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A decision support system based on Bayesian modelling for pest management: Application to wireworm risk assessment in maize fields

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ABSTRACT

Protecting crops against pests is a major issue in the current agricultural production system. In particular, assessing the risk to crops can promote integrated pest management (IPM) strategies that encourage natural control mechanisms and advocate the use of pesticides as a last resort. In this study, we focused on wireworms, major soil-dwelling insect pests inflicting severe economic damage on various crops (including maize, potatoes and cereals) across Europe and North America. We have developed an original hierarchical Bayesian model that explicitly accounts for biological knowledge and uncertainty in field observations, rather than relying solely on statistical correlations, to predict the level of wireworm infestation. The model was calibrated and validated using a substantial dataset originating from an agro-environmental survey carried out over three consecutive years (2012–2014) in France, which provides the wireworm abundance in 419 maize fields, together with information on the landscape context, field history, weather conditions, soil characteristics and farming practices associated to each field. Model outcomes show good agreement with current knowledge from literature and field expertise in terms of the effects of variables on wireworm abundance, and provide fairly good predictive capacity. Subsequently, the model was encapsulated as a software (R shiny application) to predict the risk of wireworm infestation in any field of interest, and can be used by farmers or agricultural advisors as a decision support system for the implementation of IPM strategies. The conceptual framework that we implemented can be adapted to a wide range of similar situations involving other crops and pests.

1. Introduction

Integrated Pest Management (IPM; [1]), which encourages natural pest control mechanisms and advocates the use of pesticides as a last resort, is an alternative to the systematic use of pesticides. The European Union made the implementation of IPM a requirement (Directive 2009/128/EC), and progressively banned various chemical products with undesirable effects on the environment, human health and ecosystem services (e.g., neonicotinoids for their lethal effects on pollinators; [2,3]). In some contexts, the reduced availability of insecticides has resulted in the resurgence of pests that were previously well controlled with chemical products. The wireworms, the soil-dwelling larvae of click beetles (Coleoptera: Elateridae), are a remarkable illustration of this issue. Wireworms spend most of their life in the soil: the larvae undergo a number of instars and the complete elaterid life cycle varies between two to five years depending on species, region and environmental conditions [4]. Wireworms are highly polyphagous [5], first considered as major pests during the 20th century. They are currently responsible for severe economic damage on various crops (including maize, potatoes and cereals) across Europe and North America [6]. The identification of the factors determining the level of crop infestation and resulting damage, as well as the use of this knowledge to accurately predict the pest risk, have therefore become a major issue.

Until today, a limited number of models have been developed with this respect. Building on identified risk factors (see [7], for a comprehensive state of the art), some have predicted wireworm occurrence from soil and meteorological data coupled with a hydrologic model [8, 9]; wireworm activity from soil characteristics and climate [10]; click beetle abundance from climatic and edaphic factors [11]; their

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abundance and community structure [12]; damage caused in potato fields from landscape features [13]; or have determined the key climate and agro-environmental factors impacting wireworm damage [14–16]. To the best of our knowledge, the web application VFF-QC developed and used in Quebec (https://cerom.qc.ca/vffqc/, accessed on December 16, 2022) is the only decision-support system commonly applied for wireworm risk assessment. Based on a machine learning algorithm (boosting regression trees) fitted on data collected in Quebec, the model assesses the wireworm risk level (low, moderate, or high) and determines whether the target field has reached a threshold that would justify treatment. All these data-driven models rely on correlative approaches that link a selected set of predictors to pest abundance or crop damage.

In contrast, in our study we made a point to design a model that describes the main processes driving wireworm colonization, thereby gaining in genericity. By opting for a Bayesian approach, we chose an appropriate framework to deal with risk assessment: the infestation risk expresses as a random variable with credible intervals. In particular, hierarchical Bayesian modelling allows to place the biological and ecological expertise at the core of the conceptual model and to use them to inform priors. Moreover, observations, i.e. the measurements of pest abundance from soil samples, are described as realisations of a stochastic process, thus addressing the uncertainty associated with data collection.

The main objective of this study was to develop a model with fair performance in terms of pest risk assessment (characterized by the pest abundance in the target field), applied to wireworm infestation in maize crops, and to encapsulate this model in a decision-support system (DSS) that can be used by farmers or agricultural advisors as part of a toolkit meant for the implementation of IPM strategies. We also aimed at providing a conceptual framework that could subsequently be adapted to a wide range of similar situations involving other crops and pests.

2. Material and methods

2.1. The agro-environmental survey

The data used in this study was compiled from an extensive survey carried out from 2012 to 2014 in five regions of France (Bretagne, Pays de la Loire, Poitou-Charentes and Limousin, Aquitaine, and Rhône-Alpes). A total of 419 maize fields (Fig. 1) with widely varying levels of wireworm infestation were monitored. In each field, a broad set of descriptors including pedoclimatic conditions, field history, agricultural practices and landscape context were considered (Table 1).

2.1.1. Wireworm sampling

The wireworm infestation was monitored in each field by pooling soil samples obtained from three randomized spade holes (each 20 × 20 × 20 cm^3). Samples included mostly four species of the genus *Agriotes* (*A. lineatus, A. obscurus, A. sordidus* and *A. sputator*) that are the main concern in France due to the crop damage they cause. A total of 1436 larvae were collected in the 419 fields (see Suppl. Mat., Appendix A for the proportion of species according to the five regions).

2.1.2. Soil characteristics

Click beetles spend most of their lifecycle in the soil (during the larval development). Accordingly, soil characteristics are key determinants of habitat quality for wireworms and major determinants of their abundance. Soil samples collected in fields were analysed in laboratory to assess the soil pH, the proportion of organic matter content, the proportion of active limestone, and the soil texture expressed as proportions of sand, silt and clay.

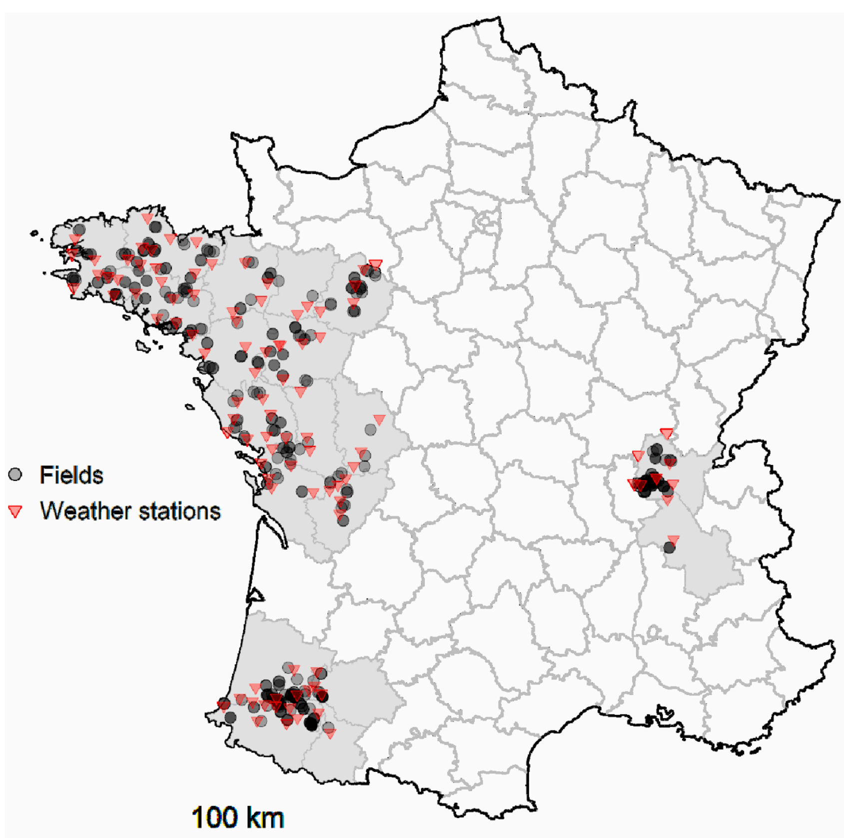

Fig. 1. Location of the monitored fields: 395 out of 419 fields were georeferenced and are plotted as grey circles (darker circles are due to the stacking of the grey circles). Weather stations are represented by red triangles.

