Aphid abundance on cereals in autumn predicts yield losses caused by barley yellow dwarf virus

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Aphid Abundance on Cereals in Autumn Predicts Yield Losses Caused by *Barley yellow dwarf virus*

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ABSTRACT

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Barley yellow dwarf virus (BYDV) damage to winter cereals and population dynamics of the aphid *Rhopalosiphum padi* during fall were monitored in fields during 10 years at various locations in the northern half of France. Logistic regression was used to examine whether a simple risk probability algorithm based only on the autumnal population dynamics of *R. padi* can accurately predict yield losses caused by BYDV and, therefore, the need for insecticide treatment. Results showed that the area under the curve of the percentage of plants infested by *R. padi* during autumn was highly significantly related to BYDV yield losses. Then, a cost/benefit analysis was performed to estimate the optimal decision threshold resulting in the lowest annual average costs of BYDV damage and control. A "model use" strategy allowed a reduction in the annual average costs of BYDV disease and control of up to 36% when compared with a "prophylactic spraying" strategy. The optimal decision threshold was highly sensitive to variation in disease prevalence. This property was used to propose an easy way to adapt the model to any production situation through the determination of the most accurate decision threshold.

Additional keywords: *Hordeum vulgare,* integrated pest management, virus epidemiology.

In the current context of agricultural production, several factors encourage farmers to reduce their use of insecticide. First, excessive use of insecticides is recognized to have negative effects on natural flora and fauna and on human health (1,30). Second, there is an increasing awareness of the risk of inducing insecticide resistance where prophylactic use of pesticides occurs. As a result, in some countries, pesticide taxes are levied in order to promote a reduction in pesticide usage. In addition, the fall in world crop prices encourages farmers to lower the number of pesticides applications. This current trend to reduce prophylactic sprays combined with the necessity to maintain a high level of productivity results in a strong need for reliable risk assessment tools. Such decision tools are especially needed when disease prevalence (46) is sporadic, varying greatly from field to field and year to year. This is the case with barley yellow dwarf disease (BYD), one of the most severe cereal diseases in the world. BYD viruses are vectored by aphids (36); therefore, one method to control the disease relies on the use of insecticide sprays. Due to the sporadic nature of epidemics, treatments are not required every year and everywhere. Consequently, a considerable reduction in the number of sprays could be derived if they were applied only when necessary.

To develop such a decision tool, an understanding of the relationship between damage (yield losses) caused to the crop and some measurable determinants of the target pathosystem are a prerequisite. Risk algorithms based on logistic regression that are commonly used in medical epidemiology (13) also can be used to assess the risk of pest outbreaks and plant disease epidemics (14,22,45). They use observations describing the pathosystem to calculate an index of the need for crop protection.

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Although the production situation of each field (i.e., the set of physical, biological, and socioeconomic factors that determine agricultural production) (7,37) can greatly affect the economic efficiency of a decision tool, this is rarely taken into account. Such factors—mainly environmental and agricultural—are known to influence the impact of BYD (9). A decision tool based on a statistical approach is necessarily imperfect. The errors in recommendations can be of two types: either the model recommends spraying unnecessarily, or it recommends not spraying when it would have been necessary. The relative frequency of the two types of error obviously will depend on the specific disease prevalence in the context of use of the decision tool (44). The costs associated with both types of error are generally different (38); therefore, disease prevalence will partially determine the economic pay-off of the use of the model and the optimal decision threshold to adopt (25). The influence of production situations then can be considered by introducing an a priori, specific, context-dependent level of disease prevalence. Then, an analysis of the model's specificity (the proportion of noninfested fields in which control is not recommended by the model) and sensitivity (the proportion of actually infested fields where control is recommended by the model) can facilitate fitting the decision threshold to any production situation through the determination of the corresponding specific optimal decision threshold.

