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Improving pest monitoring networks using a simulation-based approach to contribute to pesticide reduction

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Abstract

Conventional pest management mainly relies on the use of pesticides. However, the negative externalities of pesticides are now well known. More sustainable practices, such as Integrated Pest Management, are necessary to limit crop damage from pathogens, pests and weeds in agroecosystems. Reducing pesticide use requires information to determine whether chemical treatments are really needed. Pest monitoring networks (PMNs) are key contributors to this information. However, the effectiveness of a PMN in delivering relevant information about pests depends on its spatial sampling resolution and its memory length. The trade-off between the monitoring efforts and the usefulness of the information provided is highly dependent on pest ecological traits, the damage they can cause (in terms of crop losses), and economic drivers (production costs, agriculture product prices and incentives). Due to the high complexity of optimising PMNs, we have developed a theoretical model that belongs to the family of Dynamic Bayesian Networks in order to compare several PMNs performances. This model links

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the characteristics of a PMN to treatment decisions and the resulting pest dynamics. Using simulation and inference tools for graphical models, we derived the proportion of impacted fields, the number of pesticide treatments and the overall gross margins for three types of pest with contrasting levels of endocyclism. The term “endocyclic” refers to an organism whose development is mostly restricted to a field and highly depends on the inoculum present in the considered field. The presence of purely endocyclic pests at a given time increases the probability of reoccurrence. Conversely, slightly endocyclic pests have a low persistence. The simulation analysis considered ten scenarios: an expected margin-based strategy with a spatial resolution of four PMNs and two memory lengths (one year or eight years), as well as two extreme crop protection strategies (systematic treatments on all fields and systematic no treatment). For purely and mainly endocyclic pests (e.g. soil-borne pathogens and most weeds, respectively), we found that increasing the spatial resolution of PMNs made it possible to significantly decrease the number of treatments required for pest control. Taking past observations into account was also effective, but to a lesser extent. PMN information had virtually no influence on the control of non-endocyclic pests (such as flying insects or airborne plant pathogens) which may be due to the spatial coverage addressed in our study. The next step is to extend the analysis of PMNs and to integrate the information generated by PMNs into sustainable pest management strategies, both at the field and the landscape level.

Keywords: Dynamic Bayesian Network, Gibbs sampling, Decision rules, Pest monitoring network, Theoretical modelling, Endocyclism

1. Introduction

Pests are responsible for major quantitative and qualitative crop losses worldwide that put food security at risk. This is the reason why the United Nations General Assembly has declared 2020 as the International Year of
5 Plant Health (<http://www.fao.org/plant-health-2020>). Furthermore, climate change has been identified as a major cause of emerging and re-emerging diseases and animal pests in crops, as well as being responsible for the observed geographical shifts of several weed species (Barzman et al., 2015; Lamichane et al., 2015). Currently, conventional pest control relies primarily on
10 pesticides, which have come under intense scrutiny by society because of their negative impacts on biodiversity, livestock, and human health. More

sustainable strategies for pest management are therefore needed. Accurate information on pest dynamics is the basis of supervised chemical control. Useful information is provided by Pest Monitoring Networks (PMNs) that
15 monitor the main and most harmful pests present in commercial fields. These PMNs have been implemented in many countries. PMNs budgets are mainly funded at the national levels (ENDURE site, 2013) and most of them are supervised and evaluated by governmental institutions (e.g. in the Czech Republic, Denmark, the Netherlands, Poland, Sweden and Turkey) with the
20 cooperation and support of national stakeholders such as boards of agriculture, national and regional advisory services and research institutions (ENDURE site, 2013). In Europe, PMNs are implemented to forecast and monitor pests and diseases, detect damage thresholds and advise farmers on pest management (Jorgensen et al., 1996; von Kröcher and Rhöris, 2007; Delos et al., 2008; ENDURE site, 2013). For example, in France, the Biovigilance Network (Agricultural government site, 2015) has generated thousands of warning bulletins on pest risks, generally at the regional level (see the on-line platform: www.pestobserver.eu). PMNs provide information about the sanitary status of a subset of fields in a given region or country. Such in-
30 formation has been used to (i) build pest incidence maps (Wellings, 2011; Jiang et al., 2017) and estimators of regional and site-specific pest incidences (Michel et al., 2016), (ii) highlight the potential distribution of pests using modelling approaches (Kriticos et al., 2015), and (iii) carry out retrospective reconstructions of preferential invasion pathways (Botella et al., 2018; Mack et al., 2000).
35

Information on pest dynamics is also useful to make tactical decisions. Real-time information from PMNs may be helpful for controlling pest outbreaks (or re-emergence), while limiting both immediate and future pesticide
40 use requirements. Coupling past information with current monitoring can greatly enhance the quality of predictions and pest control efficiency. However optimising PMNs is a complex task and complexity is exponential in terms of the number of fields. First, to be useful for a timely and effective pest control, PMNs should have a meaningful spatial resolution (i.e. the number of fields selected for monitoring) and temporal sampling duration
45 (i.e. the depth of the data history used to aggregate information). However, monitoring in PMNs is generally performed by experts who visit each field within the PMN. Consequently, the spatial and temporal extents of PMNs should account for the costs in time and money, which limit the number of

50 field observations. Second, PMNs must also account for changes in the pest
or disease dynamics induced by pest management and for potential discrepan-
cies between current and future requirements in terms of the type of infor-
mation required. Because PMNs have direct effects on the cropping practices
implemented by the farmers who receive this information, as well as indirect
55 effects on pest dynamics at the landscape level, individual decisions are not
necessarily optimal with regard to the collective management of a group of
pests (tragedy of the commons, Hardin 1968). Pesticide use has hidden costs
that are difficult to precisely quantify, but that are high nevertheless (Bour-
guet and Guillemaud, 2016). These costs are not currently considered when
60 defining the economic thresholds of treatments. Finally, the efficiency of
a PMN depends on the life cycles of the considered pests. There is a wide
range of pests responsible for significant crop losses and whose life cycles vary
considerably. For instance, soil-borne pathogens (e.g. fungi, oomycetes, bac-
teria), spread for short distances but can survive for long periods without a
65 host plant (Hughes, 1996). Weed species encompass both annual and peren-
nial plants. They can persist in a given field for decades in the seed bank
and can disperse to various degrees in surrounding habitats (Bourgeois et al.,
2019). Finally, flying animal pests (such as many aphids, that can transmit
the viruses they harbour) and air-borne pathogens, can have long dispersal
70 abilities, but generally low persistence (e.g. up to 3 years for diapausing
species, Bardner and Fletcher 1974; from one year up to seven years for *Lep-
tosphaeria maculans*, Sosnowski et al. 2006, the causal agent of phoma stem
canker on oilseed rape). In this study, we evaluated the efficiency of PMNs as
a function of the pest characteristics (life cycles and the damages they cause)
75 and economic drivers (production costs, agricultural product prices, incen-
tives). We developed a stochastic model that accounts for the uncertainty on
(i) pest dynamics, (ii) the way that stakeholders make use of the information
provided, and (iii) the efficacy of treatments. We derived a spatio-temporal
Dynamic Bayesian Network model (DBN, Jensen and Nielsen 2007) to com-
80 pare PMNs with different spatial resolutions and memory length (temporal
duration). This DBN model is designed to be generic enough to represent a
wide range of pests. We focused on endocyclic pests (Aubertot and Robin,
2013), i.e. organisms whose development is mostly restricted to a field and
highly dependent on the endo-inoculum present in the considered field. En-
85 docyclic organisms are thus highly dependent on field history. We explored
the efficiency of PMNs for three types of pests with contrasting levels of en-
docyclism that are typical of soil-borne pathogens (purely endocyclic pests),

weeds (mainly endocyclic pests) and flying insects and air-borne pathogens (slightly endocyclic pests).

90 The model also integrates a treatment decision rule. To quantify the benefit of a PMN, we defined an expected gross margin based decision rule and use complex inference tools for Bayesian networks that make it possible to combine PMN information and treatment decisions. Similar decision rules have already been studied, in order to avoid systematic interventions, but
95 with the assumption of a continuous information on the pest level in the field (e.g. Tang et al. 2005). Using oilseed rape as a case study, we evaluated injury dynamics, the number of treatments and the expected gross margin for the three pest types and for PMNs with varying spatial resolution and memory length. We expected that a PMN with a large spatial extent, high
100 spatial resolution, and high temporal sampling frequency would be more efficient in providing meaningful information about species that have high spatial dispersal capabilities (slightly endocyclic pests). In contrast, a PMN with limited spatial coverage, low spatial resolution, but high memory length should be more accurate for pests with low dispersal capabilities (purely and
105 mainly endocyclic pests).

2. Materials and methods

2.1. *The PMNimpact model*

The challenge is to model the dynamics of a crop in terms of a pest that is potentially controlled at the field level on the basis of information provided
110 by a PMN. See Figure 1 for a simplified representation of the PMNimpact model.

Dynamic Bayesian Network pest dynamics model

We modelled the spatio-temporal dynamics of a pest in a set of crop fields within the framework of a DBN. A DBN is a particular case of a Bayesian
115 Network where variables are indexed by time, and the state of variables at time t depends on the state of variables at time $t-1$ (Markovian assumption). The state of a field i at time t is a random variable denoted X_i^t , and we assume that the state can take two values: 0 for a non-impacted field, and 1 for a field where the considered pest generate yield losses above a given threshold.

