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Relative influence of climate and agroenvironmental factors on wireworm damage risk in maize crops

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Abstract

A large-scale survey was carried out in 336 French fields to investigate the influence of soil characteristics, climate conditions, the presence of wireworms and the identity of predominant species, agricultural practices, field history and local landscape features on the damage caused by wireworms in maize. Boosted regression trees, a statistical model originating from the field of machine learning, were fitted to survey data and then used to hierarchize and weigh the relative influence of a large set of variables on the observed damage. Our study confirmed the relevance of an early assessment of wireworm populations to forecast crop damage. Results have shown that climatic factors were also major determinants of wireworm damage, especially the soil temperature around the sowing date, with a strong decrease in damage when it exceeds 12°C. Soil characteristics were ranked third in importance with a primary influence of pH, but also of organic matter content, and to a lesser extent of soil texture. Field history ranked next, in particular our findings confirmed that a long lasting meadow appeared favourable to wireworm damage. Finally, agriculture practices and landscape context (especially the presence of a meadow in the field vicinity) were also shown to influence wireworm damage but more marginally. Overall, the predicted damage appeared highly correlated to the observed one allowing us to produce the framework of a decision-support system to forecast wireworm risk in maize crop.

Keywords

Wireworm damage – Risk assessment - Decision-support system - *Agriotes* spp. - Boosted regression trees

Key message

- Wireworms are generalist herbivore pests causing increasing crop damage in Europe

- We carried out a large-scale survey in maize fields in France, and analysed data using Boosted Regression Trees to investigate the influence of pedoclimatic and agroenvironmental factors on the damage caused by wireworms
- Predicted damage appeared highly correlated to the observed one allowing us to produce a decision-support system to forecast wireworm risk on maize crop

Introduction

The mainstream agricultural model involving the use of pesticides is now called into question regarding sustainability, environment and human health (Wilson and Tisdell 2001; Tilman et al. 2002; Geiger et al. 2010). One of the greatest issues for agriculture over the coming years will be to conciliate productivity with other components of sustainability, notably to achieve substantial reductions in the level of pesticides use (Foley et al. 2011; Lechenet et al. 2014). Pesticides, whether used in a preventive or curative manner, have been for long the only means to protect crops with a total effect, and any alternative strategy will require a combination of techniques with partial effect. Hence, facing the challenge of a sustainable crop production entails an in-depth analysis of agro-ecological factors and biotic interactions that rule crop damage (Médiène et al. 2011).

Wireworms, the soil-dwelling larvae of click beetles (Coleoptera: Elateridae), are world-wide generalist herbivores which attack the below-ground parts of cereal, vegetable and legume crops (Griffiths 1974; Furlan 1998, 2004; Traugott et al. 2015; Milosavljević et al. 2016). During many years, crop protection against wireworms had involved the use of broad spectrum pesticides such as organochlorines which, despite removed from the market since several years, still persist in soils due to their slow degradation (Orton et al. 2013). After most molecules able to control wireworms were banned, wireworm populations have recovered in most European countries, and the management of crop damage they cause has become a prime issue. An increase in yield reduction due to wireworms has been reported in Europe on several economically important crops over the past few years, notably in maize (Eizaguirre et al. 2005; Staudacher et al. 2013b; Saussure et al. 2015).

Studies and reviews dealing with the biology and ecology of wireworms as well as existing control methods (Barsics et al. 2013; Traugott et al. 2015) have highlighted several categories of factors playing an important role on wireworm populations. Exploration of the feeding behaviour of wireworms have shown that periods of inactivity in deeper soil layers, mainly in winter and summer when soil environmental conditions are adverse, alternate with damaging phases in spring and autumn when soil conditions become more favourable in upper soil layers (Campbell 1937; Lafrance 1968; Furlan 1998; Kovacs et al. 2006). Soil characteristics, climate, and agricultural practices may influence the dynamics of these vertical migrations and mediate wireworm damage. Besides, field history as well as landscape context, through its effect on click beetles dispersal, may shape the pest abundance at the field scale.

Due to the multiannual biological cycle of most wireworm species (Evans and Gough 1942; Miles 1942; Furlan 1996, 1998), crop rotation could allow controlling damage when it includes non-host plant species. It is indeed commonly stated that wireworms preferentially lay eggs and develop in grasslands that provide favorable conditions for eggs and larvae (Parker and Howard 2001; Furlan 2004). Eventually, identifying which wireworm species are present may be of importance as wireworm damage is species-dependent (Furlan 2014; Esser et al. 2015). Predictive models have recently been proposed to predict click beetle abundance based on climatic and edaphic factors (Kozina et al. 2015), wireworm occurrence based on soil characteristics (Jung et al. 2014), their abundance and community structure (Milosavljević et al. 2016), correlation between the damage caused in potato fields and the landscape structure (Hermann et al. 2013), or to determine the chief climate and agroenvironmental factors impacting wireworm damage (Saussure et al. 2015; Furlan et al. 2016).

Underlying processes mediating wireworm damage inflicted to crops are multiple and complex. Notably, the interactions between various biological processes cannot easily be reduced to a synthetic set of relevant and independent factors. Consequently, methods enabling to screen a large number of putative relevant variables with possible correlation are very precious. In this study, we took advantage of a recent method originating from the field of machine learning, namely boosted regression trees (Friedman 2002; Elith et al. 2008; Hastie et al. 2009), to address such questions. We applied this method to a large-scale survey carried out in France on 336 maize fields, inventorying their soil characteristics, the presence of wireworms and the identity of the predominant species, climate conditions, agricultural practices, local landscape features (or landscape context) and damage levels caused by wireworms. Our research objectives were twofold: (i) examining the relative influence and the effects of putative key drivers on wireworm damage, and (ii) assessing the model's relevance in providing the cornerstone of a decision-support system for the integrated management of damage caused by wireworms in maize crops.

Materials and methods

The agro-environmental survey

The dataset examined here was compiled from an extensive survey carried out over three consecutive years, from 2012 to 2014. It includes a total of 336 fields primarily located in the western part of France (Fig. 1). Field areas ranged between 0.4 and 48 ha (median area: 4.3 ha) and represented a total surface area of 2208 ha. The monitored fields were selected in 2011 in farms affected by former or current wireworm damage. In order to broaden the range of observed levels of damage, one or two supplementary maize fields were randomly chosen in each farm and added to the dataset from 2012 onwards. This sample design guaranteed to survey a wide range of damage levels, hence it was appropriate to identify agricultural and environmental factors influencing local damage levels.