Table 1
Description of the variables considered in the model.

Category *Short name*	Description	Type
Response variable		
Y	Wireworm abundance observed in the field	Quantitative
Landscape context		
Adj_Mead	Presence of an adjacent meadow	Boolean
Adj_GS	Presence of an adjacent grass strip	Boolean
Field history		
Hist_Mead	Presence of a meadow between years N-5 and N-15	Boolean
Rota_Type	Rotation type*: MM, MMead, SR, SDRM, DR	Qualitative
Cover_Crop	Cover crop type**: BS/VO, CIPAN, IRG	Qualitative
Soil characteristics		
x.sand	Sand proportion	Quantitative
x.clay	Clay proportion	Quantitative
p.limestone	$CaCO_3$ proportion	Quantitative
OM	Soil organic matter content	Quantitative
pH	Soil pH	Quantitative
Weather conditions		
T_cum_spr	Cumulative temperature over 10 °C from April 15 to June 15 in year N-1	Quantitative
Rf_cum_spr	Cumulative rainfall from April 15 to June 15 in year N-1	Quantitative
*T****	Temperature on the sampling day (20 cm depth)	Quantitative
Tillage		
NbTiSp	Number of tillage operations in spring (March to June) in year N-1	Quantitative
NbTiSu	Number of tillage operations in summer (July to October) in year N-1	Quantitative

* MM (maize monoculture): 4 to 5 maize crops over the 5 last years and maximum 1 year of other culture/meadow. MMead (Maize & Meadow): meadow followed by 1 to 3 maize crops over the last 5 years (no other crop). SR (Short Rotation): 2 different crops with no meadow of more than 1.5 years. SDRM (Short/Diversified Rotation Meadow): short or diversified rotation with at least a 2-year meadow over the last 5 years. DR (Diversified Rotation): 3 or more different crops with no meadow of more than 1.5 years.
** BS/VO: Bare Soil & Volunteers. CIPAN: nitrite traps. IRG: Italian rye-grass.
*** Temperature at the sampling date is only used for the model calibration (see §2.2.2).

2.1.3. Weather conditions

Weather plays an eminent role in the development of wireworms, as eggs and larvae need favourable conditions in terms of temperature and soil moisture to develop [17]. Climatic conditions also determine their vertical migration when foraging [18]. As spring is the critical period for the survival of young instars, we considered two main weather variables in our model: the cumulative air temperature and the cumulative rainfall, both calculated between April 15 and June 15 for the years prior to the field survey. Both variables were estimated in each field from daily measurements reported from the closest meteorological station (amongst a network of 88 meteorological stations, see Fig. 1). The distance from the field to the nearest station was 11.0±6.1 km on average and less than 18.6 km in 90% of the monitored fields. Some preliminary analyses (not shown here) revealed that considering these two variables beyond the previous year decreased the predictive capacity of our model. Therefore, only air temperature and rainfall accumulated during the spring period prior to the study year were included in the model (see Table 1).

In each field, the soil temperature at a depth of 20 cm on the sampling day was estimated using a model from Arvalis Institut du Végétal (unpublished; main features are daily surface temperature, computed belowground thermal amplitude and mean soil temperature over past days).

2.1.4. Field history

The lifecycle of wireworms takes place over several years [19–21]. Consequently, field history is expected to influence the current level of wireworm infestation. In our study, three variables were collected to characterize the field history: the type of crop rotation over the last five years, the type of intercrops before the last maize culture, and the presence of a meadow during the period comprised between 15 years and 5 years prior to the field survey (Table 1). The presence of a meadow in the field history was considered as it is acknowledged as a favourable habitat for egg laying [22] and surviving of first instars of larvae. Crop rotation summarizes the crop succession over the past five years and was divided into five categories: Short Rotation (rotation including two different crops with less than two years of meadow), Diversified Rotation (rotation including at least three different crops with less than two years of meadow), Maize Monoculture (four to five maize crops), Maize Monoculture with Meadow (one to three maize crops with meadow during the remaining time) and Short or Diversified Rotation with Meadow (short or long rotation with at least two years of meadow). Three categories of intercrops were defined: bare soil and/or volunteers, Italian rye-grass, and green manure.

2.1.5. Landscape context

Depending on its composition, configuration and dynamics, the landscape context can facilitate or hamper the spillover of click beetles hence, following oviposition, the spatial redistribution of wireworms [23]. For this purpose, the agro-environmental survey documented the presence or absence of meadows or grass strips adjacent to each field under study, as they are considered as the main sources of click beetles (Table 1). We only considered adjacent habitats because the flight dispersal capacities of click beetles are limited, with most species preferring to disperse by walking on the ground [5,6,21].

2.1.6. Agricultural practices

Agricultural practices can affect wireworm populations. The effects of drainage [14,15], sowing date [15,16], tillage [22,24,25], fertilizer or chemical application [15] are well documented. In particular, tillage can have direct effects, such as the mechanical destruction of wireworms, or indirect effects, such as bringing the larvae to the surface, making them vulnerable to desiccation or predation. In our study, we considered the number of spring (15 March to 15 June) and summer (15 July to 15 October) tillage operations (including all types of tools for soil preparation) the year prior to the field survey. Indeed, as noted in §2.1.3, preliminary analyses showed that accounting for operations over more than one year decreased the prediction capacity of our model.

Finally, we checked that all variables were sufficiently uncorrelated to be used together (see Suppl. Mat., Appendix B for a complete table of pairwise correlations).

2.2. Model description

2.2.1. Model overview

We developed a biological-based hierarchical Bayesian model [26,27] to predict the maximum abundance, λ_{max}, of wireworms per volume unit in the upper soil layer of a maize field i (the first 20cm from the surface) from features recorded in the autumn of the previous year (Fig. 2). A latent model including three biological processes (mortality, oviposition and vertical migration) was considered, and coupled to a stochastic observation model accounting for the uncertainty in the observation process that results from the unobserved vertical distribution and the random distribution of wireworms in the field. The abundance of wireworms was inferred from values of the variables (Table 1) considered to influence key biological processes, as shown in Fig. 2.

