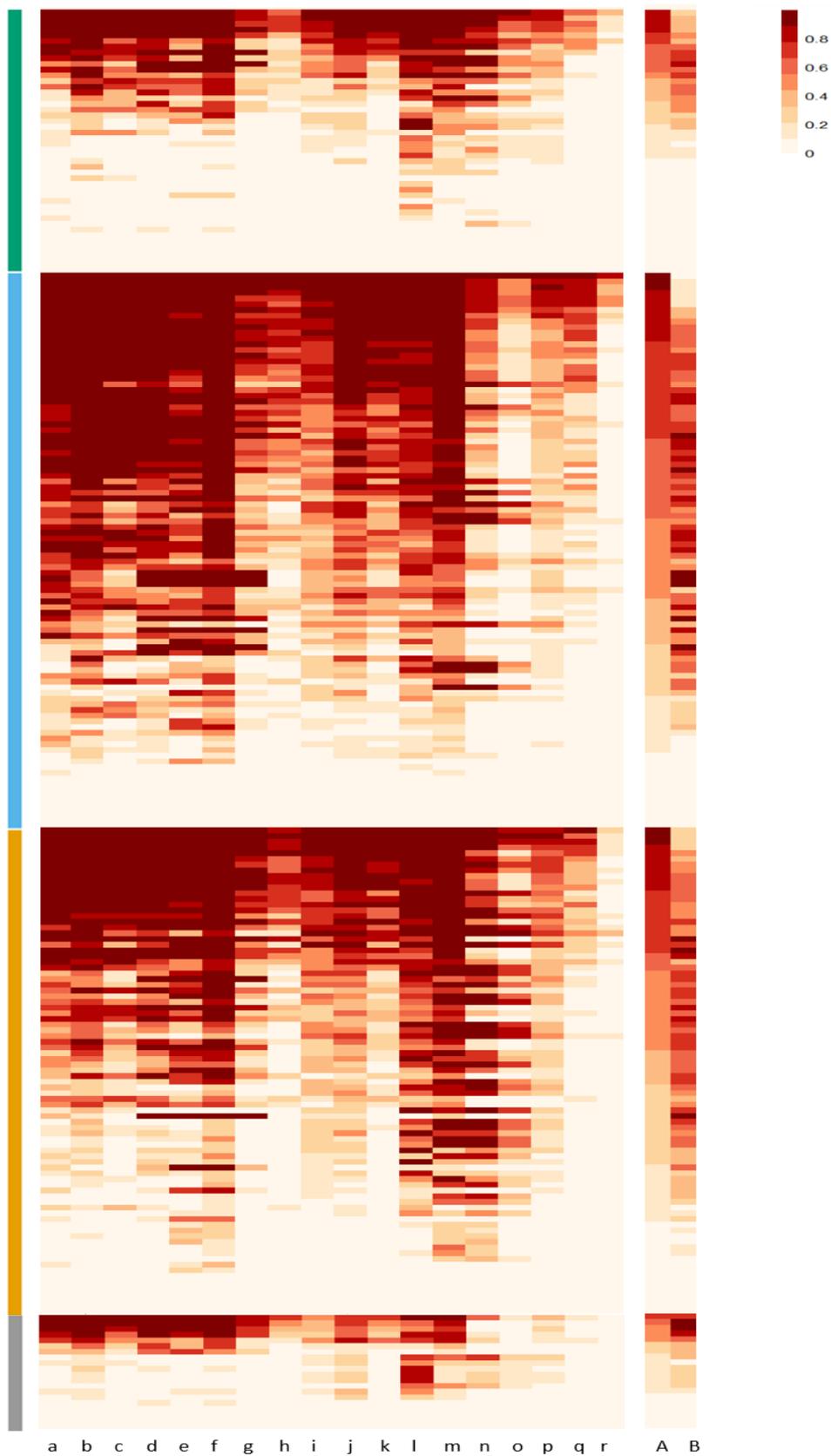


357 *Figure 2: Relationship between cropland area (log scale) and convex area, a proxy for spatial*  
 358 *extent, of groups. The spatial distribution of each group is plotted around the relationship, with*  
 359 *one map of France per group, in which postcodes forming each group are highlighted in black.*  
 360 *Groups are ordered clockwise from top left in decreasing cropland area. Note that the focus on*  
 361 *cropland area (not total area) in a postcode makes some groups with little cropland (e.g.*  
 362 *mountain areas, *q* or *m*) appear with a relatively large area on the maps, although they are*  
 363 *ranked low in terms of cropland area.*

### 364 **1.5 Substance composition of postcode groups: core and discriminating** 365 **substances**

366 Postcode groups differed in terms of the composition of substance purchased  
 367 (*Figure 3*), as expected from the clustering algorithm, but may also share common  
 368 substances. Group composition was inferred, and can be characterised by, (1) the

369 probability of a substance to be purchased by a postcode from a group ( $\hat{\gamma}_{kj}$ ), and, if  
370 the substance is purchased, (2) the estimated mean quantity purchased ( $\hat{\mu}_{kj}$ ) and (3)  
371 the estimated variance in the latter quantity ( $\sigma_{jk}^2$ ). In the following, for the sake of  
372 simplicity, we chose to focus on the probability of substances to be purchased, knowing  
373 that this probability was positively related with the estimated mean quantity (Figure S4  
374 & Figure S6,  $r = 0.2$ ) and negatively related with the estimated variance (Figure S4,  $r$   
375 = -0.15). For a given substance, this probability can also vary substantially across  
376 groups, and we used this variability to distinguish two main types of substances with  
377 interest for the definition of postcode groups, for the identification of relevant pesticide  
378 cocktails: core substances and discriminating substances (*Figure 4*).



379

380

Figure 3: Heatmap of the probability  $\gamma_{kj}$  in each group, in each of four categories of substances: insecticides (green), herbicides (blue), fungicides (orange), other targets (grey). Within each category, substances are ordered in increasing average probabilities of use across groups. For readability, substance names are not displayed and can be found in Figure S8. On the right of the figure, column A corresponds to the mean probability of use and column B corresponds to the scaled (0,1) variance in probability of use across groups.

381 Core substances, defined as substances with a high average and low variance  
382 of probability to be purchased across groups, were by definition found in most groups;  
383 they were widespread molecules that were likely to form the backbone of cocktails  
384 encountered by living organisms in farmland. Using an arbitrary threshold value of  
385 mean purchase probability of 0.85, we found 13 such core substances with high  
386 probabilities (*Figure 3 & Figure S5*): two pyrethroid insecticides (deltamethrin, lambda-  
387 cyhalothrin), seven herbicides of different chemical families (glyphosate, diflufenicanil,  
388 fluroxypyr, MCPA, 2,4-d, triclopyr, pendimethalin) and four fungicides (fludioxonil,  
389 tebuconazole, difenoconazole and thiram). Because they were found with high  
390 probability in most groups, these substances were unlikely to weight strongly in the  
391 definition of postcode groups, although they can contribute via differences in the mean  
392 quantities used across groups. For example, the average estimated amount of  
393 glyphosate purchased ranged from 30 to 634 kg/cropland m<sup>2</sup> (median= 43, Q1= 36,  
394 Q3 = 77) among groups.

