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Updating a wheat bulb fly risk prediction model

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CONTENTS

1. Abstract

Wheat bulb fly (WBF) is a significant pest of winter cereals across the eastern regions of the United Kingdom. The risk of attack can fluctuate year-on-year and is affected by a range of meteorological factors, including January and July air temperature. Chemical control of WBF is reliant on a single seed treatment Signal 300 ES (Arysta LifeScience, 300g/L cypermethrin), which is only effective in late-sown crops (November onwards). There are no sprays available for control of larvae at egg hatch or when they have invaded the plant; however, crop tolerance to WBF can be increased through earlier drilling with higher seed rates to increase shoot number. The risk of economically damaging levels of the pest needs to be estimated before the crop is drilled to determine whether a seed treatment is justified, and whether higher seed rates might be required to increase crop tolerance. Currently, the accepted economic damage thresholds for WBF are 250 eggs per m^2 for early-sown winter cereals and 100 eggs per m^2 for late-sown winter cereals (sown from November onwards). The primary method for risk determination is soil sampling, egg extraction, and egg counting. This process is labour-intensive, requires the use of bulky extraction equipment and taxonomic expertise for egg identification and can only be undertaken by a specialised laboratory. A WBF risk prediction model was developed by Young & Cochrane in 1993. This model uses January air temperature, January soil temperature, July air temperature, and rainfall during the preceding October to predict wheat bulb fly egg density, with a reported predictive power (accuracy) of 59%. In this study, the effectiveness of the Young & Cochrane model was tested by using it to predict WBF risk from 2005–19. Model predictions were then compared with the results of the 2005–19 AHDB WBF surveys. Following this, an updated risk prediction model was developed by combining the 2005–19 data with the original 1952–91 data included in the Young & Cochrane model and by incorporating a wider range of meteorological parameters. This updated model has a predictive power of 70%, an 11% increase when compared with the original Young & Cochrane model. It uses the following meteorological parameters to predict WBF risk: 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. Improving the predictive power of decision support models is likely to increase the confidence in their findings, and uptake by farmers and agronomists. This updated risk prediction model complements AHDB project report PR598 Crop management guidelines for minimising wheat yield losses from wheat bulb fly by providing an additional component to a potential IPM strategy for the pest.

2. Introduction

Wheat bulb fly (WBF), *Delia coarctata,* is a significant pest of cereals within the UK, with all cereals apart from oats susceptible to wheat bulb fly infestation. The life-cycle is illustrated in Figure 1. The life-stage that causes the most significant economic damage is the burrowing larval stage. Once hatched, the larvae infest the developing shoots of cereal crops causing the 'deadheart' symptoms of yellow and stunted shoots. Economic damage from wheat bulb fly can vary between years, and a significant infestation can result in yield losses of 4 t ha^{-1} (Rogers et al., 2014). The larvae feed on the host plant until late spring before pupating at the base of the plant, adult WBF then emerge between June and August to feed on saprophytic fungi present on plant tissue and reproduce before migrating to oviposit on bare soil. The level of WBF risk fluctuates yearly, and previous studies have indicated that this negatively correlates with January and July temperature, and is positively correlated with the number of August rain days (Young & Cochrane, 1993). WBF risk can be affected further by the previous crop grown in the rotation and the date of harvest (Young & Cochrane, 1993). The economic damage threshold for WBF is an egg density of 2.5 million eggs/ha (equivalent to 250 eggs m^2) for early-sown crops and 1.0 million eggs/ha (equivalent to 100 eggs m^2) for late-sown crops (Gough *et al.*, 1961; Ramsden *et al.*, 2017).

