# Spatiotemporal drivers of pest and pathogens abundance in arable crops at the landscape scale

**MSc Internship report**

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**Farming Systems Ecology Group**

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## Acknowledgement

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## 1. Introduction

A global concern is rising about the use of phytosanitary products for crop protection against pests and pathogens. French arable farming systems are particularly dependent on this practice with two third of the total pesticide value used on cereals and industrial crops (Butault et al., 2011). Recurrent pesticide applications have often been associated with human health hazard and environmental degradation (Stoate et al., 2001). Reduction of pesticide use in arable farming may be achieved through alternative farming practices favoring natural regulation of bioagressors (Rusch et al., 2010).

Historically, the control of crop bioagressors, such as pest and pathogens, relies mainly on the management of the plot. However, drivers of pests and pathogens epidemics in cultivated areas occur at different spatial scales (Clough et al., 2006; Rusch et al., 2010; Schellhorn et al., 2008). As bioagressors dispersal is not limited by the plot's borders, integrating the impact of the landscape in the analysis would allow to study and potentially use the effect of neighboring crop and non-crop elements (Bianchi et al., 2006; Veres et al., 2013). The design of pests and pathogens integrated management strategies has vastly been influenced by this approach (Philips et al., 2014; Tscharntke et al., 2005).

Landscape composition can be described in terms of semi-natural areas, host crops, and patchiness. The influence of these elements was demonstrated on the abundance of pests (Bianchi et al., 2006; Chaplin-Kramer et al., 2011; Rusch et al., 2016) and pathogens in crops (Margosian et al., 2009; Papaïx et al., 2015). These elements may be known to either counteract or facilitate bioagressors dispersal (Karp et al., 2018). For instance, field hedgerows may promote pest's regulation via natural enemies, while large host crop surface may provide a suitable environment for pathogen spread. As a matter of fact, these elements showed contrasted effects between organisms, farming systems, and cropping seasons (Karp et al., 2018; Menalled et al., 2003; Perez-Alvarez et al., 2018).

Agricultural landscapes are highly dynamics, the plot being a highly disrupted environment, compared to natural areas that are more stable throughout time (Veres et al., 2013). Landscape composition drivers of bioagressors abundance are then assumed to evolve between cropping seasons (Esker and Nutter, 2003; Gardiner et al., 2009; Menalled et al., 2003; Thies et al., 2008). Coupled with weather variation, it becomes complex to dissociate the drivers of bioagressors abundance variation in time and space. Temporal variation of bioagressor abundance in relation to landscape composition received little attention in literature (Chaplin-Kramer et al., 2013). Short-term studies may actually not reflect the long-term effect of the surrounding landscape on the bioagressors populations (Karp et al., 2018).

For specific cases where the amount of data in space and time is large enough (Lacasella et al., 2017), the effects of host crop dynamics and the effect of bioagressors abundance from a given year on the next one were not explicitly taken into account. Studies often focused on single pest-parasitoid interactions, and sometimes on a bioagressors cohort of a particular crop, as cruciferous species (Perez-Alvarez et al., 2018) or wheat (Yang et al., 2019).

In this study, we assess the consistency of the impacts of semi-natural areas and host crop fields in the landscape on pest and pathogens in cultivated fields. Our approach relies on the analysis of systematic French epidemiosurveillance data spanning 9 years of observations (2009-2017) over two third of the metropolitan French territory. In total, hundreds of observations for each of 30 majors bioagressors of arable crops (wheat, barley, maize, potato, rapeseed and sugar beet) were jointly studied with landscape composition as described by official CAP data and woody vegetation maps. Beyond the simple correlation between landscape composition and bioagressors abundance, we control for the presence of the host crop the former years in the plot and for bioagressors former prevalence.

## 2. Materials and methods

### *2.1. Pests and pathogens data*

The French governmental arable crop epidemiological services require since 2008 that actors involved in the monitoring record and centralize their observations of pests and pathogens. A subsystem called Vigicultures® (Sine et al., 2010), conceived by one of the main French technical institutes (ARVALIS-Institut du végétal) has since been used in most French administrative regions (17/22) to centralize the results, covering approximatively two third of the metropolitan territory (Fig. 1). A similar information system, but for non-treated sugar-beet crop, called VIGIBET (ITB – Sugar Beet Research Institute) was used to complete data. These datasets were covering the 2009-2017 period.

A different set of plots is monitored each year, georeferenced and visited approximatively once a week during the cropping season to assess the state of pest and pathogen epidemics. A diversity of organizations contributes to the monitoring following standardized protocols. Several type of observations can be made on each bioagressor, here we quantify the abundance of a bioagressor using only the metric with the highest number of observations (Table 1ab). In total, data for 13 pests of winter wheat, corn and oilseed rape (Table 1a) and 17 pathogens of winter wheat, winter barley, oilseed rape, sugar beet and potatoes (Table 1b) were analyzed.

