

ORIGINAL ARTICLE

The efficacy of spatio-temporal predictors in forecasting the risk of *Cydia nigricana* infestation

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Abstract

The ability to estimate the risk of pest infestation can help farmers to reduce pesticide application and provide guidance that would result in better management decisions. This study tested whether different combinations of spatial and temporal risk factors may be used to predict the damage potential of pea moth, *Cydia nigricana* Fabricius (Lepidoptera: Tortricidae), a major pest in field pea (*Pisum sativum* L., Fabaceae). Over four consecutive years, the abundance of pea moth was monitored by placing pheromone traps at various field pea-cultivation sites. We also assessed the phenological development stages and the percentage of damaged seeds per 100 pods collected from each growing pea field in a region of approximately 30 km in diameter. The study found the significant infestation risk indicators to be the time of flowering, the date on which male pea moths are first detected in the monitoring traps and the minimum distance to pea fields that were planted and harvested in the previous growing season. The combination of all three factors using a general additive model approach yielded the best results. The model proposed by this study accurately discriminated between low-infestation and high-infestation fields in 95% of cases.

KEYWORDS

infestation pressure, Lepidoptera, management decisions, pea moth, pheromone trap, *Pisum sativum*, reduced pesticide application, risk forecast, spatio-temporal risk factors, Tortricidae

INTRODUCTION

Within the framework of the European Union's Farm to Fork strategy, the use of chemical pesticides and the risks they pose must be reduced by 50% by 2030 (European Commission, 2022). Pesticide resistance, residue-related issues and negative environmental impacts have led to re-considering of alternative practices that focus on preventive damage reduction or, at least, reduced pesticide use. One such approach is integrated pest management (IPM). Pest forecasts play an important role in IPM. The predictions made by forecasts may facilitate important management decisions, such as the timing of insecticide application or the development of preventive procedures, thus optimising pest control (Dent & Binks, 2020; Prasad & Prabhakar, 2012).

The use of pesticides is the main option for the control of the pea moth, *Cydia nigricana* Fabricius (Lepidoptera:

Tortricidae), a major pest in peas (*Pisum sativum* L., Fabaceae). However, the field efficacy of pesticides is variable due to the moth's biology. The larvae feed on the pea seeds inside the pod. During this time, the larvae are protected from insecticidal sprays, reducing the efficacy of the sprays and making the direct control of the pea moth challenging. *C. nigricana* adults overwinter as larvae inside a cocoon in the soil of previous year pea fields and emerge as adults the next spring. Many of them mate immediately after emergence (Langenbuch, 1941; Nicolaisen, 1928; Sarwar, 1973; Stenmark, 1974). *P. sativum* is the preferred host of *C. nigricana* and is located by olfactory cues. Mated *C. nigricana* females in particular are attracted to volatiles emitted during the development of buds and flowers (Thöming et al., 2014; Thöming & Norli, 2015).

Recommendations for insecticide application to control pea moth are based on threshold values. Threshold

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values are fundamental in IPM strategies (Pedigo et al., 1986; Stern et al., 1959). A threshold is reached when pest population pressure is considered to be economically injurious and requires direct pest control. Spraying is recommended when a value of 10 male moths per pheromone trap per day is reached (Touvinen, 1982). However, the proposed number of 10 moths per trap is only a rough estimate that is currently not based on sufficient scientific evidence. The number of caught male moths does not necessarily reflect the number of moths per hectare and can vary depending on weather conditions, type of trap and surrounding infestation pressure (Touvinen, 1982). Identifying factors that can be used to forecast pest infestation risk could therefore contribute to a more reliable action threshold.

According to Huusela-Veistola and Jauhiainen (2006), damage to grain peas decreased exponentially when the minimum distance (MD) to the nearest pea field harvested the previous year increased. The authors also found that the pea-moth abundance in the pea field increased linearly with the area under pea cropping in the previous year (continuous abundance index [CAI]). The researchers therefore recommended a distance of 1.5 km between overwintering sites and new pea fields to minimise the risk of pea-moth infestation. Therefore, in addition to taking threshold levels into account, spraying only those fields that are located less than 3 km away from a previous year's pea crop is being recommended (ISIP, 2023; Jao, 2011). However, the success of this strategy seems to depend on the time and duration of pea flowering (Thöming et al., 2011). Early-flowering and short-flowering pea varieties were particularly associated with lower *C. nigricana* damage (Hanson & Webster, 1936; Nolte & Adam, 1962). For early-sown and early-flowering green peas that are harvested when immature, an MD of only 500 m was sufficient to reduce infestation pressure from maximum 4.2% infested peas to minimum 0.2% (Thöming et al., 2011). While the potential of distance (space) and flowering time to interfere with host-pest occurrence is known, a more holistic concept that embeds both predictors in a forecasting approach is potentially of great value. Such an approach could provide important insights into preventive risk avoidance by combining situation-adapted cropping strategies.

