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Development of a pest threshold decision support system for minimising damage to winter wheat from wheat bulb fly, *Delia coarctata*

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Summary

Wheat bulb fly, *Delia coarctata*, is an important pest of winter wheat in the UK, causing significant damage of up to 4 t ha^{-1}. Accepted population thresholds for *D. coarctata* are 250 eggs m^{-2} for crops sown up to the end of October and 100 eggs m^{-2} for crops sown from November. Fields with populations of *D. coarctata* that exceed the thresholds are at higher risk of experiencing economically damaging infestations. In the UK, recent withdrawal of insecticides means that only a seed treatment (Signal 300 ES) is available for chemical control of *D. coarctata*, however this is only effective for late-sown crops and accurate estimations of annual population levels are required to ensure a seed treatment is applied if needed. As a result of the lack of post-drilling control strategies, the management of *D. coarctata* is becoming reliant on non-chemical methods of control. Control strategies that are effective in managing similar stem-boring pests of wheat include sowing earlier and using higher seed rates to produce crops with greater pest tolerance.

In this study we develop two predictive models that can be used for integrated *D. coarctata* management. The first is an updated pest level prediction model that predicts *D. coarctata* populations from meteorological parameters with a predictive accuracy of 70%, a significant improvement on previous prediction models. Our second model predicts the maximum number of shoots for a winter wheat crop that would be expected at the terminal spikelet development stage. This shoot number model uses information about the thermal time from plant emergence to terminal spikelet, leaf phyllochron length, plant population, and sowing date to predict the degree of tolerance a crop will have against *D. coarctata*. The shoot number model was calibrated against data collected from five field experiments and tested against data from four experiments. Model testing demonstrated that the shoot number model has a predictive accuracy of 65.7%. The foundations for a future decision support system using these models for the sustainable management of *D. coarcata* risk is described. It should be noted that these models represent a stepping-stone towards a decision support system, and that further model validation over a wider geographic range is required.

Keywords

Agronomy, crop modelling, crop tolerance, insect pests, integrated pest management, modelling, pest forecasting

1 | Introduction

The wheat bulb fly, *Delia coarctata* (Fallén), is an important herbivorous insect of wheat in the UK. Significant economic damage to winter wheat crops is caused by *D. coarctata* larvae between January and April (Fig. 1) when larvae infest the developing shoots of cereal crops, causing shoot discolouration and stunting (‘deadhearts’). Economic damage can vary between years, reaching 4 t h^{-1} in years of significant infestation (Rogers et al., 2014). Using the average grain prices for 2021 as a guide figure, this economic damage equates to a financial loss of *c.* £600 h^{-1} for a feed crop (assuming grain prices of £150 t^{-1}). *D coarctata* larvae feed until late spring before pupating at the base of the plant, upon emergence adult *D. coarctata* feed on saprophytic fungi present on plant tissue (Jones, 1970) and reproduce before migrating to adjacent fields where oviposition occurs on the bare soil (Bardner et al., 1977).

The level of *D. coarctata* risk fluctuates yearly and can be affected by the previous crop grown in the rotation and correlates with January temperature, July temperature, and August rain days (Young & Cochrane, 1993). In the UK, recent withdrawal of insecticides means that only a seed treatment (Signal 300 ES 300 g L^{-1} cypermerthrin, UPL Europe Ltd) is available for chemical control of *D. coarctata.* This seed treatment is only effective for late-sown crops (November onwards) as the active ingredient is insufficiently persistent for crops sown at more conventional drilling dates in September and October. Therefore, alternative non-chemical means of *D. coarctata* control, capable of managing *D. coarctata* in crops sown at conventional dates, are becoming increasingly desirable.

One option for the non-chemical control of *D. coarctata* is to adjust crop management practices in order to produce a wheat crop that is able to tolerate *D. coarctata* damage. Crop tolerance, or the economic injury level, can be broadly defined as the amount of pest damage a crop can withstand before an economic consequence is observed (Stern et al., 1959). The *D. coarctata* pest thresholds of 250 or 100 eggs m^{-2} were devised during the late 1950’s / early 1960’s by Gough et al. (1961)

and only take account of pest abundance, no consideration is given to potential crop tolerance. Adjusting various agronomic factors, such as sowing date and seed rate, has been used to successfully achieve tolerance against other stem-boring pests of wheat, including the gout fly, *Chlorops pumilionis* (Bjerkander) (Bryson et al., 2005) and wheat saw fly, *Cephus cinctus* Norton (Beres et al., 2011). Modifying agronomic practices to achieve crop tolerance represents a potential method of non-chemical *D. coarcata* control, but to achieve this accurate *D. coarctata* thresholds are required.

For stem-boring insects, crop tolerance can be achieved by growing a crop with a greater number of shoots than those required to achieve an economically viable yield, this allows some shoots to be lost to insect herbivory without incurring a yield penalty. UK wheat crops require a minimum of 400–450 fertile shoots m^{-2} to achieve a commercial grain yield (Spink et al., 2000a). Wheat crops typically produce more than 1,000 shoots m^{-2} by the start of stem extension in March (Berry et al., 2003). From March to May there is a decline in shoot numbers as the weakest shoots die, leaving a final shoot number of 400–700 fertile shoots m^{-2}. In most cases, the majority of the shoots are produced during the autumn months, and are therefore present when *D. coarcata* larvae infest plant tissue (January–April; Fig. 1). The main management methods that can increase maximum shoot number are to sow early in autumn, allowing more time for extra tillers to develop, and/or to sow a high rate of seeds so that more plants establish, resulting in more shoots m^{-2} (Spink et al., 2000a). Whilst it is widely accepted that earlier sowing and higher seed rates result in more shoots m^{-2} (Darwinkel et al., 1977; Spink et al., 2000a), reliable methods for quantifying how many shoots, and therefore how tolerant a crop will be to stem-boring pests such as *D. coarcata,* do not exist.

Annual *D. coarctata* pest levels are predicted through autumn soil sampling surveys. This process is time-intensive and requires specialised equipment (Salt & Hollick, 1944; Ramsden et al., 2017). Pest levels can be effectively estimated through predictive modelling (Young & Cochrane, 1993). The Young & Cochrane *D. coarctata* prediction model is based on egg counts for East Anglia, UK between 1952 and 1991 (Young & Cochrane, 1993). The Young & Cochrane model predicts egg numbers using a range of meteorological parameters, including the departure from the long-term average for rainfall during October of the preceding year, January air temperature, January soil temperature, and July air temperature. Meteorological parameters used in the model were selected on the hypothesis that they influence the reproductive development or oviposition of *D. coarctata*. The Young & Cochrane model has a predictive accuracy of 59%, although this is satisfactory for a pest prediction model (Yonow et al., 2004) there is scope to refine and develop the model further; for example by expanding the underlying data to cover a wider range of *D. coarcata* risk regions (such as north England and east Scotland) or by improving its predictive accuracy. Accurate and reliable prediction of annual *D. coarctata* levels before crops are sown and accurate estimates of plant populations/shoot numbers are required if agronomic practices are going to be adjusted to improve crop tolerance to *D. coarctata.*

Here, we develop two predictive models that can be used for integrated *D. coarctata* control. The first is a pest level prediction model that estimates *D. coarctata* populations for two regions using meteorological parameters with a greater accuracy than the previous Young & Cochrane model. The second is a model that uses the target plant population and sowing date to predict the maximum number of shoots for a winter wheat crop prior to the start of stem extension; this will be particularly valuable when trying to produce crops able to tolerate *D. coarctata* infestation. Finally, using data extracted from the literature we produce a revised calculation of *D. coarctata* threshold levels. We combine this information and develop the foundations for a future sustainable decision support system for minimising crop damage by *D. coarctata*.