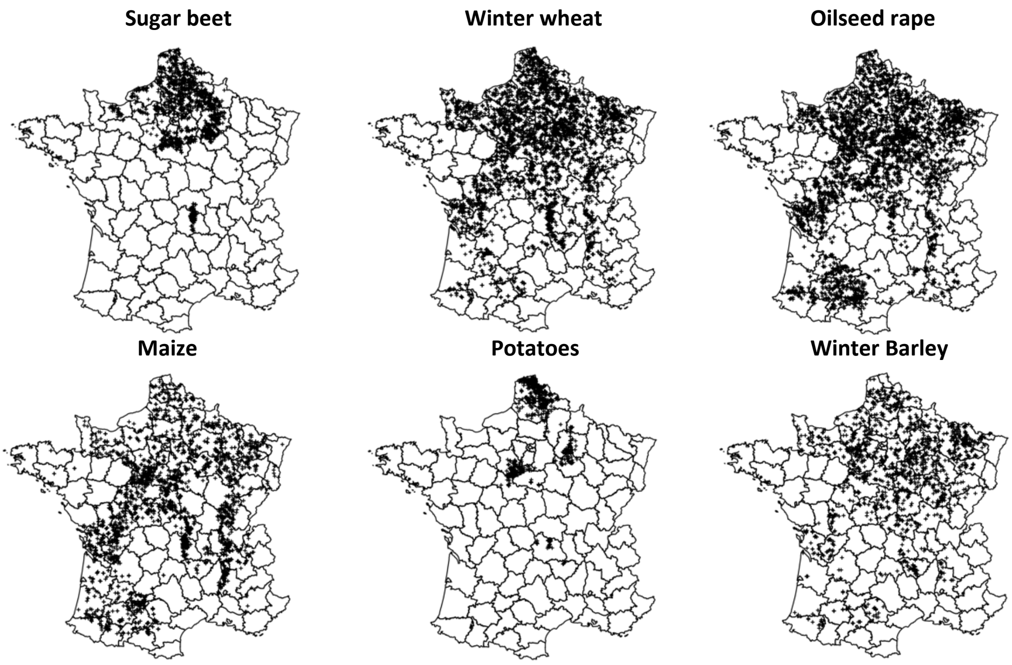


**Figure 1.** Spatial distribution of agricultural plots monitored

**Table 1a**. Pest data characteristics

| Crop species | Bioagressor group[1] | Observation period[2] | N (plot × year) | Observation metric |
|---|---|---|---|---|
| Winter Wheat | *Cecidomyiidae spp.* | March-June | 1159 | # [3] observed in yellow bowl |
| | *Deroceras, Arion, Limax spp.* | October-May | 2869 | % of seedlings with damages |
| | *Rhopalosiphum padi* | October-May | 2509 | % of plants with insect present |
| | *Sitobion avenae* | March-August | 2226 | % of plants with insect present |
| Corn | *Ostrinia nubilalis* | April-October | 1446 | # adults in pheromone traps |
| Oilseed rape | *Brevicoryne brassicae* | January-August | 4043 | # colony per $m^2$ |
| | *Ceuthorhynchus napi* | January-May | 4518 | # captured in traps |
| | *Ceutorhynchus assimilis* | February-August | 4087 | # per plants |
| | *Ceutorhynchus picitarsis* | September-January | 4111 | # captured in traps |
| | *Meligethes aeneus* | January-June | 4294 | % of plants with insect present |
| | *Myzus persicae* | August-December | 3476 | % of plants with insect present |
| | *Phyllotreta nemorum* | September-December | 2915 | # captured in vegetation traps |
| | *Psylliodes chysocephala* | August-December | 3863 | # captured in ground traps |

[1]Can be species, family or gender or of the bioagressor of interest
[2]Observations performed by Vigicultures ® experts during the 2009-2017 period
[3]# : number counted

**Table 1b**. Pathogens data characteristics

| Crop species | Bioagressor group[1] | Observation period[2] | N (plot × year) | Observation metric |
|---|---|---|---|---|
| Winter Wheat | *Blumeria graminis* | February-July | 3666 | Severity scale 1:10[3] |
| | *Fusarium Graminearum* | February-July | 1945 | % of the base stem infected |
| | *Gaeumannomyces graminis* | March-July | 1114 | Severity scale 1:100 |
| | *Helminthosporium spp.* | February-July | 2459 | Severity scale 1:10[3] |
| | *Oculimacula spp.* | February-July | 2734 | Severity scale 1:100 |
| | *Puccinia striiformis* | January-July | 3158 | Severity scale 1:100[3] |
| | *Puccinia triticina* | January-July | 3945 | Severity scale 1:10[3] |
| | *Septoria tritici* | February-July | 4350 | Severity scale 1:10[3] |
| Winter Barley | *Helminthosporium spp.* | February-July | 1585 | Severity scale 1:10[3] |
| | *Rhynchosporium secalis* | February-July | 1609 | Severity scale 1:10[3] |
| Oilseed rape | *Leptosphaeria maculans* | February-August | 3234 | % of plants with stem necrosis |
| | *Sclerotinia sclerotiorum* | March-June | 1515 | % of flower affected |
| Sugar Beet | *Cercospora beticola* | June-October | 1078 | % of infected leaves |
| | *Erysiphe betae* | June-October | 1069 | % of infected leaves |
| | *Ramularia betae* | June-October | 1070 | % of infected leaves |
| | *Uromyces betae* | June-October | 1069 | % of infected leaves |
| Potatoes | *Phytophthora infestans* | April-September | 940 | Severity scale 1:10 |

[1]Can be species, family or gender or of the bioagressor of interest
[2]Observations performed by Vigicultures ® experts during the 2009-2017 period
[3]On the third leaf (F3)

### 2.2. Landscape composition data

Landscape composition, in terms of agricultural land and semi-natural areas, was extracted from two geographic information systems. The French Land Parcel Identification System (RPG or “Registre Parcellaire Graphique”) and the BD TOPO® from the IGN.

The RPG provides detailed information on the cropland cover over the French territory. This system is the French implementation of the registration needed to manage agricultural subsidies in the framework of the European Common Agricultural Policy (CAP). The data are generated by farmers, who describe on satellite photographs of the BD Ortho®, the geometry (vector format) and cover of their fields. Each plot is anonymously registered under a code name specific to the farm, with information about the crop type, surface and geometry (Cantelaube, 2015). From 2006 to 2014 the geometrical description of the crops was by islet, in 80% of the cases with only one type of crop but in 20% of the islets a group of contiguous plots with different crops. In addition, the information on the crops was by crop types (28 crop types for 329 crops registered) of differing precisions: winter wheat, oilseed rape, winter barley, corn (including both silage and grain corn), other industrial crops (mainly beet) and flowering vegetables (mostly potatoes). From 2015 to 2017, both limitations have been lifted and the exact crop is known at the field level.

In this study, the semi-natural elements considered were woods, grasslands and hedgerows. While the RPG provides information about arable crops and grasslands (temporary and permanent are not distinguished), the BD TOPO® (version 2.1) provides information about the geometry of woody areas (vector format). The BD TOPO® is part of the Large-Scale Reference (RGE or “Referentiel à grande echelle”) from the National Institute of Geographic and Forest Information (IGN). In this database, we group as “wood” the forests of broad-leaved, conifer, mixed species, with closed (> 40% ground cover) or open (between 10 and 40% ground cover) canopy. We also extract the hedgerows, that is any field hedge of vegetation composed of wood or shrub species with a width lesser than 25m. Orchard, vineyard, poplar grove and moors were not included in the analysis. As those woody formations are less subject to change, we only used the year 2017 version of the BD TOPO®.

### 2.3. Variables calculations

The response variable, i.e. the bioagressor abundance, was calculated from the Vigicultures® observation metrics for each bioagressor. Raw data consisted in weekly measurements, per plot per bioagressors, with missing data. For each bioagressors metric, we calculated the average abundance for each plot*year combination. Then, the calculated the global median on these averages. The latter median was used as a threshold. For each plot-year and organism, we calculated how much time weekly observations were exceeded this threshold. This number of "positive observations" was accounted for the number of total observations during the year. Hence, the rate of positive observations for a given plot, a given year was our response variable.