120 This is of course a simplification since pest populations ranges consist of a continuum of values and may never be fully eradicated. However, given the actual difficulty to precisely measure these levels, it is more operational

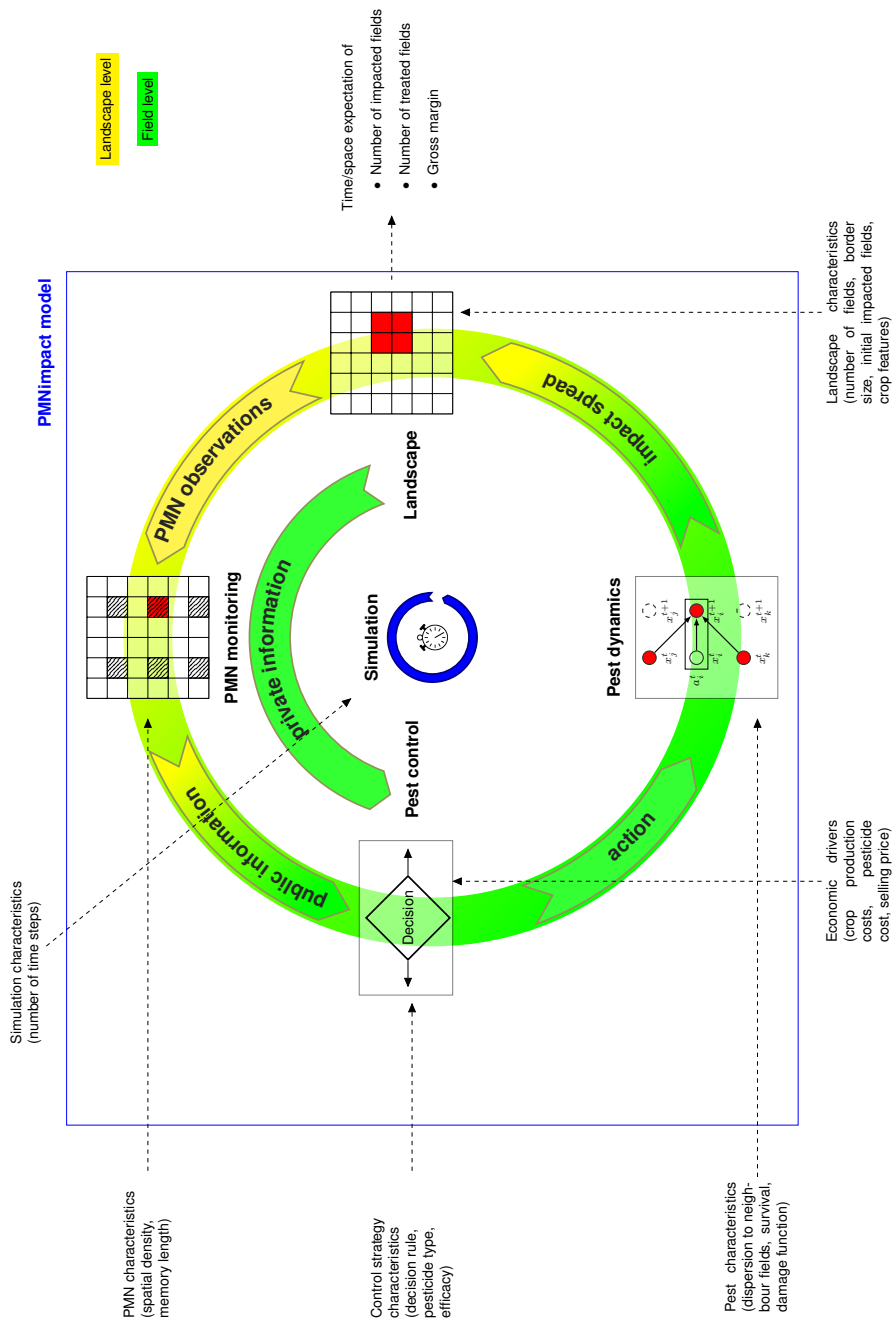


Figure 1: Simplified representation of the PMNimpact model.

to consider only two levels, referred here as "absent" and "present", that should be interpreted as being below and above the threshold above which the considered pest may significantly impact the crop.

We considered two management actions: $A_i^t = 1$ if the treatment is applied in field i at time t and $A_i^t = 0$ otherwise. The state of a field i at time t may depend (through dispersion of pests) on the number of impacted neighbour fields of i at time $t - 1$ (similarly to the spatial SIS model Harris 1974), as well as on the management action currently applied to field i , A_i^t . Assuming there are n fields, $N_i \subseteq \{1, \dots, n\}$ denotes the set of fields from which infection can spread to field i . Note that this "neighbourhood" relation may not be symmetric ($j \in N_i$ does not imply that $i \in N_j$). Indeed, local climatic conditions (dominant wind, soil conditions, etc.) may break pathogens dispersion symmetry. Then, we denote by $K_i^t(X^t)$ (K_i^t , for short, omitting the dependency to X^t), the number of neighbour fields of i , impacted at time t : $K_i^t = |\{j \in N_i, X_j^t = 1\}|$.

The probabilities of transition from state X_i^{t-1} to state X_i^t , given the action applied A_i^t and the number of impacted neighbour fields are parameterised by ϵ , the long-distance dispersal probability of the pest; ρ the probability of impact from a neighbouring impacted field; ν the probability of pest survival between $t - 1$ and t if no treatment is applied; and γ the probability of total pest control after treatment (see Figure 2). The time step length between $t - 1$ and t may vary between crop-pest systems. Indeed it should vary in particular according to the way treatment decisions are made. If treatment strategies are chosen every year and not modified within a year (even though a strategy may consist of several unconditional treatments each year), the time step length should be one year. If, on the other hand, treatment decisions are adapted within a year, on the basis of frequent observations from the PMN, e.g. 3-4 times a year, monthly or even weekly for slightly endocyclic pests (flying insects or air-borne pathogens), the time step should reflect this increased frequency and be shorter than one year.

The probabilities of pest arrival with and without treatment are

$$P(X_i^t = 1 \mid X_i^{t-1} = 0, K_i^{t-1}, A_i^t = 0) = \epsilon + (1 - \epsilon)(1 - (1 - \rho)^{K_i^{t-1}}) = P_{01}(K_i^{t-1}),$$

$$P(X_i^t = 1 \mid X_i^{t-1} = 1, K_i^{t-1}, A_i^t = 1) = (1 - \gamma)P_{01}(K_i^{t-1}),$$

where K_i^{t-1} is the number of impacted neighbours of site i at time $t - 1$.

The probabilities of persistence with and without treatment are:

$$\begin{aligned} P(X_i^t = 1 \mid X_i^{t-1} = 1, K_i^{t-1}, A_i^t = 0) &= \nu + (1 - \nu)P_{01}(K_i^{t-1}) = P_{11}(K_i^{t-1}), \\ P(X_i^t = 1 \mid X_i^{t-1} = 1, K_i^{t-1}, A_i^t = 1) &= (1 - \gamma)P_{11}(K_i^{t-1}). \end{aligned}$$

At the landscape level, the global probability of transition is:

$$P(X^t \mid X^{t-1}, A^t) = \prod_{i=1}^n P(X_i^t \mid X_i^{t-1}, K_i^{t-1}, A_i^t),$$

where $X^t = (X_1^t, \dots, X_n^t)$ and $A^t = (A_1^t, \dots, A_n^t)$ are, respectively the vectors
 155 of sanitary states of and actions applied to every field at time t . For a given
 number n of fields and their neighbourhoods, and a given sequence of actions,
 the DBN model depends on four input variables that are summarised in
 Table 1 (top). Action A_i^t is the result of a decision rule applied at field i ,
 and which depends on the information provided by the PMN, the private
 160 information of the sanitary status of field i , and economic input variables.
 We describe these different elements below and in Table 1 (bottom).

PMN information

A PMN is a subset $O \subseteq \{1, \dots, n\}$ of n fields, which are monitored at
 each time step. The state X_o^{t-1} for $o \in O$ is therefore public information
 165 available to all farmers at time t . The spatial resolution of a PMN is the
 number of fields in O . The memory length (h) is the number of past years
 (or history depth) of the observations provided.

The decision to treat a field i at time t is based on the knowledge of all $X_o^{t'}$
 for the previous h time steps: $t' \in \{t - h, t - h + 1, \dots, t - 1\}$ (less if $t < h$).
 170 The whole set of PMN spatial and temporal observations can be aggregated
 into indicators $\{p_i^t\}_{i=1, \dots, n} \in [0, 1]$, where p_i^t is the marginal probability of
 the impact of site i at time t in the DBN model, conditionally to the PMN
 observations (see Figure 3).