2 | Methods

2.1 | Modelling to predict D. coarctata egg numbers

2.1.1 | *Sources of* D. coarctata *egg numbers and meteorological data*

Delia coarctata egg number data were extracted from two sources. Historic data from East Anglia (1952–1991) were extracted from Young & Cochrane (1993) and combined with the results from the AHDB autumn survey of *D. coarctata* incidence from northern England (2005–2019) and East Anglia (2008–2019). Up to 30 fields were sampled in September or October of each survey year in areas prone to *D. coarctata* infestation, with *c.* 15 in eastern England and 15 in northern England. For each field sampled, either 32 cores (each of 7.2 cm diameter) or 20 cores (each of 10 cm diameter) were taken to cultivation depth. Fields were sampled in a standard 'W' sampling pattern across the direction of cultivation. *D. coarctata* eggs were extracted following soil washing (Salt & Hollick, 1944) and flotation in saturated magnesium sulphate. Egg numbers were expressed as eggs m^{-2}. Meteorological data were extracted from the UK meteorological office for the two regions (East Anglia and Northern England) using publicly available data, accessible via www.metoffice.gov.uk/research/climate/maps-and-data/uk-and-regional-series. Meteorological data extracted included minimum, mean, and maximum temperature, rain days, rainfall amount (mm), sunshine days, and air frost days. From the extracted data, the deviation from the long-term average was calculated. Long-term moving averages of 30-year periods were used as they limit the influence of short-term fluctuations on time-series datasets. The UK meteorological office categorises seasons into: Winter (preceding December–February), spring (March–May), summer (June–August), autumn (September–November). For each year of egg collection, the meteorological data included in the model were the autumn of the preceding calendar year, winter (starting in December of the preceding year), current spring, and current summer. For each season the meteorological parameters included were: minimum temperature, mean temperature, maximum temperature, the number of sun days, the number of rain days, and the amount of rainfall. The number of air frost days was included for the winter, spring, and preceding autumn seasons only.

2.1.2 | *Modelling approach – developing the pest level prediction models*

Data modelling for the pest level prediction model was carried out in R v.3.6.1 with additional package ggplot 2 v.3.2.1 (Wickham, 2016) used for data visualisation. Linear regressions were used to build all models and backwards stepwise model selection was employed to arrive at the final predictive models (Marill & Green, 1963). At each simplification stage analysis of variance was used to ensure model simplification was justified and did not significantly affect model structure. Model residuals were observed at each stage.

2.2 | Seasonal and monthly models for 1952–2019

An initial seasonal model was developed by including the meteorological factors described above on a seasonal basis. The parameters included in the final seasonal model were used to develop an initial monthly model (e.g. the final seasonal model included summer minimum temperature, therefore the initial monthly model included minimum temperature for June, July, and August).

2.3 | Seasonal and monthly models for 1971–2019 (air frost models)

In order to allow air frost to be included in the model a subdataset was developed comprising all observations from 1971–2019. As air frost data is only available from 1960 onwards, the 1971–2019 subdataset enabled calculation of the long-term average for a minimum period of 10-years. Seasonal and monthly models were simplified as described above and the final model was used to predict egg numbers.

The final monthly model was validated following a similar procedure to the one employed by Young & Cochrane (1993): four 5-year periods were removed from the dataset from which the model was developed and observations were made of how this affected the model predictions. Data were removed from the first five years (validation 1: years 1971–1975 removed), the last 5 years (validation 2: years 2015–2019), the 5 years with the highest recorded *D. coarctata* egg numbers (validation 3: years 1978, 1984, 1985, 1986, 2010), and the 5 years with the lowest *D. coarctata* egg numbers (validation 4: years, 2005, 2006, 2007, 2014, 2017). Four additional validations (5–8) were carried out by randomly removing five one-year periods from the dataset.

In autumn 2020, soil samples were taken from sites in England (15 north and 15 east sites), the number of *D. coarctata* eggs were determined, and these data were used in model testing.

2.4 | Shoot number model

2.4.1 | *Model of potential shoot number*

Data modelling for shoot number prediction was done using Microsoft Excel v. 2013. First, the potential shoot number of a single wheat plant growing in isolation (i.e. without any competition from neighbouring plants and unlimited resources) was determined. Secondly, this calculation was calibrated using field data to account for plant competition and environmental factors that might limit shoot production.

2.4.2 | Building a thermal time-based model for shoot production

Published principles of wheat shoot development were used to develop a thermal time-based model for shoot production (Klepper et al., 1984). The thermal duration between sowing and plant emergence was taken as 150^{o}Cd (Sylvester-Bradley et al., 1998). The end of tillering generally coincides with the start of stem extension and the formation of the terminal spikelet within the developing ear. The thermal time between sowing date and terminal spikelet production for early and late sown winter wheat crops was reported in Kirby et al. (1999). Data from Kirby et al. (1999) were used to estimate the effect of sowing date (1st September to 8th November) on the thermal duration before sowing and terminal spikelet (using a base temperature of 0^{o}C), assuming that it decreased linearly with time of sowing. Thus, from a value of 1582^{o}Cd on 1 September, it decreased by 9^{o}C for each day that sowing was delayed. The thermal time from sowing to plant emergence was then subtracted from this value, leaving the total thermal time available for leaf and shoot production.

The thermal time between emergence of successive leaves (phyllochron) decreases the later crops are sown (Equation 1) where d = the number of days after 1st September when the crop was sown (Kirby et al., 1985).

$$Phyllochron\ length = -0.5383 \times d + 140.3 \qquad \text{Equation 1}$$

The phyllochron length, along with the thermal time between plant emergence and terminal spikelet, was then used to estimate the number of leaves and shoots that could be produced over time for an individual plant. The following assumptions were made based on Klepper et al. (1984):

- Three phyllochrons after plant emergence: The first primary shoot emerges from the axil of the 1^{st} leaf on the main shoot
- Four phyllochrons after plant emergence: The second primary shoot emerges from the axil of the second leaf of the main shoot
- Five phyllochrons after plant emergence: The third primary shoot emerges from the axil of the third leaf of the main shoot. The first secondary shoot emerges from the axil of the first leaf of the first primary shoot
- Six phyllochrons after plant emergence: The fourth primary shoot emerges from the axil of the fourth leaf of the main shoot. The second secondary shoot emerges from the axil of the second leaf of the first primary shoot. The third secondary shoot emerges from the axil of the first leaf of the second primary shoot.

2.4.3 | Calibrating and testing the shoot number model

Data from five winter wheat trials (Table S1) were used to calibrate the shoot number model and data from three winter wheat trials (Table S2), alongside data from Spink et al. (2000b), were used to test the shoot number model. Each of the field trials (Table S1; S2) used the same winter wheat variety (Evolution) and included a range of seed rates (40, 80, 160, 320, 480, and 640 seeds m^{-2}). All trials were sown at either 'standard' or 'late' timings for the region. All experiments except Huggate 2016 were treated with insecticide to control *D. coarctata*. Assessments showed that less than 1% of shoots were infested with *D. coarctata* at the start of stem extension at Huggate 2016 (Tables S1; S2). Each experiment was arranged in a fully randomised block design with three or four replicates of each treatment and included six seed rates ranging from 40 to 640 seeds m^{-2} (Tables S1; S2). Experimental plots were 2 m × 12 m and were drilled using an Ojyard plot drill. Plant number and shoot number were measured at the start of stem extension (BBCH Growth Stage 31 (GS31)) in each experimental plot by counting all plants and shoots within a 0.7 m × 0.7 m quadrat. Field trial data (Table S1) were analysed in Genstat (v-14) using the General ANOVA procedure, with seed rate as 'Treatment' and replicate as 'Block'. Data used to calibrate the model were not used for model testing. The model was tested using a multiple linear regression, with Experiment included as 'Group', to compare the predicted shoot numbers against the model predictions using Genstat (v-14).

2.5 | Updating *D. coarctata* thresholds

The following factors determine how much damage a wheat crop can sustain from a stem-boring insect before the damage becomes economically damaging, and can be used to provide a more comprehensive estimation of economic thresholds for *D. coarctata*:

1. The number of shoots a larva can destroy
2. The minimum number of fertile shoots a crop requires to achieve a yield potential
3. The maximum number of shoots a crop is expected to produce in winter
4. Viability of the herbivorous insect eggs

These factors can be used to revise the *D. coarctata* threshold using Equation 2.

$$EIL = \frac{(SN - SN_{MIN})/SN_{KILL}}{Egg\ Viability} \qquad \text{Equation 2}$$

Equation 2: Economic Injury Level (EIL) equation used to estimate wheat tolerance against *D. coarctata*. SN = the number of shoots per m^{-2} in winter, SN$_{MIN}$ = the minimum number of fertile shoots per m^{-2} required to achieve a yield potential, SN$_{KILL}$ = the number of shoots killed by an individual larva, and Egg Viability the proportion of eggs that develop into larva.

3 | Results

3.1 | The *D. coarctata* pest level prediction model

Our first *D. coarctata* pest level prediction model (1952–2019 seasonal model; Fig. S1A) indicated that the number of preceding autumn rain days, the minimum winter temperature, spring mean temperature, spring maximum temperature, spring rainfall, and summer minimum temperature are the most important meteorological parameters that affect *D. coarctata* egg numbers on a seasonal basis ($F_{6,60}$ = 11.54; $P \leq 0.001$; adjusted R^2 = 0.49). *D. coarctata* egg number predictions, versus actual observations, for this seasonal 1952–2019 model are displayed in Fig. S1A.