As explanatory variables, we used the surface of semi-natural elements and of the host crop type (Table 2) around each agricultural plot in buffers of 200m, 1km, 5km, and 10km. For instance, the variable grassland surface at 1km scale represented the area of grassland in $m^2$ found in a 1km radius around the plot of interest. The buffer sizes were chosen as typical sizes of possible management units. The first buffer size corresponds roughly to including the adjacent plot: from the RPG we calculated the average and median size of french arable crop plots in 2014 to be 4.6 ha and 2.76 ha corresponding to a border size of square plots of respectively 214 and 166m. The 1km radius lousily corresponds to including a few fields around the observation, possibly managed by one farmer. The 5 km radius roughly corresponds to the square root of the average size of the territory of a French municipality. The 10km radius is on the order of magnitude of including neighboring municipalities, the maximum we envision as a bottom-up self-organized management unit.

**Table 2**. Features of the explanatory variables studied in the bioagressor models[1]

| Effect type | Description | Scale | Unit |
|---|---|---|---|
| Semi natural areas | Woods surface | 200m, 1km, 5m and 10km | $m^2$ |
| | Hedgerows surface | 200m, 1km, 5m and 10km | $m^2$ |
| | Grasslands surface (y) ** | 200m, 1km, 5m and 10km | $m^2$ |
| Cultivated area | Host crop surface (y-1) ** | 200m, 1km, 5m and 10km | $m^2$ |
| | Host crop surface (y-1) ** | 200m, 1km, 5m and 10km | $m^2$ |
| Crop rotation | Time since last cultivated grassland on plot | _ | year |
| | Time since last cultivated host crop on plot | _ | year |
| Former prevalence | Departmental bioagressor abundance (y-1)** | _ | % positive observation[3] |
| Landscape former prevalence | Departmental bioagressor abundance × Crop surface (y-1)** | 200m, 1km, 5m and 10km | % positive observation[3].$m^2$ |

[1] there is only one crop of interest per bioagressor model
[2] y is the harvesting year for the crop under observation
[3] the rate of observations the former harvesting year in the department

The effect of crop rotation on the plot was considered here as the time elapsed (in years) since the last time the host crop type was cultivated on the islets including the point of observation. As we had only 2 years of RPG data previous to the first observation, this variable was simplified to 1, 2, 3 years or more. Similarly, we considered the time elapsed since the last grassland at the point of observation.

We also accounted for the abundance of the bioagressors (as described above) the previous year, aggregated at the departmental level. The plots were not monitored every year, as a result, a higher level of aggregation, the departmental one, was considered to represent the bioagressors prevalence of the former year. The interaction between this value and the host crop surface of the of the previous year in the landscape was added as well to the candidate variables. All explanatory variables were log transformed.

Bioagressor models were all set with the quantitative variables of Table 2, plus a group of structural variables accounting for the small-scale regional farming system first, and second the interactions year × climatic zone. We did not include specific weather-related factors in this analysis. However, we accounted for potential year × climatic zone differences. These climatic zones are defined here as broad entities of pedoclimatic context for the production of wheat and are an adaptation of the climatic entities defined by Lorgeou et al. 2012. These two factors were added in the model as fixed effect controlling for potential heterogeneity but were not further investigated.

### *2.4. Statistical analysis*

Bioagressor abundance was represented in the final model by the ratio $\pi_{ij}$, the number of times the value exceeded the median threshold a given year in a given plot over the total number of observations in this plot:

$$\pi_{ij} = \frac{n_{obs.above\ threshold}}{n_{obs.\ total}}$$

This ratio was analyzed by fitting a generalized linear model (GLM) via penalized maximum likelihood (LASSO) using a binomial model (Guisan and Zimmermann, 2000). for the number of observations above the threshold among the total number of observations per plot. Among the multiple potential explanatory variable, the LASSO method provided by the *glmnet* R package (Friedman et al., 2008) automatize the selection of the most relevant variables, based on cross-validations, for each of the bioagressor models. Partial correlation coefficients were calculated in order to assess explanatory power of the variables in each model (Barbu et al., 2016).

## 3. Results

### *3.1. Data management*

Present results are based on the work of the team of C. Barbu at the National Institute of Agricultural Research since 2014 (Barbu et al., 2016). The system was originally performing analysis for 13 pests and 13 pathogens. Bioagressors abundance data were automatically retrieved from Vigicultures® website by emulating clicks in a browser. Four sugar beet pathogens were added to the existing database thanks to the Technical Institute for Beet that provided Vigicultures® data for this crop. These data were manually imported because of structure and format differences with the original Vigicultures® data.

The time period the system was analyzing increased from 2009-2014 to 2009-2017 with the importation of agricultural plot data for the 2015-2017 period. This data required a specific importation, because of the changes mentioned above (cf. 2.2.) Such data are more accurate to describe the landscape composition in term of crops present and their surface. Moreover, Vigicultures® data were the most abundant in the year 2017, followed by 2016 and 2015. Thus, the addition of the 2015-2017 agricultural plot data allowed to increase the number of plots per year per bioagressors combinations from 44785 to 78056 data points. It is important to note that the main trends observed with the reduced dataset were unchanged with this update.

Existing functions for the calculation of bioagressors abundance metrics and landscape metrics were not altered. New data were always specifically formatted and adapted to those functions. However, new variables were calculated and added in the system: the departmental bioagressors prevalence of the previous cropping season (Table 2) and its product with the surface of host crop of the previous year. Functions responsible for the statistical analysis and outputs were adapted to account for these variables.

A set of meteorological variables were also formatted to be processed by the statistical model. Meteorological data were drawn from the objective analysis module SAFRAN (Lemoigne, 2002) of the National Centre of Meteorological Research. Precipitation, evapotranspiration, minimal and maximal temperatures processed data were available at the monthly and departmental scale. However, from the first results, this resolution was judged too coarse. After importing the raw data, daily weather parameters were calculated at 8km resolution. They were then averaged into monthly periods. Each of the 12 months preceding the last bioagressors observations during a given cropping season, for each weather parameters represented a potential explanatory variable. However, lack of time prevented the integration of these variables in the statistical model, hence not presented in this report.

*3.2. Spatial effect of landscape composition*

All bioagressors models were set with the same group of variables: wood, hedgerow, grassland and host crop area in the landscape (current and previous year) at a scale of 200, 1000, 5000, 10000 m, around a given plot a given year. The time since the last grassland in the plot, and the time since the host crop was cultivated on the plot, were also included.

Contrasted responses to landscape components were observed between pests and pathogens but also among their group. From the modelling process with automated variable selection, we characterized the detrimental or protecting effect of the main components of an agricultural landscape. The number bioagressors affected by a landscape component (Fig. 2) illustrates the consistency of the effect on a group of bioagressors.