Expected margin-based pest management strategy

We considered an expected margin-based pest management strategy im-
 175 plemented yearly at the field level where the DBN time step was therefore
 the year. The decision A_i^t applied to field i at time t is the result of a decision
 rule (referred to as d) that aims at maximising the expected gross margin

Input variables	Definition
Pest dynamics input variables	
ϵ	long-distance dispersal probability
ρ	probability of transmission from a neighbouring impacted field
ν	probability of pest survival if not treated
γ	probability of treatment full efficacy
Economic input variables	
y	maximal annual yield, in $kg.ha^{-1}$
q	proportion of remaining yield when the field is impacted
$price$	selling price, in $\text{€}.kg^{-1}$
c	all production costs (seeds, fertilisers, tillage, pesticide) in $\text{€}.ha^{-1}$
c_{pest}	annual cost of treatments for a given pest, in $\text{€}.ha^{-1}$
Output variables	Definition
I	proportion of impacted fields
T	proportion of treated fields
R	mean expected gross margin in $\text{€}.ha^{-1}$

Table 1: Input and output variables of the DBN model for pest dynamics and the decision rule for treatment. For the output variables, proportions and means are taken over the last four years and all fields.

180 m_i^t of the field at time t . This margin is the difference between income and costs. The income is the product of yield price ($price$) and yield. The yield itself depends on the maximal annual yield (y), the probability of significant damage (p_i^t), the proportion of remaining yield when impacted (q), and the probability of total efficacy of the treatment (γ) (see Table 1). The costs depend on two variables: the global production cost c that includes all pesticide costs, and the cost of treatment for the pest considered c_{pest} . Since c includes 185 all pesticides costs, if the action made consists in applying a pesticide for the pest considered, then the cost of the action is simply c . If the action is not to apply the dedicated treatment, then the cost of the action is $c - c_{pest}$.

If field i is not treated ($A_i^t = 0$):

$$m_i^t(0) = \left((1 - p_i^t)y + p_i^t q y \right) price - (c - c_{pest}).$$

Indeed, we obtain the maximal yield y if the field is not impacted (which oc-

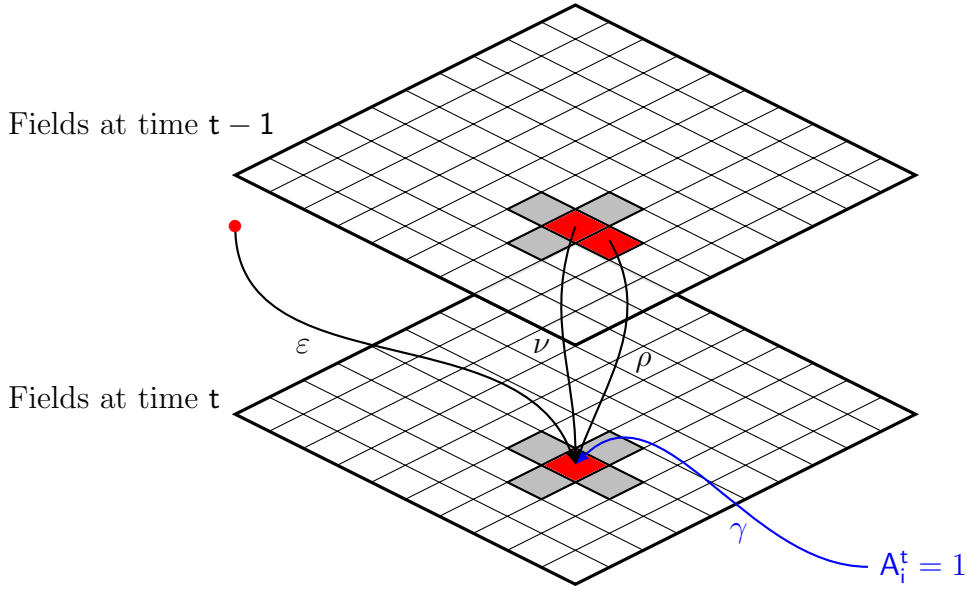


Figure 2: Pest dynamic input variables of a field i . ε , long-distance dispersal probability; ρ , short-distance dispersal probability; ν , persistence probability; γ treatment efficacy. Red squares: impacted fields ; grey squares: neighbours of field i .

190 curs with probability $1 - p_i^t$) and only yield qy when it is impacted. The yield is multiplied by the price and production costs are subtracted to compute the margin. When the field is not treated, treatment cost c_{pest} is subtracted from production costs c .

If field i is treated ($A_i^t = 1$):

$$m_i^t(1) = \left((1 - p_i^t)y + p_i^t((1 - \gamma)qy + \gamma y) \right) price - c.$$

195 If the treatment is fully effective (probability γ), the maximal yield y is obtained, whereas if the treatment does not work, only a fraction qy of the maximal yield is obtained.

The decision rule d consists in applying a treatment ($A_i^t = 1$) when $m_i^t(1) > m_i^t(0)$. This translates into a decision to treat based on a threshold of the estimated probability of significant impact (see Figure 3): Treat only when

$$p_i^t > p_0 = \frac{c_{pest}}{price\gamma(1 - q)y}.$$

We assume that farmers treat a field considering both the information from

the concerned PMN and from private information about the history of pest dynamics in the field. By private information, we mean that the information is only available to make a decision in the considered field. It is assumed to be unavailable to make a decision about other fields, even if they belong to the same farmer. This assumption is made to facilitate the exploration of the PMN influence, since taking the fact that a farmer possesses several fields means making choices about the number of farmers, the number of fields per farmers and their locations. We also assumed the probability to treat to be higher in a field previously impacted. We modelled this by taking the private information available about a field into account after the evaluation of p_0 , by decreasing the treatment threshold when the field was previously impacted. Specifically, considering the private information history of h (i.e. the h past years are considered to modulate p_0), we considered the following cases.

- If $X_i^{t-1} = 1$, then p_0 will be decreased (treatment will be privileged). More specifically, $p_0 \leftarrow p_0 - \frac{k}{2^h}$, where k is the number of years when field i was impacted in the past h years.
- If $X_i^{t-1} = 0$, the p_0 will be increased (treatment will be applied less often). More specifically, $p_0 \leftarrow p_0 + \frac{h-k}{2^h}$ where k is the number of years when field i was impacted in the past h years.

As a consequence, with the same (public information-based) probability of significant impact, a farmer will be more prone to treat a field that has recently been impacted.

2.2. Study

Pest types

Three types of crop pests were considered: purely endocyclic (e.g. soil-borne pathogens), mainly endocyclic (e.g. most weeds) and slightly endocyclic (e.g. flying insects or air-borne pathogens). These types have contrasted spatial dispersion and temporal soil persistence: a purely endocyclic pest has a low dispersal probability (both at long and short distances) and a high persistence, a mainly endocyclic pest has an intermediate dispersal probability and a high persistence, and, finally, a slightly endocyclic pest has a larger dispersal probability and a lower persistence (Aubertot and Robin, 2013). These different characteristics imply the use of different chemical treatment strategies to control them. In order to consider plausible values to parameterise our model, we considered the case of oilseed rape crops in

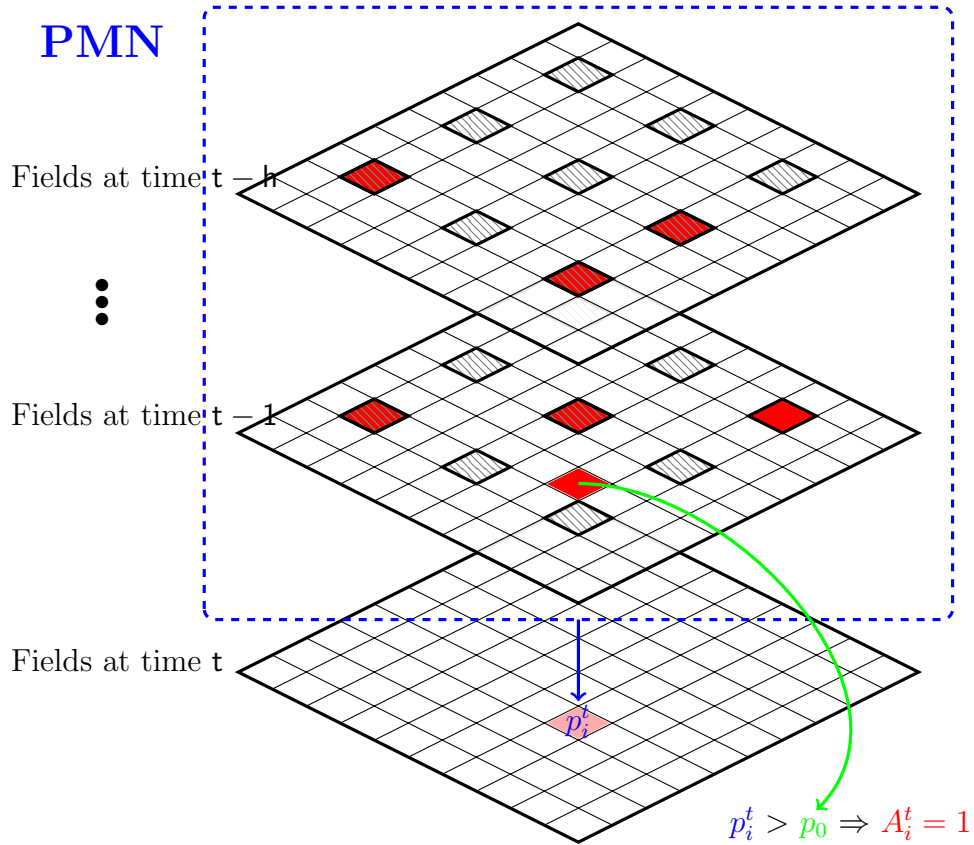


Figure 3: Treatment decision rule d : based on PMN information, the probability of field i being impacted (p_i^t) is computed (blue arrow). Based on private information, the threshold (p_0) is set (green arrow). If the probability of impact exceeds the threshold, then treatment is applied ($A_i^t = 1$). Dashed cells are monitored by the PMN; red ones are impacted.