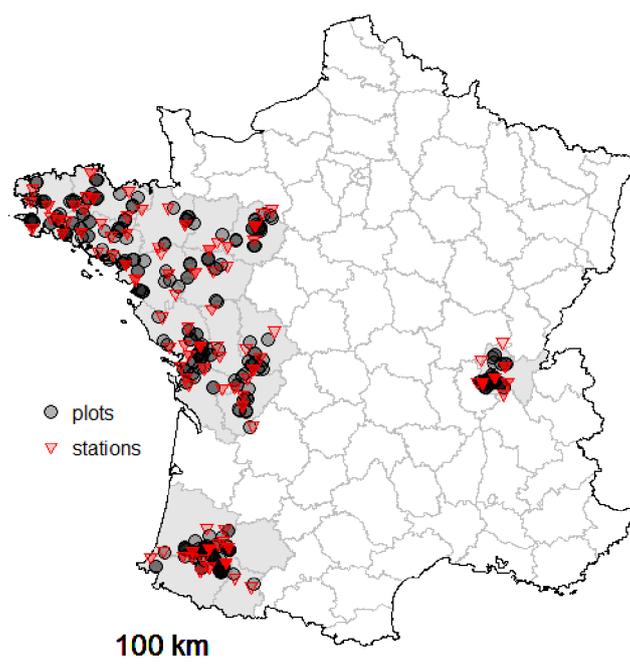


Fig. 1: Field locations: 327 of the 336 fields were georeferenced. The townships in which one or more surveyed fields were located are indicated by black circles. Red triangles indicate meteorological stations.

For each maize field, the presence of wireworms and the identity of predominant species, climate data, soil characteristics, agricultural practices, field history, and local landscape features were recorded (Table 1).

Table 1: List and description of the explanatory variables included in the model. Main categories of features are indicated by the following abbreviations: WW (wireworm assessment), P (precipitation), T (soil temperature), SC (soil characterization), FC (field configuration), AP (agricultural practices), H5 (agricultural practices for a five-year horizon), FH (field history), LC (landscape context) and CP (crop protection).

| Short name | Description | Type* |
|------------------------------|---|--------------|
| D | Level of crop damage (response variable) | Quantitative |
| <i>Climatic variables</i> | | |
| P_50BS | Mean rainfall over the 50 days before sowing | Quantitative |
| P_LS3 | Cumulated rainfall between sowing and stage leaf 3 | Quantitative |
| T_10BS | Mean soil temperature over the 10 days before sowing | Quantitative |
| T_10PS | Mean soil temperature between sowing and 10 days post sowing | Quantitative |
| T_80BS_70BS | Mean soil temperature between 80 days and 70 days before sowing | Quantitative |
| <i>Soil characterization</i> | | |
| SC_Texture | Soil texture: Clay / Loam / Sand / Silt | Qualitative |
| SC_OM | Proportion of organic matter content in the soil | Quantitative |
| SC_pH | pH | Quantitative |

| | | |
|-------------------------------|--|--------------|
| SC_RD | Root depth | Quantitative |
| SC_FC | Field capacity : <70mm , 70mm-120mm , 120mm-170mm , >170mm | Qualitative |
| SC_WS | Water sensitivity: Non drained field / Drained field / Hydromorphic field | Qualitative |
| <i>Wireworm monitoring</i> | | |
| WW_monit | Wireworm presence and identity of the predominant species: None [§] / <i>A. lineatus</i> / <i>A. obscurus</i> / <i>A. sordidus</i> / <i>A. sputator</i> | Qualitative |
| <i>Field configuration</i> | | |
| FC_Topo | Topography : Flat / Slope | Qualitative |
| FC_Expo | Exposition : N / S / E / W | Qualitative |
| <i>Agricultural practices</i> | | |
| AP_SD | Sowing date : 15 to 31 March / 1 to 15 April / 16 to 30 April / 1 to 15 May / 16 to 31 May | Qualitative |
| AP_SFe | Fertilizer application ("Starter") : Yes / No | Qualitative |
| AP_SFeD | Fertilizer dose ("Starter") | Quantitative |
| AP_TiD | Maximum tillage depth : 0-15cm / 15-20cm / >20cm | Qualitative |
| AP_NBTiSp | Number of tillage(s) in spring | Quantitative |
| AP_NBTiW | Number of tillage(s) in winter | Quantitative |
| AP_NBTiSu | Number of tillage(s) in summer | Quantitative |
| AP_Li | Liming : Yes / No | Qualitative |
| AP_OL | Organic loading : Yes / No | Qualitative |
| <i>Past practices</i> | | |
| H5_Irrig | Number of irrigations over the past 5 years | Quantitative |
| H5_TiT | Major tillage type used in the past 5 years : Tillage / Superficial soil work | Qualitative |
| H5_OL | Number of organic loadings over the past 5 years | Quantitative |
| <i>Field history</i> | | |
| FH_Mead | Historic of meadows in the field : Absence / Presence [†] | Qualitative |
| FH_RT | Rotation Type : HP [‡] / Maize monoculture (MM) / Short rotation [‡] (SR) / Long rotation [‡] (LR) | Qualitative |
| FH_IC | Type of intercrop: Bare soil (BS) / Green manure (GM) / Volunteers (VO) / Raygrass (RG) | Qualitative |
| <i>Landscape context</i> | | |
| LC_WH | Wooden hedgerow : Yes / No | Qualitative |
| LC_VH | Vegetal hedgerow : Yes / No | Qualitative |
| LC_Cult | Presence of an adjacent crop : Yes / No | Qualitative |
| LC_SepCult | Presence of an adjacent culture with a separation : Yes / No | Qualitative |
| LC_Mead | Presence of an adjacent meadow : Yes / No | Qualitative |
| LC_SepMead | Presence of an adjacent meadow with a separation : Yes / No | Qualitative |
| LC_GS | Grass strip : Yes / No | Qualitative |
| <i>Crop protection</i> | | |
| CP_Pest | Chemical Protection against pests : Yes / No | Qualitative |

In situ inspection

In this study, crop damages were directly quantified in situ at an early stage in spring. First, "healthy" and "damaged" areas were located in the field. In the "healthy" area, the number of maize plants was counted along a 10 m transect. In the "damaged" area, three 10 m transects were randomly selected, and for each transect the total number of plants and the number of damaged plants were recorded. Then, the rate of wireworm damage was defined as follows:

$$D = \frac{(N_{\text{exp}} - N_{\text{obs}})}{N_{\text{exp}}} \quad (1)$$

where N_{exp} is the expected number of maize plants in the healthy area of the field and N_{obs} is the actual number of undamaged plants in the damaged part of the field at the observation date.

Damage characterization

The main symptoms considered were perforated seeds, perforation on the crown of the plant, tillering and decoloration of the leaves. The plants exhibiting at least one of those symptoms were considered attacked. Though some damage could marginally be due to another pest, the observation of specific symptoms, the knowledge of field history (infestation during the previous years) and the sampling of numerous wireworm larvae indicated that the counted damage was in all cases actually caused by wireworms.