BYD is caused by viruses *Barley yellow dwarf virus* (BYDV) and *Cereal yellow dwarf virus* (CYDV) belonging to the family *Luteoviridae* and transmitted in the persistent manner by various aphid species living on species of *Poaceae* (36), of which the most important in autumn-sown cereals in Europe is *Rhopalosiphum padi*. Indeed, this species usually accounts for more than 90% of the total number of aphids found in cereals during this season in France (11) and in England (32). Damage caused by BYD depends on the cereal species and cultivar (2) and the virus species (2) or isolate (5,23), but especially on the proportion of plants infected (3,19,29) and the time of infection (the younger the crop when the infection occurs, the greater the loss will be) (16, 42). The spread of BYDV is strongly determined by the population dynamics of its vector (20) and some authors (8,26) developed models predicting the autumnal aphid population dynamics in cereals fields.

This article examines to what extent a simple risk algorithm based only on autumnal *R. padi* population dynamics may facilitate prediction of BYDV yield losses and, thus, the need for insecticide treatment. This algorithm was designed by fitting a logistic regression to a large data set. A general method then is proposed to adapt the model to any production situation through the determination of the optimal decision threshold associated with a given a priori disease prevalence. Finally, the usefulness of the model is tested through the assessment of the potential pay-off of the use of that decision tool compared with two other strategies ("prophylactic spraying" and "no control").

MATERIALS AND METHODS

Data collection. From 1989 to 1999, 64 field experiments sited at 15 locations in the northern part of France were monitored (Fig. 1). Plots were sown from mid-September to mid-October with winter barley, *Hordeum vulgare* (cvs. Alaska, Esterelle, Intro, Keliba, Gaelic, Labéa, and Rossini). Each experiment was conducted in a randomized complete block design with two factors ("untreated" receiving no insecticide spray and "treated" receiving two insecticide sprays) and four replications. The individual plot size was 3 by 11 m. The untreated plots were colonized spontaneously by aphids (i.e., were not artificially infested). In treated plots, aphid populations were chemically controlled by two insecticide sprays with a synthetic pyrethroid (deltamethrin, Decis; Bayer Crop Science, Leverkusen, Germany) at a rate of 5 g a.i. ha^{-1}: a first spray at the first-leaf growth stage and a second 2 weeks later, ensuring complete protection against BYD; observations were made to check the efficiency of the spray. The proportion of plants infested by *R. padi* was monitored at intervals varying between 5 to 14 days from crop emergence until approximately the end of November in the untreated plots. Observations were made in each plot in four randomly chosen locations. In each location, 25 consecutive plants along the same row were examined and the presence or absence of aphids recorded. From 1989 to 1994, the average number of aphids per tiller also was assessed. Finally, at the end of the season, each plot was harvested separately and the yield loss caused by BYD estimated by the difference between treated and untreated plots. The data set is representative of a wide range of climatic conditions and aphid infestation levels (from 2 to 100% of plants infested by at least one aphid).

Logistic regression analysis. The economic threshold justifying insecticide spraying is reached when the cost of losses due to BYDV equals treatment costs (27). When losses are greater than this threshold, an insecticide application is expected to give a positive net return. In the French economic context, this yield loss threshold corresponds to ≈500 kg ha^{-1}, including pesticide, labor, and tractor wheel damage (41). Accordingly, the data set was split into two groups. The first group contained the experiments with yield losses of ≥500 kg ha^{-1} (37 cases). The second group contained the experiments with yield losses of <500 kg ha^{-1} (27 cases). A binary variable corresponding to the need to apply insecticide was defined accordingly. This binary variable then was related to X, the natural logarithm of the area under the curve of the percentage of plants in untreated plots infested by aphids from crop emergence (t_0) to the last count done in the field at t_n (inspired by the Rautapää index) (34). At time t_0, the proportion of plants in-