France, and input variables values were established on the basis of expertise and studies made in France (FOP, 2015; Chambre d’agriculture site, 2014; Cros et al., 2017) (see Table 4 in Appendix A).

Simulation protocol

We considered $n = 144$ crop fields organised on a regular grid of 12 x 12 fields, each with an area of 1 ha. The neighbourhood of a field is composed of the four fields surrounding it. Treatments and observations are only possible in the 100 fields forming the inner 10 x 10 grid (to avoid border effects, the outer fields are not managed and are assumed to form a natural reservoir for pests). We compared four spatial resolutions for O : 1%, 10%, 25% and 50% of all fields, uniformly spatially distributed and stable over time, which are referred to as PMN1 to PMN4 (see Figure 5 Appendix C). Then, for each spatial resolution, we considered two memory lengths: the decision to treat field i at time t was based either on the knowledge of X_o^{t-1} only (memory length $h = 1$), or on the knowledge of all PMN observations since the beginning of the simulation (memory length $h = 8$).

For the purpose of comparison, we simulated two extreme decision rules that do not use the PMN information: rule d_{never} where fields are never treated, and rule d_{conv} corresponding to a conventional management system where the standard treatments are always applied. This results in the comparison of ten scenarios.

For each scenario, we considered that simulations start with four grouped impacted fields, and we used three different positions of these first impacted fields (corner, border or centre of the grid; see Figure 6 in Appendix C). For each position of first impacted fields, we generated 20 simulations of eight time steps (8 years) that account for the ecology of the studied pest. We considered short trajectories in order to study the short- to mid-term effect of the PMN. We limited the simulation plan to 60 simulations per scenario that was considered sufficient to estimate the desired criteria which are the means of space and time (see 'Criteria to compare PMNs in paragraph below).

Inference of p_i^t

For a given simulation, all the p_i^t must be estimated at each time step. p_i^t depends on public PMN information (available at time t for all fields) and private information about field i (past state-s). New observations arrive at each time step, and each farmer has a different information (only the farmer of field i knows X_i^t unless $i \in O$). Consequently, all the p_i^t cannot be inferred

simultaneously by running a single inference algorithm. We need to run one
270 inference algorithm per field and per time step. For this inference problem,
efficient computational techniques exist. If the problem is small, exact res-
olution is possible (inference of probabilities in a DBN is exponential in the
number of variables) with the Junction Tree algorithm (Lauritzen, 1996). For
our case, the problem is too big to use it and only an approximate method
275 is suitable. The Loopy Belief Propagation algorithm is often chosen because
of its good approximation and execution time. Others approaches exists as
Variational methods (the simplest example is the mean-field approximation)
or Sampling methods (Monte Carlo); a more efficient approach is called the
Monte Carlo Markov Chain (MCMC), and includes Gibbs sampling as a
280 special case. We developed the model in Matlab and used the free library
BNT *Bayesian Network* Toolbox (Murphy, 2007) to obtain a suitable generic
representation of the Bayesian Network problem and a library of inference al-
gorithms. We first used the Loopy Belief Propagation algorithm which is the
fastest one, but found inconsistency in the results probably due to the size of
285 the problem. We therefore used the version of the Gibbs sampling inference
algorithm with 200,000 samples. Even if the algorithm is time-consuming,
it computes good approximations when the number of samples is sufficient.
We made sure that the number of samples is a good compromise between the
quality of estimation and execution time. It took about 6 min per simulation
290 on a server with Intel Xeon ES processors to compute p_i^t . Therefore, for a
scenario (a PMN, decision rule d , a pest), the execution time is around 45
min.

Criteria to compare PMNs

In order to study the influence of the information provided by PMNs
295 about different spatial resolution and memory length on the extent of disease
spread, pesticide use and farmers' income, we compared the effects of the
ten scenarios on three criteria (see Table 1): proportion of impacted fields
(I), proportion of treated fields (T) and mean expected gross margin (R).
Means and proportions were taken over the last four simulated years (after
300 the emergence stage) and over fields in the inner 10 x 10 field grid of fields.
The quantities I , T and R were computed for each of the 60 simulations of
a given scenario.

Sensitivity analysis

Our simulation study revealed a higher impact of spatial resolution than
305 memory length on the number of treatments applied. Since a spatial resolution
of 50% of the fields is unrealistic in practice (due to costs), we considered
PMN3 with $h = 1$ as a good PMN candidate and we further studied the model
behaviour in this case. For each pest type, we studied which input variables
among the pest dynamic and the economic ones, had the larger influence
310 of I , T and R , using Sensitivity Analysis (SA). We focused on the analysis
of six input variables (called factors of the SA) linked to the type of crop
pest (see Table 2). Since simulations are costly over time, we first built a
statistical metamodel with a negligible computational time to approximate
the relationship between the six factors and the criteria (sometimes referred
315 to as an emulator, Prowse et al. 2016). The metamodel was estimated from
samples of the simulator. We chose 60 values for the vector $(\epsilon, \rho, \nu, c_{pest}, \gamma, q)$
according to a Latin Hypercube Sampling, obtained by combining ten values
for each factor, uniformly sampled in the domain of variation of each factor.
We then fitted a Kriging model with constant trend on these 60 samples (km
320 function of the R package DiceKriging). We did not consider a more complex
Kriging model since this one was well adapted for each criterion according
to classical evaluation methods (see Figures 9-11 in Appendix D).

We then used the metamodel to estimate the part of the model vari-
ance explained by the pest dynamic and the economic input variables (using
325 Sobol indices, Sobol 2001) for each pest type. The domains of variation
of the factors used to build the metamodel and to compute the Sobol indices
are reported in Table 2. To evaluate the Sobol indices, we performed
a Kriging-based global sensitivity analysis taking both the error from using
a metamodel and the error from estimating the Sobol indices by the Monte-
330 Carlo method into account. The three points corresponding to the three
pests are very distant in the hypercube of the factor domains. We therefore
considered that factors values too far from these points may not be repre-
sentative of any existing pest dynamics. We estimated distinct indices for
each pest type, by reducing the domains of variation of each factor to do-
335 mains centered around the expert value for the given pest used to perform
the PMNs comparison (see Table 2).

The code of the complete study (PMNs comparison and SA) is available
on figshare (<https://doi.org/10.6084/m9.figshare.7583258.v2>).

Variable	Purely endocyclic pest	Mainly endocyclic pest	Slightly endocyclic pest	Metamodel
ϵ	[0.01 0.10]	[0.1 0.2]	[0.25 0.35]	[0.01 0.4]
ρ	[0.05 0.15]	[0.15 0.25]	[0.35 0.45]	[0.05 0.5]
ν	[0.45 0.55]	[0.45 0.55]	[0.2 0.3]	[0.10 0.6]
c_{pest} ($\text{€}.ha^{-1}$)	[20 60]	[130 170]	[20 60]	[20 200]
γ	[0.7 0.9]	[0.8 0.95]	[0.6 0.8]	[0.6 0.95]
q	[0.6 0.8]	[0.6 0.8]	[0.7 0.9]	[0.5 0.9]

Table 2: Domains of variation of the model input variables considered as factors for the sensitivity analysis. The last column indicates the domains used to build the metamodel, whereas columns 2 to 4 indicate the domains used to compute the Sobol indices of each submodel associated with each pest.

3. Results

340 The main result is that we observed the same behaviour of the three criteria on simulations for the purely and mainly endocyclic pests (such as soil borne pathogens and weeds, respectively), while the results for the slightly endocyclic pest (such as insect pests or air-borne pathogens) were different (see Figure 4).

345 For the purely and mainly endocyclic pests, the most visible impact was observed on treatment applications T which was clearly reduced when the spatial resolution of the PMN increased (reduction of the median value of T of at least 46% and at most 66%, depending on the pest and the memory length). We also observed a decrease in the number of treatments when
350 increasing the temporal memory length, but to a lesser extend (reduction of the median value of T of at least 9% and at most 16%, depending on the pest and the spatial resolution).

Although impact slightly increased with the larger PMNs, because of a decrease in pesticide use, the purely and mainly endocyclic pests remained
355 under control. Regardless of the PMN, the median value for I remains between 3% (weeds) and 27% (purely endocyclic pests) of the value of I reached without treatment (d_{never}) rule. With the conventional treatment (d_{conv}) rule this same percentage is 3% for the mainly endocyclic pest and 6% for the purely endocyclic pest.