This study explores whether and to which extent a combination of spatial and temporal factors can predict the infestation risk of a given pea field in a certain region. The following spatial risk factors are considered: (i) MD between the previous and the current pea location and (ii) the CAI (previous pea area around the current field). The temporal risk factors were (i) the onset of flowering (BBCH 60) in pea fields (Meier et al., 2009) and (ii) the time at which pea moths began appearing in the traps. Given that the development of plants and insects mainly depends on temperature, this study describes the cultivation period in heat units (growing degree days [GDD]). Finally, generalised additive models (GAM) are used to identify decisive factor combinations.

MATERIALS AND METHODS

Field experiments

Location

The data were collected over five consecutive years between 2015 and 2019 in a region of approximately 30 km in diameter in North Hesse, Germany. This area is characterised by small-scale agriculture and features relatively small pea sites (0.01–15.44 ha) (Figure 1). Furthermore, the area has a high percentage of unsprayed fields, which is a prerequisite for assessing risk without interference by pesticide application. Another reason for the selection is the high diversity of winter and summer pea varieties grown in this area. The different sowing dates offer a wide range of flowering times. The pea fields were located using information obtained from Wirtschafts- und Infrastrukturbank Hesse and local farmers. From 2015 to 2019, we mapped all known pea fields within the study area using Quantum GIS v.3.4. We interviewed the farmers about sowing dates and the pest management methods they use.

Measurements

From 2016 to 2019, across all years, we monitored the pea-moth flight in all 162 of the identified pea fields. From 2017 to 2019, we also monitored 37 selected winter cereal fields with peas as preceding crops as emergence sites. We used commercial sex-pheromone delta traps for this monitoring process (Trifolio-M, Lahнау, Germany). One trap per site was placed 30 m from the edge of the field. Trap catches were recorded every third day in all the previous pea fields and once a week in all the current pea fields. Male moth flight was monitored throughout the entire flight period,

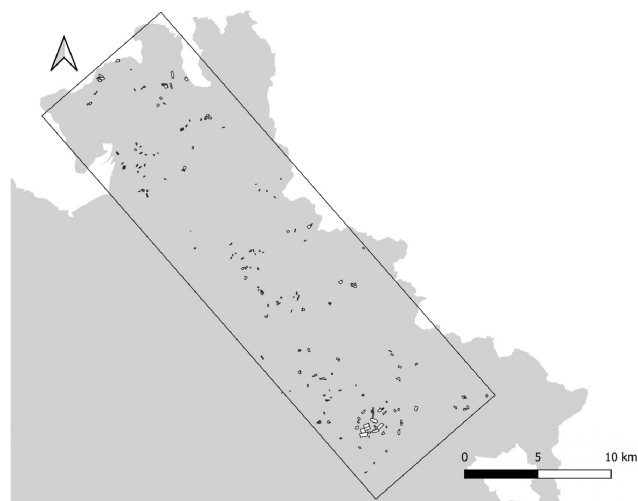


FIGURE 1 All mapped pea fields in the study area (black rectangle) between 2015 and 2019 in North Hesse. Coordinates of the study area: upper left corner: 51.348628°N, 9.700928°E; upper right corner: 51.415482°N, 9.819717°E; lower right corner: 51.189242°N, 10.167847°E; lower left corner: 51.1000504°N, 10.068283°E.

starting in calendar Week 18, from flight start (May) until pea harvest (August).

We monitored the phenological development stage of each pea field at each visit based on the BBCH scale (Meier et al., 2009). Starting in 2016, the pea-moth infestation level for every site was determined shortly before harvest. We assessed the number of infested seeds per 100 pods. The pods were randomly collected along a transect of approximately 50 m, starting from the field edge and moving towards the centre of the field. In total, we assessed 162 pea fields over 4 years. However, to prevent direct control measures from interfering with the results, only data from unsprayed fields were used for modelling. Across all years, only 20 fields were treated with insecticides. In addition, we only included fields in the model when all three parameters (distance, first moth occurrence and flower onset) were assessable. Consequently, we used 88 of the 162 fields for risk modelling.

Meteorological data

The meteorological data base used for the interpolation of hourly air temperature data (2 m above ground) for each monitored site were collected by eight automatic stations. These stations are operated by the German Meteorological Service (DWD) and the Crop Protection Services (CPS) of the federal states. For the interpolation of temperature, a multiple regression analysis including the parameters 'altitude', 'exposure' and 'slope inclination' was used to calculate data for 1-km² grids. The interpolation process is described in detail by Zeuner (2007).