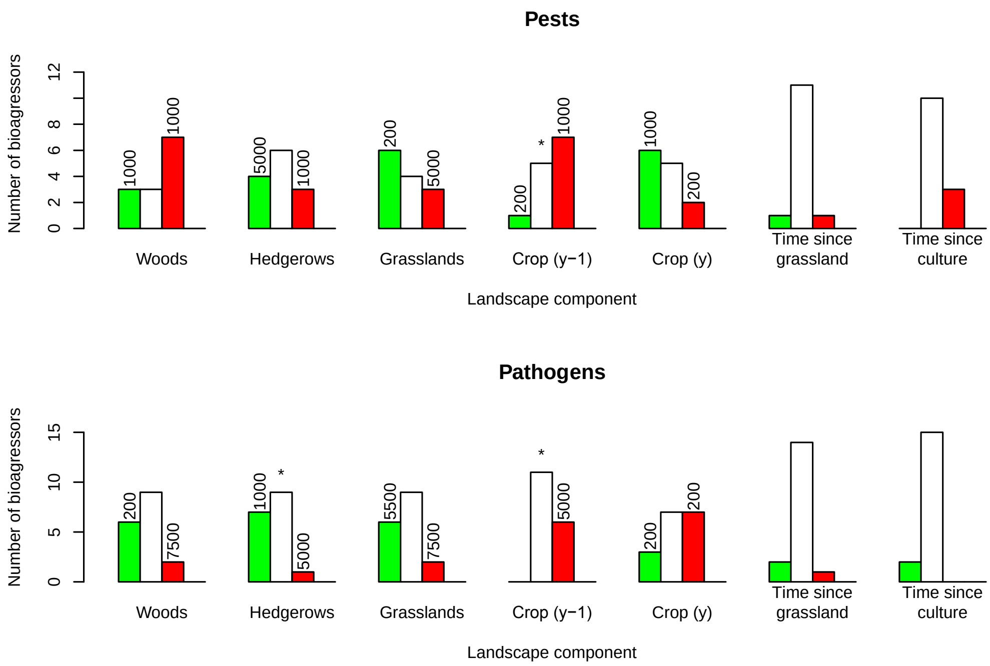


**Figure 2a.** Summary of the directions of landscape components effects on pest (above) and pathogens (below) abundance. Bars indicated the number of bioagressors affected positively by a variable (in red), unaffected (in white) or affected negatively (in green). Number above coloured bar indicates the median of the spatial scale associated with a landscape component. Significant levels of 0.1, 0.05, 0.01, and 0.001are indicated by . ,*, **, and *** respectively

Surface of grassland, hedgerows and woodlands in the landscape showed mixed effects between pests and pathogens but also among their group. Between the two model, with and without accounting for the bioagressors prevalence of the former year, the number of bioagressors affected by the area of semi-natural components changes (Fig. 2a, b). A higher number of bioagressors were unaffected in the model accounting for the prevalence of the former year (Fig. 2b), indicating a weaker influence of the area of semi-natural elements. The number of pathogens negatively affected by hedgerow surface was no more significantly higher than the number of pathogens positively affected by hedgerow surface. Woodlands areas, while not significantly detrimental in both models had a mostly positive effect on pests, but not on pathogens. Grasslands showed a negative correlation with pest and pathogens abundance in both models, however, the number of bioagressors negatively impacted was not significantly higher than the number of bioagressors positively impacted.

Relationship with the host crop surface of the same year as the observation was performed were opposed between pests and pathogens (Fig 2a, b). The number of bioagressors negatively affected was never significantly higher the number of bioagressors positively affected. A poor significance was observed for the model accounting for the prevalence of the former year in the pest group (Fig. 2b, $P < 0.1$). More pests were negatively affected by the host crop surface, 7 against 2 (Fig. 2a) for the model without former prevalence, 6 against 2 (Fig. 2b), in the model with former prevalence. As opposed, more pathogens were positively affected, 6 against 2 (Fig. 2a) and 7 against 3 (Fig. 2b). This effect was relatively consistent among the groups and between the two models (Sup. material I,II).

The absence of strong correlation between semi-natural components, extent of the host crop surface during the year of observation, and the abundance of bioagressors advised the consideration of the temporal dynamics of the landscape for the analysis.

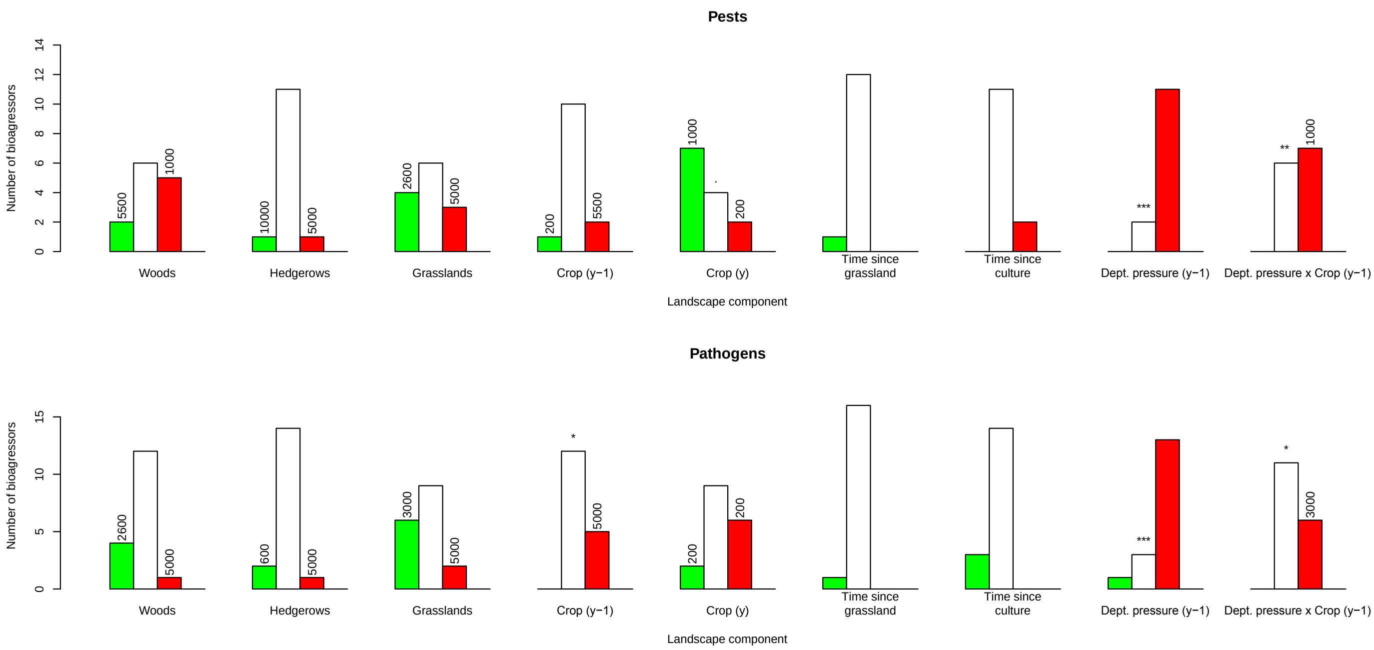


**Figure 2b.** Summary of the directions of landscape components and inoculum effects on pest (above) and pathogens (below) abundance. Bars indicated the number of bioagressors affected positively by a variable (in red), unaffected (in white) or affected negatively (in green). Number above coloured bar indicates the median of the spatial scale associated with a landscape component. Significant levels of 0.1, 0.05, 0.01, and 0.001are indicated by . ,*, **, and *** respectively.