Wireworm monitoring

Within each field, three soil samples of a standard volume of eight liters (a cube of 20 x 20 x 20 cm³) were collected inside the damaged area, in the 20 cm deep upper soil layer around the roots of the damaged plants. Wireworm larvae were counted. A sample of 10-12 larvae per field were identified using the determination key of Cocquempot et al. (1999). Identification accuracy was confirmed on some samples using bio-molecular tools (Pic et al. 2008).

Climate

Mean air temperature and rainfall were estimated on a daily basis in each field using a network of 94 meteorological stations (Fig. 1). The distance between each field and the closest station was 11.0±6.2 km on average, and less than 18.5 km for 90% of the surveyed fields. The soil temperature at a depth of 10 cm was estimated using a model from the Arvalis Institut du Végétal (unpublished; main features are daily surface temperature, computed belowground thermal amplitude, and mean soil temperature over past days). A set of climate variables was derived by averaging values on time windows of varying width and centred on meaningful dates (e.g. sowing, leaf stage 3, etc.). Those selected for the analysis are reported in Table 1.

Soil characteristics

In each field, the soil texture, proportion of organic matter content and pH were assessed (see below). Root depth, field capacity and water sensitivity (i.e. drainage) were provided by the farmers via the survey; the consistency of these values was checked by Arvalis experts in relation to the soil types existing in the considered region. Regarding the soil texture, size fraction analysis was performed after de-carbonation (NF X31.107). Soils were classified using the USDA soil texture triangle based on

analyses carried out with a sedimentation pipette (Soil Survey Staff 2014) and confirmed with the expertise of the farmers. Some soil texture categories were grouped to obtain well-balanced modalities:

- “clay”, “silty clay” and “sandy clay” classes were grouped as “Clay”
- “sand”, “loamy sand” and “sandy loam” classes were grouped as “Sand”
- “silt”, “silt loam” and “silty clay loam” classes were grouped as “Silt”
- “loam”, “clay loam” and “sandy clay loam” classes were grouped as “Loam”.

These categories comprised 50, 48, 148 and 88 fields respectively (2 fields could not be appraised). The proportion of organic matter content was calculated from organic carbon by spectrometry after oxidation in a sulfochromic medium (NF ISO 14235). Finally, soil pH was measured using a glass electrode in a 1:5 (volume fraction) suspension of soil in water (pH in H₂O), in a 0.01 mol/l calcium chloride solution (CaCl-2 pH) (NF ISO 10390).

Agricultural practices

All agricultural practices were collected via the survey filled in by the farmers. The practices selected for the analysis are reported in Table 1 and encompass the sowing date, the application of a starter fertilizer, the tillage number and depth, liming and organic loading. All forms of tillage were considered under the term of tillage including ploughing. The equipment used was not specified. Maize varieties were not considered in this study because they were too numerous in the survey, and in most cases observed in a unique field. Indeed, there were 197 categories for the variety (a maize cultivar or a mixture of maize cultivars) among which 139 were cultivated in a single field. The most abundant category included 13 fields sown with the P0725 variety.

Field history

Field history was characterized using three variables. We first focused on the presence/absence of a long-lasting meadow (more than two years) during the rotation. We considered four types of rotation according to their duration and the number of different crops over the past five years. Last, we recorded the type of intercrop vegetative cover (or its absence). A complete description of all variables is given in Table 1.

Landscape context

Landscape context was described by the presence or absence of some possibly relevant landscape elements adjacent to the field. Local landscape elements were considered as possible sources of adult click beetles. An element was considered adjacent when it was situated directly along the border of the field. When the border consisted in a road, a path, a river, a hedgerow, or a grass strip, the element was defined as adjacent with a separation.

Crop protection

Crop protection was implemented in the model according to the presence or absence of an insecticide treatment at sowing. Among the 336 fields investigated, 197 (58.6%) were treated with insecticides. The main products used for seed treatments were the neonicotinoid CRUISER 350 FS (350 g/l Thiamethoxam, Syngenta) accounting for more than half of the treated fields (54%), the pyrethrinoid BELEM 0.8 MG (8 g/kg Cyperméthrin, SBM DEVELOPPEMENT) and the neonicotinoid SONIDO (400g/l of thiaclopride, BAYER) representing respectively 22% and 13% of the treated fields.

Data analysis

Our study focused on the link between wireworm damage and explanatory variables. All statistical analyses were carried out using R 3.0.1 software (R Core Team 2014).

Regression model description

We used a gradient boosting method, namely boosted regression trees, to build a stochastic, non-linear regression model from our dataset (Friedman 2002; Death 2007; Hastie et al. 2009). Basically, a sequence of simple trees was computed, where each successive tree was built from the prediction residuals of the preceding tree: the final model can be understood as an additive weighted expansion of trees. The boosted regression trees algorithm inherits the strengths of regression trees (e.g. ability to handle different types of predictor variables, and accommodating missing data) and boosting (combining many simple models to improve prediction) (Elith et al. 2008). To avoid overfitting, regularization techniques such as shrinkage and early stopping were applied (Natekin and Knoll 2013). Shrinkage was used to reduce the influence of each additional fitted tree by penalizing the importance of each newly added term. Early stopping provides guidance as to how many trees can be added before the model begins to overfit. There are essentially four control parameters: the number of trees (N), the shrinkage parameter (λ), the tree complexity (χ) which expresses the interaction depth (e.g. $\chi=2$ implies a model with up to 2-way interactions), and the bag fraction (bf) which introduces some randomness in the model fit (Natekin and Knoll 2013). We derived the models using the R packages gbm v2.1.1 (Ridgeway 2015) and dismo v1.1.4 (Hijmans et al. 2017). We tuned the control parameters from a grid search (specifying sets of candidates), and selected the set of values that minimised the model predictive deviance measured on the excluded folds of a cross-validation procedure (Borra and Di Ciaccio 2010; James et al. 2013).

Relative influence of variables

A measure of the relative influence of predictor variables was proposed by Friedman (2001), which is based on the number of times a variable is selected for tree splitting, weighted by the squared improvement of the model resulting from each split, and averaged over all trees. This measure is

implemented in the R *gbm* library (Ridgeway 2015), and scaled so that the sum of all relative influences adds to 100, with higher values indicating stronger influence on the response variable (Elith et al. 2008).

Partial dependence between the response variable and predictors

Complementary to the measure of variable influence, partial dependence plots are useful for results interpretation. These plots provide graphical visualizations of the marginal effect of a set of variables on the outcome (here, the predicted level of damage). Partial dependence plots are extremely useful for knowledge discovery in datasets, especially when low-order interactions and main effects predominate.