Data analysis

To choose relevant factors that affected pea-moth infestation, we first investigated the influence of the factors distance, first male moth occurrence in pheromone traps and onset of pea flowering separately. We applied two indices to describe the spatial relation between pea field location and infestation: the CAI and the MD (Huusela-Veistola & Jauhiainen, 2006). We used R v.4.2.2 (R Core Team, 2022) for all data calculations. We used GDD with a developmental threshold of zero to describe the relation between onset of flowering, time of the first pea-moth arrival and infestation level using the following equation:

$$\text{GDD} = \sum_{i=1}^n \left(\frac{\sum_{24}^1 (T_{\text{hour}} - T_{\text{min}})}{24} \right), \quad (1)$$

with $T_{\text{min}} = 0^{\circ}\text{C}$ and T_{hour} = the temperature every full hour, with 1 January as the biofix.

Continuous abundance index

The CAI displays the abundance of pea fields grown the previous season around the pea field that is currently

growing. For the CAI, we summed up the area of all previous year's pea fields within the range of a 0.5, 2 or 4 km radius around the current pea field and divided it by the total area (Huusela-Veistola & Jauhiainen, 2006). As the data were not normally distributed, we used the Spearman's rank correlation coefficient to describe the relationship between CAI and infestation rate.

Minimum distance

The MD model describes *C. nigricana* infestation risk as a function of MD between the current pea field and the closest pea field grown the previous year. We calculated the MDs using the nearest neighbour analyses in ArcGIS, Esri v.10.6. Following the approach of Huusela-Veistola and Jauhiainen (2006), we used Equation (2) to model the infestation risk (r_1)-minimal distance (MD₁ in m) relation for each year and for all years:

$$r_1 = a_1 \exp\left(-\frac{\text{MD}}{b_1}\right), \quad (2)$$

where b_1 is the slope parameter and a_1 is the infestation risk of a nonrotated or directly adjacent field. The model was assumed to result in a statistically significant fit when the value of a_1 or b_1 was significantly different from zero. We used the R package nls2 v.0.3-3 (Grothendieck, 2022) for the analysis.

First moth occurrence

Like the MD model, we used a negative exponential model to describe the time of first moth occurrence (moth in GDD) in the traps:

$$r_2 = a_2 \exp\left(-\frac{\text{moth}}{b_2}\right), \quad (3)$$

with a_2 and b_2 as the slope parameters. The model was assumed to result in a statistically significant fit if the value of a_2 or b_2 was significantly different from zero. The nls2 v.0.3-3 (Grothendieck, 2022) package from R was used for this analysis. For GDD calculation, we applied Equation (1).

Flowering

We calculated the GDD until the pea fields reached the BBCH of 60 using Equation (1). We modelled the relationship between flower time and pea moth by a GAM from the R mgvc package v.1.8-41 (Wood, 2022). The general form of GAM is:

$$Y_i = \alpha + f(X_i) + \varepsilon_i \quad (4)$$

where Y_i is the value of the response variable of sample i and X_i is the explanatory variable. The smoothing function is $f()$. We used s as smooth term and applied a thin plate regression spline with sp as smoothing parameter. We checked for concurvity for all factors using the concurvity function. Model

fitness was assessed by `gam.check` function. We controlled for overfitting visually using `visreg` and `vis.gam` and adopted the degrees of freedom accordingly. All functions are either part of the R `mgvc` package v.1.8-41 (Wood, 2022) or belong to the `visreg` package v.2.7.0 (Breheny & Burchett, 2017).

Final model formulation

General additive model was also used to model the relationships between infestation rate, floescence, distance and first moth occurrence. Model validation was carried out as described above. Assuming that flower time and pea-moth arrival are nonlinearly correlated, we included an interaction between those terms.

Model validation

For GAM model validation of the two final models, we used a simple linear regression and the leave-one-out cross-validation (LOOCV; Holmes, 2021). The goodness of prediction was evaluated by LOOCV-mean absolute error (LOOCV_MAE), LOOCV-root mean square error (LOOCV_RSME) and the Akaike information criterion (AIC; Akaike, 1974). We computed AIC differences (Δ AIC) to compare the candidate models according to Burnham and Anderson (2010). In addition, we evaluated the ability of the models to predict the infestation correctly within a certain range. The prediction was considered correct if the observed value and the predicted value ranged between two infestation level categories with 0%–13% (low-infestation field) or above 13% (high-infestation field). These two categories were based on economic considerations, which are described as follows.