360 The mean gross margin increased when spatial resolution and memory length increased, with a stronger effect of spatial resolution once again (see

Figure 5 in Appendix B). The permutation test on the equality of the median values for the purely endocyclic pests did not reveal any significant differences in R at $h = 1$ and $h = 8$ for a given spatial resolution (at 0.001). Differences were significant for the mainly endocyclic pests (e.g. weeds) because their annual treatment cost is much higher. The increase in the median value of R was at most of 6% between PMN1 and $h = 1$ and PMN4 and $h = 8$. Regardless of the PMN, the median value for R remains between 104% and 126% of the value of R reached without treatment (d_{never} rule), and remains between 99% and 106% of the value of R reached with conventional treatment (d_{conv} rule).

We observed a higher number of impacted fields in the absence of treatment for the slightly endocyclic pest (median value of 90% of impacted fields) compared to the purely endocyclic pest (19%) and the mainly endocyclic pest (64%) (Figure 4 and Figure 5). This is due to the higher dispersal probability at short and long distances. The consequence is that with rule d , treatment decision was always chosen regardless of the PMN considered. Indeed, the probability of significant impact of a field estimated from the PMN observations, p_i^t , was always higher than the decision rule threshold. Information from the PMN was not sufficient to decrease treatment frequencies because treatment cost is low, which implies that the threshold is low. This systematic treatment made it possible to reduce I to a median value of 16%. Another consequence is that the mean gross margin is almost the same for d_{conv} and for rule d regardless of the PMN (see figure 6 in Appendix B), and its median value (€606/ha) is 13% more than without treatment (d_{never} rule.)

These results were obtained for a decision rule d where only the private information of the previous year was used. When we increased the memory length of the private information using the three previous years to determine the treatment threshold in the decision rule d , we observed the same trends (see Figure 5 in Appendix B). However, for the purely and mainly endocyclic pests, the proportion of treatment applications was always lower than when using only the private information from the previous year.

Focusing now on PMN4 with $h = 1$ as a good compromise between monitoring efforts and treatments impact, the sensitivity analysis made it possible to evaluate the influence of some input variables on the model behaviour. The analysis performed showed that regardless of the pest type, varying the long-distance dispersal (ϵ) and the probability of persistence (ν) had little

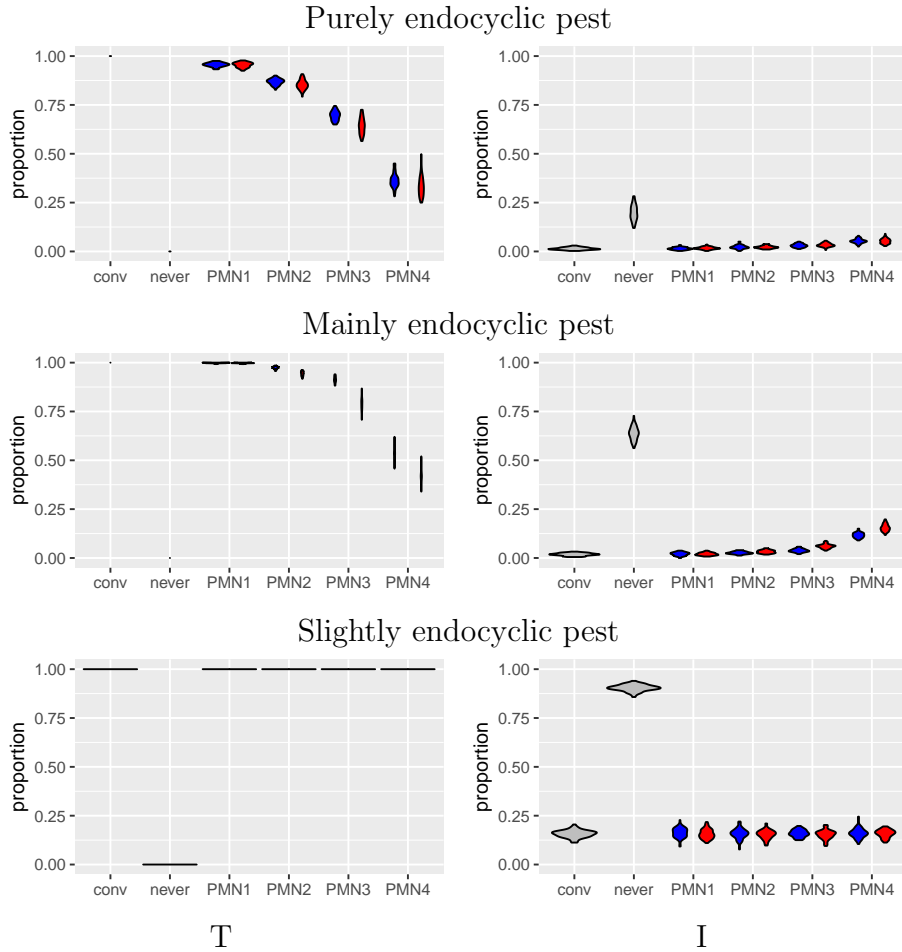


Figure 4: Influence of PMN spatial resolution and memory length on pest management. In each graph, the scenarios are represented on the horizontal axis: from left to right, conventional treatment (rule d_{conv}), never treat (rule d_{never}), then rule d with PMN1 to PMN4 and for those cases with two history depths, $h = 1$ (blue), $h = 8$ (red). Left hand column: proportion of treatment decision (T); right hand column: proportion of impacted fields (I).

400 influence on I , R and T (Sobol index estimators are reported in Table 3).

Consequently, for the purely and mainly endocyclic pests, the most influential input variables on I and T are the annual cost of specific treatment (c_{pest}), and the yield when impacted (q), whereas the main influential input variables on R are the probability of transmission from neighbouring fields
 405 (ρ) and q .

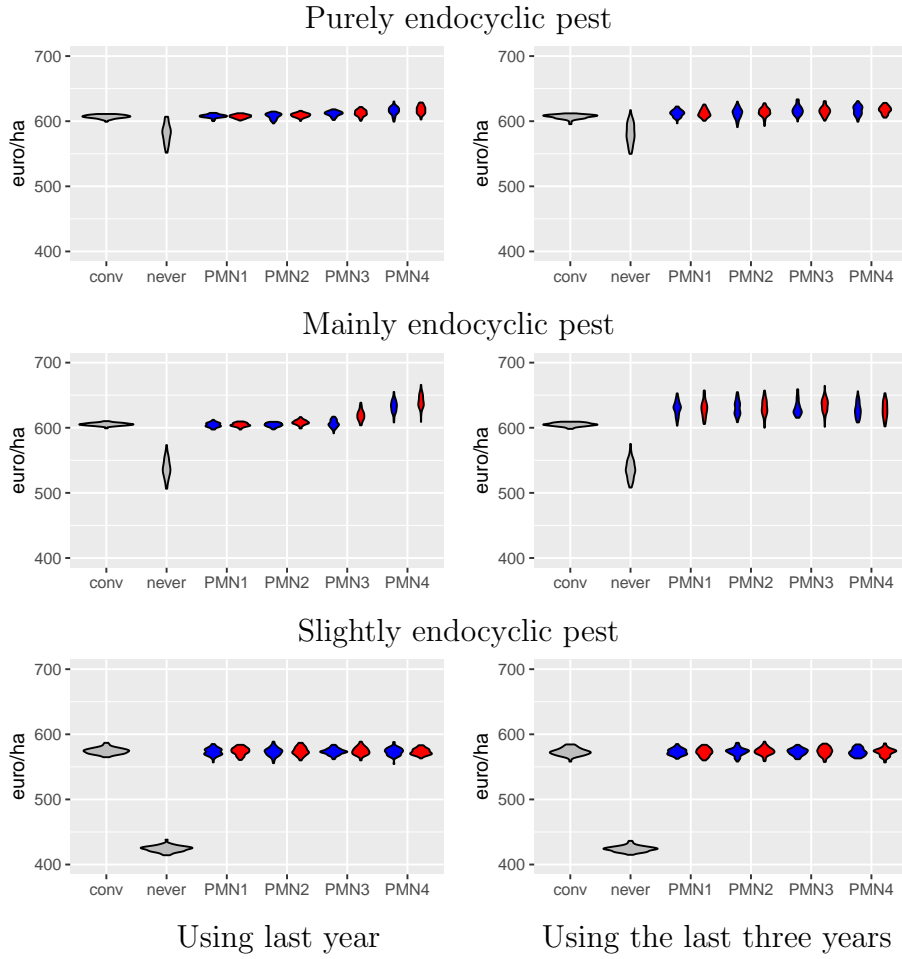


Figure 5: Considering mean gross margin (R); Influence of PMN spatial resolution and memory length on pest management. In each graph, the scenarios are represented on the horizontal axis. From left to right, conventional treatment (rule d_{conv}), never treat (rule d_{never}), then rule d with PMN1 to PMN4 and with two history depths $h = 1$ (blue) and $h = 8$ (red). Left hand column: Only the last year is used ; right hand column: the last three years are used for private information with rule d .

For the slightly endocyclic pests, the factors that have the most influence on I are q and the probability of treatment efficacy (γ); for T , they are q and c_{pest} ; and for R , it is ρ .