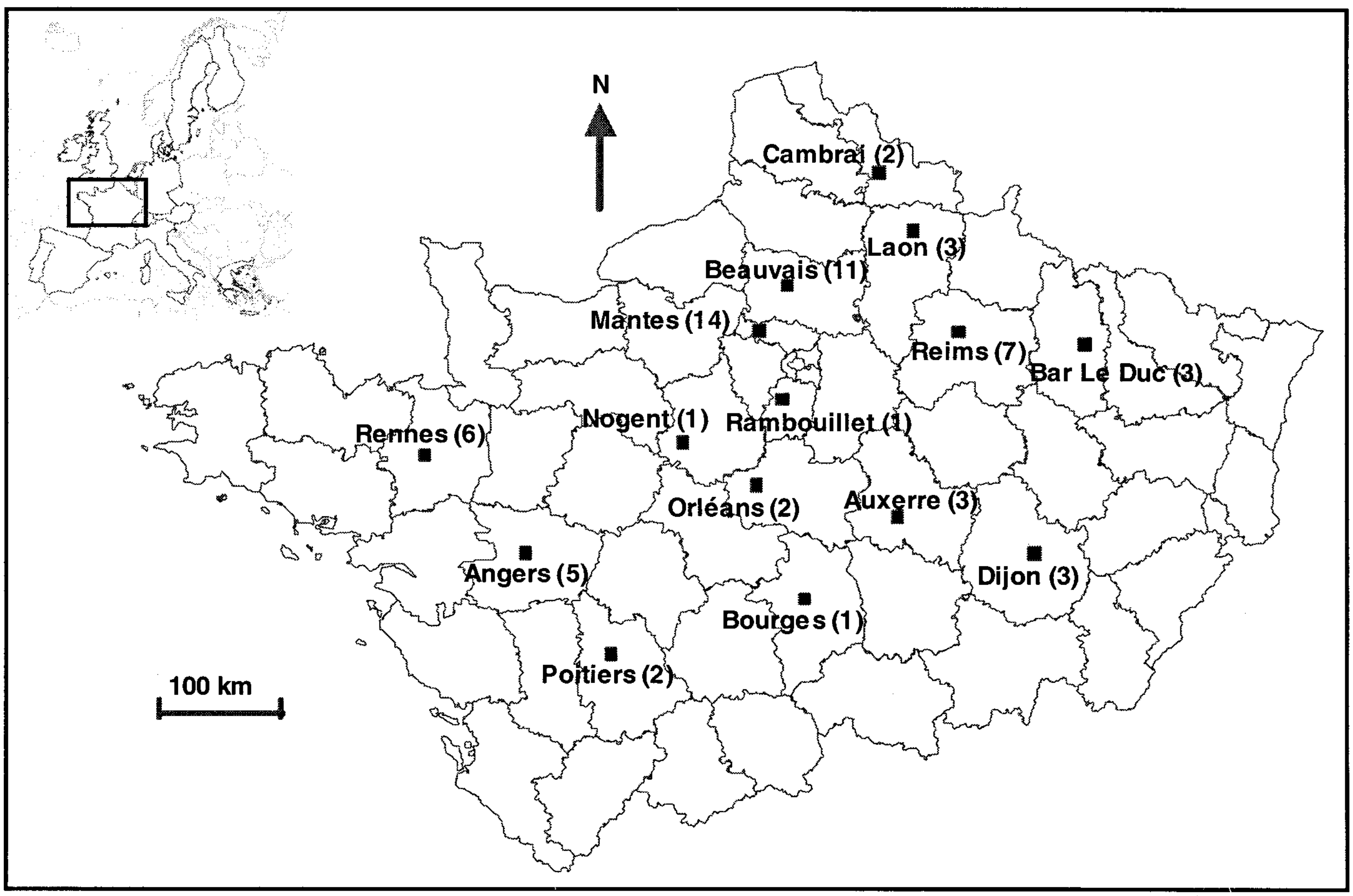

Fig. 1. Map of France showing the nearest town relative to the 15 field experiment locations. In parentheses, the number of field experiments in each region is indicated.

fested by aphids was assumed to be zero. The trapezoidal integration method (4) was used to approximate the area under the curve. The monitoring duration differed among experiments; therefore, X was standardized by dividing by t_n. Let p denote the predicted value of probability that an insecticide spray will give a positive net return. Then,

$$\text{Logit}(p) = \beta_0 + \beta_1 X \tag{1}$$

where Logit(p) is the logarithm of $p/(1 - p)$ and β_0 and β_1 are parameters (24). Regression coefficients were estimated using logistic regression with the maximum likelihood method with S-Plus 2000 (Math Soft, Seattle, WA).