395 Discriminating substances are defined as substances with medium to high mean  
396 probability of purchase, mechanically associated with a large variance across groups  
397 in this probability (*Figure S5*). Because of their contrasting probability of purchase  
398 across groups, discriminating substances were likely to contribute greatly to the  
399 formation of groups. We used the arbitrary range of average probabilities from 0.5 to  
400 0.85 to define discriminating substances. Using these thresholds, we found a set of 85  
401 discriminating substances, including 42 herbicides, 28 fungicides, 10 insecticides and  
402 5 with other targets (*Supplementary information 2*). In the following, we focus on  
403 discriminating substances that are highly probable ( $\hat{y}_{kj} > 0.85$ ) in at least one postcode  
404 group, i.e. substances that are likely major components of pesticide cocktails occurring  
405 in a given group. We found five widespread discriminating substances purchased with  
406 a probability higher than 0.85 in 13 out of 18 groups: azoxystrobin, iodosulfuron-  
407 methyl-sodium, mesotrione, metsulfuron-methyl and prothioconazol. These  
408 substances are very close to core substances. Conversely, eight substances were  
409 highly specific, being purchased with high probability (>0.85) in three groups only (e.g.  
410 dimethachlore in groups *d*, *c*, and *f*). Within a group, the number of discriminating  
411 substances with high probability of purchase (> 0.85) varied strongly among groups,  
412 from 2 for group *h* to 80 for group *f* (mean= 42 ± 26). This cross-group variation in the  
413 number of highly probable discriminating substances has implication for the  
414 composition and complexity of the pesticide cocktails in French agroecosystems: from

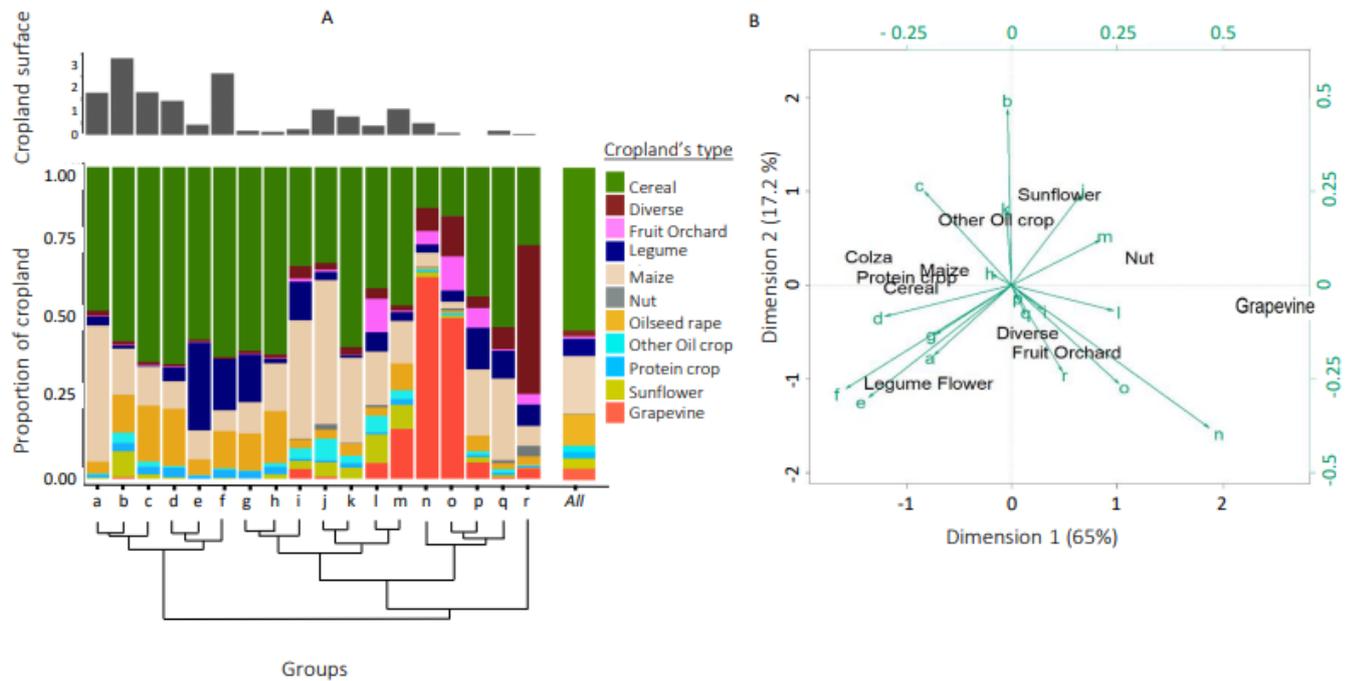
415 relatively “simple” (13 core substances and two discriminating substance in group *h*)  
416 to highly complex (13 core substances and 80 discriminating substances in group *f*).

417 The 181 remaining substances, with a low average probability to be purchased  
418 (<0.5), also had a role in group identification, but were seldom purchased and will not  
419 be described further (*Figure 3*).

## 420 **1.6 Postcode groups differ in terms of crop composition, but active** 421 **substance purchase may not be solely driven by crop identity**

422 Groups of postcodes, which by construction are composed of different cocktails  
423 of substances, also differed in terms of proportions of cropland grown with various  
424 crops, such that groups with close pesticide composition sometimes, but not always,  
425 also exhibited similar crop usage (*Figure 4*). The possible relations between pesticide  
426 composition and crop composition can be visualized either on *Figure 4*, where crop  
427 composition of groups similar in terms of pesticides purchases are plotted next to each  
428 other, or on the biplot of the log ratio analysis (*Figure 5*), in which groups with similar  
429 crop composition are plotted next to each other. For example, groups *o* and *n*,  
430 characterized by a large proportion of vineyards, were close to each other both in the  
431 log-ratio analysis, which is indicative of similar crop compositions (*Figure 5*) and in the  
432 hierarchical clustering, which is indicative of similar pesticide purchases (*Figure 4*).  
433 The same was true for groups *e* and *f*, and, to a lesser extent, *d*, characterized by an  
434 appreciable proposition of crops from the legumes/flowers category. However, some  
435 groups such as *f* and *g* were different in terms of substances (not in the same sub-  
436 group, *Figure 1 & 4*) while exhibiting comparable proportions of crop types (*Figure 4*).  
437 Alternatively, some groups that were closely related in terms of substance purchases,  
438 such as groups *a* and *b*, could be characterized by dissimilar crop compositions. The  
439 latter patterns may suggest regionalisation of substance use, such that neighbouring  
440 regions tend to use similar products or substances even with variations in crops grown  
441 (e.g. *a* and *b*), or distant regions tend to use different products or substances even with  
442 similar crops (e.g. *a* and *k*).

443



444

445 *Figure 4: A. Distribution of crop type area across groups. The top grey histogram shows the*  
 446 *distribution of total cropland area across groups (in 10<sup>4</sup> km<sup>2</sup>). The dendrogram was obtained*  
 447 *using an agglomerative hierarchical clustering on the basis of Ward's method among groups*  
 448 *(see 2.2.1). B. Biplot of the log ratio analysis relating the proportion of crop types in each group.*  
 449 *Only groups identified as spatially coherent are displayed (see 3.2). For readability, the groups*  
 450 *and crop types are displayed on two different scales: black for crop types, green for groups. The*  
 451 *size of arrows corresponds to the contribution of each group. Groups that appear close to each*  
 452 *other on the biplot have similar crop composition, which can be inferred from the contribution*  
 453 *of each crop type to the axes.*

454

455 Despite the abovementioned associations between the crop composition and  
 456 active substance compositions of groups, we found no significant correlation between  
 457 distance matrices: the distance in substance composition among groups was not  
 458 correlated with the distance in crop composition (Mantel test,  $\rho = 0.12$ ,  $P = 0.12$ ).  
 459 However, we found a correlation between the geographic distance and active  
 460 substance compositions of groups (Mantel test,  $\rho = 0.12$ ,  $P = 0.12$ ) indicating that  
 461 spatially closer postcodes groups are more similar in composition of actives  
 462 substances.