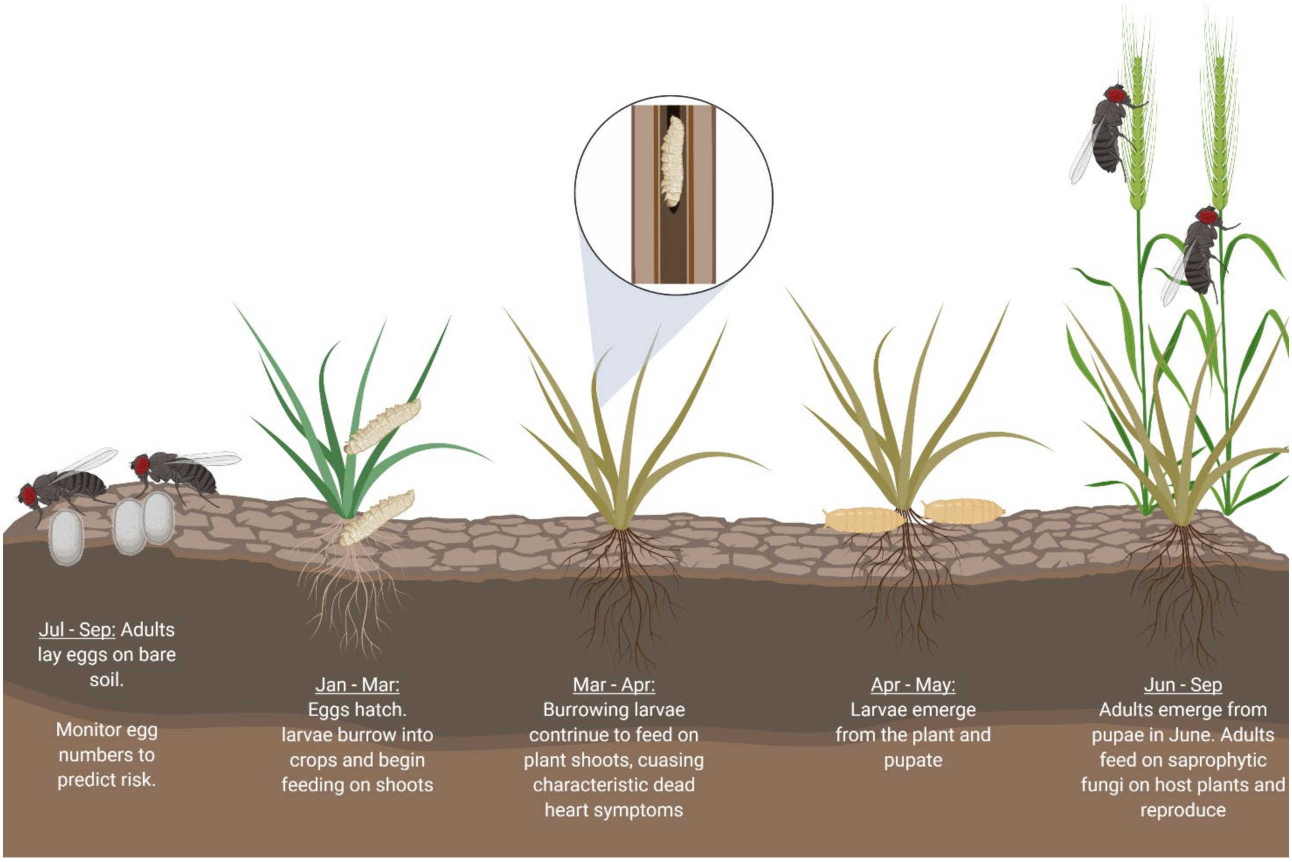

Figure 1: Illustrative example of the annual life cycle of the wheat bulb fly (image created in BioRender©)

The resources available for WBF control are very limited. Chemical control in the UK is restricted to a single seed treatment (Signal 300ES, Arysta LifeScience, 300 g/L cypermerthrin); however, this is only effective for late sown crops (November onwards) as if used with earlier drilling it is not sufficiently persistent to still be active at the time of WBF egg hatch (late January/early February). Also, a limited knowledge of the biology and phenology of the pest limits the extent to which alternative pest management programmes can be devised and implemented. Resistance against WBF has been detected in the wild relatives of commercially grown cereals (Aradottir *et al*., 2017), however these resistance traits have yet to be identified and used in breeding programmes. Natural enemies of WBF have been described for most of its life stages. Various carabid beetles feed on the eggs (Jones, 1975) and entomopathogenic fungi infect the adults (Wilding & Lauckner, 1974). WBF pupae appear to be the life-stage at highest risk of predation and parasitism, with numerous natural enemy species recorded (Ryan, 1975; Roloff & Wetzel, 1989). Despite numerous natural enemies, exposure to predation and parasitism has not been shown to lead to a significant decrease in larval survival (Ryan 1973; Jones 1975). Cultural control options have also been described (Glen, 2000). Those that can influence WBF risk are drilling date and sowing density, with late drilling (from November onwards) leading to increased WBF risk and sowing at higher seed rates increasing crop tolerance to WBF (Storer *et al.*, 2018). The primary chemical control method for WBF is a seed treatment, and an effective cultural control option is to produce a crop sufficiently robust to withstand pest attack by increasing seed rate. Both these options require an effective means of determing risk before drilling and this can be provided by the model described in this project.