Prop. of impacted fields, I	ϵ	ρ	ν	c_{pest}	γ	q
Purely endocyclic pest	0.06	0.27	0.03	0.54	0.02	0.32
Mainly endocyclic pest	0.05	0.28	0.03	0.53	0.02	0.31
Slightly endocycli pest	0.10	0.21	0.02	0.16	0.48	0.69
Prop. on treatment, T	ϵ	ρ	ν	c_{pest}	γ	q
Purely endocyclic pest	0.04	0.03	0.01	0.41	0.15	0.41
Mainly endocyclic pest	0.03	0.03	0.01	0.40	0.12	0.37
Slightly endocycli pest	0.03	0.02	0.00	0.30	0.13	0.48
Mean net margin, R	ϵ	ρ	ν	c_{pest}	γ	q
Purely endocyclic pest	0.14	0.45	0.01	0.23	0.29	0.60
Mainly endocyclic pest	0.14	0.45	0.01	0.23	0.30	0.57
Slightly endocycli pest	0.07	0.86	0.08	0.00	0.00	0.00

Table 3: Sobol indices for proportion of impacted fields, proportion of treatment and mean gross margin in the case of PMN3 and a memory length $h = 1$. The background colours of indices (white, yellow, orange, red, purple) represent the increasing importance of Sobol indices.

4. Discussion and Conclusion

410 In this study, we aimed at investigating the structure of Pest Monitoring
 Networks (PMNs) that provide information meaningful enough to reduce
 pesticide use while maintaining gross margins for farmers. Using a stochastic
 model, we explored eight spatio-temporal structures for a PMN and exam-
 ined their efficiency to control varying pest families regarding their level of
 415 endocyclism (function of their ability to disperse and their level of persistence
 in a field). PMN performances were evaluated using three criteria: final pro-
 portion of impacted fields, proportion of fields that have been treated, and
 the economic benefit to the farmer as a compromise between the cost of crop
 protection, pest monitoring and the benefits of avoiding crop losses.

420 We proposed a Dynamic Bayesian Network model of development and
 control of several types of pests at the landscape level. The model allows
 us to take a decision rule for treatment into account and we designed an
 expected margin-based decision rule that takes account of both PMN infor-
 mation and private information about the decision-maker’s field in order to
 425 choose whether to apply treatment actions.

Extensive simulations of the model allowed us to highlight the relative
 impact of the spatial resolution of a PMN and the length of considered histo-

430 ries on the efficacy of the control of purely and mainly endocyclic pests (like soil-borne diseases and weeds, respectively), and on the number of treatments required. The study showed that densifying a PMN spatially is more useful than increasing the history depth of information in order to obtain more effective overall control of the pests with less pesticides. For purely and mainly endocyclic pests, increasing the spatial resolution of a PMN made it possible to significantly decrease the number of treatments (up to a median value of 435 67%, among simulations between the smaller and the larger resolution), with a clear control of the proportion of impacted fields. Increasing the history depth only had a second-order effect (a reduction of up to a median value of 16%). This may appear to be in contradiction with some recent studies (Holden et al., 2016), where a long-term surveillance effort was recommended (possibly with a varying effort). However, our results do not indicate that 440 surveillance should only be restricted to short periods but, instead, that a good decision about whether to treat or not only requires that the decision-maker be informed by the past short-term surveillance data.

PMNs had almost no impact on treatment reduction in the case of a 445 slightly endocyclic pest (such as a flying insect, or an air-borne pathogen). This may be due to the spatial scale of our simulation study, whose scope appears to be rather small compared to the dispersion capacity of slightly endocyclic pests. For purely and mainly endocyclic pests, dispersal is low and local information at the field scale provides sufficient information to control 450 them. Conversely, slightly endocyclic pests disperse too well and are likely to very rapidly impact distant fields and even the whole area considered if not controlled early on. Thus, in our model, it is likely that for slightly endocyclic pests, treatment decisions should be decided at a larger scale (several thousands hectares) on the basis of poorly distributed information 455 about fields in the region, rather than decided at as small a scale like for the two other types of pests. However, a study at a larger scale would be limited by the cost of inference, since it is exponential in terms of the number of fields.

Even though the interest of a PMN has been highlighted for purely and 460 mainly endocyclic pests, the results also showed the importance of considering the past private information of a field for making a treatment decision. In practice, this private information is more widely shared than in our model: farmers manage more than one field and they often exchange information about their fields with other farmers. Therefore the impact of private information is probably even larger than predicted by our model. In addition, 465

digital applications may further help to share this information.

Finally, for a given PMN, Sensitivity Analysis (SA) was a way to assess the relative importance of population development and economic input variables on the simulation model outputs. It allowed us to identify some important input variables of the model that would influence the treatment intensity induced by a given decision rule. We identified leverage effects via the factors that have a strong influence on the proportion of impacted fields, the proportion of treatments and the mean net margin. They depend on the level of endocyclism. For example, modifying the cost of pesticides may have an impact on the number of treatments and of impacted fields for purely and mainly endocyclic pests. On the contrary, for slightly endocyclic pests, these two outputs are more highly influenced by the remaining yield when the considered pest caused yield losses, which is not a factor that humans can easily modify. SA was also a way to evaluate the model’s robustness: the proportion of impacted fields, the proportion of fields treated and the mean gross margin have a low sensitivity to the variations of some of the model input variables. This is true, in particular, for the strength of long distance dispersal and the probability of survival in the case of the three pest types. This is consistent with the fact that primary inoculum is generally considered as non-limiting in epidemiological models (Madden et al., 2007). These results are obtained for a PMN covering 25% of the fields and with a history of length 1 (only observations from the previous year). They may differ for another PMN structure and for another decision rule.

The next step for concretely designing efficient PMNs would be to actively look for a PMN that minimises three objectives: pesticide use, crop losses caused by pests, and costs. It would also be interesting to identify PMNs that reach an ”optimal” joint control of several pest types. Since we use a stochastic simulation model for assessing PMN, it would be natural to apply *Reinforcement Learning* approaches (Sutton and Barto, 2018) to tackle PMN optimisation problems. *Reinforcement Learning* approaches have already been used for crop production optimisation (Trépos et al., 2014). The incorporation of data with *Reinforcement Learning* in the domain of agriculture management has been recently proposed, through the use of deep Q-learning (Bu and Wang, 2019). However, given the complexity of the PMN optimisation problem and the lack of available accurate data concerning the transition model and the actual damage (impact) on crops, such on-line optimisation approaches may be harder to put into action than the PMN comparison approach we propose. Still, these approaches are certainly

worth exploring.

505 Beyond PMNs analysis or design, our model can also serve as a support for discussions between farmers, advisers, and policy-makers to better understand the spatial and temporal connections underlying pest dynamics and to help design management strategies at the landscape level (Debaeke et al., 2019) and to identify the most promising ones. To do so, the model should be extended in two directions to increase its representativity. The 510 first one would be to include more heterogeneity in the model's components. The second one would be to enrich management options. Regarding the first direction, heterogeneity could be introduced in the spatial distances between the fields. They are dispatched on a regular grid in the study, but the fields 515 could be connected by an arbitrary dispersal network. We can expect that monitoring the field from which infection can spread to the larger number of fields will be more efficient. Furthermore, only a single crop was considered throughout the landscape for the simplicity of interpretation. This may be true only in some specific agricultural areas. We could first include landscape 520 heterogeneity by incorporating several crops (e.g. wheat, barley) with different sensitivities to and hosting capacities for pests, as well as several crop sequences. In order to adapt to each region's specificity, the simulator could also easily be extended to include information about climate variations (successions of dry and humid years, warm and cold years) into account and/or 525 the evolution of economic input variables over time. In the same way, our model could include spatial heterogeneity, not only in terms of crop diversification, but also in terms of interstitial spaces (e.g. field edges, hedgerows) and semi-natural habitats (e.g. deciduous woodlands). It is well-known that diversified crop sequences (and intercrops) disrupt the cycles of soil-borne 530 diseases. Similarly, alternating sowing periods makes it possible to limit weed specialisation in a given field. As for animal pests, it is considered that the planned biodiversity will increase the associated biodiversity, including natural enemies, that can limit pest development. A substantial improvement in the approach presented in this paper could be to take landscape 535 heterogeneity into account as an important driver of pest development.

In the second direction, we could enrich the PMN-based pest-management decision rule. A decision rule is composed of a set of available actions among which the decision-maker must choose, and a criterion (the expected margin in this case) that will be maximised by the action choice. We could consider 540 a criterion other than the expected margin to take account of the fact that the decision-maker could possibly be risk-averse. Indeed, it has been exper-

imentally verified for a long time now that even though risk-aversion has an impact on pesticide use by farmers (Pannell, 1991), this impact depends on the variables considered and especially on expected yields, and may not
545 always result in an increase in pesticide use (Aka et al., 2018). Our model should therefore be of use to test the plausibility of different risk-averse treatment decision rules.

Moreover, the current computation of the expected gross margin relies on the assumption that the costs to build and manage the PMN are paid
550 for by a third party such as a human health care entity or a drinking water company. However, if the PMN information can be of benefit to farmers, the possibility could be considered that the PMN costs could be shared between them. It would be interesting to see how the results of the study are modified in this case. In the same way, the decision to treat could be deeply affected
555 by accounting for the hidden costs attached to pesticides, notably, decontamination costs (Bourguet and Guillemaud, 2016). In addition, pesticide reduction would contribute to the limitation of biodiversity loss, cattle and human health hazards.