## DISCUSSION

463 A major challenge in pesticide risks assessment is to characterise cocktails of  
464 pesticides used in the field (Lydy et al., 2004), partly because of the large number of  
465 substances used but also because of the limited information on the combinations of  
466 used substances contaminating the environment. Here, we developed a methodology  
467 to analyse a newly available database on pesticide purchases across France. It aimed  
468 to identify groups of postcodes with similar compositions of pesticide purchases and  
469 characterise their spatial structure, two critical pieces of information to unravel the  
470 composition of pesticide cocktails. Our method resulted in the clustering of the 5,631  
471 French postcodes into a relatively low number of groups. These groups represent as  
472 many potential pesticide cocktails, which is much lower than the possible combinations  
473 among the 279 substances included in the data. In the following, we discuss how our  
474 findings can help understand the impacts of pesticides in the environment (e.g. by  
475 identifying relevant pesticide cocktails) and how this approach can be improved in the  
476 future and the possible mechanisms underlying the groups.

### 477 ***1.7 Significance of the identification of highly probable active substances and*** 478 ***of cocktails of active substances characteristic of postcode groups for the*** 479 ***study of the impacts of pesticides in the environment***

480 The identification of active substances that are purchased with high probability in  
481 all (core substances) or a subset (discriminating substances) of postcode groups might  
482 contribute to reducing the potential street light effect, whereby most research efforts  
483 focus on molecules that are either easy to study (Hendrix, 2017) or that were  
484 popularized by previous studies (Tsvetkov and Zayed, 2021). Unsurprisingly, most  
485 core substances identified here are already well-known, widely-used substances.  
486 Glyphosate is the most widely used broad-spectrum herbicide (Jatinder Pal Kaur Gill  
487 et al. 2017; Myers et al. 2016), with associated concerns regarding pervasive direct  
488 and indirect effects (Van Bruggen et al., 2018). Tebuconazole and difenoconazole, two  
489 triazole fungicides, are widely used and studied (Zubrod et al., 2019). Deltamethrin and  
490 lambda-cyhalothrin, two pyrethroids impacting nervous systems (Ray and Fry, 2006;  
491 Soderlund and Bloomquist, 1989), are known to have adverse effects on a large range

492 of non-target species such as fish, birds and amphibians (Ali et al. 2011). Yet, a  
493 preliminary literature search on these 13 core substances suggests that the research  
494 effort on their adverse effects on biodiversity is still highly variable. For core herbicides,  
495 a simple search of the molecule name together with “biodiversity” or “ecotoxicology” in  
496 the abstract of articles on ISI Web of Science yields more than two hundred research  
497 articles for glyphosate and around seventy for 2,4-d, but only 2 to 17 articles for  
498 diflufenican, fluroxypyr, MCPA, triclopyr and pendimethalin. For core insecticides, the  
499 same search returns ca. 40 articles for lambda-cyhalothrin and deltamethrin. The four  
500 core fungicides were no exception, with a number of research articles of less than ten  
501 for thiam, fludioxonil and difenoconazole and around thirty for tebuconazol. Ultimately,  
502 our method eases the bottom-up approach in the laboratory by providing a selection of  
503 understudied substances deserving further attention.

504 Studying all possible (combinations of) substances is prohibitive (Wolska et al.,  
505 2007); beyond the identification of single substances, our approach chiefly contributes  
506 to identifying combinations of active substances that are likely to be encountered in  
507 farmland environments, i.e. pesticide cocktails. The mixture model identified a  
508 relatively small number of postcode groups (18 to 24 depending on the temporal  
509 coverage of pesticide data). Each group is characterized by a specific combination of  
510 purchases of active substances and can be interpreted as potential cocktails of  
511 pesticides occurring in the location of the postcodes, under the assumption that all  
512 purchased substances are used within the buying area during the year of purchased  
513 (see “Limitations” below). Among the 269 active substances considered in these  
514 analyses, we highlighted the core substances included in most cocktails and the  
515 discriminating substances specific to particular cocktails. Within each postcode group,  
516 both types of substances might be a good starting shortlist of substances within which  
517 one can investigate potential interactive effects on biodiversity. Indeed, these  
518 substances are purchased with high probability in at least some large groups of  
519 postcodes, hence potentially part of widespread cocktails. Although this list is much  
520 shorter than the total list of authorized active substances, it still contains 13 core  
521 substances, plus 2 to 80 discriminating substances depending on the postcode group.  
522 Since our approach to identifying core and discriminating substances was based on  
523 probability of purchase only, this shortlist of substances could be narrowed down  
524 further by selecting active substances bought in large quantities (see also “Limitations  
525 and perspectives”, 1.8) or with high toxicity. The appreciable number of core and

526 discriminating substances composing cocktails is anyway consistent with surveys  
527 showing that active substances are rarely found alone in the environment (Silva et al.,  
528 2019). It also further substantiates the need for a broader assessment of the synergistic  
529 effects of pesticides on biodiversity, often completed on a limited set of substances  
530 only (Schreiner et al., 2016; Silva et al., 2019). For core substances, for example, some  
531 cocktails effects have already been studied. but mostly on pairs of substances (Brodeur  
532 et al., 2014; Peluso et al., 2022) and more rarely for cocktails of three or more  
533 substances (Cedergreen, 2014), but in any cases, many more combinations remain  
534 untested. Focusing on the reasonable number of relatively complex cocktails identified  
535 by the present approach would contribute to improve our understanding of the  
536 synergistic effects of realistic cocktails on organisms.

## 537 **1.8 Limitations & perspectives**

### 538 **1.8.1 Limited spatio-temporal resolution of the BNV-d data**

539 The first limitation of our study is associated with the BNV-d database, which  
540 provides information on quantity and year of pesticide purchase, as well as on the  
541 administrative location of the buyer, but not on the actual date and location of pesticide  
542 treatments, nor on the actual pesticide contamination of the various postcodes. For  
543 simplicity, we assumed that the pesticides were used in the year of purchase and in  
544 the postcode of purchase. These assumptions may not be verified under all  
545 circumstances because farmers are sometimes known to store some pesticide  
546 products despite their high prices, e.g. to anticipate increased taxes, and because  
547 farms are sometimes spread across several postcodes. Yet, there are a couple of  
548 indications that the assumption of immediate and local use of pesticides is generally  
549 correct. For example, our results are consistent with those of an extensive European  
550 study on soil contamination (Silva et al., 2019) which identified glyphosate and the  
551 fungicides boscalid, epoxiconazole, and tebuconazole as the most frequent and most  
552 abundant contaminants. These substances either belong to the core substances we  
553 identified (glyphosate and tebuconazole) or to discriminant substances (boscalid and  
554 epoxiconazole) with a high probability of being used over half of the postcode groups.

555 Although our estimation of pesticide cocktail composition may be roughly correct  
556 at the resolution of a postcode and of a year, the actual use of pesticides in space and  
557 time varies at much finer scales than those of available data. Pesticide substances  
558 bought within a given postcode and year may be spread in contrasting fields and times  
559 and may not be found together in the environment, depending on their half-life and  
560 transport in the environment. The actual cocktail composition of a site hence depends,  
561 among others, on the crop cover in the landscape and associated farming practices.  
562 Downscaling the BNV-d database to the field scale is challenging (Cahuzac et al. 2018;  
563 Ramalanjaona, 2020), but it might reveal other patterns than the ones we highlighted  
564 here, probably decreasing the number of substances that are part of local cocktails.  
565 Such fine-grained data on pesticides might be more relevant to assess the impact of  
566 pesticide contamination on biodiversity.

### 567 ***1.8.2 Going beyond the use of purchase probabilities and arbitrary thresholds*** 568 ***to identify the substances of interest for risks assessment***

569 The method we developed is continuous, with quantitative estimates of purchase  
570 probabilities, as well as mean and variance of quantities purchased per postcode  
571 group. Still, we used arbitrary thresholds to identify core and discriminating  
572 substances. The cocktails composition we highlighted here are then dependent on the  
573 chosen thresholds. Depending on the question of interest, these thresholds can and  
574 should be adapted. For example, by changing the threshold to 0.80, there are nine  
575 more core substances, and among these substances there are, for example,  
576 imidacloprid and boscalid, both known for high use and effects on biodiversity (Lopez-  
577 Antia et al., 2015; Qian et al., 2018; Simon-Delso et al., 2017; Yang et al., 2008).