Regression model evaluation

The prediction performance of the regression model was estimated using a ten-fold cross-validation procedure that provides means for testing the model on withheld portions of data (Borra and Di Ciaccio 2010; James et al. 2013), and expressed in terms of root mean squared error of prediction (RMSEP),

$$RMSEP = \sqrt{\sum_{k=1}^n (\text{predicted_damage} - \text{observed_damage})^2 * 1/n} \quad (2)$$

This performance criterion illustrates the prediction capacity of the model. Lower the prediction error (RMSEP), better the model performance.

Decision-support system

In our study, wireworm damage was expressed as the proportion of attacked plants, thereby ranging between 0 and 1. We defined an economic threshold D_{eco} such that if the observed damage level in a field is strictly lower than this value the field is considered as “not damaged”, otherwise “damaged”. The economic threshold was set to 0.15, meaning that the field was considered as damaged when the proportion of damaged plants exceeded 15%, in accordance with Furlan et al. (2016) who did not observe any significant yield reduction below this damage level. This value split our data in two balanced subsets, comprising respectively 169 damaged and 167 undamaged fields. The use of the regression model as a binary classifier for risk assessment requires the determination of a decision threshold D_{dec} to assign the status “damaged” or “not damaged” to each field based on its predicted damage level. The two threshold values may differ due to some bias in predicted damage levels.

There are four possible outcomes: (i) true positive (TP) when both the predicted and the observed status are “damaged”, (ii) false positive (FP) when predicted status is “damaged” while observation status is “not damaged”, (iii) true negative (TN) when both the predicted and the observed status are “not damaged”, and (iv) false negative (FN) when the predicted status is “not damaged” while the observed status is “damaged”. The ROC curve illustrates the performance of the binary classifier as its decision threshold is varied. The curve is obtained by plotting the true positive rate (TPR), or probability of detection, against the false positive rate (FPR), or probability of false alarm, at various threshold settings.

The area under the curve (AUC) provides a metric ranging between 0 and 1 for the classifier performance: the closer AUC for a model comes to 1, the better it is. We computed the AUC using the R package pROC v1.8 (Robin et al. 2011). The expected cost associated with each decision threshold D_{dec} can be written

$$C(D_{dec}) = c_{FN} \cdot P(FN) + c_{FP} \cdot P(FP) + c_{TN} \cdot P(TN) + c_{TP} \cdot P(TP) \quad (3)$$

where coefficients c_i , $i \in \{FN, FP, TN, TP\}$ weigh the cost associated to the four possible model outcomes and $P(i)$, their frequency. Costs usually mostly depend on the monetary value of yield losses caused by pests and on the cost of pest control. Equation 3 allows selecting the optimal decision threshold in the specified cost context by minimizing the expected cost.

3. Results

Model evaluation

We first selected the set of parameters providing the best model predictive performance. The best model was defined by the number of trees $N=1850$, the shrinkage parameter $\lambda=0.005$, the tree complexity $\chi=7$ and the bag fraction $bf=0.75$ (see §Regression model description for detailed comments on parameters). The model accuracy, as estimated using the root mean square error of prediction (RMSEP, Equation 2), equaled 0.19 which can be seen as a moderate performance: the prediction error was 19.2% of the scale of the response variable. However, a significant ($R^2=0.93$; F-statistics, $p\text{-value}<2.2 \cdot 10^{-16}$) linear relationship was clearly revealed between predicted and observed damage as shown in Figure 2. Overall, predictions were biased but strongly (and linearly) related to observations, which we consider as satisfactory for our purpose.

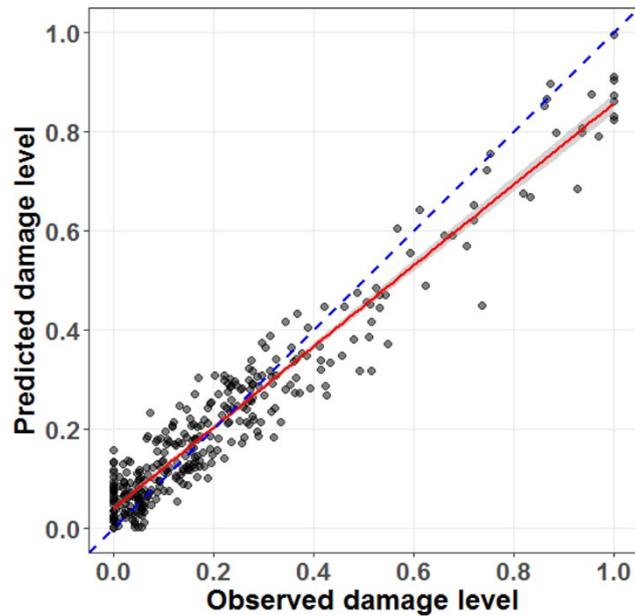


Fig. 2: Predictions of field damage plotted against observed field damage. The blue dashed line is the bisector representing perfect prediction. A linear model fit is given by the red line with 95% confidence intervals (grey shaded area). Linear regression equation $Y=0.04+0.82*X$ and coefficient of determination $R^2=0.93$.

Relative influences and effects of variables

The relative influences of variables on the level of wireworm damage D (Equation 1) are shown in Figure 3, and the main effects considered here were derived from partial dependence plots illustrated in Figure 4. Figure 3 shows the set of variables whose influences sum up to 95%, ranked by decreasing order of influence, with the total influence being normalized to 100. Influences were also classified into three groups (high, medium, low) using the method of hierarchical clustering on principal components (Lê et al. 2008; Husson et al. 2010) to facilitate the visualisation of results.

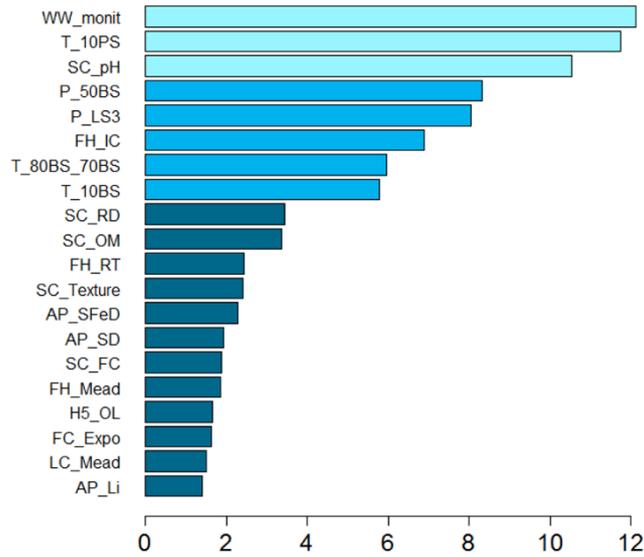


Fig. 3: Relative influences of explanatory variables in decreasing order. Only the first variables whose relative influences sum up to 95% are represented. The colour code distinguishes three classes of variable influence: high (light blue), medium (medium blue) and low (dark blue).