To identify the months which influence *D. coarctata* egg numbers the meteorological parameters included in the seasonal 1952–2019 model were assessed on a monthly basis for the relevant seasons: preceding September – preceding November for preceding autumn season, preceding December–February for winter season, and June–August for summer season. Linear regression modelling indicated that the most important monthly meteorological parameters for predicting *D. coarctata* egg numbers were preceding October rain days, preceding December minimum temperature, January minimum temperature, March mean temperature, May mean temperature, March maximum temperature, May maximum temperature, May rainfall, June minimum temperature, July minimum temperature, and August minimum temperature ($F_{11,55}$ = 6.66; $P \leq 0.001$; adjusted R^2 = 0.49). The predictions of this model, compared with the observed values, are shown in Fig. 2A.

3.2 | Introducing air frost into the pest prediction model increases predictive power

One key factor that might influence *D. coarctata* egg numbers is air frost. A seasonal model was produced using data from the 1971–2019 subdataset. This comprised all meteorological parameters described above as well as the departure from long-term average for preceding autumn, winter, and spring, air frost days. Following model simplification, this air frost seasonal model had a higher predictive power compared with the previously developed models ($F_{9,38} = 8.42$; $P \leq 0.001$; adjusted $R^2 = 0.59$) and the final meteorological parameters included departure from long-term average for: preceding autumn rain days, preceding autumn sun days, winter mean temperature, winter air frost days, spring maximum temperature, spring rainfall, summer minimum temperature, summer mean temperature, and summer maximum temperature. The predictions of this model, compared with the observed values, are shown in Fig. S1B.

A refined 1971–2019 monthly model was created using monthly average data for the seasons shown to be important in the seasonal model, using the same approach described above for the 1952–2019 model. The meteorological inputs for this refined monthly model were the departure from long-term average for: preceding September sun days, preceding October rain days, January mean temperature, January frost, April maximum temperature, May maximum temperature, April rainfall, and July minimum temperature. This model had the highest predictive power ($F_{8,39} = 14.88$; $P \leq 0.001$; adjusted $R^2 = 0.70$). The predictions of this model, compared with the observed values, are shown in Fig. 2B. On average, the predicted values only deviated from the observed values by -9% (median = -2%; range = -155% to +50%). The relationship between the observed and predicted values of the final 197 –2019 monthly model is shown in Fig. S2.

3.3 | Validating the final pest prediction model

The 1971–2019 monthly model was validated by removing a series of years from the model, re-running the model, and observing the effect the removal of these years had on the ability of the model to predict *D. coarctata* egg numbers for all years. Eight validation models were developed in total (Fig. S3). Validations had no significant detrimental effect on the predictive power of the models; average deviation from the predictive values of the full model were: -20.20% (validation

1), +0.05% (validation 2), +0.58% (validation 3), -17.10% (validation 4), +2.72% (validation 5), -1.28% (validation 6), +2.70% (validation 7), -1.94% (validation 8).

3.4 | Testing the *D. coarctata* prediction model

The model was used to predict mean *D. coarctata* egg numbers for each region in 2020, model predictions were then compared with the mean egg counts per region obtained by soil sampling. The model predicted a mean *D. coarctata* egg number of 60 eggs m^{-2} for east England and 107 eggs m^{-2} north England. Soil sampling indicated that the observed regional risk was 111 eggs m^{-2} for north England, and 173 eggs m^{-2} for east England. For east England, higher values than were estimated were mainly driven by three sites with very high counts of 1000, 850, and 404 eggs m^{-2}.

3.5 | Predicting shoot production number for individual plants growing in isolation

The shoot production of a single plant grown in isolation at a range of sowing dates between 1 September and 30 December was modelled (Fig. 3). The model predicted that a single plant sown on 1 September has the potential to produce 38 shoots by terminal spikelet (which approximates to the start of stem extension), whereas at the other extreme a single plant sown in mid-November would only produce ten shoots.

3.6 | Calibrating the shoot production number model

It was recognised that achieving a shoot population of 38 shoots per plant (Fig. 3) was unrealistic under field conditions. Shoot number data from specific treatments in a series of field trials (Table S1) were used to calibrate the model to ensure that it provided a realistic estimation for the number of shoots expected under field conditions. The ratio of observed to predicted shoots per plant was negatively related to the observed plants m^{-2} (Fig. 4). This was because the shoot number model predicted the highest potential number of shoots m^{-2} for high plant populations, but these populations also had the greatest competition between shoots resulting in the lowest ratio of observed to predicted shoots per plant. The relationship between the observed plants m^{-2} and ratio of observed to predicted shoots per plant described in Fig. 4 was used to calibrate the potential shoot number model for field conditions.

The calibrated shoot number model predicts a decline in maximum shoot number due to reduced plant population and delayed sowing date, as is generally observed in practice (Fig. 5). A crop sown at the end of September with a plant population of 200 plants m^{-2} is predicted to produce a maximum shoot number of approximately 1039 shoots m^{-2}. The model can be used to estimate the minimum plants m^{-2} required to achieve 500 shoots m^{-2} (the minimum number of shoots required to achieve a typical commercial UK wheat yield). To achieve 500 shoots m^{-2} by terminal spikelet the model estimates a required minimum of 56 plants m^{-2} for late September sowing, 92 plants m^{-2} for mid-October sowing, 165 plants m^{-2} for late October sowing, and 500 plants m^{-2} for mid-November sowing. These plant populations are similar, or slightly greater, than estimates of the economic optimum plant density reported by Spink et al. (2000b), providing confidence that the model is giving plausible predictions. Although the number of shoots can occasionally increase between terminal spikelet and harvest, shoot production up to terminal spikelet was considered most appropriate for developing a *D. coarctata* tolerance scheme, as *D. coarctata* damage occurs prior to terminal spikelet (Fig. 1). The shoot production model has been used to quantify the increase in maximum shoot number by terminal spikelet from sowing earlier and establishing a higher plant population (Fig 6). Sowing earlier generally results in a larger increase in shoots m^{-2} compared with increases in plant population. This information can be used to help estimate changes in sowing date and seed rate to minimise the risk of yield loss to *D. coarcata*.

3.7 | Testing the shoot number prediction model

Data from three winter wheat field experiments (Table S2) were combined with data from two other field experiments (Spink et al., 2000b) to test the predictive power of the model. (Fig. 7).

The number of shoots m^{-2} at GS31 were measured in each of the field trials (Table S2), which approximates to the timing of terminal spikelet production and the shoot number model was used to predict the GS31 shoot number based on the measured plant population for each site. Multiple linear regression analysis showed that a single best fit line explained 65.7% of the variation ($F_{1,28}$ = 56.60; $P \leq 0.001$). Fitting separate best fit lines to each experimental site with the same slope but different y axis intercepts did not significantly improve the fit.

3.8 | Revising the economic injury level of wheat to *D. coarctata*

Using values from the literature the parameters required for equation 2 (pest threshold revision) were estimated: Egg viability is estimated at 56% (Gough, 1947; Raw, 1967; Ryan, 1973A), SN_{KILL} is estimated at four shoots destroyed per larva (Ryan, 1973b, 1975; Young & Ellis, 1996), SN is estimated at 1000 shoots m^{-2} (Sylvester-Bradley et al., 1998), and SN_{MIN} is estimated at 400–450 shoots m^{-2} (Spink et al., 2000a). Using these assumed values, but increasing the SN_{MIN} to 500 shoots m^{-2} to allow a modest degree of insurance against achieving too few shoots. An updated threshold for *D. coarctata* in winter wheat is presented in Table 1 and can be used as the foundation to develop targeted agronomic approaches for minimising the risk of economic damage by *D. coarctata* control using crop tolerance.