578 In addition, most of our interpretation of pesticide cocktail composition relies on  
579 the estimated purchase probabilities, but these cocktails were also identified using  
580 information on the mean and variance of purchased amounts within postcodes, hence  
581 cocktails differ for these variables as well. For example, glyphosate, a core substance  
582 with high purchase probability in all postcode groups, was bought in contrasting  
583 quantities across postcode groups: the average amount was  $8.8 \times 10^7$  Kg/m<sup>2</sup> and  
584 ranged from  $3 \times 10^7$  Kg/m<sup>2</sup> in group *q* to  $6 \times 10^8$  Kg/m<sup>2</sup> in group *r*. Although the purchase  
585 probability was positively correlated to the mean purchased quantity and negatively to

586 its variance, the correlation is not strong, and further analysis is needed to fully uncover  
587 variation in substance quantities within the cocktails we identified.

### 588 ***1.8.3 Taking into account the yearly variation of pesticides use***

589 Our analysis appeared relatively robust to yearly variation in pesticide purchase  
590 when comparing the postcode groups obtained between the 2017 and the 2015-2018  
591 datasets. This strong correlation between the 2017 and the 2015-2018 analysis is not  
592 entirely surprising because of the presence of the 2017 data in both analyses. Yet,  
593 adding three years of data into the analysis did not affect much the composition of  
594 postcode groups, which suggests relatively stable patterns of pesticide purchase in  
595 France over a short time period. Nonetheless, we observed some differences, mainly  
596 due to the split of some groups, which were also expected due to climatic variation,  
597 changes in legislation on pesticide use (Urruty et al., 2016) or changes in crop areas  
598 (Levavasseur et al., 2016). A better integration of the temporal dynamics of pesticide  
599 purchases in the characterisation of pesticide cocktails is needed if we are to monitor  
600 pesticide cocktails across France. This can be achieved by applying the mixture model  
601 to each year of data separately. Investigating the spatial stability of groups and  
602 cocktails compositions across years would contribute to either estimate annual  
603 cocktails or to find temporarily stable cocktails. Finding recurrent cocktails could  
604 facilitate risk assessment over years. Indeed, this could provide key information on  
605 frequency of cocktails encountered by organisms as repeated contact might increase  
606 risks (Stuligross and Williams, 2021).

### 607 ***1.9 Postcode groups are related to the crop they grow but also to other*** 608 ***regional factors, but the underlying mechanisms remain to be fully*** 609 ***identified***

610 Although no spatial information was included in the mixture model analysis, the  
611 postcode groups exhibited a strong spatial structure, in which most groups are strongly  
612 aggregated and only a few small groups are scattered across France. Such spatial  
613 structure was expected since pesticide use is strongly crop-dependent. For example,  
614 acetamiprid, a substance used to protect fruit trees or grapevine against aphids, is  
615 bought with high probability in group / only, a group with a high proportion of fruit

616 orchard and grapevine. Similarly, cyproconazole, a substance with a broader spectrum  
617 of use, is bought with high probability in several groups with contrasting crop  
618 compositions (*a, b, c, d, e, f, g, j, k, m*) (Figure 4). However, differences from this pattern  
619 were found: some postcode groups spatially close can have different set of crops but  
620 similar substance purchases or some postcode groups spatially distant can have  
621 similar set of crops but different substance purchases. This result suggests that local  
622 conditions, such as climate or pests, or some regional patterns in the pesticide market  
623 and/or distribution, can drive the purchase of active substances more than the set of  
624 crops grown (Silva et al., 2019; Storck et al., 2017). Hence, the differences among  
625 postcode groups were related to a combination of crop identity effects and other  
626 regional effects that will need additional analysis to be identified.

## CONCLUSION

627 This study shows that a finite reasonably low number of cocktails of substances  
628 can be identified at the scale of France. It is important to pursue ecotoxicological  
629 studies on the synergistic effects of mixtures to identify risks and better understand the  
630 effects of pesticide products on organisms. The mapping of these pesticide cocktails  
631 makes it possible to identify the regions under different regimes of pesticide  
632 contamination. This might be particularly useful to plan *in situ* tests for both pesticide  
633 contamination and effects on biodiversity. Here we did not investigate the effects of  
634 cocktails on wild organisms, and further work should be done on this aspect.

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### Conflict of interest

None.

### SUPPLEMENTARY MATERIALS

Supplementary materials to this article can be found online at

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# Appendix

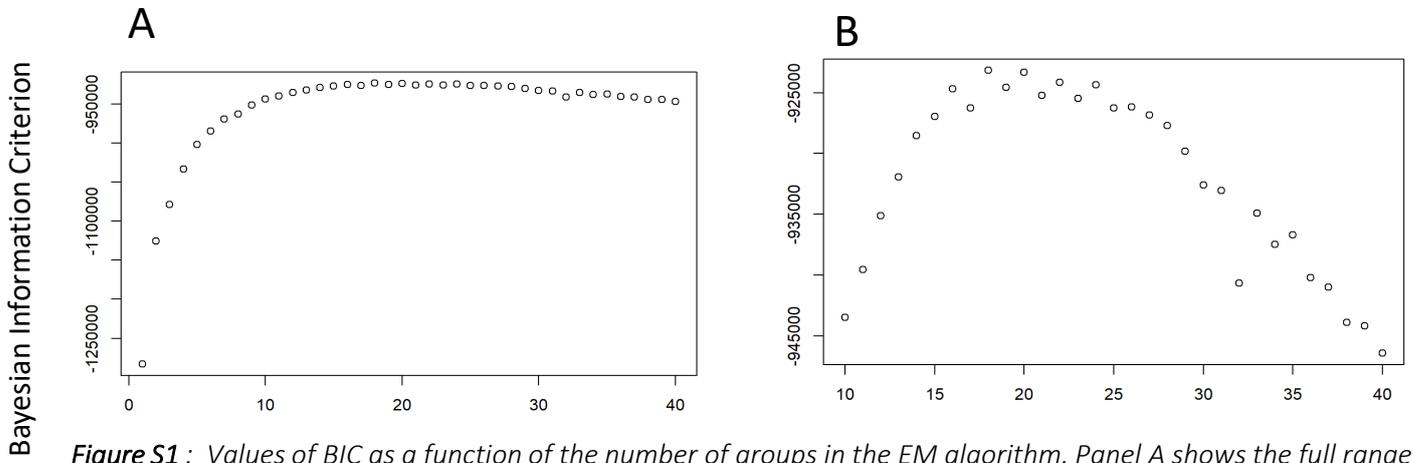


Figure S1 : Values of BIC as a function of the number of groups in the EM algorithm. Panel A shows the full range of number of groups tested (from 1 to 40). Panel B is a closeup around the maximum BIC value