The stock (total abundance of wireworms at year t-1) is the resident population of wireworms. We assume that it is determined by the field history. Total abundance in the current year t is the stock augmented by eggs laid at year t-1 by adult click beetles coming from adjacent

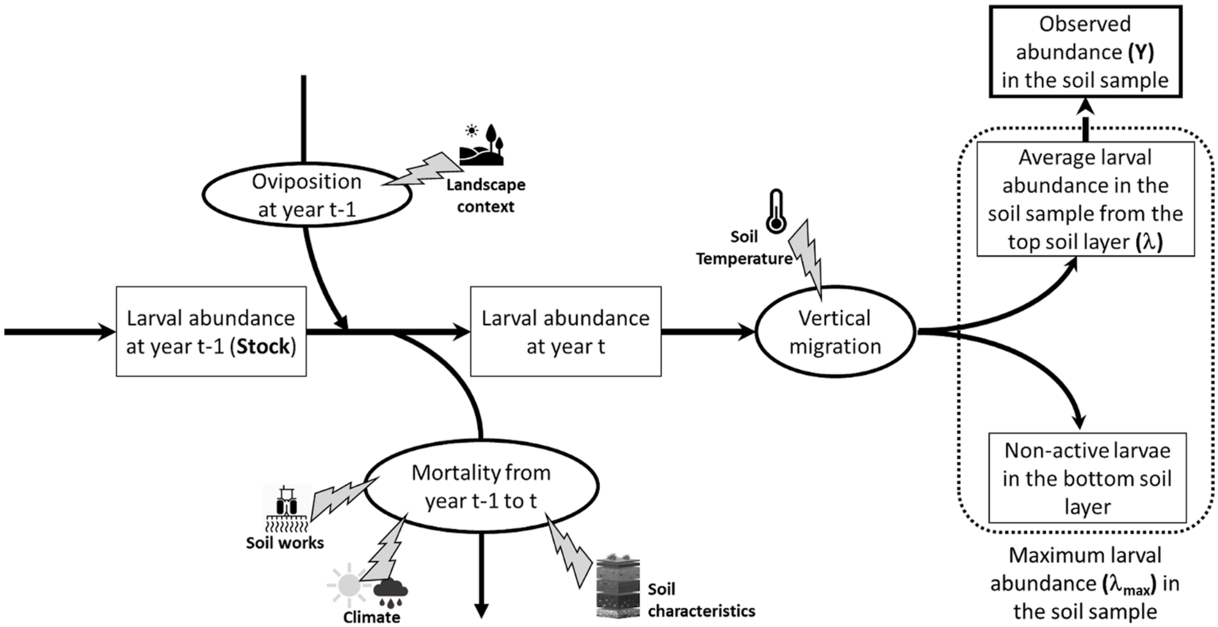

Fig. 2. Conceptual scheme of the state space model. Rectangles stand for state variables, and bubbles are key biological processes. Lightning symbols highlight the main variables assumed to influence the processes under consideration.

elements (changes resulting from the balance between local reproduction and adult emergence are considered as part of the stock) and reduced by the mortality resulting from soil properties (e.g. texture suitability), climatic conditions, and soil disturbance (e.g. tillage operations). Population is divided into two subpopulations inhabiting the upper soil layer (top 20cm) and the bottom soil layer (below 20cm), whose relative sizes depend on the soil temperature. Only the upper subpopulation is observed because only the top 20cm soil layer is sampled (§2.1.1).

2.2.2. Bayesian model

The model can be expressed by the following system of equations:

$$Y_i \sim Pois(\lambda_i) \tag{1}$$

$$\lambda_i = (\lambda_{max_i}) * VM(T_i) \tag{2}$$

$$\lambda_{max_i} = exp\left(\sum_k \alpha_k * x_{quanti\ (i,k)} + \sum_l \beta_{l,x_{quali\ (i,l)}} + C_{ref}\right) \tag{3}$$

Eq. (1) represents the stochastic observation model. The observed wireworm abundance, Y_i, is the total number of larvae collected in the field i according to the protocol described in the Section 2.1.1. The sampling process is assumed to conform to a Poisson distribution of parameter λ_i, the average abundance in a 24 dm^3 soil sample taken from the upper soil layer of the field i of interest.

Eq. (2) states that the average abundance λ_i in the upper layer soil sample on the observation date corresponds to a fraction of its maximum value, λ_{max_i}, that we seek to predict. The magnitude of this fraction is driven by the vertical larval migration process which we assume depends on the soil temperature T_i at 20cm depth in field according to Eq. (4):

$$VM(T_i) = e^{-\frac{1}{2}*\left(\frac{(T_i - T_O)^2}{b}\right)} \tag{4}$$

where T_0 (the optimal temperature) and b are parameters to be estimated. Following Jung et al. [10], the function $VM(T_i)$ was considered as bell-shaped. However, contrary to Jung et al. [10], soil moisture was not included as data were not available and could only be estimated using a model based on temperature. Thus, as given by Eq. (4), the function $VM(T_i)$ is equal to 1 when soil temperature is T_0, and close to 0 for low (overwintering) or high (aestivation) soil temperatures. It is worth mentioning that the temperature T_i is only useful in the calibration phase (i.e. parameter inference) of the model, to make the link between the wireworm abundance measured on the sampling date (Y_i) and the latent variable λ_i.

Finally, Eq. (3) expresses the expected maximum wireworm abundance in the upper soil layer of a maize field as determined by the field features recorded in the autumn of the previous year (Table 1). Although the variables have been conceptually grouped according to the process they are assumed to determine (Fig. 2), they were treated indiscriminately in the linear model in the absence of independent observations of the different processes. In this Equation, i is the field identification number, α_k the coefficient associated to the k^{th} quantitative variable, $\beta_{l,x_{quali\ (i,l)}}$ the coefficient associated to the level of the l^{th} qualitative variable, and C_{ref} a constant characterising a reference situation. Actually, for each qualitative variable, the most frequent level within the dataset was selected as the reference level. The effect of any level of each qualitative variable is expressed in terms of the difference from the baseline determined by the reference level. Therefore, the reference baseline was based on the following set of conditions: no adjacent meadow and no adjacent grass strip, no meadow in the history of the crop, maize monoculture and bare soil during the cover cropping period.

Once the model has been calibrated, i.e. the coefficients have been determined, Eq. (3) constitutes the core of the decision support system described in §4.3.

2.2.3. Parameter inference

Parameter inference was carried out using a Markov Chain Monte Carlo (MCMC) algorithm. Based on Jung et al. [10], the prior distribution for T_0 was set to a Gaussian distribution with the mean parameter equal to 12 and a low variance (sd=1). Prior distribution for parameter b was a uniform law between 1 and 100 as this parameter must be positive. In the absence of prior knowledge for all other parameters, prior distributions were Gaussian centred on zero and with high variances (sd=100), i.e. non-informative priors. We ran three MCMC chains with 300,000 iterations. The first 150,000 iterations were removed as burn-in iterations and the last 150,000 were thinned every 50 iterations to assess the posterior distributions of parameters. Parameter inference was performed using the Openbugs software [28] running from R v4.0.4 software [29] thanks to the package "R2OpenBUGS" [30].

2.3. Model evaluation

2.3.1. Convergence of the parameter inference procedure

The convergence of the random Markov chains was checked using the Gelman-Rubin statistic, *R.hat*, which is embedded in the R2OpenBUGS R package [30]. An R.hat value close to 1 indicates good MCMC convergence, whereas an R.hat value greater than 1.1 indicates poor convergence.

2.3.2. Model performance

Model performance was assessed in terms of (i) goodness-of-fit, by considering the full dataset, and (ii) predictive capacity, by applying a ten-fold spatial cross-validation procedure (with five repetitions) using the R package BlockCV [31]. This cross-validation was spatially stratified to avoid overestimation of the model predictive capacity by ensuring no test data abuts training data (see Suppl. Mat., Appendix C). We retained two metrics: the Mean Absolute Error (MAE), and the coefficient of determination (R^2) associated with the linear relationship between median model predictions and field observations. For the sake of clarity, the subscript *p* (MAEp and R^2p) refers to the performance in terms of predictive capacity. The performance metrics of the hierarchical Bayesian model were compared to those associated with a null model for which the value of λ equals the mean field abundance across the dataset (λ=3.4).