### *3.3. Spatiotemporal effect of host crop surface*

Host crop surface of the previous year was the only component positively correlated with both pests and pathogens abundance. For both groups (model without prevalence), a significantly higher number of organisms showing a positive relationship was observed (Figure 2a, P. < 0.05). Wheat and sugar beet pathogens were generally unaffected (Sup. material I.B). Among all organisms, partial correlations ranged from 0 up to 13% for *Sclerotinia sclerotiorum* (Sup. material I.B). Consistent correlations highlighted that large host crop surface is likely to provide more favorable conditions for the organisms to develop during the following cropping season. For the pests, organisms that were affected as well by the surface of the host crop the current and previous year showed consistently a negative correlation with the former and a positive correlation with the latter. This trend concerns mainly the weevils of the *Ceuthorhynchus* family (Sup. material I.A). While pathogens showed a tendency to be positively correlated with the host crop surface of the current year, there was no noticeable relationship for a particular crop.

It was expected that the surface of the host crop between two years can be highly correlated. The strong effect of the host crop surface of the previous year at the landscape could mask the effect of crop rotation on the plot. The latter was included explicitly in the analysis under two variables: the number of years since the host crop was cultivated and the number of years since the last grassland. Most bioagressors were unaffected at the exception of two pests and three pathogens (Fig. 2a). In addition, the scale associated with the host crop surface was large, 5 km for the pathogens and 1km for the pests (Fig. 2a), indicating that these processes were occurring well beyond the field scale.

These findings also highlight the spatiotemporal aspect of the relationship between the surface of the host crop and the bioagressors abundance. For pathogens, the median scale to which the host crop surface has the highest correlation with abundance is lower for the current year (200 m) than the previous year (5 km) (Fig. 2a). For the group of pests, the scale is similar (1 km) between the host crop surface of the current and previous year (Fig. 2a).

### *3.4. Former bioagressors prevalence and host crop surface*

Under the assumption that the host crop surface of the previous year is positively related to bioagressors colonization, a second model was performed. We explicitly took into account the bioagressors prevalence of the previous year (the departmental level), to model its effect on the abundance the next year on the plot. A positive relationship was found for 25 of the 30 bioagressors. The number of bioagressors positively affected was then was highly significant (Fig. 2b, P < 0.001) for pest and pathogens. The relationship was not only found often, it was also very strong: partial correlations were the highest among explanatory variables for the different models (Sup. material II)

For the pest, the values ranged from 7% for *Phyllotreta nemorum* to 13% for *Meligethes aeneus* (Sup. material II.A). The range was larger for the 13 significant association among the 17 pathogens: from 1% for *Leptosphaeria maculans* to 27% for *Cercospora beticola* (Sup. material II.B). *Phytophthora infestans* was the only organism showing a negative correlation with the departmental abundance of the previous year (Sup. material II.B).

Interactions with the host crop surface of the previous year was also significant for pests (Figure 2b, $P < 0.01$) and pathogens (Figures 2b, $P < 0.05$). A higher number of organisms was positively correlated with this variable for both groups. When including the departmental abundance of the former year and its interaction. Values of partial correlations for the interactions were lower than the former prevalence alone (Sup. Materials). Concerning the pest group, the interaction was sometimes selected instead the host crop surface of the previous year. The number of pests affected by the latter variable was no longer significant (Fig. 2b). In contrast, pathogens were often affected by both the interaction and the host crop surface of the previous year.

As a result, the host crop surface of the previous year was related to the former year prevalence, indicating that the amount of host crop in the landscape may be a transmission path for bioagressors to remain from a cropping season to the next.

### *1.1. Bioagressor models performances*

Most of the bioagressor models attained a reasonable goodness of fit, however, for a small number of bioagressors, the test of goodness of fit was not passed. Adjusted $D^2$ was used to quantify how much landscape components and bioagressor prevalence could explain variation of bioagressors abundance. Adjusted $D^2$ varied from 5.4% in the *Phyllotreta nemorum* model to 34.9% in the *Psylliodes chysocephala* model, among the crop pest models (Table 3a). For the crop pathogens models (Table 3b.), values ranged from 0.0 % in the *Helminthosporium spp.* model to 53.5 % in the *Phytophthora infestans* model. In average, we were able to explain 19.3 % of the pest abundance variation and 21.2 % of the pathogens abundance variation.

**Table 3a**. Pest models' amount of deviance accounted for the landscape and inoculum variables

| Crop | Pests | $D^2$ (%) |
|---|---|---|
| Winter wheat | *Cecidomyiidae spp.* | 3.9 |
| | *Deroceras, Arion, Limax spp.* | 17.8 |
| | *Rhopalosiphum padi* | 8.7 |
| | *Sitobion avenae* | 11.2 |
| Corn | *Ostrinia nubilalis* | 17.6 |
| Oilseed rape | *Brevicoryne brassicae* | 26.4 |
| | *Ceuthorhynchus napi* | 21.5 |
| | *Ceutorhynchus assimilis* | 20.9 |
| | *Ceutorhynchus picitarsis* | 32.0 |
| | *Meligethes aeneus* | 20.4 |
| | *Myzus persicae* | 27.6 |
| | *Phyllotreta nemorum* | 5.8 |
| | *Psylliodes chysocephala* | 36.7 |

**Table 3b**. Pathogen models' amount of deviance accounted for the landscape variables and inoculum variables

| Crop | Pathogens | $D^2$ (%) |
|---|---|---|
| Winter wheat | *Blumeria graminis* | 24.4 |
| | *Fusarium Graminearum* | 9.7 |
| | *Gaeumannomyces graminis* | 12.0 |
| | *Helminthosporium spp.* | 0.0 |
| | *Oculimacula spp.* | 12.8 |
| | *Puccinia striiformis* | 24.7 |
| | *Puccinia triticina* | 18.6 |
| | *Septoria tritici* | 24.0 |
| Winter barley | *Helminthosporium spp.* | 19.7 |
| | *Rhynchosporium secalis* | 19.3 |
| Oilseed rape | *Leptosphaeria maculans* | 9.5 |
| | *Sclerotinia sclerotiorum* | 11.7 |
| Sugar Beet | *Cercospora beticola* | 37.8 |
| | *Erysiphe betae* | 8.7 |
| | *Ramularia betae* | 33.9 |
| | *Uromyces betae* | 41.0 |
| Potatoes | *Phytophthora infestans* | 53.7 |