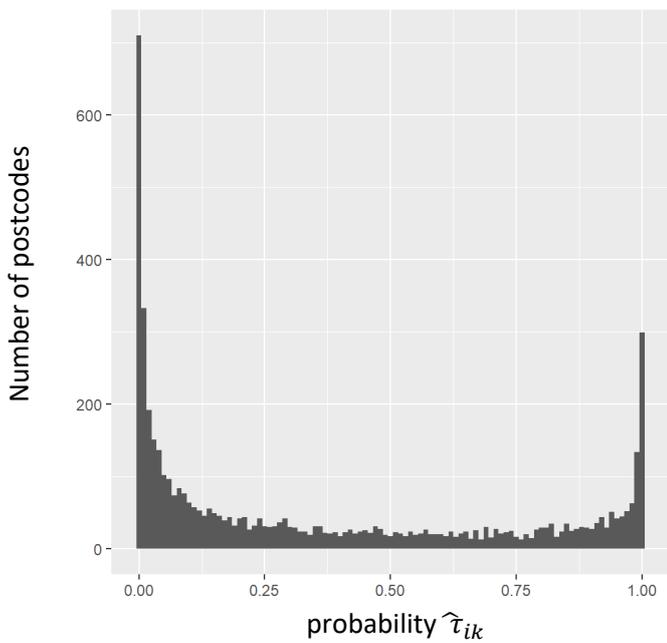
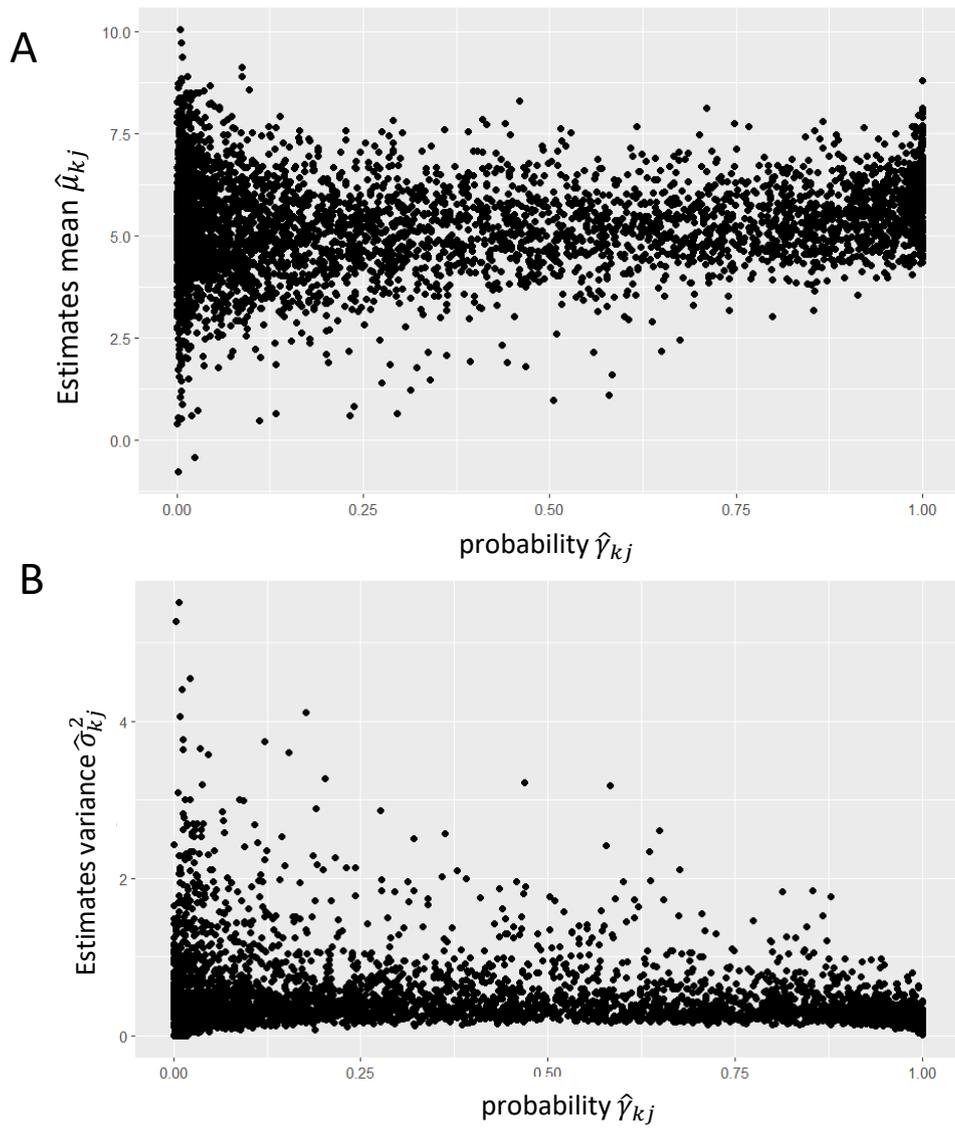
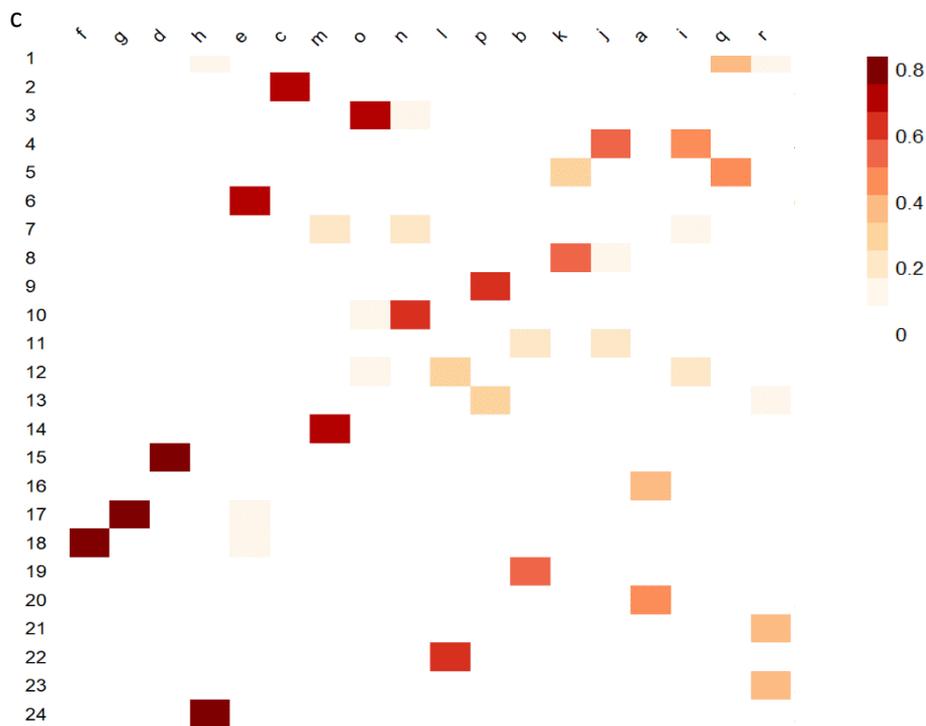
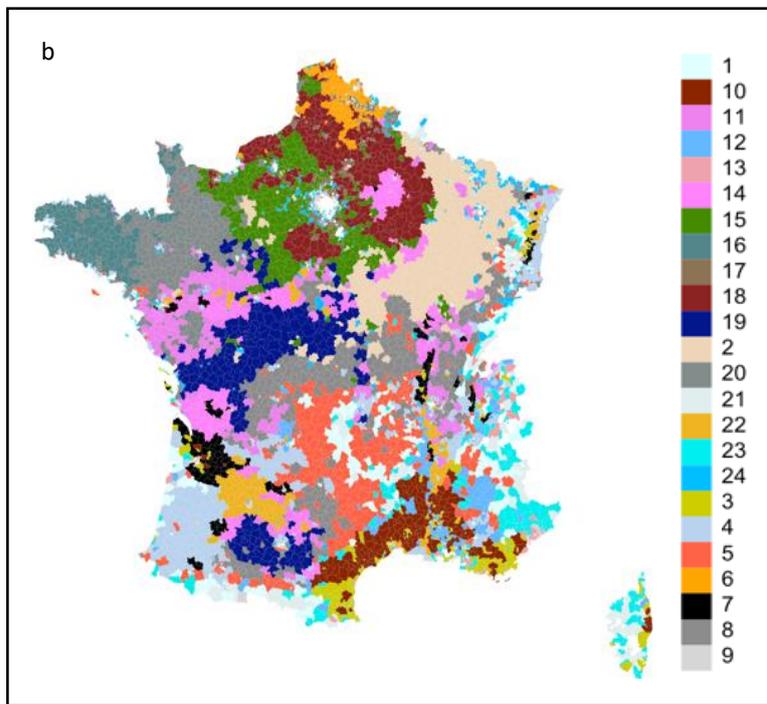
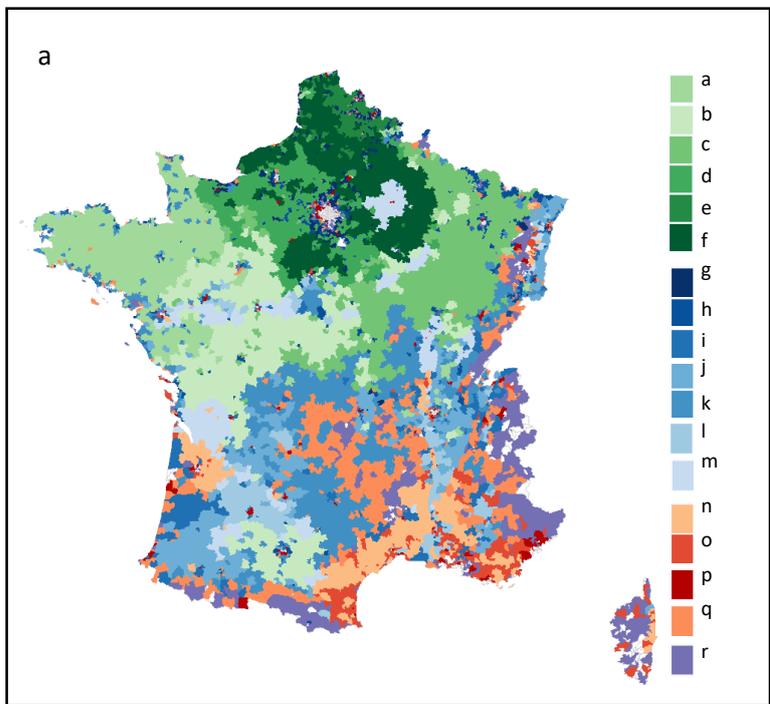