2.3.3. Relative effects of variables

All quantitative variables, except the response variable *Y* (wireworm abundance), were initially standardised (centred-reduced). Consequently, the posterior distributions associated to the model coefficients can be directly compared to assess the relative effects of the explanatory variables. Furthermore, as the response variable follows a Poisson distribution with a log link function and the effects are additive, coefficients can be directly interpreted as multipliers of wireworm abundances.

3. Results

3.1. Parameter inference

The Gelman-Rubin statistic was lower than 1.1 for all model parameters (Table 2), thus indicating a good convergence of the Markov chains and providing confidence in the inference procedure. In addition, the posterior distributions of all model parameters were unimodal and bell-shaped (Fig. 3), suggesting accurate parameter estimations. This applies to each of the five repetitions of the cross-validation procedure.

3.2. Model performance

The goodness-of-fit appears satisfactory as the mean absolute error of prediction (MAE) on the whole dataset equals 2.7 while the value of the response variable ranges from 0 to 42 (Table 3). In contrast, the null model had a MAE of 4.1. The proportion of variance in wireworm abundance explained by the model is R^2=0.5. In terms of model predictive ability, the outcome of the ten-fold spatial cross-validation procedure provided the values 0.3 and 3.6 respectively for the coefficient of determination and the mean absolute error (Table 3). Reasonable decrease between the performance in fit and validation suggests the absence of overfitting.

In addition, 83% of the wireworm abundance observations fall within the 95% credible interval of the posterior probability distribution of the predicted (mean) abundance (see Suppl. Mat., Appendix D). No spatial patterns in model performance were observed (see Suppl. Mat., Appendix E), however the predictive performance seemed slightly lower is in the region Bretagne than in the others regions under investigation.

3.3. Effects of variables on the wireworm abundance

The posterior distributions of the parameters associated with each quantitative variable or level of categorical variables included in the model are reported in Fig. 3, while Fig. 4 shows the marginal effects of the quantitative variables on the wireworm abundance. Overall, the most influential variables are (in decreasing order) the proportion of clay in soil, the proportion of soil organic matter content, the pH, the diversification in the rotation type, the proportion of sand in soil, the presence of a meadow adjacent to the field under survey, and the number of tillage operations the summer prior to the monitoring year.

Table 2
Summary of the main outcomes (mean, standard deviation, percentiles and Gelman-Rubin statistic) associated with each model parameter.

Variable (or factor) name	Coefficient	mean	sd	2.5%	50%	97.5%	Rhat
Adj_Mead:YES	a1.1	0.26	0.06	0.14	0.26	0.38	1.00
Adj_GS:YES	a2.1	0.07	0.06	0.03	0.07	0.18	1.00
Hist_Mead:YES	b1.1	0.10	0.07	−0.05	0.10	0.24	1.00
Rota_Type:MP	b2.1	0.03	0.11	−0.05	0.03	0.11	1.00
Rota_Type:SR	b2.2	−0.10	0.11	−0.31	−0.10	0.10	1.00
Rota_Type:SDRM	b2.3	−0.14	0.14	−0.40	−0.14	0.13	1.00
Rota_Type:DR	b2.4	0.30	0.10	0.10	0.30	0.49	1.00
Cover_Crop:CIPAN	b3.1	0.08	0.08	−0.09	0.08	0.24	1.00
Cover_Crop:IRG	b3.2	0.17	0.10	−0.2	0.17	0.36	1.01
x.sand	c1.1	−0.26	0.03	−0.33	−0.26	−0.20	1.00
x.clay	c1.2	−0.86	0.07	−0.99	−0.86	−0.72	1.00
p.limestone	c1.3	−0.08	0.05	−0.18	−0.08	0.01	1.00
pH	c2	−0.31	0.04	−0.39	−0.31	−0.23	1.00
OM	c3	0.37	0.03	0.30	0.37	0.43	1.00
T_cum_spr	d1	0.21	0.03	0.15	0.21	0.28	1.00
Rf_cum_spr	d2	−0.18	0.05	−0.28	−0.18	−0.08	1.00
NbTiSp	e1	−0.09	0.04	−0.17	−0.09	0.00	1.00
NbTiSu	e2	−0.25	0.06	−0.36	−0.25	−0.15	1.00
To	T_0	15.80	0.60	14.30	15.90	16.67	1.00
b	b	13.31	3.05	9.12	12.72	21.14	1.00
Reference baseline	Cref	0.99	0.08	0.84	0.99	1.15	1.00

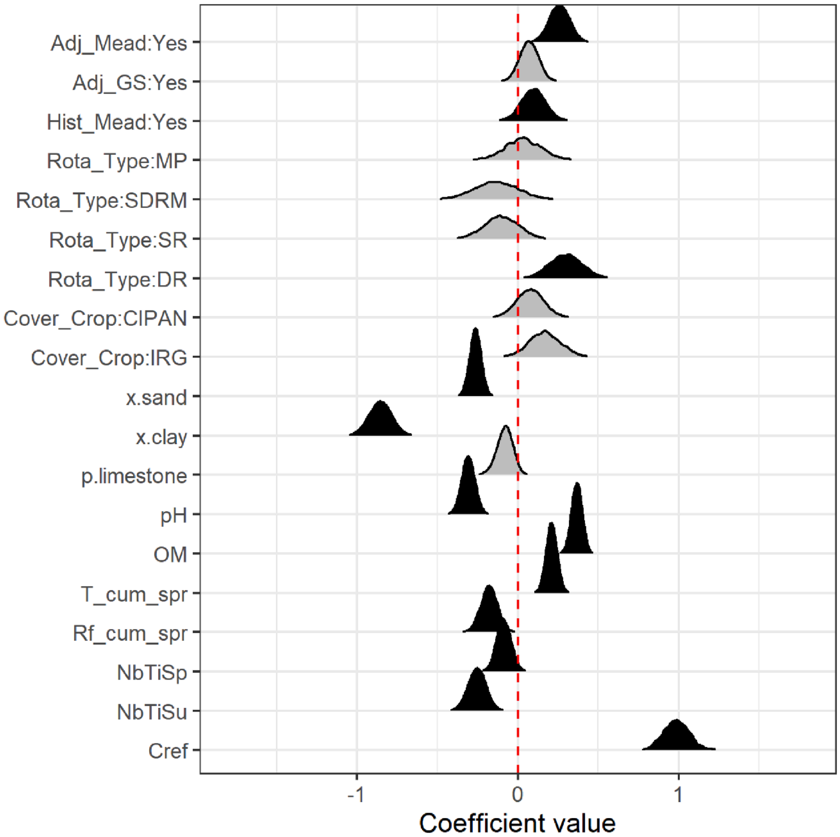

Fig. 3. Posterior distributions of the parameters associated with each quantitative variable or level of categorical variables included in the model. Black colour indicates that zero is not in the 95% credible interval.

Table 3
Goodness-of-fit and predictive capacity of the hierarchical Bayesian model and the null model.

	Goodness of fit		Predictive capacity	
Model \ Metrics	R^2	MAE	Mean R^2_p	Mean MAE_p
Hierarchical Bayesian model	0.5	2.7	0.3	3.6
Null model	0	4.1	0	4.1

3.3.1. *Effect of tillage*

An increase in the number of tillage operations during the spring and summer prior to the monitoring date results in a decrease in wireworm abundance with respectively a median value of coefficient e1 and e2 of −0.09 and −0.25 (Fig. 3 and Table 2). Indeed, when no tillage is applied the previous spring (resp. the previous summer), wireworm abundance increases by 10% (resp. 15%). In contrast, wireworm abundances decrease by 22% and 52% when three tillage operations were applied in spring or summer respectively (Fig. 4G-H).