Optimal decision threshold and effect of disease prevalence. The logistic regression analysis provides an estimation of p. The use of the model requires, in addition, the definition of a decision threshold (i.e., a value p_T such that if $p \geq p_T$ the treatment is recommended and if $p < p_T$ the treatment is not recommended). Let D^+ denote the event "a treatment is required" and T^+ denote the event "a treatment is recommended". Conversely, D^- and T^- represent the events of treatments not being required and recommended, respectively. The sensitivity of the algorithm, *Se*, is the conditional probability $P(T^+/D^+)$, and its specificity, *Sp*, the conditional probability $P(T^-/D^-)$. Let *Prev* be the a priori probability that yield loss will exceed the threshold value of 500 kg ha^{-1}, which is related to disease prevalence. Finally, let C^{**} be the costs associated with the event T^* and D^*, where * denotes either + or –. The expected cost associated with p_T ($C[p_T]$) for a given level of disease prevalence *Prev* is

$$C(pT) = Prev \times [Se \times C^{++} + (1 - Se) \times C^{-+}] + (1 - Prev) \times [Sp \times C^{--} + (1 - Sp) \times C^{+-}] \tag{2}$$

Basically, equation 2 means that the expected cost is the sum of the costs associated to any event multiplied by their probabilities of occurrence, which depend on the model efficiency (*Se* and *Sp*) and on disease prevalence (*Prev*).

Both C^{++} and C^{+-} are equal to the cost of chemical control (equivalent to 500 kg ha^{-1}). The 64 yield loss estimates derived from our data set combined were used to determine C^{-+} and C^{--}. C^{-+}, the average yield loss with no insecticide control when the economic threshold was exceeded, was estimated to be 2,160 kg ha^{-1}. C^{--}, the average yield loss with no insecticide control when the economic threshold was not reached, was estimated to be 122 kg ha^{-1}. The conditional probabilities were estimated by the corresponding frequencies observed in our data set for any possible value of p_T. The optimal decision threshold then was defined by the value of p_T minimizing $C(p_T)$ for a given basic *Prev*. This can be calculated by setting to zero the derivative of C with respect to p_T. This criterion leads to

$$\Delta Sp \times (1 - Prev) \times (C^{--} - C^{+-}) = -\Delta Se \times Prev \times (C^{++} - C^{-+}) \tag{3}$$

where ΔSe and ΔSp are the derivatives of *Se* and *Sp* with respect to p_T. Equation 3 means that the optimal decision threshold is met when the decrease in the cost incurred by an increase in specificity (cost of false positive), caused by an increase in p_T, is compensated by an increase in the cost due to a reduction in the sensitivity (cost of false negative). To get an analytical approximation of the functions ΔSp and ΔSe, *Sp* and *Se* were estimated by fitting the following models to the observed data:

$$\begin{cases} Sp(p_T) = rp \times \ln(kp \times p_T + 1) \\ Se(p_T) = 1 - ke \times \exp(re \times p_T - 1) \end{cases} \tag{4}$$

The values of *rp*, *kp*, *re*, and *ke* were calculated by a least-squares method using the function Solver of Excel (Microsoft, Redmond, WA). Finally, the quantity $[\Delta Sp \times (1 - Prev) \times (C^{--} - C^{+-}) + \Delta Se \times Prev \times (C^{++} - C^{-+})]^2$ was minimized using the function Solver of Excel to assess the optimal p_T for any value of *Prev*.

RESULTS

Logistic regression analysis. The model fit was highly significant ($P < 10^{-3}$) (Table 1). In general, no major yield losses (exceeding 500 kg ha^{-1}) were observed for $X < 1.8$ (Fig. 2). Conversely, substantial losses always were observed when $X > 3.3$. For X lying between those two values, the frequency of major losses increased with X (Fig. 2).