4 | Discussion

4.1 | Predicting D. coarctata *risk to inform control measures*

Delia coarctata larva infest cereal shoots between January and April, where they can cause devastating crop damage resulting in yield losses of up to 4 t ha^{-1} (Rogers et al., 2014). Depending on the sowing date, current thresholds indicate that a pest pressure of 250 eggs m^{-2} can cause significant crop damage for crops drilled before October, with a pressure of 100 eggs m^{-2} causing significant crop damage for crops drilled from November (Gough, 1961). Chemical-based options for *D. coarctata* control in the UK are limited to a pre-drilling seed treatment. This is only effective for late sown crops (November onwards) and is insufficiently persistent for earlier sowings. Therefore, decisions on whether to apply a seed treatment need to be made before sowing and should account for the risk of *D. coarctata* infestation. Currently, the most accurate means of determining *D. coarctata* risk requires soil extraction and manual egg counting, this is both time- and cost-intensive (Ramsden et al., 2017). Predicting pest levels and risk is an important Integrated Pest Management (IPM) tool and represents a cost-effective means of estimating annual risk for a wide range of important insect pests (Herms, 2004). The pest level prediction model developed in this study provides an alternative to soil sampling and has the significant advantages that it is less time consuming, less arduous, and provides an earlier estimate of pest levels, which is crucial when deciding whether to treat seed. Similar prediction models have been developed for a range of other agriculturally important insect pests, including the tea leaf roller, *Caloptilia theivora* Walsingham (Satake et al., 2005), leafhoppers, whiteflies, and thrips (Arya et al., 2015), and wireworm, *Agriotes spp.* (Jung et al., 2012). Generally, pest level and risk prediction models either estimate when a phenological event has occurred that increases the in-season crop risk (such as pest egg hatch, development, or emergence of an additional generation) to help time the application of pest management strategies (Milonas et al., 2001; Herms, 2004; Satake et al., 2005), or predict annual risk by estimating pest population densities (Arya et al., 2015). As *D. coarctata* can only be controlled chemically using a seed treatment, it is important that any pest level prediction model can accurately predict pest populations before sowing, so that seed coating can be applied if necessary.

The *D. coarctata* pest level prediction model developed here is based on the Young & Cochrane model (Young & Cochrane, 1993) but incorporates a wider range of meteorological parameters than the original and expands the geographical range to include northern England. The meteorological parameters included in the Young & Cochrane model were selected to include the factors hypothesised to have the greatest influence on *D. coarctata* biology and phenology (Young & Cochrane, 1993). The Young & Cochrane model had a predictive accuracy of 59%, limiting its uptake as a decision support tool. When developing our models, we included meteorological factors available from open-access data sources. The benefits of building models using open-access meteorological data are that the model inputs are standardised across regions and freely available. The meteorological parameters included in the models were departure from the long-term average for: minimum, mean, and maximum temperature, rainfall, the number of rain days (days with rainfall > 0.2 ml), the number of sun days, and days of air frost. Our final model (1971–2019 monthly model) had a predictive accuracy of 70%, an 11% increase in accuracy when compared with the Young & Cochrane model. This is a significant improvement of the potential for using predictive modelling to estimate *D. coarctata* risk. Furthermore, as the model can be run prior to sowing in August/September, it is a possible alternative to soil sampling that can also be used to advise on targeted soil sampling efforts (i.e. supplementary soil sampling in seasons and regions of high risk).

During model testing the model performed well and predicted regional *D. coarctata* risk accurately for the northern region; however, the level of risk predicted for the eastern region was lower than observed. Further model development and refinement (through the potential inclusion of model moderators such as soil type and previous crop) would enable a more robust and dynamic model to be developed. Soil type is likely an important factor to consider in future model development, as the three 2020 test sites with the highest *D. coarctata* counts were associated with clay soils, indicating that soil type might influence *D. coarctata* oviposition preference. Furthermore, the previous crop in the rotation has been reported to affect *D. coarctata* oviposition (Gough, 1946; Young & Cochrane, 1993). Therefore, including these two factors as components in subsequent model improvements represents the logical next step in future model development. The predictive accuracy of our model is similar to the accuracy of other pest prediction models that use meteorological data to predict seasonal risk, including models that predict the population dynamics of the Queensland fruit fly, *Bactrocera tryoni* (Diptera) Froggatt (R^2 = 0.28 and 0.32; Yonow et al., 2004), annual populations of the whitetail, *Paronychiurus kimi* (Collembola) (Lee) (R^2 = 0.79; Choi

& Ryoo, 2003), and the abundance of two moth species, *Helicoverpa spp.*. (Lepidoptera) (R^2 = 0.84–0.96; Zalucki & Furlong, 2005).

4.2 | Improving tolerance to *D. coarctata* through shoot number prediction

Non-chemical methods for *D. coarctata* control are becoming increasingly desirable, from both an agronomic and an environmental perspective. Insecticidal sprays are no longer approved for *D. coarctata* control in the UK and a growing body of evidence indicates that pesticides can have far-reaching environmental consequences (Leather, 2018), resulting in a need to develop non-chemical pest management methods. Cultural control can be an effective means of limiting pest damage (Glen, 2000) and can involve the adjustment of both pre-drilling and in-season agronomic practices. Non-chemical control of stem-boring pests of wheat can be effectively achieved through adjustments to pre-drilling agronomic practices, such as increased seed rates and earlier sowings (Glen, 2000). These practices have the potential to increase crop shoot numbers and improve crop tolerance to herbivorous insects (Bryson et al., 2005; Beres et al., 2011; Wenda-Pieskik et al., 2017).

Higher seed rates have been used to confer tolerance against other stem-boring pests, including the wheat stem sawfly, *Ce. cinctus* (Beres et al., 2011) and the gout fly, *Ch. pumilionis* (Bryson et al., 2005). Earlier drilling has also been reported to improve tolerance against cereal leaf beetles, *Oulema spp.* (Wenda-Pieskik et al., 2017). This showcases the potential to achieve cultural control of herbivorous insect pests through the adjustment of pre-drilling agronomic practices. Therefore, accurate means of predicting crop shoot numbers will be an important component of any IPM strategy based on these methods. The shoot number prediction model we developed in this study can be used in conjunction with our revised *D. coarctata* thresholds (Table 1) as a component of an integrative *D. coarctata* risk management system.

Our shoot number model has an overall predictive accuracy of 65.7% and the predicted values were close to the 1:1 relationship across all the experiments the model was tested against. For some sites the model made more accurate predictions (e.g. Foxholes, 2017) and for others a weaker relationship was observed (e.g. Bardwell, 2017). This contrast in accuracy could be related to specific environmental factors that limited shoot production, such as soil capping or water logging (Robertson et al., 2009). Our revised thresholds for *D. coarctata* in winter wheat demonstrate that the current *D. coarctata* pest threshold of 250 eggs m^{-2} (Gough et al., 1961) is too simplistic and likely represents either an overestimation of the potential pest damage, an underestimation of the amount of damage that can be tolerated by a winter wheat crop, or a combination of both factors. Sensitivity analysis (achieved by adjusting each parameter used in Equation 2 from its likely minimum value to its maximum value; Fig. 8) demonstrates that thresholds for *D. coarctata* could be smaller or greater than 250 eggs m^{-2}, and that the thresholds are particularly sensitive to the number of shoots a crop will produce. Combining the shoot prediction model with the revised *D. coarctata* thresholds will facilitate the production of a winter wheat crop that is capable of tolerating the predicted level of *D. coarctata* damage through adjustments to seed rate, sowing date, or both. This approach is similar to those devised by Bryson et al., (2005), Beres et al. (2011), and Wenda-Pieskik et al. (2017). Although, increasing shoot number would need to be considered alongside higher crop production costs and the increased risk of crop lodging (Berry & Spink, 2012).

4.3 | Limitations of the current models and avenues for future development

The two models we have developed, pest level prediction and crop tolerance prediction (via shoot number estimation), have the potential to represent central components of an IPM strategy for *D. coarctata* control. However, both models will require further optimisation before they can be fully utilised by growers across the UK; currently the models are geographically restricted to two regions of the UK and expanding the geographical coverage to include data from other *D. coarctata* risk areas (e.g. east Scotland; Rogers et al., 2014) would greatly improve them. Specific development, testing, and validation would also be required for each model to ensure these represent systems that growers can use with confidence. These are discussed below.

Further development of the pest level prediction model could involve the inclusion of model moderators (soil type, previous crop) to adjust the value using bespoke farm-specific traits. Model testing carried out in this study showed that model predictions were good for the north England region but less optimal for the east England region, with egg count data from the east England region indicating that soil type influences egg numbers (high egg counts were associated with clay soils). Soil type has been used as an input in similar predictive models, including a wireworm population prediction model (Jung et al., 2012), and represents a clear next-step in model development for the pest level prediction model. Expanding the model to include data from other *D. coarctata* risk regions would also increase confidence in the model results amongst growers.