More complex actions, beyond treatment/no treatment, could also be considered, by combining several types of actions. This would better represent
560 the situation that farmers are faced with. PMN information and treatment choice could be combined with other actions including agricultural practices that reduce biotic risks or that increase treatment efficacy. For example, in Cros et al. (2017), pest-control through crop sequence and cultivar choices
565 was optimised at the landscape scale. A stochastic model of pest dynamics was used, which was very similar to the one we used in this study. For example, Lo-Pelzer et al. (2010) developed a spatially explicit model to manage phoma stem canker at the landscape level. This model represents the effects of many cropping practices in interaction with weather scenarios: crop sequence, tillage, nitrogen management at the cropping system level, cultivar
570 choice, sowing date and rate, and fungicide treatments. The choice of a combined action could then be taken yearly or for a sequence of years (multi-year pest-management strategies, such as crop rotations). This could be done independently for each field, or as the result of a coordinated decision between
575 decision-makers. Finally, the decision rule could target several pests at the same time since some treatments are multi-purpose.

As long as the PMN influence is explored through simulations, all these enhancements should not lead to major technical difficulties being integrated into the model. The PMN impact model can thus be seen as the first step

580 in building richer simulators of pest dynamics under the influence of control
strategies based on PMN observations.

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Appendix A. Input variable values

Variable	Definition	Unit	Value	Reference
$yield$	maximal annual yield	$kg.ha^{-1}$	3500	FOP (2015); Cros et al. (2017)
$price$	selling price	$€.kg^{-1}$	0.35	FOP (2015); Cros et al. (2017)
c	all production costs (seed, fertilisers, work carried out by third parties, phytosanitary treatments)	$€.ha^{-1}$	849.4	FOP (2015); Chambre d'agriculture site (2014)
c_{pest}	cost for fungicide products	$€.ha^{-1}$	38	Cros et al. (2017)
	cost for herbicide products	$€.ha^{-1}$	147	Chambre d'agriculture site (2014)
	cost for insecticide products	$€.ha^{-1}$	32	Chambre d'agriculture site (2014)
ϵ	long-distance dispersal probability for purely endocyclic pests	-	0.05	expertise
	for for mainly endocyclic pests	-	0.15	expertise
	for for slightly endocyclic pests	-	0.30	expertise
ρ	spreading probability from neighbouring fields for purely endocyclic pests	-	0.10	expertise
	for mainly endocyclic pests	-	0.20	expertise
	for slightly endocyclic pests	-	0.40	expertise
ν	probability of pest survival if not treated for purely endocyclic pests	-	0.50	expertise
	for mainly endocyclic pests	-	0.50	expertise
	for slightly endocyclic pests	-	0.25	expertise
γ	probability of treatment efficacy for purely endocyclic pests	-	0.8	expertise
	for mainly endocyclic pests	-	0.9	expertise
	for slightly endocyclic pests	-	0.7	expertise
q	when significant impact, proportion remaining of yield for purely endocyclic pests	-	0.7	expertise
	for mainly endocyclic pests	-	0.7	expertise
	for slightly endocyclic pests	-	0.8	expertise

Table 4: Values for the input variables of the pest dispersal model and the decision rule for the case of oilseed rape in France.

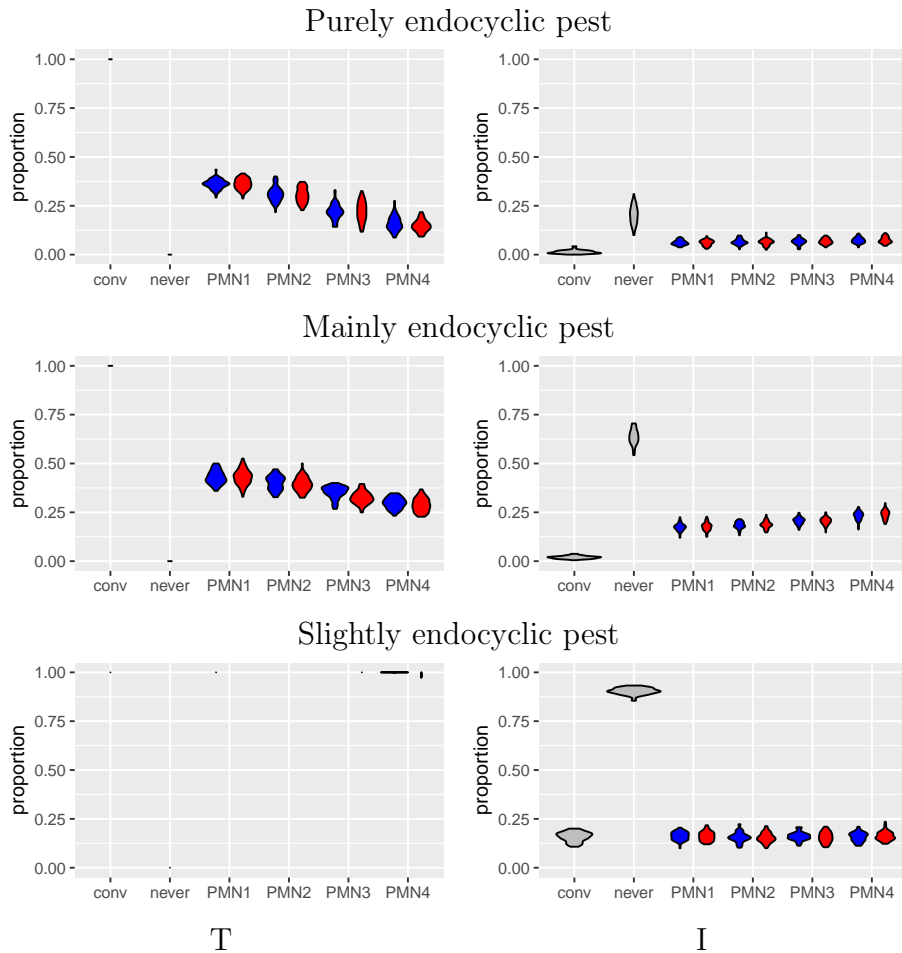
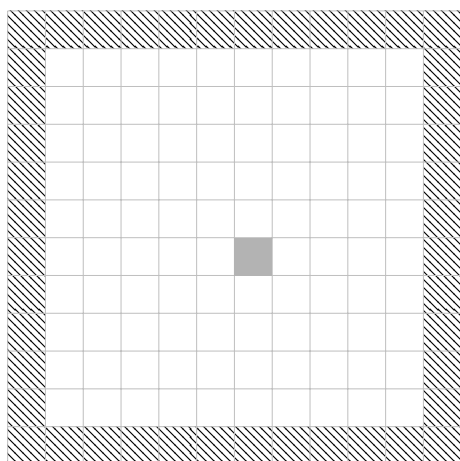
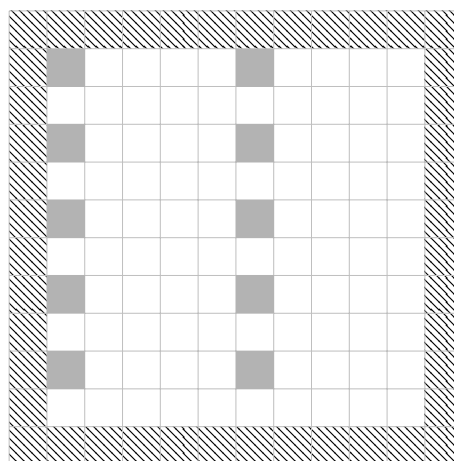


Figure 6: Considering the last three years for private information in rule d ; Influence of PMN spatial resolution and history depth on pest management. In each graph, the scenarios are represented on the horizontal axis. From left to right, conventional treatment (rule d_{conv}), never treat (rule d_{never}), then rule d with PMN1 to PMN4 and with two history depths $h = 1$ (blue) and $h = 8$ (red). Left hand column: proportion of treatment decision (T); right hand column: proportion of impacted fields (I).

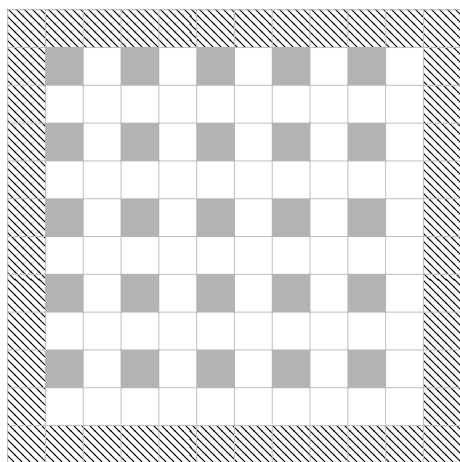
Appendix C. Considered PMNs



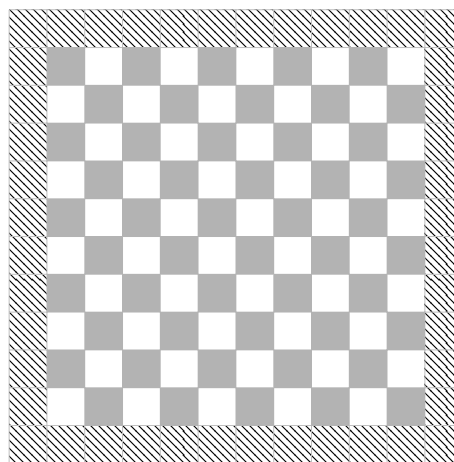
PMN1



PMN2



PMN3



PMN4

Figure 7: The four spatial resolutions considered for the PMN. Grey squares represent monitored fields. Dashed squares represent side fields where no treatment (and consequently, no decision) was applied.