Threshold calculation

Damage caused by pea moths reduces the thousand-grain weight of damaged grain peas to 71% in comparison to non-damaged peas (Visotsching, 1998). If the harvest is sold as fodder, the quality of the grains is not important; damaged grains can be sold. Starting from a selling price of 19.20 €/dt and an average yield of 34.5 dt/ha (KTBL, 2022), an infestation level of 1% would result in a yield loss of 0.10 dt/ha, which amounts to 1.92 €/ha. To calculate the costs of an insecticide application in fodder peas, we also used

KTBL data (2022). We included machine, labour and fuel costs (in total, 14.64 €/ha), as well as the costs for the insecticide Karate Zero in the necessary application quantity (126.91 €/L; BayWa, 2022), resulting in 24.11 €/ha as total treatment costs. Based on a cost–benefit ratio of 1:1, one insecticide application in grain feed peas is advisable only if pea-moth infestation exceeds 13% damaged peas.

RESULTS

Table 1 presents an overview of the yearly mean infestation levels and the infestation range. The highest mean infestation rate, at 16.4%, and the highest individual infestation level, at 71.9% damaged grains, occurred in 2018. In 2016 and 2019, the mean infestation rate was comparatively low, at 2.6% and 4.4%, respectively (Table 1).

Pea-moth emergence at overwintering sites

Pea-moth emergence was assessed as the mean trap catch of male pea moths starting at 819.46 GDD. At 1202.03 GDD, 75% of the total moth counts were achieved (Table 2). The mean (\pm SE) number of moths caught per trap was highest in 2018, but did not differ significantly between the years (2017: 309.55 ± 52.88 ; 2018: 551.73 ± 129.08 ; $282.92.73 \pm 107.07$; $\chi^2 = 4.5843$, $df = 2$, $p = 0.10$).

Effect flower onset (BBCH 60) on the infestation rate

We found a significant relationship (Table 3) between flower onset and infestation level, with the highest mean infestation of 36.3% (range: 13.1%–71.9%) at sites where flowering started between 819.46 GDD (mean GDD when first moth emerged at previous year's pea fields) and 940.54 GDD (mean GDD when 10% moth had been detected in previous years pea fields; Figure 2; Table 2). In 2016 and 2019, at low mean infestation levels of 2.6 and 4.4 (Table 1), no flower onset occurred during this 'period of high infestation pressure'. Pea fields flowering before 819.46 GDD and those that flowered after 940.54 GDD showed a considerably lower mean infestation (5.9%) ranging from 0.0% to 25.6%, with a smaller, second infestation peak at 1120.49 GDD in 2018 only (Figure 2).

TABLE 1 Average pea-moth infestation level and infestation range from 100 randomly collected pea pods per field of organic and conventionally managed pea fields in a region 30 km in diameter in Northern Hesse (2016–2019).

Pea-moth infestation (%)	2016	2017	2018	2019
Mean (\pm SD)	2.6 \pm 1.8	11.3 \pm 12.6	16.4 \pm 15.9	4.4 \pm 3.5
Range (min–max)	0.0–8.4	1.1–44.1	0.0–71.9	0.2–13.2
Pea sites (<i>n</i>)	17	30	28	13

Note: No pesticides were used on these fields in the respective years.

The highest infestation rates corresponded with the early season occurrence of the first moth in the actual currently growing pea fields in a range between 694 and 831 GDD and decreased exponentially with increasing GDD ($a=7969.40$, $p=0.12$; $b=134.95$, $p<0.001$, $R^2=0.559$; Figure 3). Even though, in 2019, some pea fields started flowering between 605.69 and 753.33 GDD, in 2016 and 2019, we found no moths in the traps before the accumulation of 890.00 GDD, resulting in low-infestation levels (Table 1; Figure 3).

Field distance and infestation risk models

The infestation level significantly increased with the proportion of area under pea cropping in the previous year (CAI) for all tested CAI in 2018 (CAI0.5: $\rho=0.434$, $p=0.012$; CAI2: $\rho=0.644$, $p<0.001$; CAI4: $\rho=0.467$, $p=0.012$) and for the CAI0.5 in 2019 ($\rho=0.588$, $p=0.038$). For all other combinations, the CAI did not significantly affect the infestation (Figure 4). When the data of all 4 years were included in the analysis, we found no significant correlation between CAI and the infestation level, independent of the selected radius. The CAI was therefore not included in the final model.

The relationship between infestation and distance calculated by the MD model, viz., Equation (2), showed the highest fit in 2017 ($R^2=0.79$) with one significant parameter. A less good fit was found for 2018 ($R^2=0.28$) with both

parameters being significant. In contrast, the results for 2016 and 2019 showed the poorest fit, as demonstrated by R^2 values of 0.09 and 0.18, respectively (Figure 5). The final result is an overall fit for 4 years with $R^2=0.233$ and all parameters significant ($a=23.38$, $b=405.97$).