Optimal decision threshold and effect of disease prevalence. The two models fitted to the observed values of *Se* and *Sp* described the data very well, with coefficients of determination of 0.99 and 0.96 for *Se* and *Sp*, respectively (Fig. 3). When disease prevalence was <4% or >92%, p_T was 1 and 0, respectively; that is, the recommendation was, to spray not at all ($p_T = 1$) or to spray always ($p_T = 0$) (Fig. 4). When disease prevalence was in the range 4 to 92%, the algorithm performed better than both the no-treatment and prophylactic-spraying strategies. Indeed, based on the logistic regression model, in the range 4 to 92%, the percentage of accurate decisions ranged from 74 to 91% (Fig. 4,

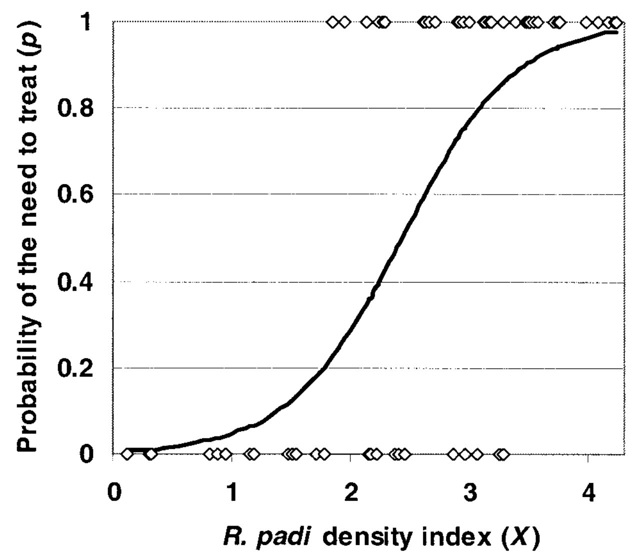

Fig. 2. Probability of the need to treat with insecticide (p) as a function of the value of the *Rhopalosiphum padi* density index (X, the natural logarithm of the area under the curve of the percentage of plants infested by virus-vector aphids during autumn), predicted by the logistic regression model (—) shown in Table 1. The need to treat was based on a yield loss >500 kg ha^{-1} due to *Barley yellow dwarf virus.* Symbols represent experimental data.

TABLE 1. Analysis of deviance table of the logistic regression model predicting the need to spray insecticide according to X, the value of the *Rhopalosiphum padi* density index in the fall[a]

Parameter	Deviance	df	F value	$P(F)$	Parameter estimate (SE)
β_0	87.15	63	…	…	–5.15 (1.4)
β_1	53.98	62	41.12	2.2×10^{-8}	2.12 (0.52)

[a] Regression model: logit(p) = $\beta_0 + \beta_1 \times X$, where p is the probability that spray will give a positive net return. X is the natural logarithm of the area under the curve of the percentage of plants in untreated plots infested by aphids in the fall.

curve T). The errors were due mainly to recommendations to spray when it is unnecessary (Fig. 4, curve W^+). By contrast, the percentage of recommendations to not spray when it is required never exceeded 4% (Fig. 4, curve W^-). Finally, the use of the model could allow a substantial reduction in the cost of disease management, up to a yield equivalent of ≈180 kg ha^{-1} for a disease prevalence of about 20% (Fig. 5).

DISCUSSION

This work documented a strong relationship between yield losses due to BYD and the autumnal populations of *R. padi* in cereals on a large geographical scale for data collected during 10 years. This relationship may facilitate the design of a decision tool for BYD control based on knowledge of autumnal aphid population dynamics in winter cereals.

The overall measure of yield losses did not allow distinction between direct damage caused by *R. padi* feeding on plants and indirect damage caused by BYDV transmission. Riedell et al. (35) demonstrated that, at the seedling stage in four winter wheat cultivars, grain yield was reduced 21% by *R. padi* feeding, 46% by BYDV infection, and 58% when infestation by aphids and infection by BYDV were associated. Their results were established with densities of ≈25 to 30 aphids per plant. Similarly, Kieckhefer and Kantack (18) concluded that *R. padi* could significantly reduce yield in winter grains by feeding for 1 week during the seedling stage (two to three leaves) at densities of 15 to 20 aphids per plant. In the data used here, the average aphid density per infested plant in fields where major yield losses (>500 kg ha^{-1}) occurred was 2.78 (SD ± 2.69), which appeared to be too low to result in a significant yield loss due to aphid feeding alone. Moreover, no other insect damage was noted on untreated plots in autumn. Thus, the present study has provided new evidence that BYDV damage to cereals is associated consistently with the autumn population dynamics of *R. padi* (20). Such a strong association between a viral disease progress and its vector population dynamics is a typical feature of vector-borne virus disease epidemiology (6,15).