## 4. Discussion

This study highlighted that landscape composition holds consistent effects on variation of pest abundance, for 30 bioagressors major arable crop, supported by 9 years of field observations over two third of the French territory. The most consistent effect is the positive relationship of bioagressor abundance with the surface of sensitive crops the former year. For most of the bioagressors, their abundance is highly correlated to their abundance of the preceding year. Semi-natural areas, while also affecting bioagressors abundance, were inconsistent in the direction of their effects, either detrimental, neutral or beneficial depending on the bioagressor population.

These findings are supporting the well-recognized evidence that landscape composition is regulating bioagressors epidemics in crops. Its role on pest arthropods has been extensively reported for multiple organisms (Bianchi et al., 2006; Chaplin-Kramer et al., 2011; Karp et al., 2018). Crop pathogens received less attention regarding the effects of landscape (Plantegenest et al., 2007) with a lack of empirical results (Burdon and Thrall, 2008; Claflin et al., 2017). However, their relation is well-recognized as well. Our global approach combining long term pests and pathogens data, following Barbu et al., (2016), is original in the investigation of bioagressors and landscape relationship. As crop cover spatiotemporal variations tend to affect most of the organisms, this gives potential for bioagressors modulation at the landscape scale through crop cover management.

### *4.1. Host crop cover and interannual variation of bioagressors abundance*

The extent of host crop surface in the landscape during the previous cropping season had the most significant and consistent effect among landscape components for pest and pathogens (Fig. 2,4). As opposed, the host crop surface of the current year that (1) tend to have opposite effects for pests and pathogens. This highlight the importance of integrating the temporal dimension of landscape effect in bioagressors epidemic studies. This is unfortunately rarely considered as denoted by (Karp et al., 2018) resulting in potential bias in the conclusion of short term studies (Chaplin-Kramer et al., 2011).

Accounting for cropland temporal dynamics allowed us to observe contrasted effect of the host crop. Indeed, host crop surface was positively correlated with pest abundance the previous year, and negatively the current year. Our results align with the literature regarding the sole spatial effect of cultivated area on pest abundance, when considering total cropland (Perez-Alvarez et al., 2018) or the host crop area (Veres et al., 2013). It is observed here that large host crop area is not linked to high abundance of pest arthropods within the cropping season. Nevertheless, expansion of host crop area from a year to another have been linked to reduced pest abundance through a dilution effect and reduction of host crop to a crowding effect of the population in the landscape (Schneider et al., 2015; Thies et al., 2008). In this study, we did not explicitly account for the dynamic change of host crop area, but rather study the combined effect of two temporal states, the current cropping season and the previous one. However, our results are coherent with these findings. In addition, these dynamics of pest abundance related to landscape diversity have a relative importance regarding the potential biocontrol of natural enemies, that can be reduced in low diversity landscape (Gardiner et al., 2009; Rusch et al., 2016).

Pathogens prevalence in the landscape, on the other hand, in showing a different behavior regarding the effect of the host crop area. As observed here, high host abundance during the cropping season have been reported to increase pathogens prevalence (Carrière et al., 2012; Claflin et al., 2017; Gilligan et al., 2007; Rodelo- Urrego et al., 2013). High host crop density, regardless landscape configuration, is likely to facilitate diseases transmission with increasing crop connectivity (Margosian et al., 2009).

While we recognized that crop protection management and crop rotation can disrupt bioagressors populations, other factors are affecting interannual variation (Head et al., 2005). We argue that former prevalence is a key component (Fig. 4) for bioagressors abundance temporal variation. The regional pool of the previous year determines the one in the subsequent year and act as a feedback on the bioagressors prevalence (Levins and Schultz, 1996). Significant interactions between host crop area of the previous year and the prevalence of the previous year implies that host crop surface is the limiting factor for bioagressors population to sustain throughout time. For pathogens, inoculum density is a major factor underlying the probability of pathogens occurrence. Landscape composition can be determinant for the abundance of inoculum reservoirs (Plantegenest et al., 2007). Such reservoir could consist in cultivated or wild host (Gilligan et al., 2007; Papaïx et al., 2015; Plantegenest et al., 2007). Temporal correlation in pest variations has been observed for pest (Bommarco et al., 2007; Chaplin-Kramer et al., 2013; Day et al., 2010; Lewellen and Vessey, 1998). However, yearly variations of pests abundance need to be analyzed cautiously because yearly aggregation may hide important information depending on the organism life cycle (Chaplin-Kramer et al., 2013; Lewellen and Vessey, 1998).

### *4.2. Semi-natural areas and landscape diversity*

Despite frequent pest level significant relationships, the pest prevalence did not show consistent responses to semi-natural habitat area. The pathogens response was generally lower and no more consistent.

The role of landscape composition regarding the proportion of semi natural area to sustain natural enemy communities has been extensively studied. However, they often yield contrasted conclusions regarding their effect on pest abundance. They concluded either on suppressive (Bianchi et al., 2006; Veres et al., 2013) or mixed effect (Karp et al., 2018; Yang et al., 2019). Contrast between studies have been discussed (Tscharntke et al., 2016) involving several mechanisms preventing beneficial effect of non-crop elements in the agricultural landscape: pest-predator equilibrium, potential role of the crop as habitat for predators and semi-natural area for pests, landscape configuration and agricultural practices.

Concerning pathogens, the effect of natural areas on their prevalence is recognized as well but lack of empirical studies. While some elements in the landscape may act as barrier preventing the spread of pathogens, the presence of alternative wild host in semi-natural areas can actually offer secondary habitat for diseases to remain in the landscape (Papaïx et al., 2015). Plus, the ecological interface between crop and non-crop area have been discussed to be a potential reservoir to non-crop host (Burdon and Thrall, 2008).

In this regard, the role of landscape configuration might be a more relevant pathway to study the relationship between bioagressors and semi-natural areas. The amount and composition of crop-non crop and crop-crop borders is recognized as determinant for pests (Bosem Baillod et al., 2017; Martin et al., 2016) and pathogens (Plantegenest et al., 2007). These interfaces, associated to the crop dynamics, are likely to evolve more rapidly than the proportion of natural area itself, and could explain more.