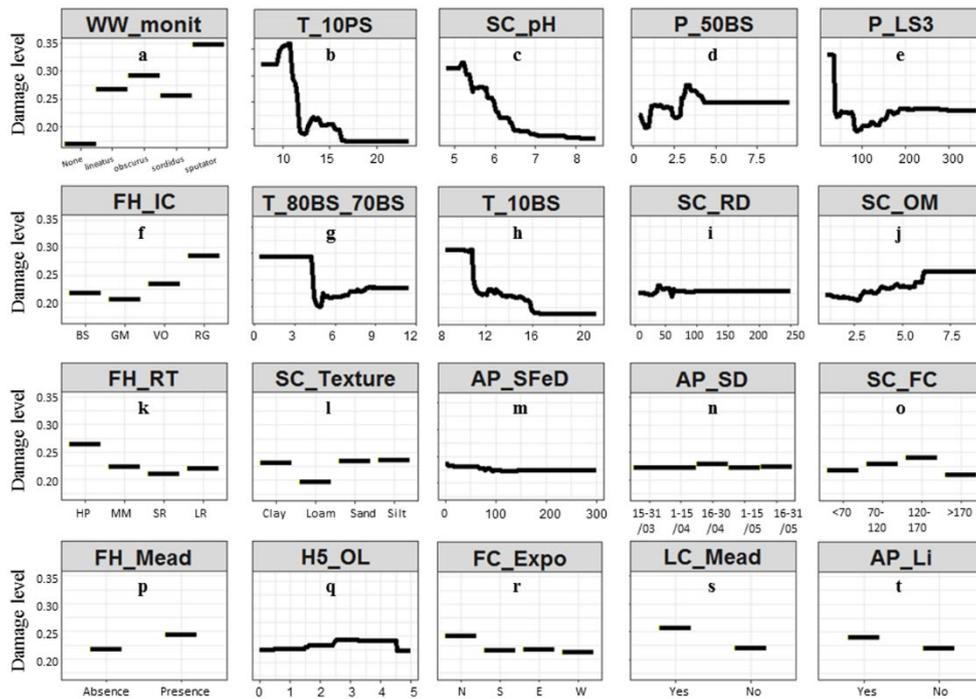


Fig. 4: Marginal effects of the main influential variables on the wireworm damage level. Detailed description of variables and their units are reported in Table 1.

The most important predictor of crop damage was the presence of wireworms and the identity of the predominant species in soil samples coming from the monitoring procedure implemented in this study; it accounted for 12% of the total influence (Fig. 3). Next, listed in descending order of relative influence,

climate, soil characteristics and field history were the main factors explaining damage. All climate variables included in the model ranked among the first factors and were graded as highly or moderately influential. Together, they accounted for 39% of the total influence on crop damage. Soil characteristics (SC), especially pH, also notably influenced crop damage and summed to 20% of the total influence. Field history (FH) was represented by three moderately influential variables which accounted for 11.2% of the total influence. Agricultural practices (AP) and landscape context (LC) also influenced damage but to a lesser extent than previously mentioned categories. Finally, 17 variables did not belong to the set of predictors whose relative influences sum up to 95%.

Wireworm monitoring

The monitoring procedure allowed to detect the presence of wireworms in 183 maize fields out of 336, while no larvae were found in 153 fields. When detected, wireworms belonged to four different *Agriotes* species: *A. lineatus*, *A. sordidus*, *A. sputator* and *A. obscurus*. Among these species, *A. sordidus* and *A. lineatus* were the most present and nearly predominant in 87 and 62 fields (respectively 47.5% and 33.9% of colonised fields). *A. sputator* and *A. obscurus* were predominant in 29 and 5 fields (respectively 15.8% and 2.7% of colonized fields). The mean number of larvae per field were 5.4, 8.0, 11.6 and 15.8 when the prevalent species were *A. sordidus*, *A. lineatus*, *A. obscurus* and *A. sputator* respectively. The partial dependence plot (Fig. 4a) shows that the damage level drastically increased when wireworms were detected in soil samples, switching from 0.17 to 0.25, 0.27, 0.29 or 0.35 (respectively for *A. sordidus*, *A. lineatus*, *A. obscurus* and *A. sputator*).

Climate variables

Soil temperatures around the sowing date showed a noticeable importance (Fig. 3). Mean soil temperature during the 10 days post sowing (T10_PS) accounted for 11.7% of the influence on crop damage while mean soil temperature during the 10 days before sowing (T10_BS) accounted for about 5.8%. Dependence plots shown in Fig. 4b and Fig. 4h pointed out a threshold temperature around 12°C above which the damage level was remarkably reduced, falling from about 0.36 to 0.20 in the case of the variable T_10PS. As for the mean soil temperature between 80 days and 70 days before sowing (T_80BS_70BS), it represented about 5.9% of the total influence (Fig. 3). A less pronounced temperature threshold value for this period arised at approximately 5°C (Fig. 4g): below this temperature, the damage level increased from 0.21 to 0.26. The pattern associated with these three variables was quite similar, higher temperatures leading to lower damage.

Rainfall variables encompassed about 16% of the total relative influence (Fig. 3) but with opposite effects (Fig. 4d and 4e). Mean rainfall over the 50 days before sowing (P50_BS) represented 8.3% of the total influence, however its effect on damage was moderate (Fig. 4d), the drier conditions leading to the reduction of damage levels of about 0.05 on the response variable scale. Cumulated rainfall between sowing and stage leaf 3 (P_LS3) accounted for 8.0% of the total influence and showed a marked effect

on the damage level as illustrated in Fig. 4e. Below 50mm, damage dramatically increased until 0.36, then it fell down to 0.20 between 80mm and 140mm, and finally reached a plateau at about 0.23 over 150mm.

Soil characteristics

Soil pH (SC_pH) accounted for 10.5% of the total influence and ranked as highly influential (Fig. 3). Higher pH (i.e. more basic soils) was associated with lower damage, with nearly half damage over the 4.8-8.5 range under study (Fig. 4c). The level of damage substantially decreased between pH 5.4 and pH 6.4, otherwise following plateaus. Root depth (SC_RD) represented 3.4% of the total influence, but with a minor effect on the damage level (Fig. 4i). Soil organic matter (SC_OM) encompassed 3.4% of the related influence. Higher percentage of organic matter content in soil was associated to higher damage levels, with an effect corresponding to approximately 0.08 on the response variable scale (Fig. 4j). Soil texture (SC_Texture) ranked next with a 2.4% relative influence (Fig. 3). Though the effect is low, it appears that loam soils, referring to soils with comparable proportions of sand, silt and clay, exhibited lower level of damage (Fig. 4l). Finally, field capacity (SC_FC) encompassed only 1.9% of the total influence (Fig. 3). The dependence plot shown in Fig. 4o highlights a 0.03 increase of the damage level between soil with low reserve (SC_FC<70mm) or very high capacity (SC_FC>170mm) and soil with a field capacity comprised between 120 and 170mm.