For the shoot number prediction model, additional development could include the introduction of crop variety and site factors as variables to estimate shoot number using more detailed agronomic factors. Thermal time is often used in models for wheat development, including for modern varieties (e.g. Brown et al., 2018). However, tillering potential for different phenological types of wheat is unclear (Hyles et al., 2020), and varietal differences in GS31 and GS32 shoot number have been reported (Spink et al., 2000b; Storer et al., 2018). It is therefore important to investigate whether accounting for any varietal differences in potential shoot number improves the predictive model of the shoot number model. Expanding the shoot number model to include winter and spring sown wheat types would enable the model to be used for other winter and spring herbivorous insects of wheat. The model has been calibrated using field data from a range of UK conditions. However, while some sites had typical shoot numbers for the given sowing date (e.g. Huggate 2016 standard sowing date; Foxholes 2017 late sowing date and Bardwell 2017 late sowing date; Table S1 & S2), the other standard sowing date sites in Table S1 had lower shoot numbers in the 40 and 80 seeds m^{-2} treatments than expected when compared with Spink et al. (2000b). The shoot number prediction model will therefore benefit from calibration and testing at a wider range of sites and seasons, particularly at lower seed rates. It would also be beneficial to better understand the relationship between seed rate and plant population for specific sites as establishment is known to vary by soil type and other environmental conditions (Blake et al. 2003) so this would help to make the model site specific. The revised threshold scheme will also require experimental validation.

4.4 | A new *D. coarctata* IPM strategy

Although our current models are geographically restricted and require some additional development, we believe that our models represent a stepping-stone towards a future IPM strategy for sustainable *D. coarctata* control. In Fig. 9 we outline a potential *D. coarctata* IPM scenario based on the pest level prediction model, the revised threshold level, and the shoot number prediction model. We believe that this strategy would facilitate non-chemical risk-based control of *D. coarctata* and would comprise the following steps:

1. A seasonal estimation of *D. coarctata* risk per region to advise on the potential level of control required and to enable targeted soil sampling in high-risk regions;
2. Use of the revised thresholds to compare predicted *D. coarctata* risk with the minimum number of shoots required to tolerate pest damage while obtaining a viable crop yield;
3. Utilisation of the shoot number prediction model to estimate the number of shoots that will be produced for the planned sowing date and sowing rate;
4. Subtraction of the estimated number of shoots required to achieve *D. coarctata* tolerance at the predicted level of *D. coarctata* risk from the estimated number of shoots expected with the planned agronomic practice: A positive value indicates that *D. coarctata* damage can be tolerated naturally, a negative value indicates that additional crop protection or risk-mitigation steps are required, e.g. earlier drilling, higher seed rate, seed treatment (if sown late);

5. The shoot number prediction model can then be used to estimate the minimum plant population required to achieve the minimum shoot number for a given sowing date, or the latest sowing date that could be achieved for a given target plant population.

This prescriptive pest management scheme will provide a framework for sustainable *D. coarctata* management. Where the framework indicates that additional crop protection steps are required this could be achieved by adjusting sowing date and/or target plant population to produce a crop with sufficient shoots to tolerate the pest and still achieve potential yield. During seasons of high risk, the option of combining manipulation of sowing date and/or plant population with seed treatment could be employed for late sown crops (November onwards).

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Conflict of interest

The authors have no conflict of interests to declare

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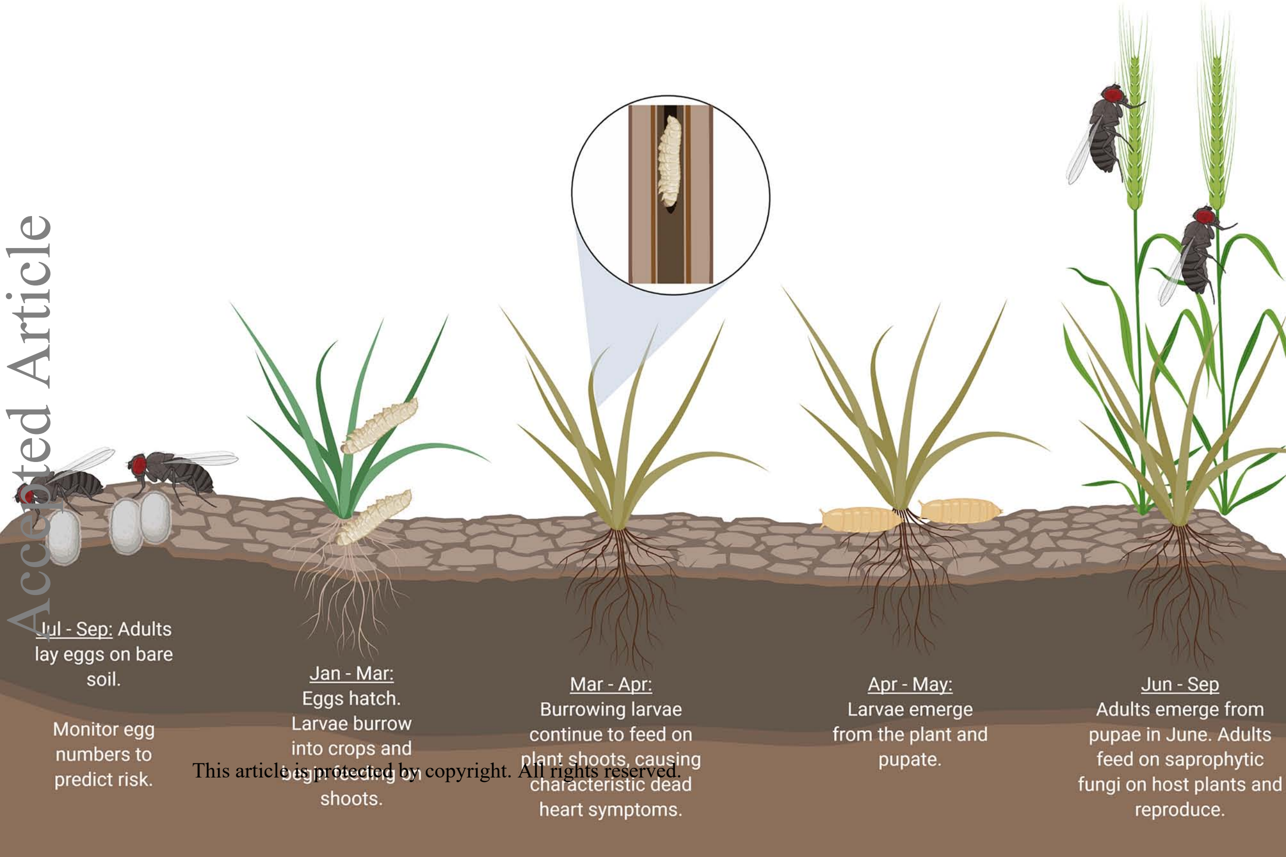


Jul - Sep: Adults lay eggs on bare soil.

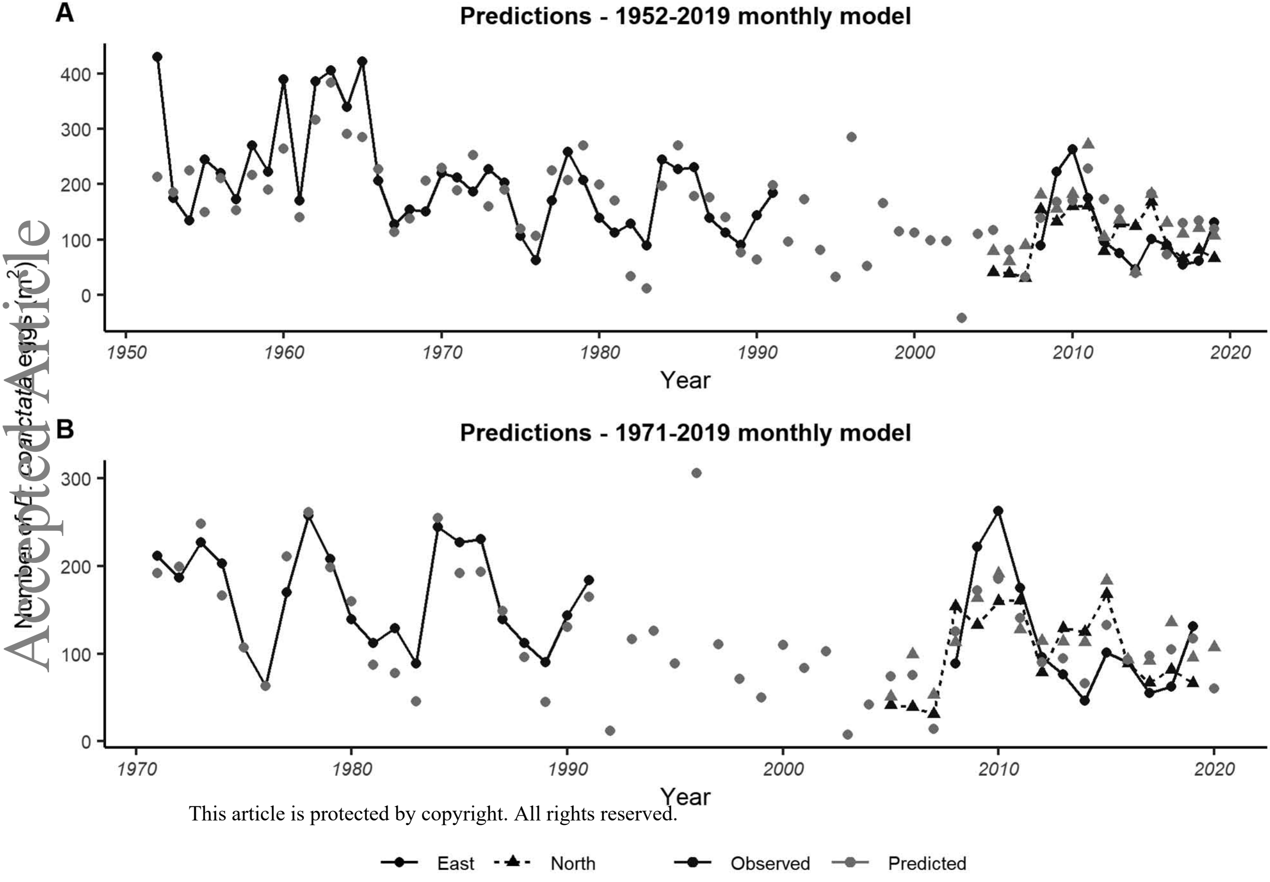
Monitor egg numbers to predict risk.