3.3.2. *Effect of weather conditions*

Considering the period spanning from April 15 to June 15 the year prior to the field survey, the cumulative rainfall has a negative effect on the wireworm abundance (median value −0.18 of coefficient d2, Table 2) whereas the cumulative temperature above 10 °C has a positive effect (median value of 0.21 for coefficient d1, Table 2). Indeed, 160mm cumulative rainfall appear as a tipping value below which, resp. above which, the effect on wireworm abundance is positive, resp. negative (Fig. 4F). However, the 95% credible interval associated to the coefficient is broad, especially for high value. In a similar way, around 300 degree-day accumulation in spring temperature highlights a shift in the effect on wireworm abundance. A degree-day accumulation as low as 100 decreases abundance by about 30% compared to 300 degree days; in contrast, a degree-day accumulation of 500 results in an average increase the abundance of about 50% (Fig. 4E).

3.3.3. *Effect of soil characteristics*

Amongst the soil characteristics, the organic matter content, the pH, and the proportion of sand and clay (indirectly the proportion of loam that immediately stems from these two values of proportion), exhibit clear effects on the wireworm abundance, as the associated coefficients show narrow posterior distributions which do not encompass zero (Fig. 3). Increasing values of the pH, the proportion of sand and the proportion of clay, have a negative effect on wireworm abundance (with median value for coefficients c2, c1.1, c1.2 of −0.31, −0.26 and −0.86, respectively) while increasing the proportion of soil organic matter content has a positive effect (median value of coefficient c3 of 0.37) (Table 2). Although the posterior distribution of the coefficient associated with the amount of active limestone suggests a negative effect on wireworm abundance (median value of coefficient c1.3 of −0.08), its right tail encompasses zero hence preventing from drawing a categorical conclusion.

The variation in wireworm abundance ranges between 55% and −72% over the range of the sand proportion in soil (Fig. 4A). Regarding the proportion of clay in soil, values typically lower than 15% dramatically increase the wireworm abundance: it is increased by a factor 2.5 in the absence of clay (Fig. 4B). Acidic pH increases wireworm abundance, e.g. by about 90% at pH=4.7, whereas basic pH decreases it, e.g. by half at pH=8.5 (Fig. 4C). Finally, and remarkably, highest values of soil organic matter content are accompanied by a sharp increase in wireworm abundance, e.g. by a median factor of 3 at the value 8.5% (Fig. 4D).

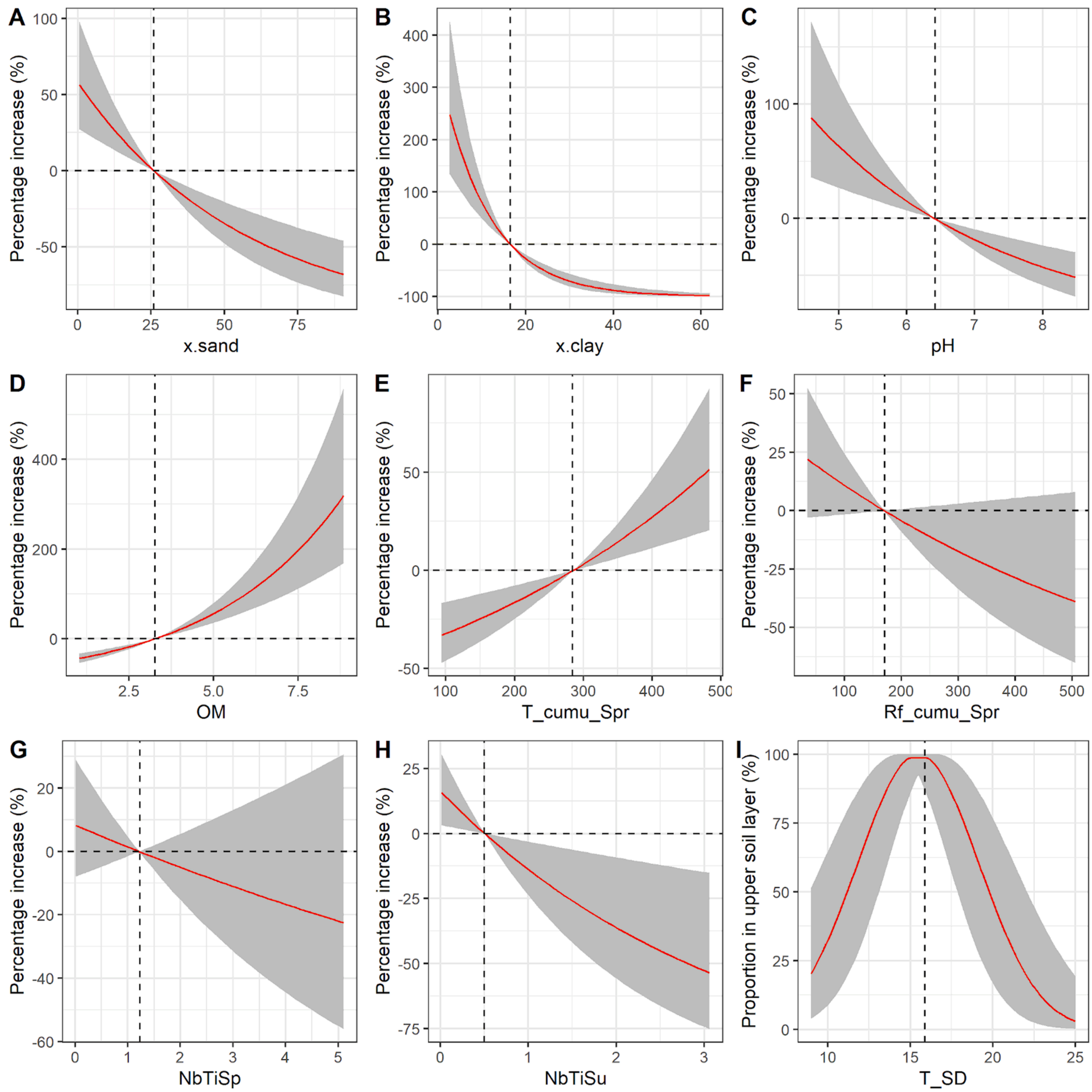

Fig. 4. Marginal effects of the quantitative variables on the wireworm abundance as a percentage of increase. Red line is the median effect. Grey area shows the 95% credible interval. The vertical dot line emphasizes the tipping value for which the effect switches from positive to negative (or vice-versa) in panels A-H; and the optimal temperature value in panel I.

3.3.4. *Effect of field history*

Diversified rotations, and the presence of a meadow in the period spanning from 15 to 5 years previous to the field survey increase wireworm abundance. The median values associated with the corresponding coefficients b2.4 and b1.1 equal respectively 0.30 and 0.10, which corresponds respectively to an increase of 35% and 11% compared to the wireworm abundance observed in the reference situation (i.e. maize monoculture, cf. §2.2.2).

Effects of cover cropping as well as of the other rotation types must be cautiously analysed as the corresponding posterior distributions encompass zero. However, the presence of winter intercrops, be it Italian rye-grass (IRG) or nitrate-trapping crop (CIPAN), seems to have a slight positive effect on wireworm abundance.