WBF risk is routinely determined by soil sampling, egg extraction, and egg counting. This process is time-intensive, the assessment of one sample can take up to three hours (Ramsden, *et al*., 2017), and requires a suite of bulky technical equipment (Salt & Hollick, 1944), only available in specialist analytical laboratories. Technicians also need to be skilled in picking off and identifying WBF eggs from the range of material extracted. Alternative risk determination methods have been trialled. These have included in-field light trapping (Bowden & Jones, 1979) in-field water trapping of migrating females (Cooper, 1981), and the use of oviposition trays to reduce the volume of soil that needs to be extracted using standard methology (Oakley & Uncles, 1977), all of these methods showed a linear relationship with egg surveys but have not been developed further. One of the most efficient alternative means of predicting WBF risk is through predictive modelling (Young & Cochrane, 1993). The Young & Cochrane WBF risk prediction model is based on egg counts for East Anglia, UK undertaken between 1952 – 1991 (Young & Cochrane, 1993). It predicts WBF egg density using the departure from long-term average for rainfall during October of the preceding year, January air temperature, January soil temperature, and July air temperature. The model parameters used in the Young & Cochrane model were selected based on the hypothesis that these meteorological parameters will most likely influence the reproductive development and oviposition of the emerging WBF generation (departures from long-term average for mean temperature, rainfall, the number of rain days, and sunshine hours for June, July, and August) and factors that will likely influence the establishment and growth of the cereal crop and therefore the survival of the preceding WBF generation (departure from long-term average for mean temperature, 30 cm soil temperature, rainfall, and sunshine hours for the previous September – January). Model simplification indicated that departure from long-term average for rainfall during October of the preceding year, January air temperature, January soil temperature, and July air temperature are the most important meteorological factors included that predict WBF egg density.

The primary aim of this research project was to examine how effective the Young & Cochrane model is at predicting WBF egg density from 1992 – 2019. Following this, various avenues for improving the Young & Cochrane model were explored. This involved refining the meteorological parameters included in the model on a seasonal basis in order to identify which time periods (during the preceding autumn, winter, spring, summer) and meteorological parameters (minimum, mean, and maximum air temperature, rain day, rainfall, sunshine days, air frost days) are the most important in influencing WBF egg density, and therefore WBF risk. Seasonal models were refined further on a monthly basis. From these models, WBF egg density was predicted for all years and compared against observed data for 1952 – 1991 and 2005 – 2019. A secondary aim of the project was to explore the datasets to determine how agronomic factors (previous crop and soil type) can influence WBF egg density.

3. Materials and methods

3.1. Sources of WBF egg density and meteorological data

WBF egg density data were extracted from two data sources. Historic data from East Anglia (1952 – 1991) were extracted from Young & Cochrane (1993). The second data source comprised regional ADAS WBF surveys from Northern England (2005 – 2019) and East Anglia (2008 – 2019). Meteorological data were extracted for each region from UK meteorological office data (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 (ml), sunshine days, and air frost days. From the extracted data, the deviation from the long-term average was calculated. Long-term averages of 30-years were used, the only deviation for this was for air frost where reporting did not commence until 1960. The UK meteorological office categorises seasons into: winter (preceding December – February), spring (March – May), summer (June – August), autumn (September – November). For each year, the meteorological data included in the model were the previous autumn, current winter, 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 rainfall (ml). The number of air frost days was included for the winter, spring, and preceding autumn seasons only.

3.2. Modelling approach

All data modelling was carried out in R v.3.6.1 with 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. At each simplification stage analysis of variance was done to ensure model simplification was justified and did not significantly affect model structure. Model residuals were observed at each stage.

3.2.1. Using the Young & Cochrane model to predict WBF risk from 2005–2019

The meteorological factors used in the Young & Cochrane model were selected based on the hypothesis that these factors are most likely to affect WBF biology at specific life-stages (Young & Cochrane, 1993). They included the rainfall during the preceding October, January air temperature, January soil temperature, and July air temperature. A linear regression model was developed, and these parameters (apart from January soil temperature) were used to predict WBF egg density for 2005 – 2019.