Model prediction quality

We predicted the infestation rate using different combinations of the factors 'onset of flowering', 'MD' and 'first occurrence of the moth in trap'. All tested factors were significant in all tested models, except for MD in model M4, which includes all three factors. The linear regression between predicted and observed infestation rate was significant ($p<0.001$) in all models, with an R^2 ranging between 0.58 and 0.79 (Table 3). Model M4, had the lowest AIC and RSME of LOOVC-7.16 compared to the other models. However, model M4 had a slightly higher LOOVC-MAE (4.70) compared to model M3 (Table 3). We used the following R code for M4: `M4 <- mgcv::gam(infestation pressure ~ s(flower time, first moth in trap, sp=0.1) + s(minimal distance, sp=0.5), data=data, method="REML")`.

When the ability of the models to correctly assign the fields to infestation groups of either low or high infestation is considered, model M4 yielded the best results. However, M3 and M4 both classified 95.5% of the fields correctly (Table 4). Only three fields were classified as low-infestation fields, although they had an infestation rate of >13%. The forecast was less accurate when the first occurrence of moths in traps was not included in the models. Model M1, which has flowering time as the only explanatory variable, misclassified 11 fields (12.50%) as low-infestation fields (Table 4).

DISCUSSION

Pest infestation levels are subject to various biotic and abiotic factors that impact population dynamics (Khalig et al., 2014). The coincidence of various risk factors in

TABLE 2 Mean (\pm SE) growing degree days (GDD) and moth capture at 37 emergence sites (previous pea fields) in North Hesse 2017–2019.

Moth eclosion (%)	Mean GDD	Range
First moth in trap	819.46 \pm 18.41	666–1102
10	940.54 \pm 16.46	708–1146
30	1030.70 \pm 15.88	807–1245
50	1092.46 \pm 15.90	867–1297
75	1202.03 \pm 20.21	920–1496
100	1890.38 \pm 53.35	1199–2597

TABLE 3 Model parameters and goodness of fit estimators of four general additive models (GAM) fitted to the pea-moth infestation data of 88 pea fields in North Hesse (2016–2019).

Model	Parameter ^a	sp	p	Predicted vs. observed R^2	Δ AIC	LOOVC MEA (%)	LOOVC RSME (%)
M1	Flower	0.001	<0.001	0.58	44.28	6.42	9.2
M2	MD	0.5	0.011	0.65	32.35	6.15	8.61
	Flower	0.001	<0.001				
M3	Moth \times flower	0.1	<0.001	0.78	4.84	4.81	7.36
M4	MD	0.5	0.103	0.80	0	4.85	7.16
	Moth \times flower	0.1	<0.001				

Abbreviations: AIC, Akaike information criterion; sp, smoothing parameter.

^aFlower, onset of flowering (BBCH 60) in growing degree days (GDD); MD, minimum distance from the current pea field to the closest overwintering site of the moth; Moth, arrival of the first moth in the current pea field in GDD.

both space and time can either amplify or reduce the potential harm caused by an insect pest. This coincidence can be favourably exploited in environmental control (Teetes, 1991). This study tested the combined effects of three risk factors: (i) flowering of the host plant; (ii) arrival of first male moths in pheromone monitoring traps; and (iii) crop distance, as potential predictors, defining *C. nigricana* pest status in peas. Low infestation was mainly associated with the co-occurrence of an asynchronous flower onset outside a certain GDD range, the late arrival time of the first moths in the actual fields, and an

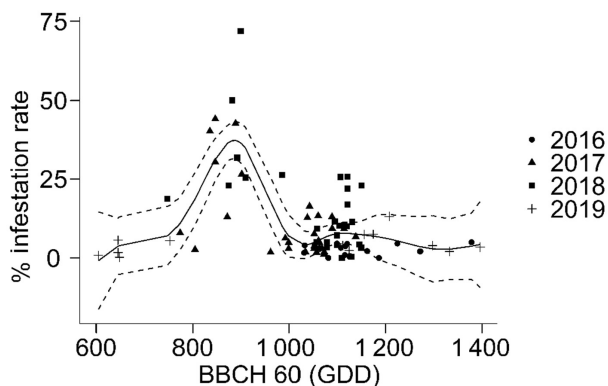


FIGURE 2 Relation between the onset of flowering (BBCH 60 in growing degree days [GDD]) and the percentage of infested seeds of 88 non-sprayed pea fields in North Hesse 2016–2019. Solid line = mean, dashed line = standard error.