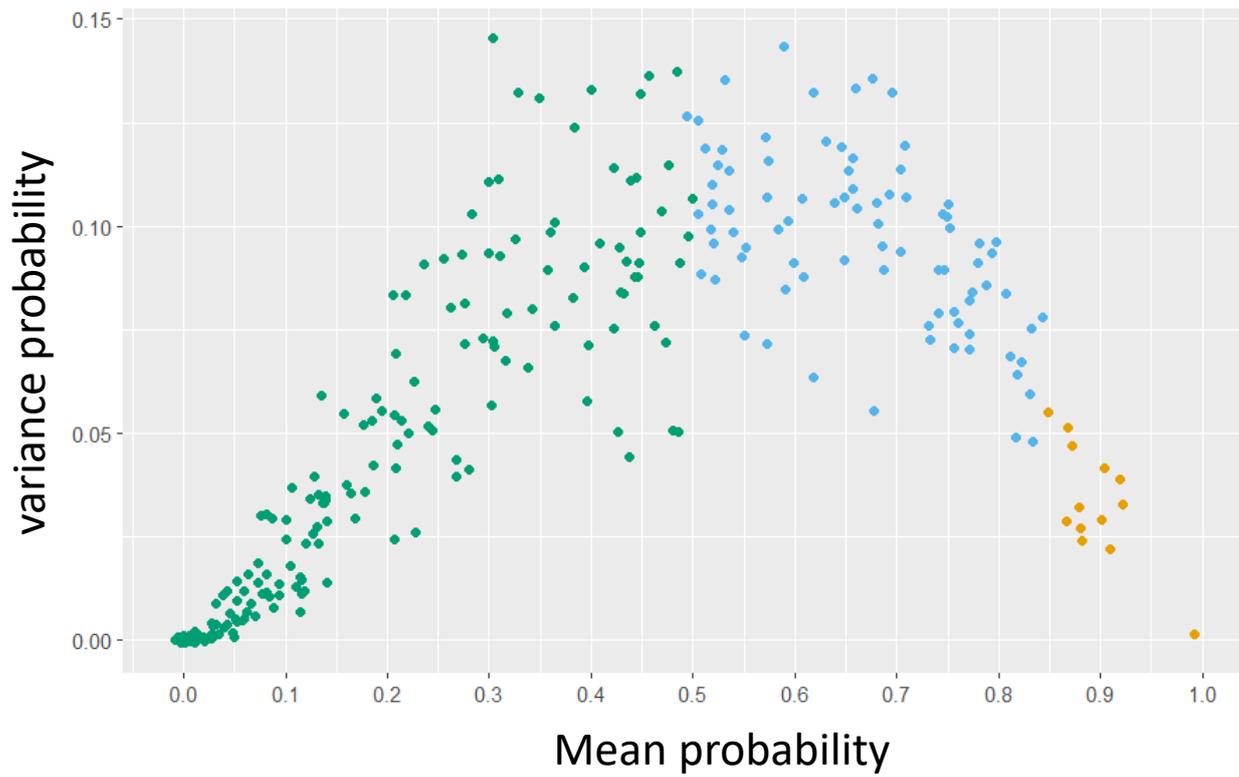
Figure S2: Distribution of the,  $\hat{\tau}_{ik}$  probability of a postcode  $i$  to be in a group  $k$



**Figure S3:** Estimated mean ( $\hat{\mu}_{kj}$ , panel A) and variance ( $\hat{\sigma}_{kj}^2$ , panel B) of substance quantities purchased in a group as a function of the probability of a substance  $j$  to be in a group  $\hat{\gamma}_{kj}$