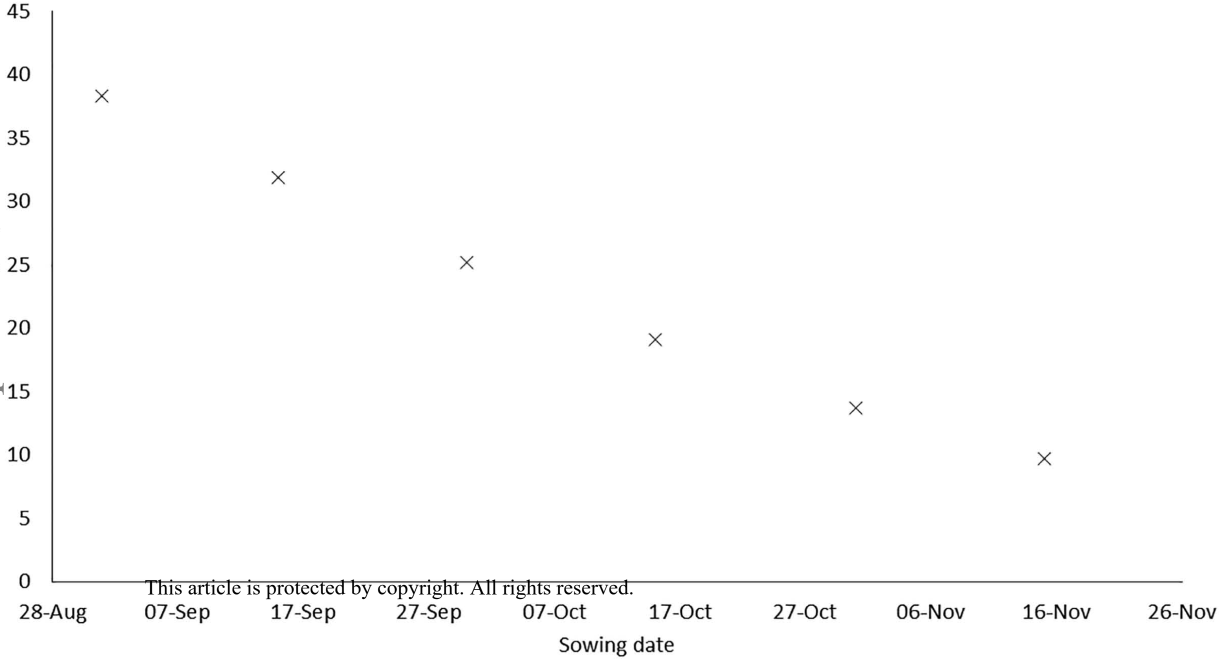
Jan - Mar:
Eggs hatch. Larvae burrow into crops and begin feeding on shoots.

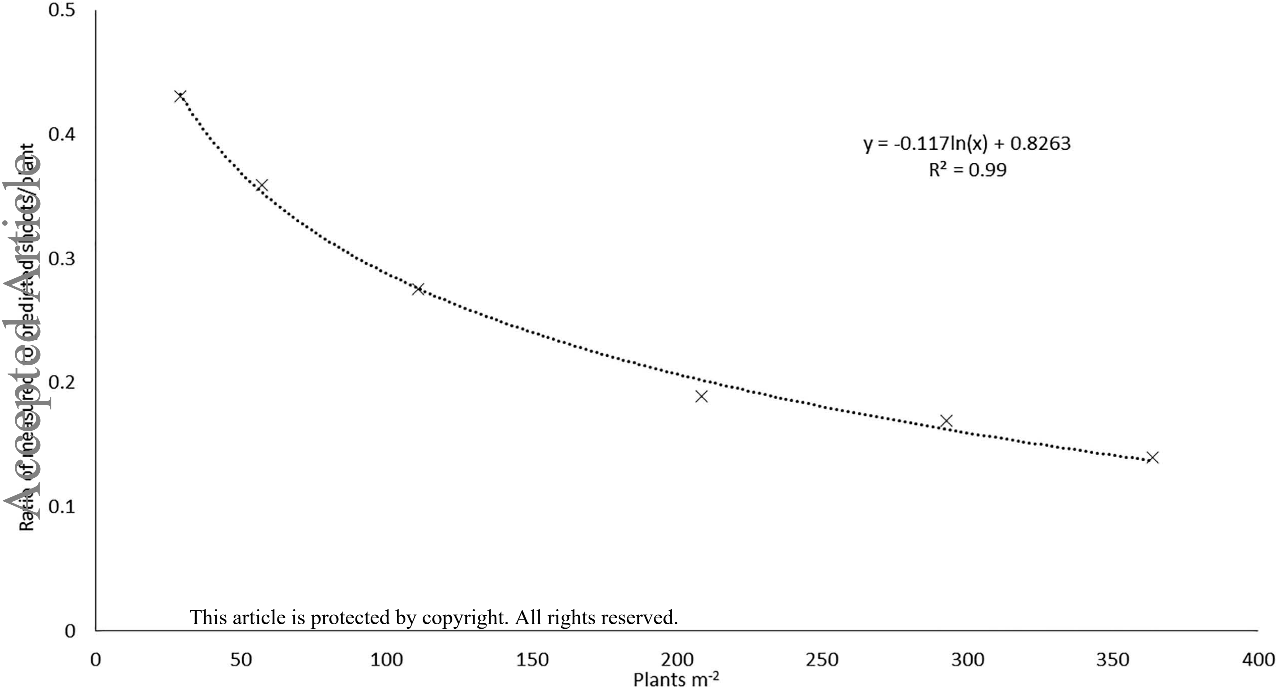
Mar - Apr:
Burrowing larvae continue to feed on plant shoots, causing characteristic dead heart symptoms.