Field history

Interculture (FH_IC) and rotation type (FH_RT) accounted for 6.9% and 2.4% of the total influence respectively (Fig. 3). Damage levels around 0.20 were obtained when green manure (mustard, phacelia) or bare soil (involving tillage) preceded maize implantation (Fig. 4f), while volunteers and, more importantly, ray-grass increased damage by up to 0.07. Regarding the crop rotation system (Fig. 4k), the most detrimental situation appears when a recent maize crop (i.e. implanted in the past 2 years) was following a long meadow (i.e. more than 3 years long). Short rotations (i.e. only 2 different crops over the past 5 years) were associated with the lowest damage level. Finally, the presence of at least one meadow during the rotation (FH_Mead) and the number of organic loadings (H5_OL) increased the damage level (Fig. 4p and Fig. 4q).

Agricultural practices

Agricultural practices influenced damage but to a lesser extent than the categories previously mentioned. The “Starter” fertilizer dose (AP_SFeD) encompassed 2.3% of the total influence (Fig. 3). The input of 18-46 fertilizer (i.e. 18% nitrogen, 46% phosphorous) slightly decreased the damage level when the applied dose exceeded 110 kg/ha (Fig. 4m). The sowing date (AP_SD) accounted for 1.9% of the total influence and showed a marginal effect of 0.01 on the response variable scale (Fig. 4n). Finally, liming

(AP_Li) slightly increased damage (Fig. 4t), but this counter-intuitive result may be explained by the fact that liming occurred in low pH contexts.

Landscape context

Field exposition (FC_Expo) accounted for 1.2% of the total influence and produced only a weak discrepancy (about 0.03) in terms of damage level (Fig. 4r). The relative influence of a meadow in the immediate vicinity of the field under consideration (LC_Mead) amounted to 1.5% (Fig. 3). The presence of a meadow entailed a 0.02 decrease in the observed damage level (Fig. 4s).

Risk assessment

We simplified our prediction model as a binary classifier to assign any field an outcome featuring the damage risk. The ROC curve for the classifier is shown in Figure 5a. The area under the curve, AUC, is 0.97 with the 95% confidence interval 0.95-0.98, confirming that our model differs significantly from a random predictor.

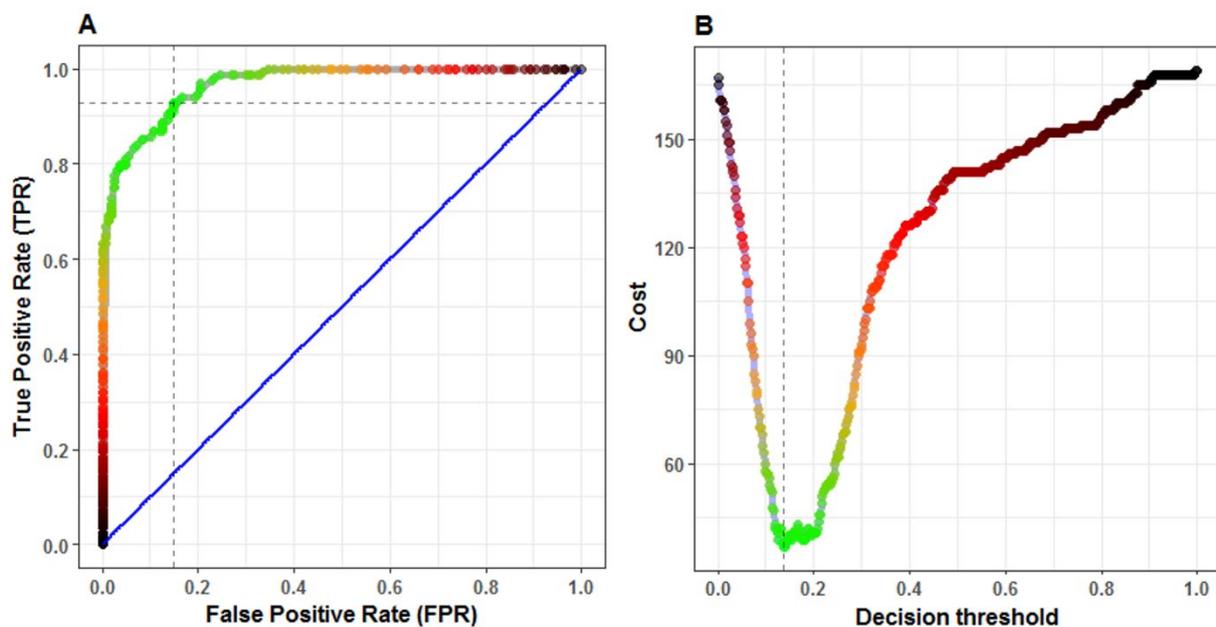


Fig. 5: (a) ROC curve of the prediction model. The solid blue line corresponds to a random predictor. Dashed lines highlight the coordinate values associated to the optimal decision threshold which costs of an inaccurate decision $c_{FN}=c_{FP}=1$ and costs of an accurate decision $c_{TN}=c_{TP}=0$. (b) Expected total cost as a function of the decision threshold D_{dec} for the same cost values. The color scale relates to the value of the expected cost, from low (green) to high (black).

In the absence of accurate estimates of the economical costs associated to the four different model outcomes, the coefficients weighting the cost associated to the model outcomes were set to the following values:

$$\begin{cases} c_{FN} = c_{FP} = 1 \\ c_{TN} = c_{TP} = 0 \end{cases}$$

Choosing such cost values would be to consider that the accuracy of the model is simply assessed on the basis of the frequency of accurate decisions whatever their economic consequences. More realistic values could obviously be determined, however we considered it beyond our purpose (see §Discussion). Figure 5b shows the expected cost issued from model predictions, and defined in Equation 3, as a function of the decision threshold D_{dec} . Cost is minimal when the decision threshold sets to 0.14, leading to a sensitivity (TPR, or probability of detection) of 0.93 (95% CI: 0.88-0.96) and a specificity (1-FPR) of 0.85 (95% CI: 0.79-0.90), which corresponds to a false positive rate (FPR, or probability of false alarm) c.a. 0.15. Overall, our risk status (i.e. prediction stating “damaged” or “not damaged”) estimator presents fairly good sensitivity and specificity (Fig. 6). We found 12 false negative cases and 25 false positive cases, resulting in a 11% classification error.