3.2.2. Updating the Young & Cochrane model: Developing the seasonal and monthly 1952–2019 models

In order to build a model which better predicts WBF egg density, and therefore WBF risk, a range of meteorological factors were extracted and used to develop an updated Young & Cochrane model. A linear regression model was developed using the following meteorological factors on a seasonal basis: minimum air temperature, mean air temperature, maximum air temperature, rain days, rainfall, and sun days. Backward stepwise model selection was used to arrive at a final model and this model was used to predict WBF density for all years. This seasonal model was refined by expanding model parameters from a seasonal basis to a monthly basis for each significant meteorological parameter (i.e. winter minimum air temperature was determined as a significant parameter in the seasonal model, so the minimum air temperature for preceding December, January, and February were included in the initial monthly model). The monthly model was simplified through backward stepwise model selection and the final model was used to predict WBF egg density with model predictions visualised against observed data. Correlations between WBF egg density and the final parameters in both models were carried out using Pearson's product-moment correlations.

3.2.3. Updating the Young & Cochrane model: Incorporating air frost and developing the seasonal and monthly 1971–2019 models

In order to allow air frost to be included in the updated Young & Cochrane models a subdataset was developed. This comprised all observations from 1971 – 2019, the removal of data from 1952 – 1960 was required as air frost was not reported until 1960, and therefore preceding autumn air frost data was not available until 1961. Furthermore, data from 1961 – 1970 were removed in order to enable deviation from long-term average to be calculated on at least a ten-year average. Seasonal models were developed and simplified as described above and the final model was used to predict WBF egg densities. A further monthly model was developed from the final seasonal model and simplified through backward stepwise model selection. The final monthly model was used to predict WBF egg density and predictions were compared against observed values. Correlations between egg density and the final parameters in both models were carried out using Pearson's product-moment correlations.

The final monthly model was validated using two validation methods. For method one, validation was done by removing four five-year periods from the dataset, rerunning the model, and observing how these predictions compared with the full model (similar to the validation method employed by Young & Cochrane, 1993). Data were removed from the first five years (validation 1: years 1971 – 1975 removed), the last five years (validation 2: years 2015 – 2019), the five years with the highest recorded WBF density (validation 3: years 1978, 1984, 1985, 1986, 2010), and the five years with the lowest recorded WBF density (validation 4: years, 2005, 2006, 2007, 2014, 2017). For method two, validation was done by randomly removing five years from the dataset (1971 – 1991; 2005 – 2019) and rerunning the model, this was done four times (validations 5 – 8) and the effect of these removals on model predictions was observed.

3.2.4. Developing an improved WBF prediction model: Using 2005–2019 regional data

A final series of models were developed using the 2005 – 2019 WBF egg density data. Seasonal models were developed and simplified as described above and the final model was used to predict WBF egg densities. A further monthly model was developed from the final seasonal model and simplified through backward stepwise model selection. The final monthly model was used to predict WBF egg density and predictions were compared against observed values. The final monthly model was validated following the same methodology described above. For method one, four five-year periods were removed from the dataset, the model was rerun, and the predictions made from the validation models were compared with the predictions of the full model. Data were removed from the first five years (validation 1: years 2005 – 2009 removed), the last five years (validation 2: years 2015 – 2019), the five years with the highest recorded WBF density (validation 3: years 2008, 2009, 2010, 2011, 2019), and the five years with the lowest recorded WBF density (validation 4: years, 2005, 2006, 2007, 2014, 2017). For method two, validation was done by randomly removing five years from the dataset and rerunning the model, this was carried out four times (validation 5 – 8) and the effect of these removals on model predictions was observed.

3.3. Identifying agronomic factors that influence WBF risk

Within the 2005 - 2019 dataset various agronomic factors were reported alongside WBF egg density. The two most frequently reported agronomic factors were the previous crop in the rotation and soil type. To identify whether either of these two factors influence WBF egg density, and therefore impact on WBF risk, a linear mixed effects model was used to examine whether egg density (eggs m^2) is influenced by the previous crop (categorised into seven categories: cereals & oilseeds, fallow, peas & beans, beets, leeks & onions, and potatoes) or soil type (categorised into seven categories: clay, fen, light, loam, mineral, organic, and silt). Variation between the different monitoring years was accounted for by including year in the model as a random factor. Statistical models were analysed for significance using a Type II Wald χ^2 analysis of deviance tests with *post-hoc* analysis done using estimated marginal means with Tukey adjustments for multiple comparisons. Statistical analysis was carried out in R v.3.6.1 with additional packages car v.3.0-3 (Fox & Weisberg, 2016) lme4 v.1.1-21 (Bates *et al*., 2015) and emmeans v.1.4.1.