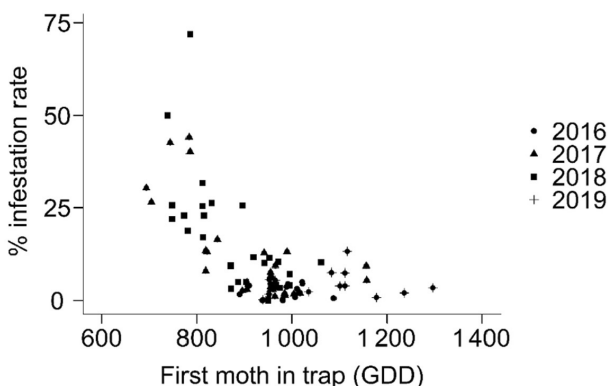


FIGURE 3 Infestation rate in relation to the arrival of the first moths in traps in current pea fields in growing degree days (GDD) in 2016–2019.

increased distance between the previous and the currently growing pea field, as expressed by MD.

Infestation risk was significantly related to the onset of flowering (BBCH 60). Pea varieties that started flowering in a specific GDD range (820–940 GDD), showed the highest attack levels, up to 72% (Figure 2). This also explained the low infestation in the first (2016) and final year (2019) of the study, when all monitored fields started flowering only before or only after this particular GDD timespan. This flowering pattern resulted in a significantly lower mean infestation when compared to 2017 and 2018. During flower development, pea plants are olfactorily more attractive to mated *C. nigricana* females than during other development stages, for example, when leaves or pods are forming (Thöming et al., 2014). In line with the preference–performance theory for phytophagous insects, female pea moths' preference reflects offspring performance (Gripenberg et al., 2010). The arrival of pea moths in pea fields during this critical developmental stage is important because pod formation starts shortly thereafter, and pods are the nutrient source for *C. nigricana* larvae. The importance of flowering time and duration for potential pea-moth damage has been reported by several authors (Hanson & Webster, 1936; Nolte & Adam, 1962). As an environmental control measure (Pimentel & Goodman, 1978; Teetes, 1991), early sowings in combination with the use of an early-flowering variety were the most recommended approach to prevent pea-moth damage in green vegetable peas (Thöming et al., 2011; Wright et al., 1951). Conversely, a similar effect was reported for sowing dates that were significantly late (Anonymous, 1948). Thus, even when only flower onset was included in our model as a single factor, 85% of the fields in high- and low-infestation areas were classified correctly. This finding highlights the importance and value of flowering time as an infestation risk predictor (Table 4, M1).

Furthermore, the study found that the arrival of the first male moth in the currently growing pea fields was a further indicator for pest-host synchronisation. The extent of pea-moth attack decreased exponentially with a later arrival time (Figure 3). Infestation risk was high only when the male moth arrived early in the season, which occurred in 2017 and 2018. Our findings suggest that fields that have attracted male moths earlier in the season are likely to accumulate more individuals over time, resulting in higher damage. Fields that started flowering significantly early or late were characterised by the late arrival of moths in

TABLE 4 The prediction quality of four GAM models to forecast pea-moth infestation risk in 88 fields in North Hesse (2016–2019) in a range of 0%–13% and above 13% damaged pea seeds.

Model	Overestimated (%)	Predicted correctly (%)	Underestimated (%)
M1	2.27 (n=2)	85.23 (n=75)	12.50 (n=11)
M2	4.54 (n=4)	85.23 (n=75)	10.23 (n=9)
M3	1.14 (n=1)	95.45 (n=84)	3.41 (n=3)
M4	1.14 (n=1)	95.45 (n=84)	3.41 (n=3)

Abbreviation: GAM, general additive model.

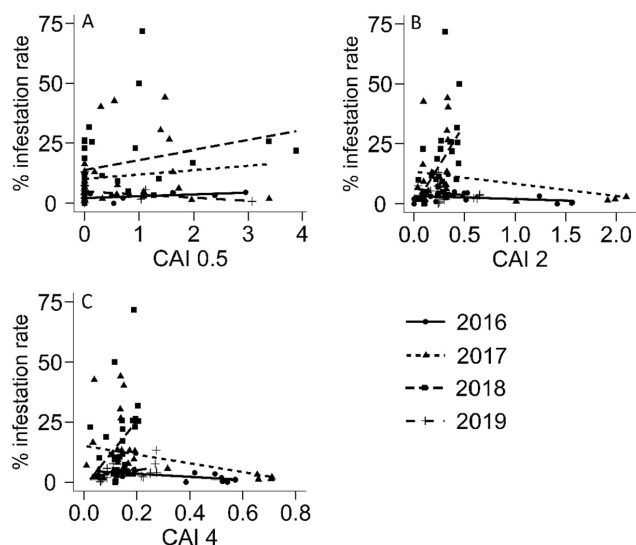


FIGURE 4 Pea-moth infestation (%) as a function of the abundance of pea fields grown the previous season within the range of a 0.5 km (A), 2 km (B) or 4 km (C) radius around the current pea field, divided by the total area. CAI, continuous abundance index.