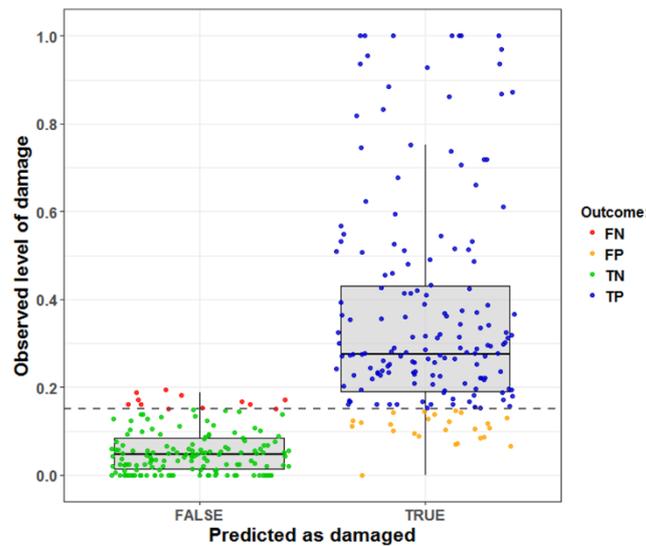


Fig. 6: Outcomes of the decision-support model obtained with the optimal decision threshold $D_{dec}=0.14$. Boxplots depict the distributions of the observed damage disaggregating by the predicted risk status, “damaged” or “not damaged”. Symbol colors indicate the four possible classifier outcomes. The dashed dark grey line highlights the economic threshold ($D_{eco}=0.15$) discriminating the observed “damaged” and “not damaged” fields out of the 336 fields under study.

4. Discussion

The current study falls within the framework of integrated production management, focusing on the identification of putative key drivers for pest control. We considered crop damage as a response variable, that depended both on wireworm life history traits but also on crop needs and its pest tolerance. We fitted a nonlinear model to regress the level of wireworm damage in a maize field on a set of variables for the twofold purpose of (i) understanding the relative influence of these variables on damage, and (ii) using the model as the cornerstone of a decision-support system for risk assessment. We found a strong linear relationship ($R^2=0.93$) between predicted and observed damage from the survey dataset, meaning a high goodness of fit. The prediction capacity of the model was estimated at 19% of the response variable scale which is satisfactory regarding the numerous sources of variability encompassed in the survey data, including for example those sources associated to the observation process (random process of observation from which we infer the damage level, measurement error, etc.). Such variability is highlighted by the density distribution in figure 2. Building from this model, we first analysed the relative influence (Fig. 3) as well as the marginal effect of each variable on the predicted damage level (Fig. 4). Then we simplified our prediction model as a binary classifier to assign any field an outcome featuring the damage risk.

Factors driving the risk of wireworm damage in maize crops

Wireworm infestation and species composition

In our survey, the wireworm population was monitored by counting larvae and identifying species in standard field samples collected in an area expertised as “damaged” (when damage occurred). Wireworms were detected in 55% of the maize fields. The main species were *A. sordidus*, *A. lineatus*, *A. sputator* and *A. obscurus* which are widespread in France (Cocquempot et al. 1999; Larroude et al. 2015). In the fields where wireworms were found, the damage level sharply increased respectively from 0.17 to 0.26, 0.27, 0.35 and 0.29 depending on the identity of the predominant species. *A. sputator* appeared more harmful than the other species identified, but we remain cautious because of a possible interaction between species prevalence and larvae abundance. As a matter of fact, infestation was generally more important in fields where *A. sputator* was the prevalent species. Overall, these results confirm that a successful implementation of an integrated pest management strategy implies a pest population monitoring (Furlan and Kreutzweiser 2015; Barzman et al. 2015). This is also in line with Furlan (2014) and Furlan et al. (2017) who recommended an identification of the species present in soil and of the infestation level to assess the damage risk.

Climate

Climate conditions, i.e. soil temperatures but also rainfall, prior to and at the period of sowing significantly influenced the wireworm damage risk in maize crop and should be considered as key drivers in crop protection management. Our findings confirmed that, over a ten days period covering sowing date, the soil temperature threshold of 12°C previously described by Jung et al. (2014) significantly determines the damage level. Particularly after the sowing date, above this threshold, damage level remarkably decreases, falling from about 0.36 to 0.20. Those results may be explained on one side by the effect of soil conditions driving the feeding behaviour of wireworms and their vertical migration as described by Lees (1943), Lafrance (1968) and Furlan (1998). On the other side, those conditions accelerating maize growth rate shorten the period of sensitivity to wireworm attacks. Our results also brought to light that if soil did not warm up reaching a minimum of 5°C between 80 and 70 days before sowing, damage increased. We assume that spring climatic conditions delaying the wireworm overwintering termination increase the risk that the feeding phase coincide with the period of plant vulnerability (i.e. seedling stage). Rainfall also proved to notably influence the damage level, but with opposite effects depending on the period relative to sowing. Our results demonstrated that, over the period of 50 days before sowing, higher soil moisture increased damage level, confirming that wet ground conditions in spring potentially promote wireworms and their rising toward upper soil layer (Furlan 1998). On the contrary, after sowing, driest conditions, while supposed to be harmful for wireworms, increased damage level. This is probably because such soil conditions penalized first maize crop for which the seedling stage is a sensitive period to shortage of water. Another hypothesis is that wireworms may stay in the close vicinity of the rhizosphere during drought, the rhizosphere providing food and conditions less prone to desiccation.

Soil characteristics

This study also confirmed previous published findings in particular risk associated with soil characteristics (pH and organic matter). The survey data covered a wide range of soil pH values ranging from 4.8 to 8.5 homogeneously distributed and enabled to highlight a strong effect of this factor on damage level. Fields with pH value under 5.5 should be considered as risky environment and those with pH value above 6.5 as safest. This result is consistent with previous works, which took into account larval abundance and species distribution as response variables (Ibbotson 1958; Staudacher et al. 2013a). In particular, Staudacher et al. (2013a) showed that lower pH value promotes wireworm's infestation of *A. obscurus* and *A. lineatus*. Previous studies dealing with adult click beetle abundance (Kozina et al. 2015) also brought to light the importance of pH as a key driver for the abundance of *A. obscurus* and *A. ustulatus*. As expected, soil organic matter content appeared influencing damage level. And as previously demonstrated (Furlan 1998, 2004; Traugott et al. 2008; Kozina et al. 2015; Furlan et al. 2016), we found that high percentage of organic matter content in the soil increased damage. Soil with organic matter content above 5.5% should be considered as risky. Finally, field capacity and soil texture

also influenced damage level. The link between soil type and larval activity has not yet been fully clarified, and is likely to interact with climatic conditions as shown by Jung et al. (2014) who demonstrated that larval movement and ability to harm maize roots were influenced by soil moisture and texture resulting from an interaction between climate and soil.