3.3.5. *Effect of landscape context*

Both the presence of a meadow or a grass strip adjacent to the field result in an increase in the wireworm abundance compared to the reference situation (no adjacent meadow and no adjacent grass strip). Associated median values of coefficients a1.1 and a2.1 equal 0.26 and 0.07 that correspond to respective percentages of increase of 30% and 7%.

3.3.6. *Effect of the vertical migration of wireworms*

Estimations of parameters T_0 and b are respectively 15.8±0.6 °C and 13.3±3.0 (mean ± sd, Table 2). At the optimal temperature T_0, the whole wireworm population is present in the upper soil layer, whereas the proportion decreases to 32% at 11 °C and 21 °C, and is quasi-null above 25 °C (Fig. 4I). This makes the vertical migration process an important determinant of wireworm abundance in the upper soil layer where soil sampling is achieved at the monitoring date.

4. Discussion

In our study, we have developed a model to predict the wireworm infestation risk while (i) placing the biological expertise at the core of the conceptual model (Fig. 2), and (ii) using a hierarchical Bayesian framework to provide an estimation of the wireworm abundance with a credible interval. In this section, we discuss the model performance and show that results are consistent with the scientific literature or confirm stakeholders' expertise, thereby attesting to the suitability of our model for use as a decision support system.

4.1. Model performance

Model performance was assessed in terms of goodness-of-fit and of predictive capacity. The associated mean absolute errors are 2.7 and 3.6 respectively (Table 3), which is fairly good given that (i) the response variable ranges from 0 to 42, and (ii) the uncertainty in the assessment of the wireworm abundance in field. The relatively low increase in the mean absolute error provided as outcome of the spatial cross-validation procedure allows confidence in the estimation of the model performance (i.e. absence of overfitting). Furthermore, we did not observe any strong spatial patterns in model performance (see Suppl. Mat., Appendix E).

Altogether, all these properties confirm that the model can be used as the core of a decision support system to inform farmers on the risk of wireworm infestation.

4.2. Effects of agro-environmental variables

4.2.1. Tillage

Our findings show that tillage operations have a negative effect on wireworm abundance. This is consistent with expert knowledge: tillage may expose underground larvae to the surface and increase their predation rate [25,32] or cause desiccation [32,33], especially in summer when the weather is hot and dry. The impact of tillage was found greater in summer. This suggests that summer is the key season for applying tillage with the purpose of controlling wireworm populations. However, the beneficial effect of summer tillage operations could be mitigated by the negative effect of diversified rotation (see below).

4.2.2. Weather conditions

Mild temperatures in spring the year prior to the field survey were associated with an increase in wireworm abundance, as previously observed by Kozina et al. [11]. This may result from an increase in the development rate of larvae after hatching, shortening the duration of the first larval stage during which they are particularly vulnerable [17], thereby increasing the survival rate of young larvae. Conversely, spring precipitations the year prior to the field survey had a negative effect on wireworm abundance (also consistent with [11]). Excessive rainfall in spring might reduce the survival rate of first instar larvae. Obviously, these two variables cannot be controlled by farmers. However, understanding the influence of past weather conditions can help farmers to assess the current wireworm risk and apply appropriate pest management strategies.

The function $VM(T_i)$ was derived from the estimation of coefficients T_0 and b (see Eq. (4) and Fig. 4I) and shows the proportion of larvae present in the upper soil layer as a function of the soil temperature on the monitoring date. We found an optimal value of $15.8\pm0.6\,^{\circ}$C (Table 2) for which the whole wireworm population is present in the upper soil layer. It can be used to guide the date of field sampling, favouring dates when the probability of finding larvae is important.

4.2.3. Soil characteristics

Unsurprisingly, soil properties were found highly influential on wireworm abundance, with the coefficients associated with the proportion of clay, the soil organic matter content and the soil pH being the most influential. We found that high proportions of clay or sand in soil texture had a negative effect on wireworm abundance (this conversely also indicates that loamy soils are favourable to wireworm build-up). It is actually acknowledged that sandy soils decrease the chances of survival of eggs and early instars due to their drying and abrasive effect. However, it should be mentioned that during the survey, years of monitoring were wet, which may have amplified the asphyxiation phenomenon and explain the particularly strong effect of the proportion of clay in soil.

Our results show that acidic rather than neutral of basic soils fostered wireworm abundance. This is consistent with Poggi et al. [15] and Hermann et al. [13]. We also found a negative effect of limestone amount on the wireworm abundance which cannot be directly linked to pH since there was no correlation in our dataset between pH and limestone content (see Suppl. Mat., Appendix B). Finally, we showed a positive effect of the soil organic matter content on wireworm abundance that may result from its buffering capacity. Organic matter makes environment more stable, enabling wireworm population to settle and persist.

Farmers can hardly control soil properties, but pH for example can be manipulated by calcareous additives. As for weather, improving knowledge on the effects of soil characteristics on wireworm abundance can help farmers to assess the wireworm risk in their fields and adjust their agricultural practices accordingly.

4.2.4. Landscape context

We examined the effect of the presence of a meadow or a grass strip adjacent to the surveyed field: in both cases, we found a positive effect on wireworm abundance, which is consistent with Kozina et al. [11]. Such effect can reasonably be linked to population settlement as meadows and grass strips provide favourable conditions for egg and first instars survival and development compared to arable land [34]. Then, emerging click beetles can spill over into neighbouring fields, thereby increasing wireworm populations in the adjacent fields where they subsequently lay their eggs. As shown by Poggi et al. [23], the arrangement of grassy landscape elements in space and time can mitigate crop infestation by soil-dwelling pests, thereby emphasizing the relevance of managing grassland regimes, bearing in mind the necessary trade-off imposed by their role of reservoir of many insect natural enemy populations.

4.2.5. Field history

Overall, only a diversified rotation and the presence of a meadow in field history (15 to 5 years prior to the field survey) showed a significant effect on wireworm abundance, positive in both cases. The positive effect of a meadow in field history is likely due to the established wireworm populations, thus calling for preventive measures (e.g. tillage) to decrease these populations before sowing maize in the field. Regarding diversified rotations, they refer to successions including winter crops that limit tillage operations, which may partly explain their positive effect on wireworm abundance.

A possible explanation of the low influence of the variables that we considered to describe the field history may stem from confounding effects (e.g. with agricultural practices) that may have obscured the direct effect of crop successions.

In summary, our results are in remarkable agreement with available knowledge and expertise, and provide confidence in the use of our model as the core of a novel decision support system for the wireworm risk assessment.