Although it is generally considered that BYDV epidemics cannot be predicted from aphid densities alone, the model's accuracy varies in the range of 74 to 91% when tested with data used in the development of the logistic regression model. However, accounting for aphid infectivity (i.e., the proportion of migrant aphids that carry and are able to transmit the viruses) could allow further improvement in model's accuracy (17,21,31). Indeed, the remaining misclassified experiments may have been due to variability in the level of aphid infectivity (32). This assumption is supported by the trends in sensitivity and specificity shown in Figure 3. Sensitivity decreases very slowly when p_T increases for low values of p_T. Conversely, specificity decreases more rapidly when p_T decreases for high value of p_T. These characteristics are easily understandable: a good sensitivity suggests that no yield loss is observed when aphids are at lower densities. In

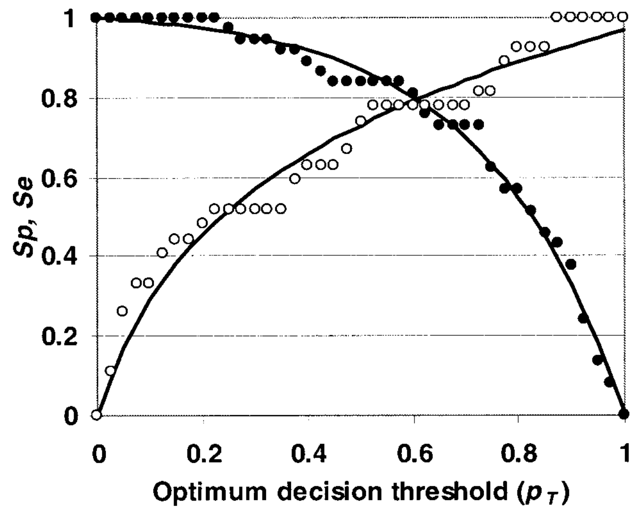

Fig. 3. Observed data and models fitted to sensitivity (*Se*, ●) and specificity (*Sp*, ○) as a function of the decision threshold (i.e., a value p_T such that if $p \geq p_T$ the treatment is recommended and if $p < p_T$ the treatment is not recommended, where p is the probability that an insecticide spray against *Rhopalosiphum padi* will give a positive net return). The sensitivity of the algorithm, *Se*, is the conditional probability $P(T^+/D^+)$, and its specificity, *Sp*, the conditional probability $P(T^-/D^-)$ where D^+ denotes the event 'a treatment is required', D^- the event 'a treatment is not required', T^+ the event 'a treatment is recommended', and T^- 'a treatment is not recommended'.

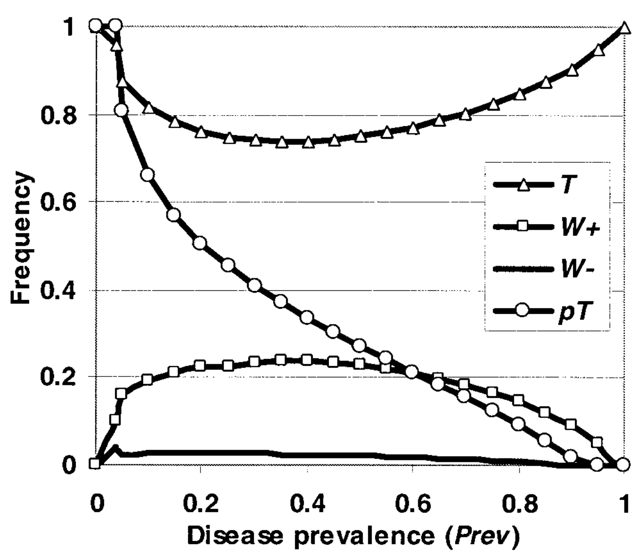

Fig. 4. Optimal decision threshold (p_T), percentage of accurate decisions (*T*) and frequency of wrong decisions (W^+ and W^-) as a function of disease prevalence (*Prev*) caused by *Barley yellow dwarf virus*. W^+ is the frequency of recommendations to treat when it is not worthwhile and W^- is the frequency of recommendations not to treat when treatment would have been useful.