Field history and landscape context

Field history and landscape context appeared also influential. We evidenced the influence of the presence of grassland both in space (through their presence in the surrounding landscape) and in time (through their presence in the field history). The presence of grassland in the history or in the vicinity of the investigated fields, which is known as a favourable and stable environment for wireworms (Parker and Howard 2001; Blackshaw and Vernon 2006; Schallhart et al. 2011; Hermann et al. 2013), increased the damage level.

Crop protection

Across the 37 explanatory variables, crop protection is conspicuous by its absence among the set of variables representing 95% of the total influence and with significant effect on damage. Among the panel of maize fields investigated, almost 60% were treated with insecticides. The results of this study emphasize that molecules used for controlling wireworms were not effective enough to drive damage levels. In short, if maize crop was sown in a potentially harmful situation as defined by Furlan et al. (2016), the seed treatment with neonicotinoid or pyrethrinoid did not protect the crop.

Decision-support system for risk assessment

Stating the satisfactory performance of our nonlinear regression model, we used it as a binary classifier to promote a decision-support system for the risk assessment of wireworm damage. We applied it to the 336 surveyed fields which were labelled as “damaged” or “not damaged” depending on whether the observed damage level exceeded the economic threshold value 0.15. This threshold value was chosen following Furlan et al. (2016) who did not observe any yield reduction below this wireworm damage level. Our risk estimator performed well as evidenced by the area under the ROC curve (AUC=0.97).

The classifier produces four possible outcomes, depending on whether a field is accurately assigned to one of the two status. In our study, the associated cost function was computed by setting null cost to the true outcomes (i.e. true positive and true negative cases), and unit cost to the false outcomes (i.e. false positive and false negative cases). The cost function (Fig. 5b) shows the existence of a minimum value for a decision threshold, D_{dec} , about 0.14: cost is then valued 37 whereas it is 167 at $D_{dec}=0$ and 169 at $D_{dec}=1$. Indeed, choosing $D_{dec}=0$ amounts to assign all fields to the class “damaged”, leading to the wrong affectation of the 167 fields observed as “not damaged”, hence 167 false positive cases. This may correspond to the situation where farmers have adopted a strategy which consists in treating all fields

by default (referred to as a “prophylactic spraying strategy” by Fabre et al. (2003)), assuming that treatment fully protects the field crop. Given that treatment efficacy is partial, an additional cost stems from the fraction of true positive cases for which the crop protection is expected to fail. At the other extreme, choosing $D_{dec}=1$ amounts to assign all fields to the class “not damaged”, leading to the wrong affectation of the 169 fields observed as “damaged”, hence 169 false negative cases. This may correspond to the situation where farmers have adopted a strategy which consists in never treating. Hence, in the specific cost context highlighted here, using our decision-support model would allow reducing by more than four the frequency of wrong decision when compared to systematic strategies. At the optimal decision threshold ($D_{dec}=0.14$), our decision-support system features good scores in terms of sensitivity (0.93) and specificity (0.85). In particular, high sensitivity indicates that the system predicts reasonably well the situation at risk, i.e. the assignment to the status “damaged”. Selecting the optimal decision threshold lead to the result shown in figure 6 where model outcomes are depicted by colors. In the context of pest management, the key issue consists in minimising the number of false negative cases (here 12 out of 169 actual “damaged” fields); false positive cases entail a lower incidence on decision in the common situation of prophylactic strategies. Beyond our results, it is clear that a benefit analysis can be conducted with values arising from the real cost of treatment and loss due to damage. Our decision-support system brings a stone for the identification of situations at risk, and could then contribute to evaluate strategies depending on the cost context, essentially specified here by the economic threshold and the cost coefficients associated to the model outcomes.

Avenues for future research

Forecasting crop damage caused by wireworms is a challenging task as underlying processes mediating crop damage caused by wireworms are multiple and complex. In the absence of a theoretical framework expliciting the link between processes and damage, survey data inventorying damage and their putative drivers are the major resource for investigation. In this study we applied a method originating from machine learning, namely boosted regression trees (Friedman 2002; Elith et al. 2008; Hastie et al. 2009), to model the relationship between damage and a set of predictors. Practical advantages of this method are that it can handle different types of variables without data transformation, fit potentially nonlinear relationships, accommodate missing data, and does not need variable pre-selection as non-informative predictors are ignored (Death 2007). Our nonlinear model fitted particularly well observed data (Fig. 2), and we quantified its predictive performance (RMSEP=0.19 on the scale of the response variable) on withheld portions of data using a cross-validation procedure. Next step lies in testing the model on new data. An exciting development would consist in evaluating the outputs of our modelling approach on other available datasets, e.g. those discussed in earlier work (Hermann et al. 2013; Furlan et al. 2016; Milosavljević et al. 2016), and appraise consensus with previous analyses. More broadly, our work

highlights a relevant approach to analyse a wide range of similar situations involving other crops and pests.

Damage is driven by two main features: (1) the potential for wireworm infestation, which is mainly driven by colonization process and local population development, and thus particularly sensitive to agricultural practices, field history and landscape context, and (2) the pedoclimatic conditions which govern the vertical movements of larvae and the vulnerability of the crop. Disentangling the effects of variables on these two main features would undoubtedly enhance our understanding of the risk factors. Thus, one research strategy involves monitoring population dynamics to assess dispersal, colonization and persistence of click beetles, and their link to landscape elements and agricultural practices. Some studies have already brought significant contributions (Toepfer et al. 2007; Schallhart et al. 2009; Burgio et al. 2012; Hermann et al. 2013; Blackshaw et al. 2017) but knowledge remains partial. Knowledge is especially scarce regarding the foraging behaviour of adult click beetles though it could possibly provide a new opportunity for pest management. Indeed, the spatial arrangement of potentially competing resources (e.g. feeding and laying sites) at the landscape scale may affect the pest foraging efficiency and designing and implementing pest suppressive landscapes could allow reducing the damage risk (Bourhis et al. 2017).

Other studies are needed to develop a better evaluation of the effect of the interactions between soil characteristics and climate on larvae upwelling by, for example, extending preliminary results (Jung et al. 2014) to a wider range of soils and climatic conditions.

Finally, another research perspective to better understand and forecast wireworm damage on crops consists in developing mechanistic models embedded in frameworks appropriate for parameter inference on heterogeneous data, e.g. data collected in fields under contrasted contexts regarding climate and soil characteristics. This would offer a suited way to handle measurement errors and uncertainties inherent to survey data.

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Author Contribution

SP, MP, JBT and PL conceived and designed research. SP and JBR analysed data. All authors discussed results. SP, RLC and MP wrote the manuscript. All authors read and approved the manuscript.

Conflict of Interest

The authors declare that they have no conflict of interest.

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