### *4.3. Methodological considerations and limitations*

While generalized linear modeling has been widely employed in the field of ecology for habitat distribution (Guisan and Zimmermann, 2000), in particular in the presence of relative abundance data, our analysis need to be interpreted cautiously. Variables selection was very discriminant, by accounting for year, climate and farming system potential heterogeneity and thanks to the restrictive regularization of the lasso algorithm (Hastie et al., 2009). However, the very high number of potential features (27) and the potential collinearity between the spatial scales (200, 1000, 5000, 10000) or between periods (y, y-1) increases the risk of arbitrarily selecting features for each individual bioagressor though it should not affect a general significant tendency across bioagressors. Consequently, we emphasize the interpretation of significant tendency across bioagressors (Fig. 2, 3) and avoid interpretation of individual bioagressor-explaining factor relationship.

Bioagressors abundance was represented in this study as the percentage of observations that exceeded a threshold during a year of observation on a plot. In the presence of multiple metrics for measuring prevalence (Table 2) such as abundance (count), crop colonization (%), crop damage (severity scale) it was necessary to standardize prevalence under a general variable representing the potential number of outbreaks during the observation period. This approach is also recommended by (Chaplin-Kramer et al., 2011) to provide a more robust understanding of the bioagressors prevalence dynamics. It is important to notice, that such metrics may reduce undesirable variability due to data quality regarding (1) the precision of national landscape database and (2) potential bias due to numerous observers on the field (3) the subjectivity of measurement metrics such as severity scale.

The study was tailored to identify general tendencies applying exactly the same modeling approach to all the bioagressors. Applying similar explanatory variable on different bioagressors response metrics might lead to different conclusions, and other bioagressor observations may be more related to the economic impact on the crop (Devaud and Barbu, n.d.). In addition, individual studies of the different organisms would benefit from a better consideration of organism functional traits to unravel hidden effect of landscape composition for some groups of bioagressor (Karp et al., 2018; Martin et al., 2019; Schellhorn et al., 2014).

A reasonable part of variation was explained by landscape components and former department prevalence, 20% in average between the bioagressors models. However, the modelling technic used here leave potential to complexify the pest and pathogens models. Such models could integrate (1) variables related to crop management (Martin et al., 2016), and (2) abiotic factors related to known pedoclimatic conditions of the field or predictable meteorological conditions. In addition, the effect of landscape configuration on pest and pathogens may also be included  (Martin et al., 2019; Papaïx et al., 2015) to go beyond our conclusions on plain landscape composition.

## 5. Conclusion

Considering that crop cover can easily be manipulated in the landscape from a year to another, this gives opportunity for the design of landscape crop cover optimizing control of bioagressors abundance and limiting outbreak in arable crop (Schneider et al., 2015). The joint study of pest and pathogens, while having different spreading strategies has potential for a global crop protection management.

Our findings support the idea that landscape simplification around a same crop does not in general favor epidemic outbreaks during the current growing season, but rather that its detrimental effect lie in the season ahead. Under current management practices, landscape wide rotation of the main crop types might decrease abundance of bioagressors, by preventing bioagressors spillover between cropping seasons (Gilligan et al., 2007). This lever may be debatable regarding the potential effects on the non-pests biodiversity (Rusch et al., 2016).

Toward the conception of bioagressors management practices at the landscape scale, this study brings responses on the consistency of landscape effects by using available tools and data to quantify automatically in an interpretable way the general impact of landscape components. Further work is needed to move toward bioagressors predictions for seasonal forecasting. Early warning system tools based on this approach may provide an advantage to assess the risk of potential yield loss and an opportunity to moderate the use of phytosanitary products (Lacasella et al., 2017). Alternative practices for bioagressor control, as highlighted here by the large scale at which the landscape has an impact, have potential if implemented at a large scale. However, the challenge lies in the organization of new land management units involving a maximum number of stakeholders of the agricultural landscape, who often mismatch in term of objectives and perceptions (Kleijn et al., 2019) regarding potential benefits of ecosystem services.

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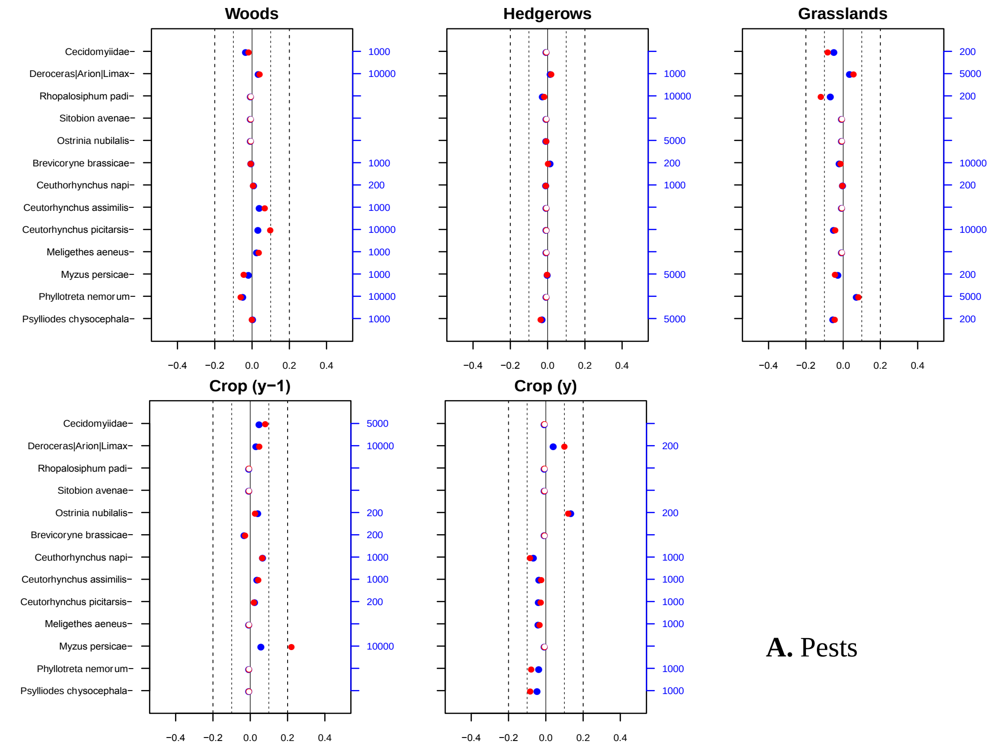
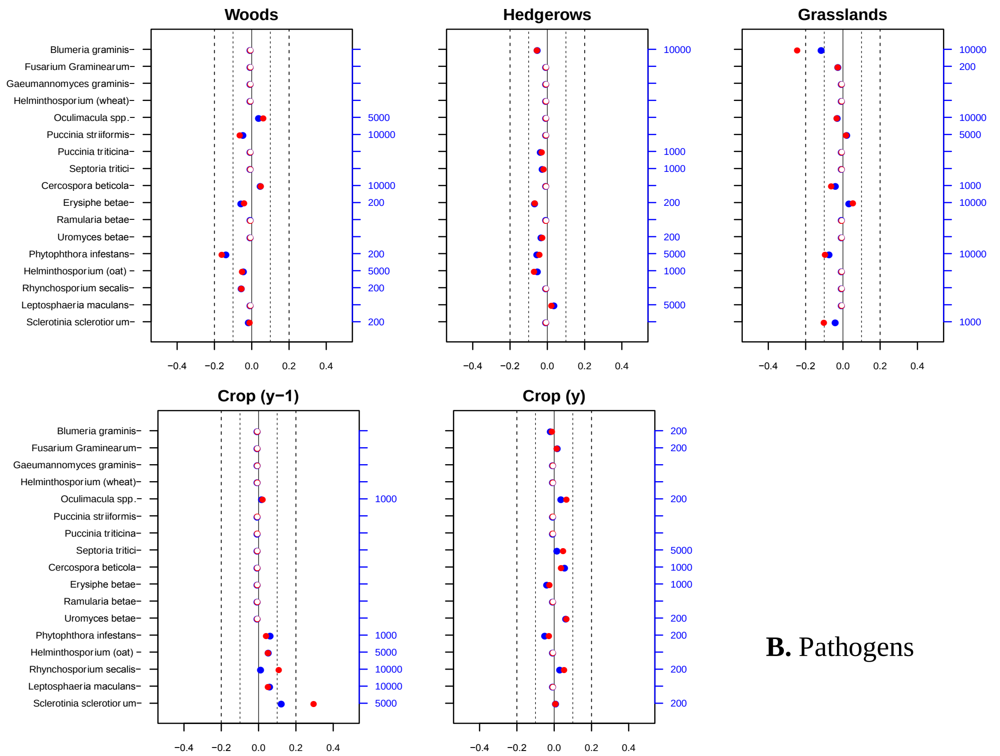
# Supplementary materials