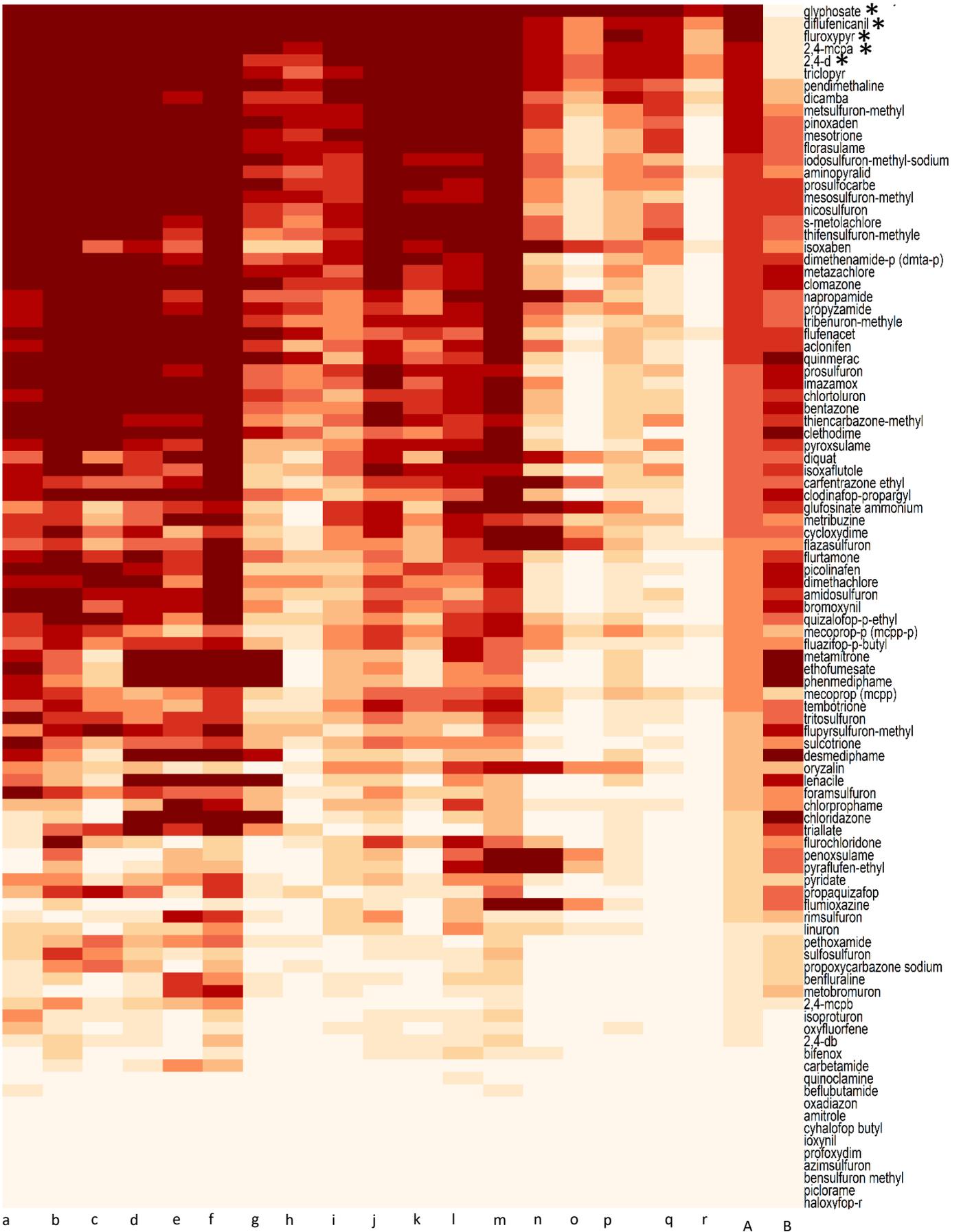


**Figure S4:** Differences and similarities in the clustering of postcodes produced by the mixture model with only 2017 substance purchase data (a) or 2015-2018 data (b). Postcode within a group share the same colour. Panel c shows proximity of the 2017 groups with 2015-2018 groups on a heatmap, expressed as the percentage of postcodes from 2017 groups that were found in the various 2015-2018 groups. The graph should be read vertically: for example, 2017 group r is split mostly into 2015-2018 groups 21(38%) and 23 (37%), with a small fraction of postcodes also found in 2015-2018 groups 1 (12%) and 13 (10%). In contrast, virtually all postcodes of 2017 group f are found in 2015-2018 group 18.

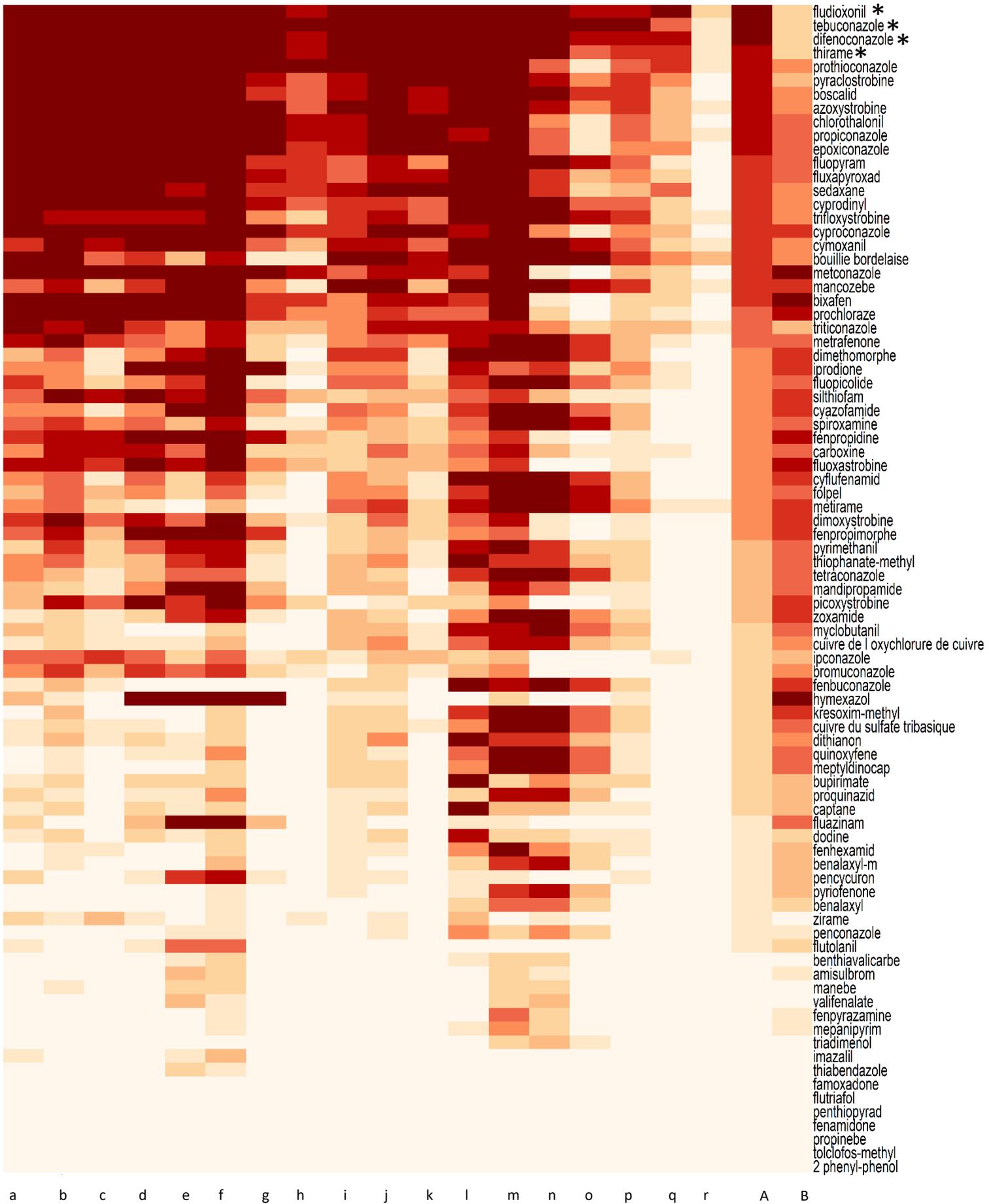


**Figure S5:** Variance in probabilities of substances to be in a group as a function of their mean probability to be in a group. Colours indicate core (orange), discriminant (blue) and other (green) substances.