4.3. Novel decision support system

On the basis of the estimation of its performance (§4.1), and on the good agreement between the model outcomes and available literature and field expertise (§4.2), the model has the ability to predict correctly the level of wireworm infestation in new fields. So we encapsulated it in a user-friendly software using the R shiny development package [35]. In the current version, under development, the graphical interface (Fig. 5) states the variables whose values must be reported for the field description, and it graphically gives the posterior probability

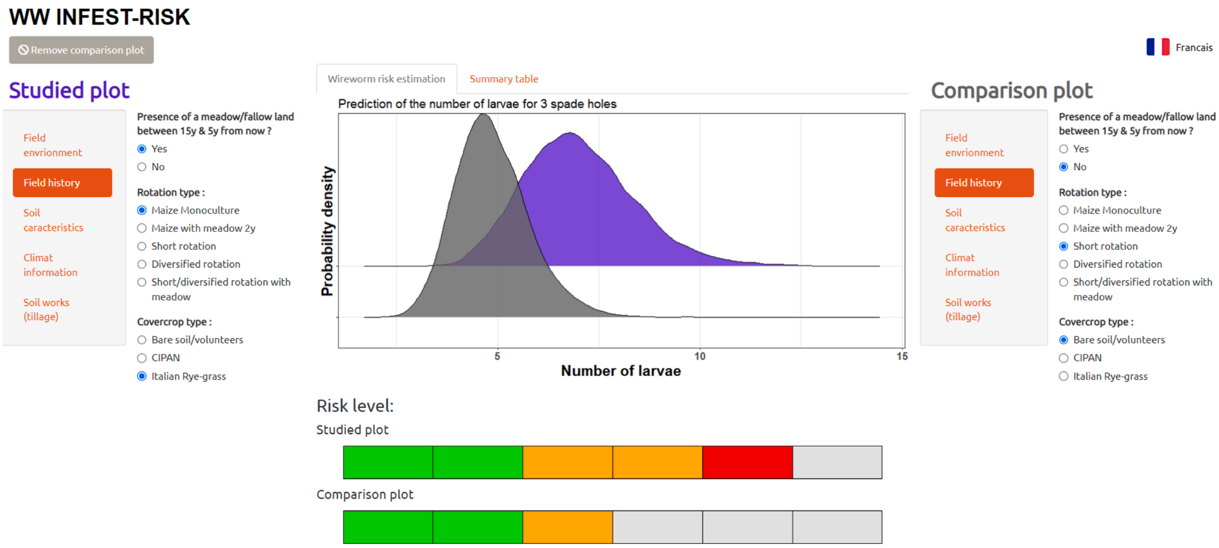

Fig. 5. Screenshot of the R shiny application. The left and right columns allow to fill in the characteristics of the field by means of buttons and sliders. The central figure displays the posterior distribution of the predicted larval abundance, for the studied field (in purple) and for the reference or comparison field (in grey). A coloured indicator at the bottom of the central panel displays the infestation risk level (green: low, orange: medium, red: high).

distribution of the larval abundance with the corresponding infestation risk level indicated by a colour bar (green: low, orange: medium, red: high). The risk levels should be derived from expert knowledge (those in Fig. 5 have been chosen arbitrarily for illustrative purposes). An additional panel can be activated to compare the current infestation risk assessment with that associated with different field characteristics. The two posterior distributions are superimposed to visualise readily the two situations, i.e. the prediction of the wireworm abundance and the associated credible intervals. This can be used, for example, to visualise the effect of changes in agricultural practices with regard to a reference situation. Once informed, the farmer may consider implementing relevant control measures.

Through the French agricultural technical Institute ARVALIS that is partner of this research, the dissemination of the decision support system can be serenely envisaged to the target community of farmers and agricultural advisors, which is currently waiting for concrete means to protect crops against wireworms. In particular, our DSS may be implemented in the range of tools offered by Arvalis (see http://oad.arvalis-infos.fr/, accessed on December 16, 2022) in order to be quickly made available to future users. Furthermore, Arvalis can communicate via a number of channels that are privileged sources of information for many technicians and farmers concerned by the control of wireworm populations.

The interest of a quick dissemination of the software and its use is that the feedback from the first users should eventually allow improving the goodness-of-fit and predictive performances of the model to situations not well represented in the current data set. The virtuous circle of data assimilation will facilitate the uptake of the software.

Conclusion

Wireworms are major soil-dwelling pests currently responsible for severe economic damage on various crops (including maize, potatoes and cereals) across Europe and North America. In our study, we developed an original Bayesian model that describes the main processes driving wireworm abundance, thus bringing the biological and ecological knowledge at the forefront rather than relying solely on statistical correlations to predict the level of wireworm infestation. Model outcomes showed good agreement with available literature and field expertise as well as fairly good predictive capacity. Subsequently, the model was encapsulated as a software to predict the risk of wireworm infestation in any field of interest, and can be used by farmers or agricultural advisors as a decision support system for the implementation of IPM strategies. Furthermore, our study provides a conceptual framework that can be adapted to a wide range of similar situations involving other crops and pests.

Software availability

The Decision Support System is provided as an R shiny application available on the French Research Data repository at the following link: https://entrepot.recherche.data.gouv.fr/dataset.xhtml?persistentId=doi:10.57745/CBVYQ1.

Author contributions

SP, MP and JR conceived and designed the research. JR programmed the model and developed the R shiny application. JR, SP, MP, RLC analysed data. All authors discussed results. JR and SP wrote the original draft. All authors read, edited, and approved the manuscript. RLC, SP, PL and JBT acquired the funding.

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Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Sylvain Poggi reports financial support was provided by SEMAE (formerly GNIS).

Data availability

The Decision Support System is made available on the French governmental reporsitory Recherche Data Gouv.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.atech.2022.100162.

References

[1] M. Barzman, P. Bàrberi, A.N.E. Birch, P. Boonekamp, S. Dachbrodt-Saaydeh, B. Graf, B. Hommel, J.E. Jensen, J. Kiss, P. Kudsk, J.R. Lamichhane, A. Messéan, A.-.C. Moonen, A. Ratnadass, P. Ricci, J.-.L. Sarah, M. Sattin, Eight principles of integrated pest management, Agron. Sustain. Dev. 35 (2015) 1199–1215, https://doi.org/10.1007/s13593-015-0327-9.

[2] L. Pisa, D. Goulson, E.-.C. Yang, D. Gibbons, F. Sánchez-Bayo, E. Mitchell, A. Aebi, J. van der Sluijs, C.J.K. MacQuarrie, C. Giorio, E.Y. Long, M. McField, M. Bijleveld van Lexmond, J.-.M. Bonmatin, An update of the worldwide integrated assessment (WIA) on systemic insecticides. Part 2: impacts on organisms and ecosystems, Environ. Sci. Pollut. Res. (2017), https://doi.org/10.1007/s11356-017-0341-3.

[3] A. Veres, K.A.G. Wyckhuys, J. Kiss, F. Tóth, G. Burgio, X. Pons, C. Avilla, S. Vidal, J. Razinger, R. Bazok, E. Matyjaszczyk, I. Milosavljević, X.V. Le, W. Zhou, Z.-. R. Zhu, H. Tarno, B. Hadi, J. Lundgren, J.-.M. Bonmatin, M.B. van Lexmond, A. Aebi, A. Rauf, L. Furlan, An update of the Worldwide Integrated Assessment (WIA) on systemic pesticides. Part 4: alternatives in major cropping systems, Environ. Sci. Pollut. Res. (2020), https://doi.org/10.1007/s11356-020-09279-x.

[4] M. Sufyan, D. Neuhoff, L. Furlan, Effect of male mass trapping of Agriotes species on wireworm abundance and potato tuber damage, Bull. Insectol. 66 (2013) 135–142.

[5] W.E. Parker, J.J. Howard, The biology and management of wireworms (*Agriotes* spp.) on potato with particular reference to the U.K.: biology and management of wireworms on potato, Agric. For. Entomol. 3 (2001) 85–98, https://doi.org/10.1046/j.1461-9563.2001.00094.x.

[6] M. Traugott, C.M. Benefer, R.P. Blackshaw, W.G. van Herk, R.S. Vernon, Biology, ecology, and control of elaterid beetles in agricultural land, Annu. Rev. Entomol. 60 (2015) 313–334, https://doi.org/10.1146/annurev-ento-010814-021035.

[7] S. Poggi, R. Le Cointe, J. Lehmhus, M. Plantegenest, L. Furlan, Alternative strategies for controlling wireworms in field crops: a review, Agriculture 11 (2021) 436, https://doi.org/10.3390/agriculture11050436.