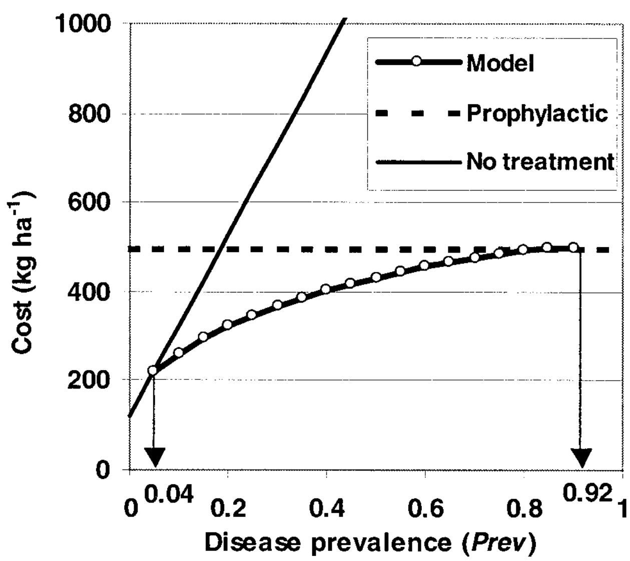

Fig. 5. Variation of the annual average costs of *Barley yellow dwarf virus* damage and control according to disease prevalence (*Prev*) for the three simulated control strategies (prophylactic spraying against virus-vector aphids, no control, and spraying according to the model recommendation). Costs are expressed in yield loss equivalents. Arrows define the range of *Prev* where using the decision threshold based on the logistic regression allows reducing the cost of barley yellow dwarf disease management.

contrast, the lower specificity suggests that, in some cases, high aphid density does not result in an important yield loss. This could be due to differences in aphid infectivity. This conforms to the finding that damage is caused mainly by virus transmission rather than by the direct effect of aphids feeding. Thus, taking into account some measure of aphid infectivity could result in an improvement in model specificity rather than in an improvement in its sensitivity. Whether such an improvement would be of importance depends on the goal of the model user. From an economic point of view, because the potential cost of damage caused by BYD largely exceeds (by four times) the cost of the treatment, a high sensitivity is required. If the main goal were to reduce environmental costs or if the economic parameters were changed (decrease in commodity prices or increase in spraying costs), a better specificity would become more critical. However, it is difficult to assess aphid infectivity in fields because costly laboratory live assays or laboratory molecular techniques would be needed (10).

This study illustrates that the optimal control strategy depends on the a priori information about *Prev*. In a low- (*Prev* < 4%) or high-prevalence (*Prev* > 92%) situation, a constant strategy is optimal (no treatment or prophylactic spray). Conversely, in a large range of *Prev* (4 to 92%), basing the decision on the model will minimize the average cost of BYD damage and control. These findings are in agreement with the conclusion of Yuen and Hughes (44), who advocate that it is generally impractical to develop prediction systems for diseases that fall into the infrequent or frequent occurrence categories. In contrast, for diseases that are neither very common nor very rare, such models are useful. This is likely the case for BYD. For instance, in our data set, the average *Prev* is 0.58 (≈37/64). Introducing a priori information about *Prev* in the model allowed us to show that the impact of the production situation is of decisive importance for deriving the optimal decision threshold. As expected, a low prevalence tended to increase the relative frequency of false positives for a given decision threshold. Increasing the decision threshold may compensate for this effect. Conversely, the increase in the relative frequency of false negatives when the prevalence was high resulted in a decrease in the optimal decision threshold. Unfortunately, despite the importance of prior information about disease prevalence, *Prev* remains difficult to estimate. The effect of sowing date on *Prev* is well known: the later the sowing date, the smaller the risk of epidemics (15). Nevertheless, other agronomic considerations encourage earlier drilling (33). Reproductive patterns of *R. padi* also influence *Prev*: in temperate zones with mild autumns and moderately cold winters (typical of western France and southern England), *R. padi* populations are at least partially anholocyclic, overwintering parthenogenetically on cereals. Therefore, these zones are at risk with respect to BYD (39). In continental or northern zones, most *R. padi* are holocyclic, overwintering as eggs on the primary host, *Prunus padus,* and residual populations on cereals are commonly killed by frost. Therefore, these climatic zones could be less risky with regard to BYD. Apart from these factors affecting *Prev* through their effect on aphid density, *Prev* also depends on the average level of aphid infectivity in a given production situation. Distinguishing between these two sources of variability of *Prev* would be of great value because their effects on model performance are expected to be very different. A modification in the frequency of aphid outbreaks would result in a change in the value of *Prev* that easily can be taken into account through the methodology proposed in this article. A change in the proportion of viruliferous aphids might have a stronger effect, because this would change not only *Prev* but also the specificity curve: for lower levels of aphid infectivity, a higher aphid density would be required to obtain the same level of damage. This could reduce the reliability of the model, because it does not take into consideration possible variation in the specificity and sensitivity curves.