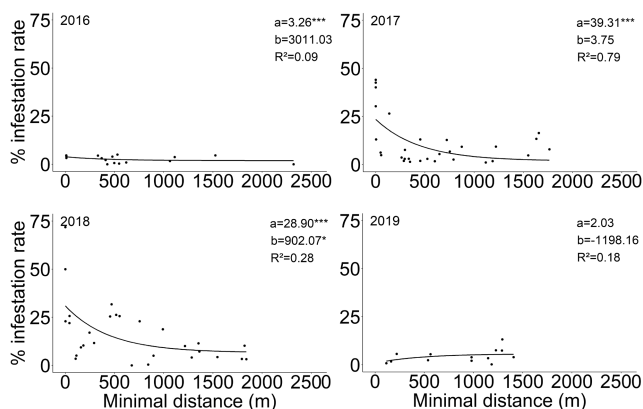


FIGURE 5 Pea-moth infestation (%) as a function of minimal distance (Equation 2) between previous and current pea fields in 2016–2019. * $p < 0.05$, *** $p < 0.001$.

monitoring traps towards the end of the season. This scenario resulted in a low percentage of damaged grains. Therefore, infestation was highest if the susceptible development stage of the plant coincided with the beginning of the pest emergence period. For most crops, the time of infestation in a susceptible plant growth stage and yield loss are closely related (Awuni et al., 2015; Bardner & Fletcher, 1974). The results of this study confirm that the same applies to *C. nigricana*: A favourable match in space and time between crop and pest population development is a prerequisite for high damage.

However, in this study, not all the fields with a high-infestation rate were flowering within the GDD of mean early pea-moth emergence. The dispersion of the insect

in space is likely another important factor. In accordance with the results of Thöming et al. (2011) and Huusela-Veistola and Jauhiainen (2006), CAI was significantly correlated with damage in this study, but only in 2018 for all tested areas and in 2019 for CAI 0.5 km. For all other years and CAIs and across all years, we found no significant correlation between CAI and *C. nigricana* damage. CAI was therefore not included in the study's final model. MD significantly affected the infestation rate only in the high-infestation years, 2017 and 2018 (Figure 4). In those 2 years, a negative exponential decrease in infestation rate with increasing distance to the previous year's pea fields was observed. This finding is in accordance with that of Huusela-Veistola and Jauhiainen (2006). No correlation was found in low-infestation years, which explains the poor fit overall.

Combining MD and flower time in one model increased the prediction quality significantly. Pea fields closely located to the overwintering sites, and thus characterised by low MDs, were substantially infested only when they were also olfactorily most attractive, which is from bud development until the end of flowering (Thöming & Knudsen, 2014). This means that if a pea site is closer than another but not flowering, the directional movement of the moths would be towards the more distant but flowering pea site, resulting in a higher infestation that is independent from MD. In the case of the leaf-defoliating Colorado potato beetle *Leptinotarsa decemlineata* (Say), which is less dependent on a certain plant development stage for offspring survival than the pea moth, host location is less directional and less stage specific. Weisz et al. (1996) were therefore able to model the intensity of attack as a function of only the migratory distance with much greater precision than it was possible in this study. The wide range of flowering patterns in our study region and the related variable olfactorial attraction negatively affected CAI- as well as MD-only-based damage predictions. Including spatial risk factors might lead to better predictions in environments with a more synchronised crop phenology, which applies to either early vegetable pea varieties or grain pea cultivars being more synchronised at Scandinavian agroclimatic conditions described in Thöming et al. (2011) and Huusela-Veistola and Jauhiainen (2006), respectively.