[8] L. Furlan, B. Contiero, F. Chiarini, I. Benvegnù, M. Tóth, The use of click beetle pheromone traps to optimize the risk assessment of wireworm (Coleoptera: elateridae) maize damage, Sci. Rep. 10 (2020) 8780, https://doi.org/10.1038/s41598-020-64347-z.

[9] S.A. Lefko, L.P. Pedigo, W.D. Batchelor, M.E. Rice, Spatial modeling of preferred wireworm (Coleoptera: elateridae) habitat, Environ. Entomol. 27 (1998) 184–190, https://doi.org/10.1093/ee/27.2.184.

[10] J. Jung, P. Racca, J. Schmitt, B. Kleinhenz, SIMAGRIO-W: development of a prediction model for wireworms in relation to soil moisture, temperature and type, J. Appl. Entomol. 138 (2014) 183–194, https://doi.org/10.1111/jen.12021.

[11] A. Kozina, D. Lemic, R. Bazok, K.M. Mikac, C.M. Mclean, M. Ivezić, J. Igrc Barčić, Climatic, edaphic factors and cropping history help predict click beetle (Coleoptera: elateridae) (*Agriotes* spp .) abundance, J. Insect Sci. 15 (2015) 100, https://doi.org/10.1093/jisesa/iev079.

[12] I. Milosavljević, A.D. Esser, D.W. Crowder, Effects of environmental and agronomic factors on soil-dwelling pest communities in cereal crops, Agric. Ecosyst. Environ. 225 (2016) 192–198, https://doi.org/10.1016/j.agee.2016.04.006.

[13] A. Hermann, N. Brunner, P. Hann, T. Wrbka, B. Kromp, Correlations between wireworm damages in potato fields and landscape structure at different scales, J. Pest Sci. 86 (2013) 41–51, https://doi.org/10.1007/s10340-012-0444-z.

[14] L. Furlan, B. Contiero, F. Chiarini, M. Colauzzi, E. Sartori, I. Benvegnù, F. Fracasso, P. Giandon, Risk assessment of maize damage by wireworms (Coleoptera: elateridae) as the first step in implementing IPM and in reducing the environmental impact of soil insecticides, Environ. Sci. Pollut. Res. 24 (2017) 236–251, https://doi.org/10.1007/s11356-016-7692-z.

[15] S. Poggi, R. Le Cointe, J.-.B. Riou, P. Larroudé, J.-.B. Thibord, M. Plantegenest, Relative influence of climate and agroenvironmental factors on wireworm damage risk in maize crops, J. Pest Sci. 91 (2018) 585–599, https://doi.org/10.1007/s10340-018-0951-7.

[16] S. Saussure, M. Plantegenest, J.-.B. Thibord, P. Larroudé, S. Poggi, Management of wireworm damage in maize fields using new, landscape-scale strategies, Agron. Sustain. Dev. 35 (2015) 793–802, https://doi.org/10.1007/s13593-014-0279-5.

[17] M. Sufyan, D. Neuhoff, L. Furlan, Larval development of Agriotes obscurus under laboratory and semi-natural conditions, Bull. Insectol. 67 (2014) 227–235.

[18] J. Lafrance, The seasonal movements of wireworms (coleoptera: elateridae) in relation to soil moisture and temperature in the organic soils of southwestern quebec, Can. Entomol. 100 (1968) 801–807, https://doi.org/10.4039/Ent100801-8.

[19] Balachowski, A., Mesnil, L., 1935. Les taupins, in: tome I “Les insectes nuisibles aux plantes cultivées.” Paris.

[20] L. Furlan, The biology of Agriotes sordidus Illiger (Col., Elateridae), J. Appl. Entomol. 128 (2004) 696–706, https://doi.org/10.1111/j.1439-0418.2004.00914.x.

[21] L. Furlan, The biology of *Agriotes ustulatus* Schäller (Col., Elateridae). II. Larval development, pupation, whole cycle description and practical implications, J. Appl. Entomol. 122 (1998) 71–78, https://doi.org/10.1111/j.1439-0418.1998.tb01464.x.

[22] G. Salt, F.S.J. Hollick, Studies of wireworm population: III. Some effects of cultivation, Ann. Appl. Biol. 36 (1949) 169–186, https://doi.org/10.1111/j.1744-7348.1949.tb06407.x.

[23] S. Poggi, M. Sergent, Y. Mammeri, M. Plantegenest, R. Le Cointe, Y. Bourhis, Dynamic role of grasslands as sources of soil-dwelling insect pests: new insights from in silico experiments for pest management strategies, Ecol. Model. 440 (2021), 109378, https://doi.org/10.1016/j.ecolmodel.2020.109378.

[24] E.J. Kladivko, Tillage systems and soil ecology, Soil Tillage Res 61 (2001) 61–76, https://doi.org/10.1016/S0167-1987(01)00179-9.

[25] P. Müller, D. Neuhoff, M. Nabel, K. Schiffers, T.F. Döring, Tillage effects on ground beetles in temperate climates: a review, Agron. Sustain. Dev. 42 (2022) 65, https://doi.org/10.1007/s13593-022-00803-6.

[26] J.S. Clark, Why environmental scientists are becoming Bayesians: modelling with Bayes, Ecol. Lett. 8 (2004) 2–14, https://doi.org/10.1111/j.1461-0248.2004.00702.x.

[27] N. Cressie, C.A. Calder, J.S. Clark, J.M.V. Hoef, C.K. Wikle, Accounting for uncertainty in ecological analysis: the strengths and limitations of hierarchical statistical modeling, Ecol. Appl. 19 (2009) 553–570, https://doi.org/10.1890/07-0744.1.

[28] D. Spiegelhalter, A. Thomas, N. Best, D. Lunn, WinBugs Version 1.4 User Manual, MRC Biostatistics Unit, Cambridge, UK, 2009.

[29] R Core Team, R: A Language and Environment for Statistical Computing, R Foundation for Statistical Computing, Vienna, Austria, 2021.

[30] S. Sturtz, U. Ligges, A. Gelman, R2WinBUGS: a Package for running WinBUGS from R, J. Stat. Softw. 12 (2005) 1–16.

[31] R. Valavi, J. Elith, J.J. Lahoz-Monfort, G. Guillera-Arroita, blockCV: an r package for generating spatially or environmentally separated folds for k-fold cross-validation of species distribution models, Methods Ecol. Evol. 10 (2019) 225–232, https://doi.org/10.1111/2041-210X.13107.

[32] J. Saguez, G. Labrie, Les vers fil-de-fer dans les grandes cultures au Québec, Antennae 24 (2017) 5–9.

[33] R. Le Cointe, Y. Girault, T. Morvan, J.-.B. Thibord, P. Larroudé, G. Lecuyer, M. Plantegenest, D. Bouillé, S. Poggi, Feeding pests as an IPM strategy: wireworms in conservation agriculture as case study, 3rd Int. Branch Virtual Symp. Entomol. Soc. Am. (2020). https://hal.inrae.fr/hal-02566016.

[34] H.C. Gough, A.C. Evans, Some notes on the biology of the click beetles Agriotes obscurus L. and sputator L, Ann. Appl. Biol. (1942) 275–279.

[35] Chang, W., Cheng, J., Allaire, J.J., Sievert, C., Schloerke, B., Xie, Y., Allen, J., McPherson, J., Dipert, A., Borges, B., 2021. Shiny: web application framework for R.