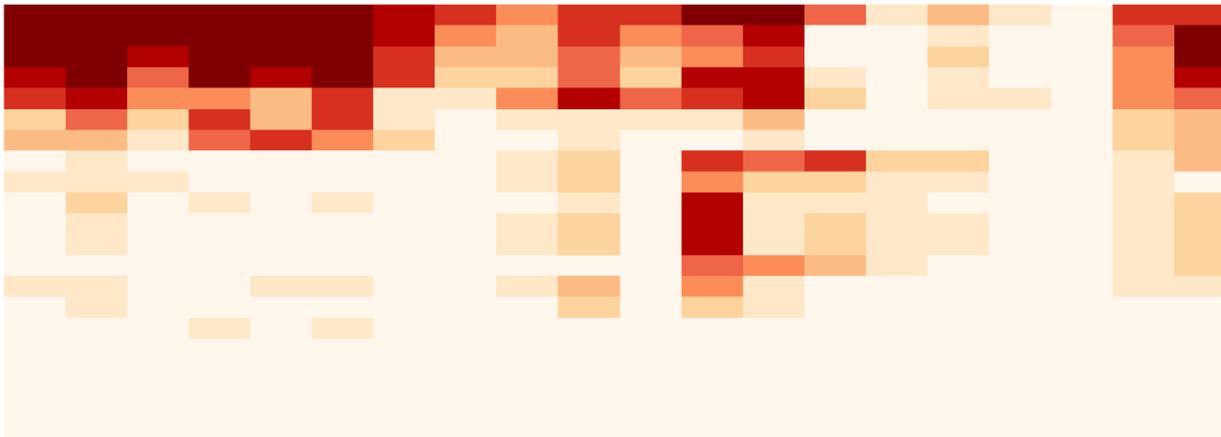
# Herbicides



# Fungicides

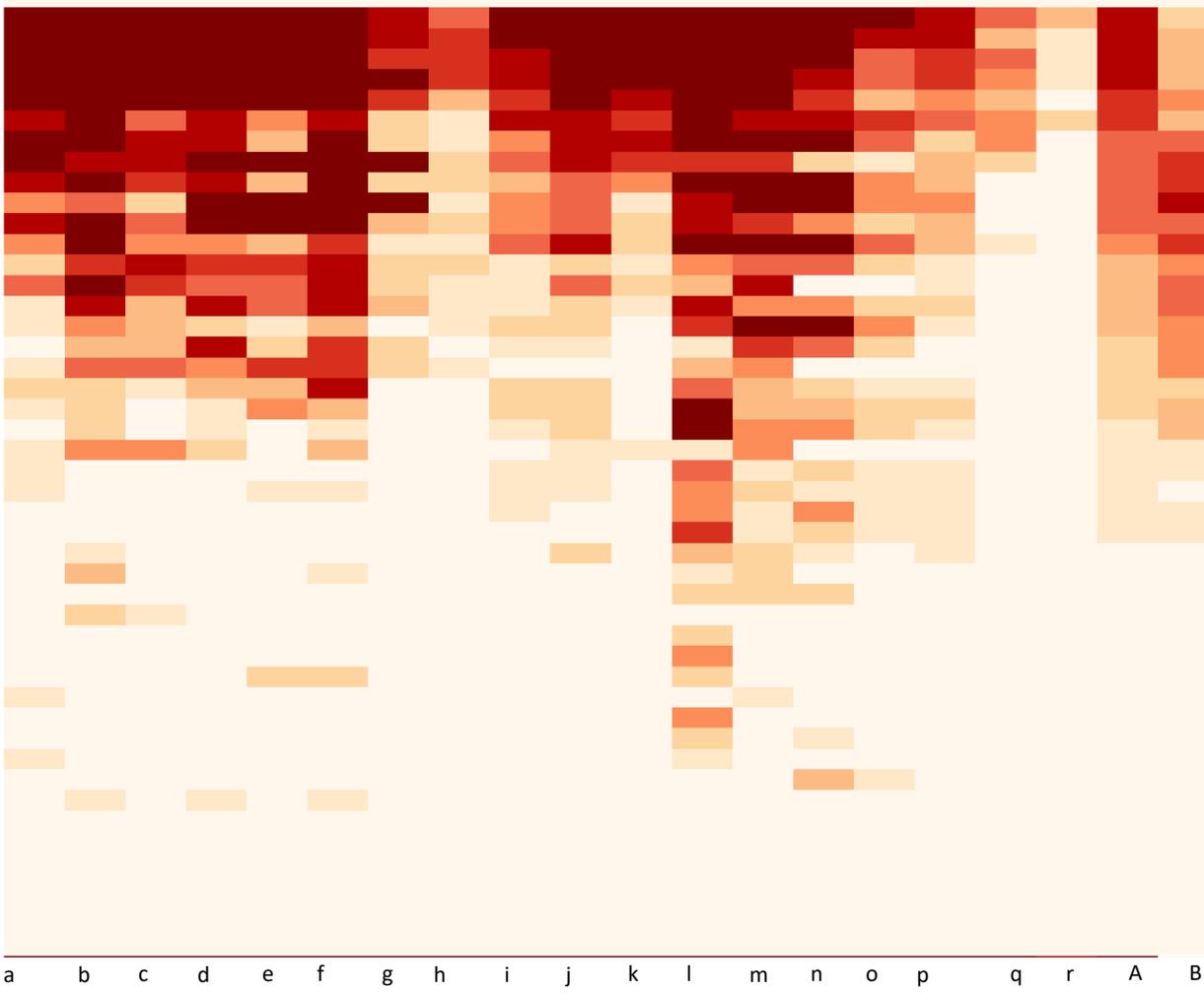


Other targets



- ethephon
- mepiquat-chlorure
- trinexapac-ethyl
- prohexadione-calcium
- isoxadifen-ethyl
- paclobutrazol
- imazaquine
- acrinathrine
- tebufenpyrad
- acide alpha naphtylacetique (ana)
- 1-dodecanol
- 1-tetradecanol
- fenazaquin
- acibenzolar-s-methyl
- decane-1-ol
- hypochlorite de sodium
- 1,3-dichloropropene
- alpha naphtyl acetamide (nad)
- forchlorfenuron
- bromadiolone
- cintofen

Insecticides



- deltamethrine \*
- lambda-cyhalothrine \*
- cypermethrine \*
- imidaclopride \*
- thiaclopride
- acetamipride
- chlorpyrifos-methyl
- tefluthrine
- tau-fluvalinate
- thiamethoxam
- pyrimicarbe
- chlorantraniliprole
- alphamethrine
- zetacypermethrine
- phosmet
- indoxacarbe
- betacyfluthrine
- esfenvalerate
- pymetrozine
- spirotetramat
- fenoxycarbe
- etofenprox
- hexythiazox
- bifenazate
- spinetoram
- pyriproxyfene
- diflubenzuron
- methiocarbe
- etoxazole
- pyrimiphos-methyl
- fosthiazate
- spirodiclofen
- clothianidine
- chlorpyrifos-ethyl
- acequinocyl
- tebufenozide
- ethoprophos
- methoxyfenozide
- gamma-cyhalothrine
- phosphure d aluminium
- oxamyl
- phosphure de magnesium
- cyfluthrine
- pyridabene
- malathion
- fluorure de sulfuryle

**Figure S8:** Heatmap of probability  $\gamma_{kj}$ , that substance  $j$  is used in postcode  $k$ . Groups were obtained from a mixture models optimised by maximum likelihood with an iterative method: Expectation Maximisation. Groups were ordered by similar composition of substance purchases. Substances belong to four categories: herbicides, fungicides, insecticides and other targets. Within each category of substances, substances were ordered in increasing number of groups in which they were used. Column A corresponds to the mean probability of use and column B corresponds to the scaled (0,1) variance in probability of use across groups. Asterisks (\*) highlight core substances.

**Table S1:** Complete list of substance's targets name associated with the "other" category

<b>Substance's targets</b>	<b>Number of substances</b>
Acaricide	5
Algicide	1
Attractant	2
Bactericide	1
Nematicide	1
Plant activator	1
Plant growth regulator	11
Rodenticide	2
Safener	1

**Table S2 :** Correspondence table between crop categories from the Land Parcel Identification System (LPIS) and aggregated crop categories used in our analyses

<b>CATEGORY FROM RPG</b>	<b>CATEGORY USED</b>
Common wheat	Cereals
Barley	Cereals
Other cereals	Cereals
Miscellaneous	Miscellaneous
Arboriculture	Orchard
Olive tree	Orchard
Fruit Orchard	Orchard
Legumes/Flowers	Legumes/Flowers
Maize	Maize
Nut	Nut
Other oil crops	Other oil crops
Protein crop	Protein crop
Rapeseed oil	Rapeseed oil
Sunflower	Sunflower
Grapevine	Grapevine