Combining all three of the factors discussed above yielded the best model results. Information about flowering time, pea-moth arrival and MD makes it possible to discriminate between high- and low-infestation fields with greater precision. However, these results are preliminary, and, at this stage, implementation of the model requires data monitoring of the fields, which is time intensive. Farmers do not have the required time to perform such monitoring. Thus, for the practical application of the model, the future development of digital data-acquisition processes is of major importance. In recent years, the technological means of remote sensing have expanded rapidly in agriculture. Crop classification methods using satellite data are already widely studied (Meng et al., 2021;

Sun et al., 2018; Wang, Zhang, et al., 2022). The automatic recognition of pea fields based on satellite imaging would allow for MD calculations without the need to involve farmers. In addition, even without including MD, the model suggested by this study correctly classified 95% of the fields. Schieler et al. (2024) developed a temperature- and photoperiod-based model that can predict development stages, including florescence, based on sowing date and pea variety. Furthermore, in the future, the practical implementation of satellite remote sensing in predicting crop phenology can facilitate the recognition of a particular growth stage, like florescence, without requiring actual field visits (Gao & Zhang, 2021).

The detection of the first male moth arrival was of great significance for the quality of the proposed model. The manual monitoring of pheromone traps would require at least weekly control of all currently growing pea sites subsequent to moth emergence in previous pea sites. A temperature-based model that predicts pea-moth emergence already exists and can help to limit the time span needed for placing and maintaining pheromone monitoring traps in currently growing pea sites (Riemer et al., 2021). Automatic pest-counting insect traps using deep-learning techniques (Bjerge et al., 2021; Hong et al., 2021; Sütő, 2021; Wang, Li, et al., 2022) would be a substantial improvement on these traps, but they are not market-ready yet.

Limitations and recommendation for future research

This study faced certain limitations. Although weather data were interpolated from a height of 2 m, reproducible results were achieved. However, temperature data logger placed directly inside the pea fields might have produced greater precision. Data collected over only 4 years were included in the model, and the number of fields was reduced by almost half due to the exclusion of fields with missing information, especially about the first moth in trap due to a late detection of pea fields during the season or the removal of traps by walkers. The limited data can influence the precision of the model, which therefore requires validation by independent datasets of successive years. This study's data are also restricted to the local conditions of one model region. Therefore, the data require validation before generalising it to other agroecological pea-cultivation areas. Furthermore, this preliminary model was developed with data from grain peas; the prediction needs to be refined and expanded to other grain pea and vegetable pea varieties.

Regarding the factor 'first male moth trapped', two aspects must be pointed out. First, even detecting just the male fraction of the pest population resulted in reproducible predictions. Nevertheless, predictions could be improved in the future by addressing the fact that specifically mated females being more attracted to the floral odour

of flowering peas than males (Thöming & Knudsen, 2014). Monitoring the females with kairomone-baited monitoring traps could improve the prediction results, in analogy to *Cydia pomonella* L. monitoring (Knight, 2010; Knight & Light, 2005; Light et al., 2001). When this study was conducted, such traps containing pea plant volatiles (kairomones) were not commercially available yet. Second, *P. sativum* is the preferred and most abundant host plant within the model region in terms of acreage. However, other cultivated and non-cultivated grain legumes, such as *Vicia faba* L., *Vicia sepium* L., *Lathyrus odoratus* L., *Orobus* sp. and others, have also been reported as potential host plants (Hoffmann & Schmutterer, 1999; Kruess & Tschardtke, 2000; Wright & Geering, 1948). Although the reproductive potential in alternate hosts can be regarded as comparably low in general (Thöming & Norli, 2015), the extent to which alternate host plants may affect the forecasting value of first moth arrival in monitoring traps and the factor MD remains unknown.

CONCLUSION

The adverse effects of pesticides on the environment and human health are numerous and widely documented. Nevertheless, in Germany, the application of insecticides in the past 25 years has not decreased (BVL, 2021). For the effective use of insecticides, pest-host interactions should be studied extensively. However, such studies are often lacking. A lack of confidence in the outcome may lead to the unnecessary application of insecticides, which is both costly and harmful to the environment. This study presents a preliminary combined model for the prediction of infestation risk as a function of crop phenology, pest emergence and insect movement. The findings can contribute to the improvement of environmental controls and facilitate good management decisions by farmers, thus reducing the use of insecticides in pea cultivation.

AUTHOR CONTRIBUTIONS

Natalia Riemer: Conceptualization (equal); data curation (equal); formal analysis (lead); investigation (lead); methodology (lead); software (lead); validation (lead); visualization (lead); writing – original draft (lead); writing – review and editing (lead). **Manuela Schieler:** Data curation (equal); methodology (supporting); writing – review and editing (supporting). **Helmut Saucke:** Conceptualization (equal); formal analysis (supporting); funding acquisition (lead); methodology (supporting); project administration (lead); resources (lead); supervision (lead); visualization (supporting); writing – review and editing (supporting).

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CONFLICT OF INTEREST STATEMENT

The authors have no relevant financial or non-financial interests to disclose.

DATA AVAILABILITY STATEMENT

The datasets generated and analysed during the current study are available from the corresponding author on reasonable request.

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