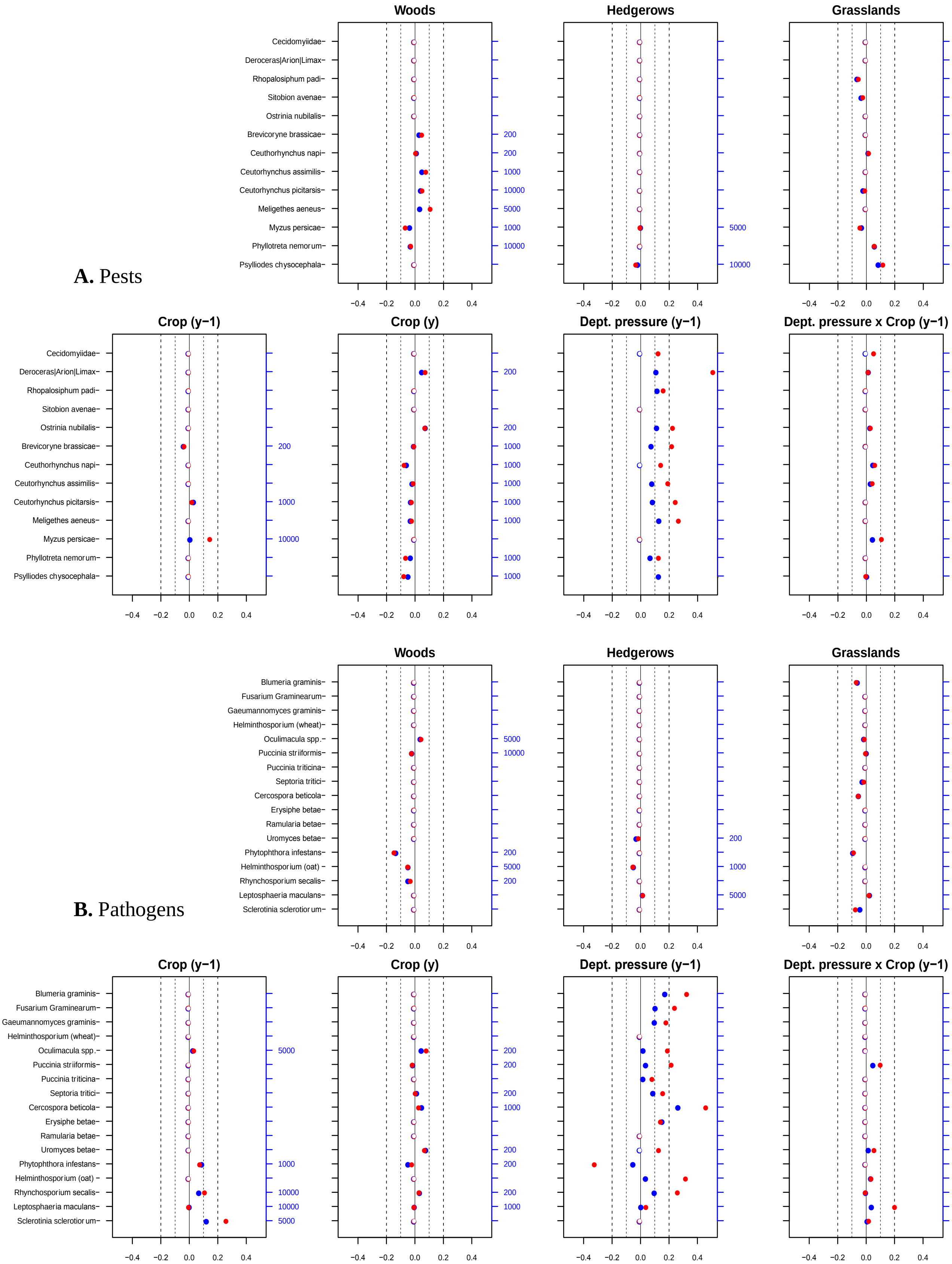



**A.** Pests




**B.** Pathogens

**S.P. I.** Normalized partial correlation (blue) and estimate (red) for each variable, blue numbers of the right indicate the selected spatial scale associated with the variable. Vertical lines indicate milestone value of 0 (full), 0.10 (small dash), 0.20 (large dash). Pest models (A) and Pathogens (B)




**S.P. II.** Normalized partial correlation (blue) and estimate (red) for each variable, blue numbers of the right indicate the selected spatial scale associated with the variable. Vertical lines indicate milestone value of 0 (full), 0.10 (small dash), 0.20 (large dash). Pest models (A) and Pathogens (B)