One important limitation of our model is that it considered the costs C^{-+} and C^{--} to be constant whatever the value of X, the variable based on aphid population dynamics. This arose from the choice to consider yield loss as a binary variable (greater or lesser than 500 kg ha^{-1}) instead of a quantitative one. As a consequence, logistic regression analysis was applied in this study. This choice was dictated by the data. Indeed, analysis by conventional regression showed a very weak relationship between yield losses and X (data not shown). This suggests that aphid population dynamics are a good predictor of the occurrence of major yield losses but not of their actual level. Numerous other variables play a role on the determination of the yield loss (15). Consequently, on the basis of the value of X, it was impossible to provide a better estimate of the yield loss (and of the cost associated) than the mean of the category C^{-+} and C^{--}. This requires some estimates being available from a representative data set. The data set we used can be considered representative at the scale of the northern part of France. Of course, as for the prevalence, providing estimates specific of the production situation would, in practice, render the model more accurate.

Our approach assumes that farmers are risk neutral (i.e., their main concern is to minimise average costs). This neutrality framework disregards psychological aspects of decision making. Even if this assumption is verified in some cases (28), it is widely accepted that the farmer's objective is to maximize a utility function instead of simple expected monetary returns. Utility is a wider concept proposed by economists that reflects the user's preferences for risky situations (40). On one hand, farmers frequently are reluctant to accept a significant frequency of important yield losses even if this strategy is optimal on average. This tendency is often termed "risk aversion" (28). Welch et al. (43) have suggested that, to be acceptable, a model should exhibit a risk of failure <5 to 15%. On the other hand, more and more farmers are willing to reduce chemical control to the lowest possible level. These psychological costs could be introduced in the algorithm by weighting the costs in equation 2 accordingly. Alternatively, the decision threshold could be defined as the value minimizing the cost of BYD control but under some constraint on the maximal frequency of errors from one or the other type (false-negative or false-positive recommendation). The frequency of false negative recommendations never exceeded 4% (Fig. 4, curve W^{-}). Thus, the algorithm is convenient for a risk-adverse user. Conversely, the frequency of false positives was >20% for a wide range of a priori prevalence values. This could appear too high if the main goal was to maintain the number of unnecessary sprays below a given threshold.

This study suggests that a decision tool improving BYD management through *R. padi* control in autumn-sown cereals could be based on the prediction of the area under the curve of the proportion of plants infested by aphids during autumn. However, the accuracy of the prediction made by the model should be validated on an independent data set. Moreover, a multisite periodic validation and maintenance of the decision tool is recommended. Indeed, one cannot exclude local variation in the relative importance of the different aphids and virus species in the BYD pathosystem, as well as long-term trends related to global change (12). To be of practical use, our model has to be completed by a predictive model of population dynamics of *R. padi* in autumn. Such a global system could provide the basis for a decision tool improving BYD management. More generally, this study proposed a general way to fit an optimal decision threshold tailored to the production situation by determining the a priori prevalence of the considered pest or disease.

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