Three initial positions of impacted fields for simulation

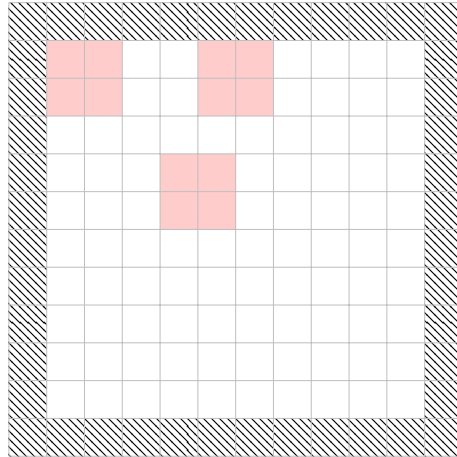


Figure 8: Position of impacted fields at the beginning of simulations. Simulations start with four grouped impacted fields (red squares). Three different positions were used corresponding to the three red 2 x 2 squares.

Appendix D. Complementary results on the sensitivity analysis

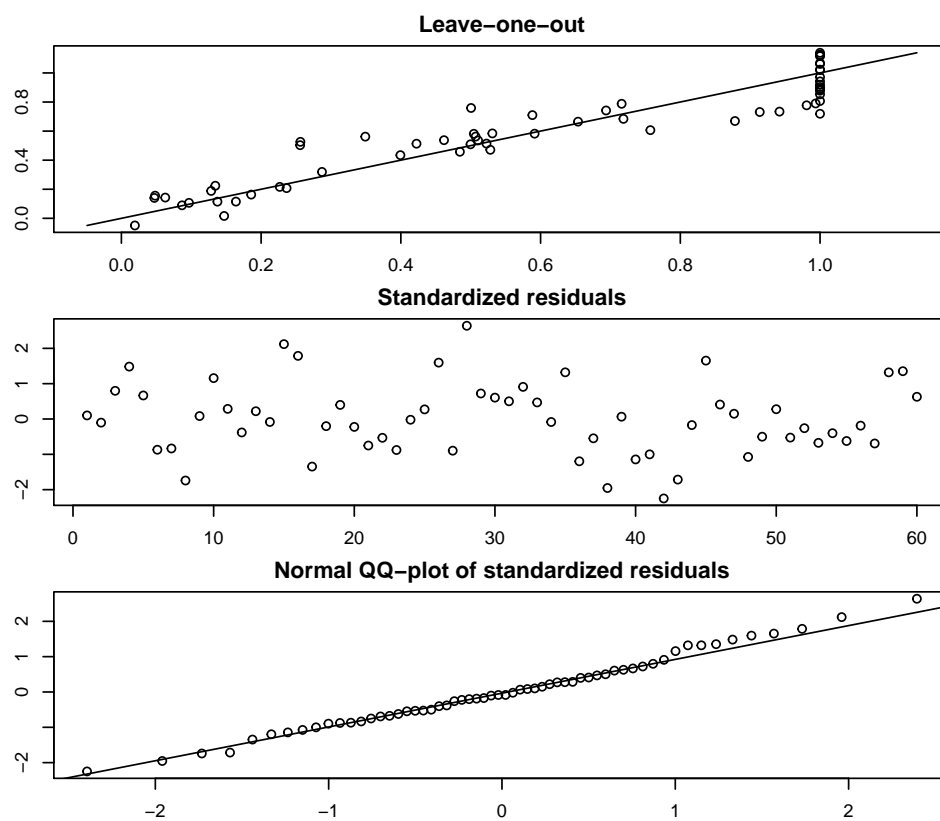


Figure 9: Evaluation of Kriging model with constant trend for criterion T.

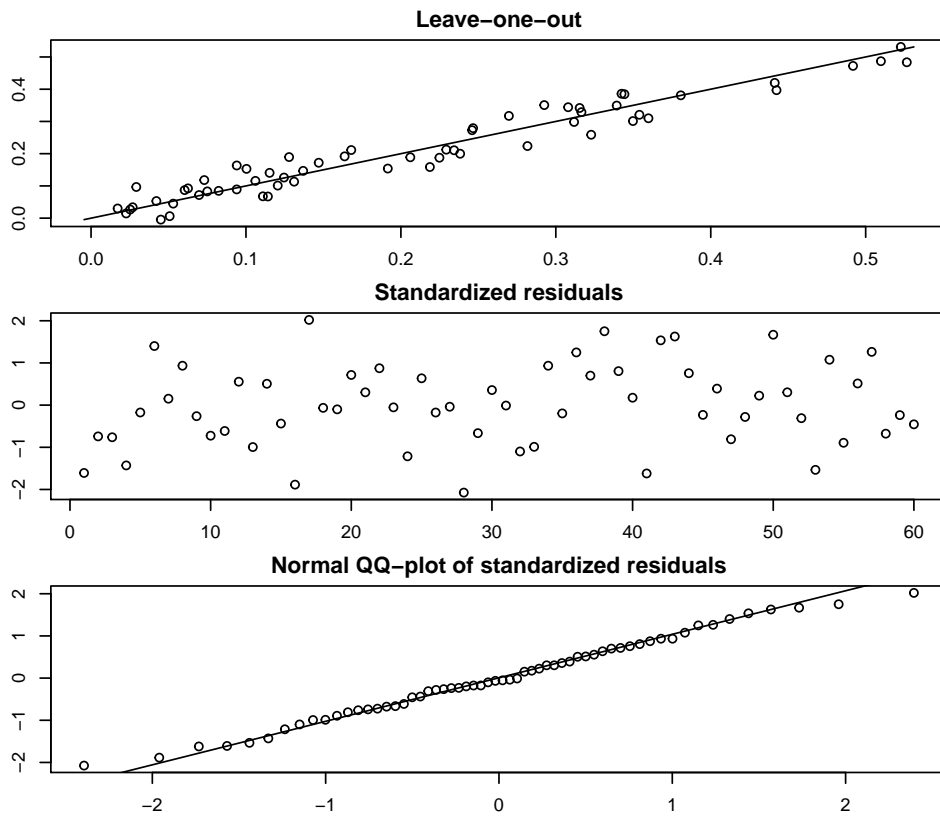


Figure 10: Evaluation of Kriging model with constant trend for criterion I.

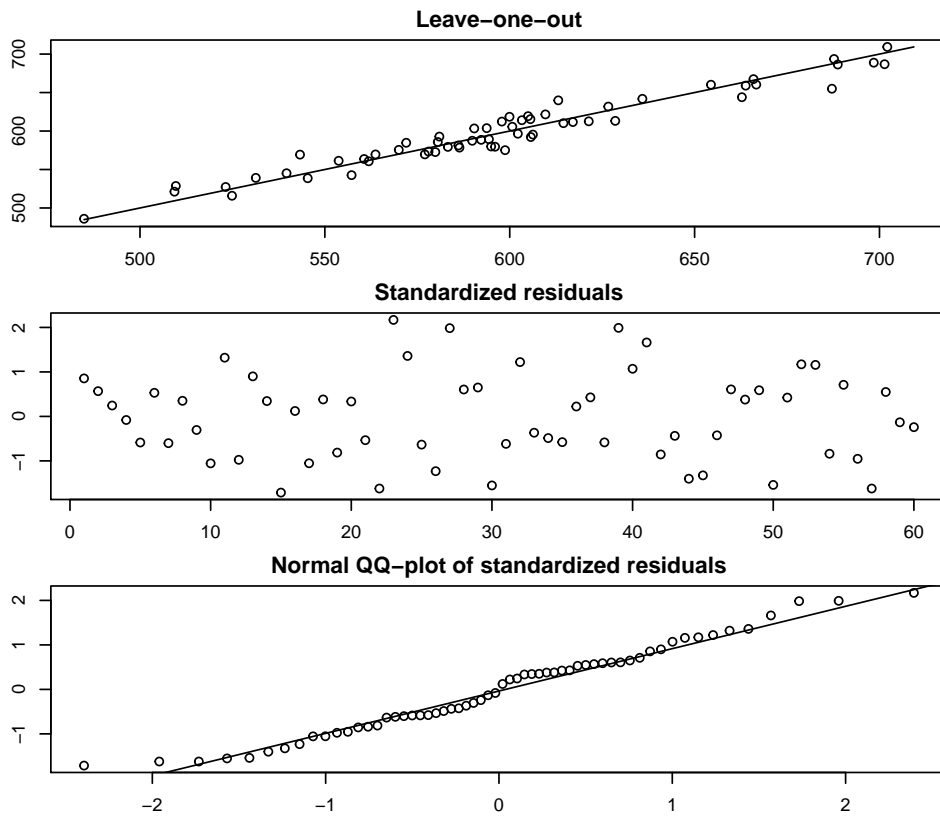


Figure 11: Evaluation of Kriging model with constant trend for criterion R.