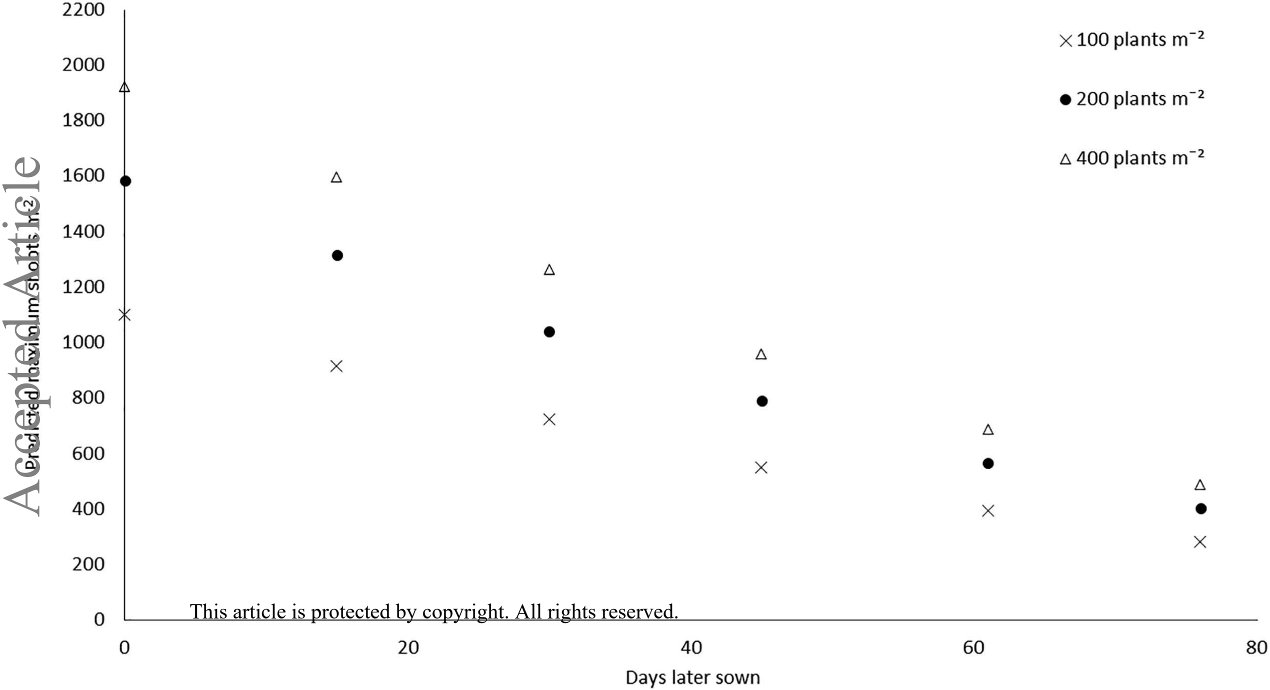
Apr - May:
Larvae emerge from the plant and pupate.

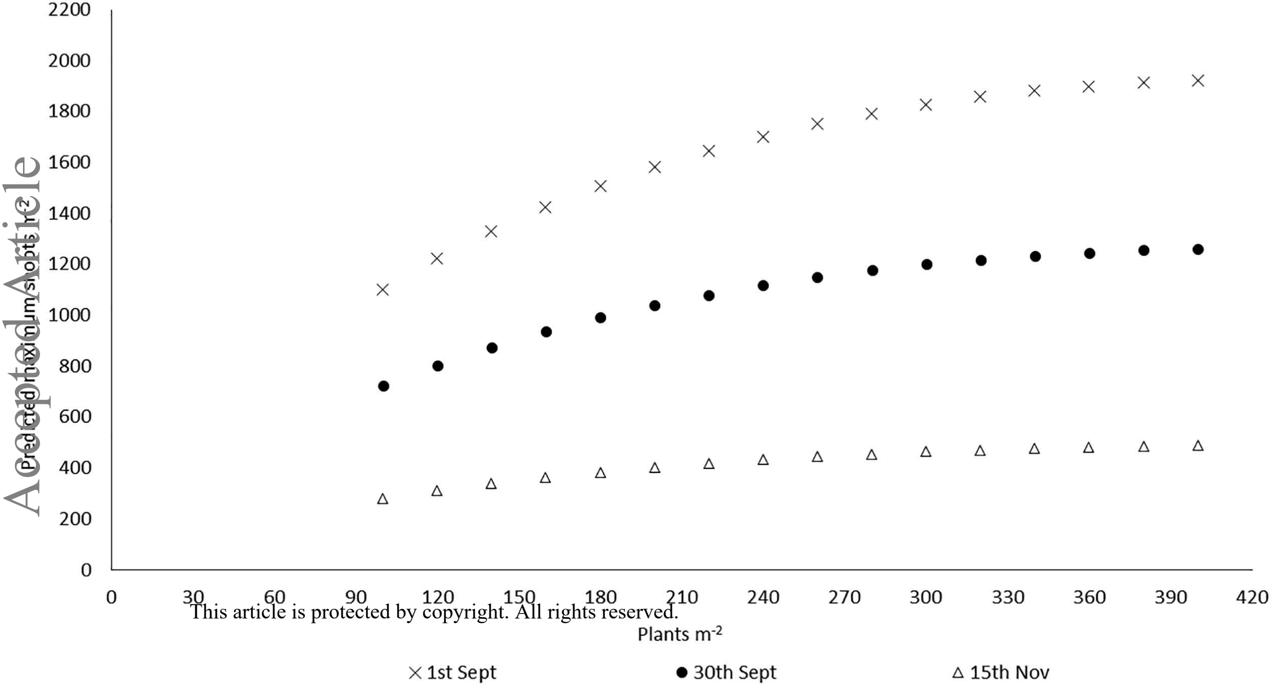
Jun - Sep
Adults emerge from pupae in June. Adults feed on saprophytic fungi on host plants and reproduce.

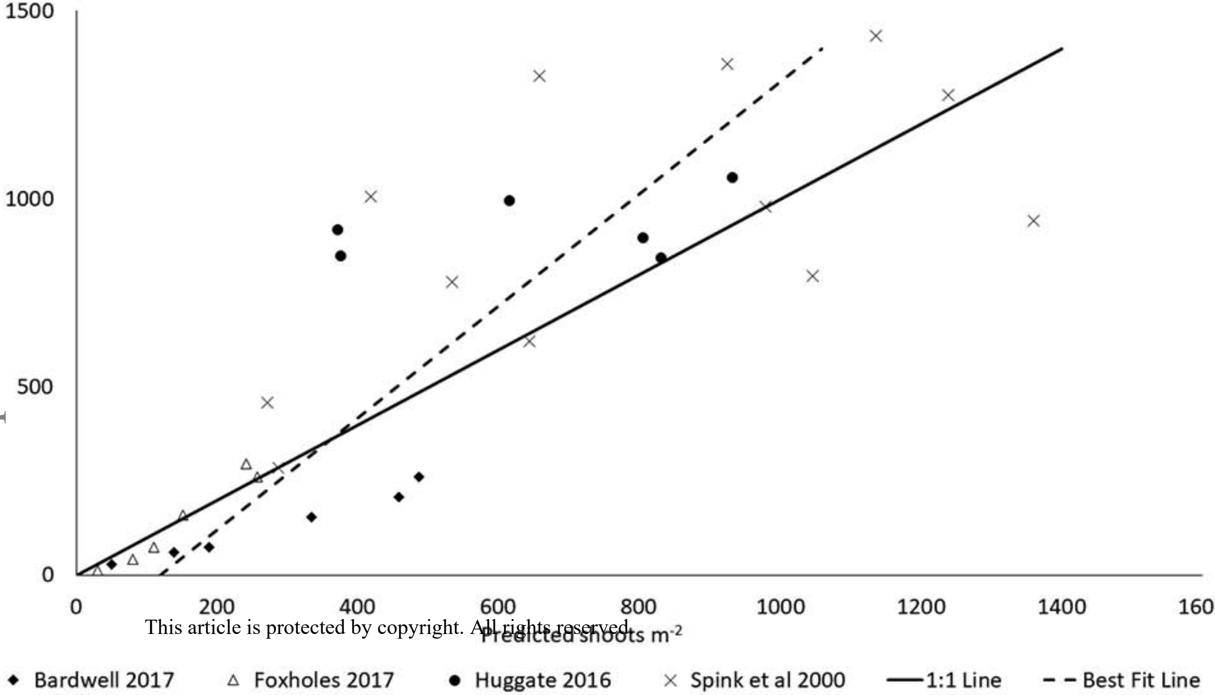

A
Predictions - 1952-2019 monthly model
400
300
200
100
0
1950
1960
1970
1980
1990
2000
2010
2020
Year
B
Predictions - 1971-2019 monthly model
300
200
100
0
1970
1980
1990
2000
2010
2020
Year
Number of F. coarctata eggs (m²)
East
North
Observed
Predicted

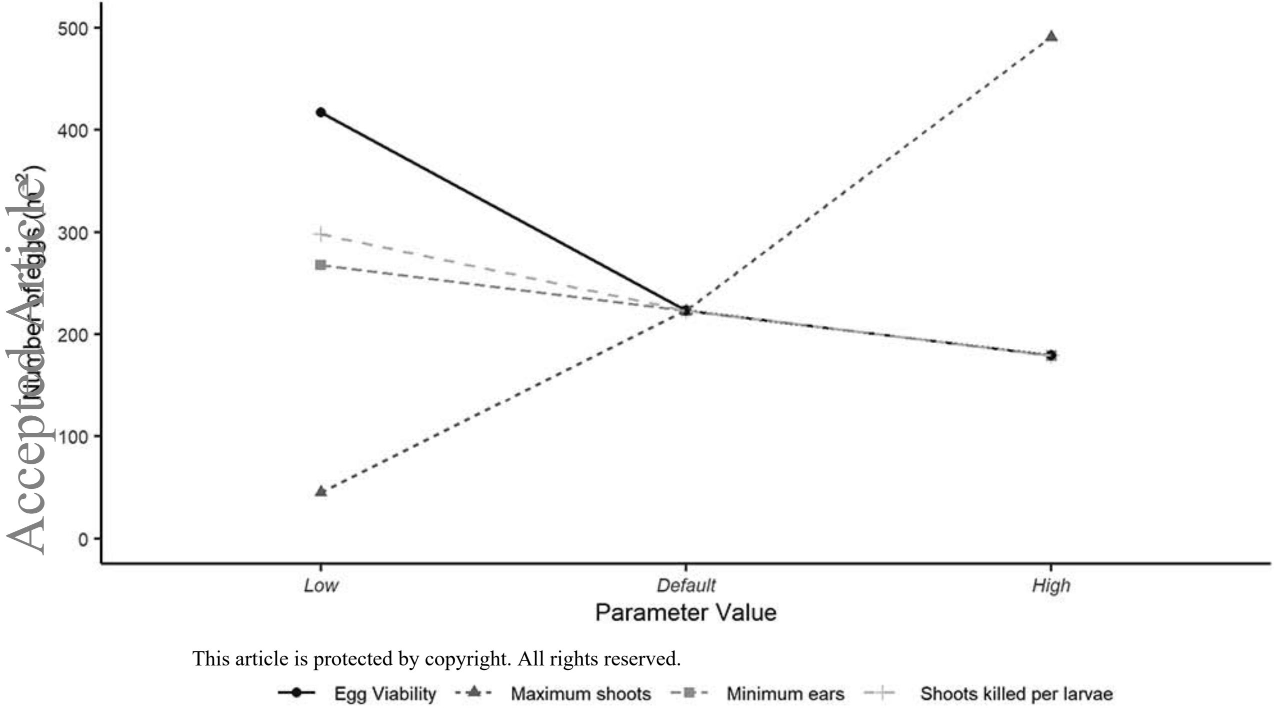

45
40
35
30
25
20
15
10
5
0
Number of shoots per plant
28-Aug
07-Sep
17-Sep
27-Sep
07-Oct
17-Oct
27-Oct
06-Nov
16-Nov
26-Nov
Sowing date

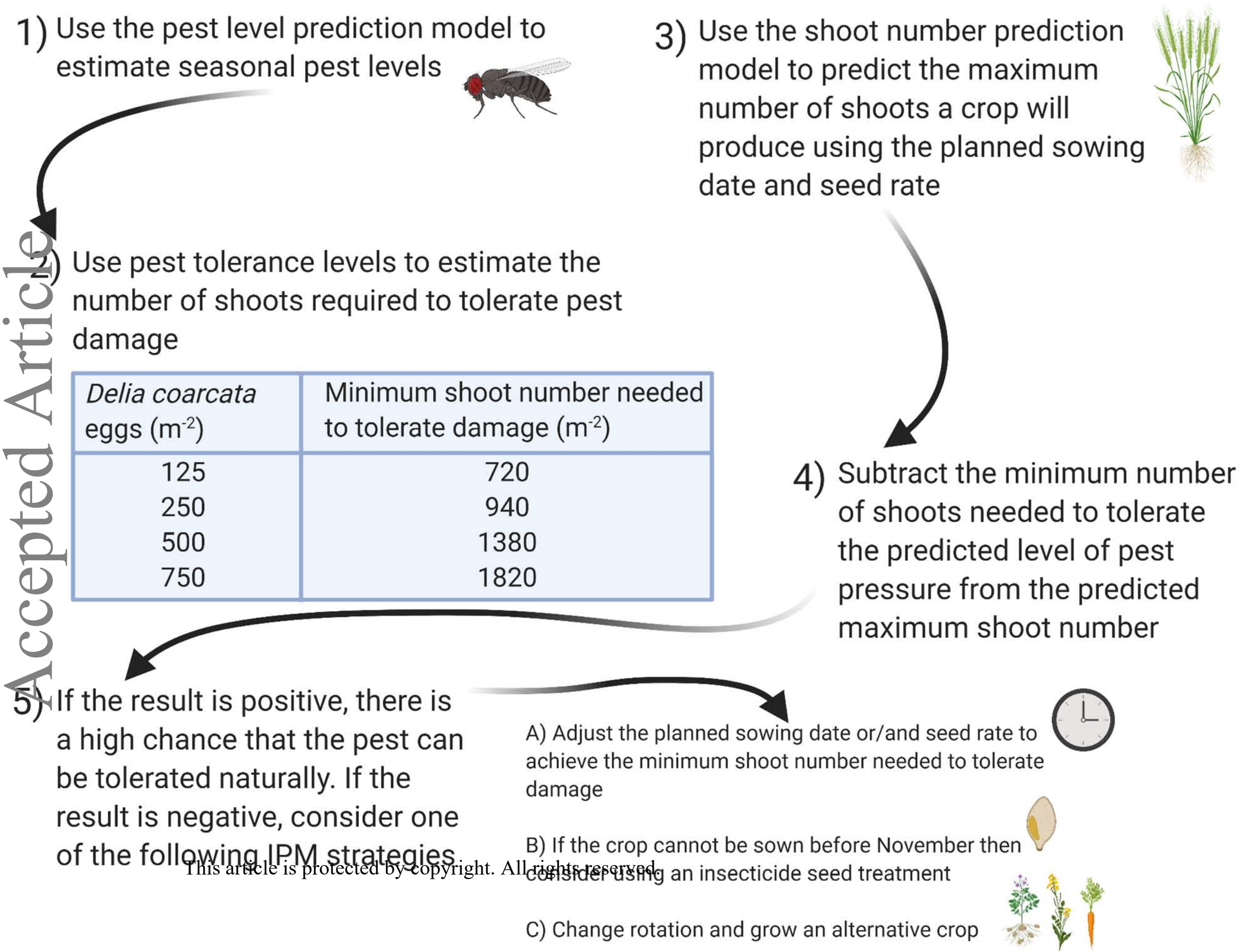

0.5
0.4
0.3
0.2
0.1
0
Ratio of measured to predicted shoots/plant
y = -0.117ln(x) + 0.8263
R² = 0.99
0
50
100
150
200
250
300
350
400
Plants m-2


Predicted maximum shoots m-2
0
200
400
600
800
1000
1200
1400
1600
1800
2000
2200
0
20
40
60
80
Days later sown
× 100 plants m⁻²
● 200 plants m⁻²
△ 400 plants m⁻²


Predicted maximum shoots m-2
2200
2000
1800
1600
1400
1200
1000
800
600
400
200
0
0
30
60
90
120
150
180
210
240
270
300
330
360
390
420
Plants m-2
× 1st Sept
● 30th Sept
△ 15th Nov


1500
1000
500
0
Observed shoots m-2
0
200
400
600
800
1000
1200
1400
1600
Predicted shoots m-2
◆ Bardwell 2017
△ Foxholes 2017
● Huggate 2016
× Spink et al 2000
1:1 Line
Best Fit Line


Number of eggs (m⁻²)
500
400
300
200
100
0
Low
Default
High
Parameter Value
Egg Viability
Maximum shoots
Minimum ears
Shoots killed per larvae



1) Use the pest level prediction model to estimate seasonal pest levels

2) Use pest tolerance levels to estimate the number of shoots required to tolerate pest damage

Delia coarcata eggs (m^{-2})	Minimum shoot number needed to tolerate damage (m^{-2})
125	720
250	940
500	1380
750	1820

3) Use the shoot number prediction model to predict the maximum number of shoots a crop will produce using the planned sowing date and seed rate

4) Subtract the minimum number of shoots needed to tolerate the predicted level of pest pressure from the predicted maximum shoot number

5) If the result is positive, there is a high chance that the pest can be tolerated naturally. If the result is negative, consider one of the following IPM strategies

A) Adjust the planned sowing date or/and seed rate to achieve the minimum shoot number needed to tolerate damage

B) If the crop cannot be sown before November then consider using an insecticide seed treatment

C) Change rotation and grow an alternative crop

Table 1: Minimum shoot number at GS31 needed to tolerate different levels of *D. coarctata* damage

Egg count (eggs m^{-2})	Shoot number m^{-2} required to tolerate *D. coarctata* damage
125	720
250	940
500	1380
750	1820

Calculations assume 500 shoots m^{-2} is the minimum required to achieve a typical UK commercial wheat yield.