4. Results

4.1. Using the reduced Young & Cochrane model to predict WBF egg abundance from 2005–2019

The linear regression model developed by Young & Cochrane predicts WBF egg density based on departure from long-term average mean July temperature, departure from long-term average for preceding October rainfall, departure from long-term average mean January temperature, and departure from long-term average mean January soil temperature. A reduced Young & Cochrane model (incorporating departure from long-term average for January mean air temperature, July air temperature, and preceding October rainfall) was used to predict WBF egg density from 2005 – 2019, with model predictions compared with observations (Figure 2). Generally, this predictive model over-estimated WBF egg counts made in 2005 – 2019, although the model still predicted seasonal fluctuations.

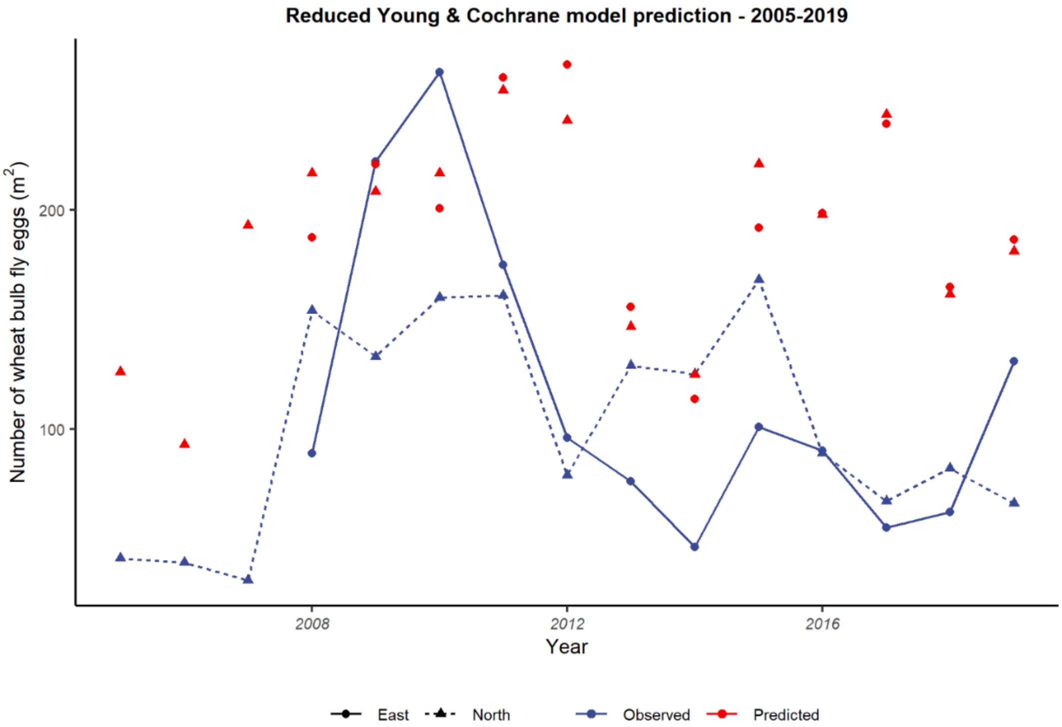

Figure 2: Predicted and observed WBF egg density for 2005 – 2019 for north (triangle; dashed line) and east (circle; solid line) regions. Predictions based on the reduced Young & Cochrane model (red) are plotted alongside the mean observed value per region per year (blue). For clarity, trendlines are included for the observed values only.

4.2. Updating the Young & Cochrane model

The Young & Cochrane model was parameterised using a hypothesis-driven approach, with the meteorological factors included in the model selected on the hypothesis that these factors will influence the phenology and biology of WBF (Young & Cochrane, 1993). To update the Young & Cochrane model, open-access meteorological data (published by the UK Meteorological Office) were extracted on a seasonal and monthly basis and incorporated into two linear models. This allowed model development to include a wider range of meteorological parameters. To identify which seasonal meteorological parameters are most important in determining WBF egg density an initial model was developed on a seasonal basis. This model (1952 – 2019 seasonal model; Figure 3) 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 affecting WBF egg abundance on a seasonal basis (adjusted $R^2 = 0.49$; $F_{6,60} = 11.54$; p = <0.001). The seasonal meteorological parameters listed above were used as inputs for the predictive model. Model predictions versus observations for the seasonal 1952 – 2019 model, including model predictions for 1992 – 2004, are displayed in Figure 3.

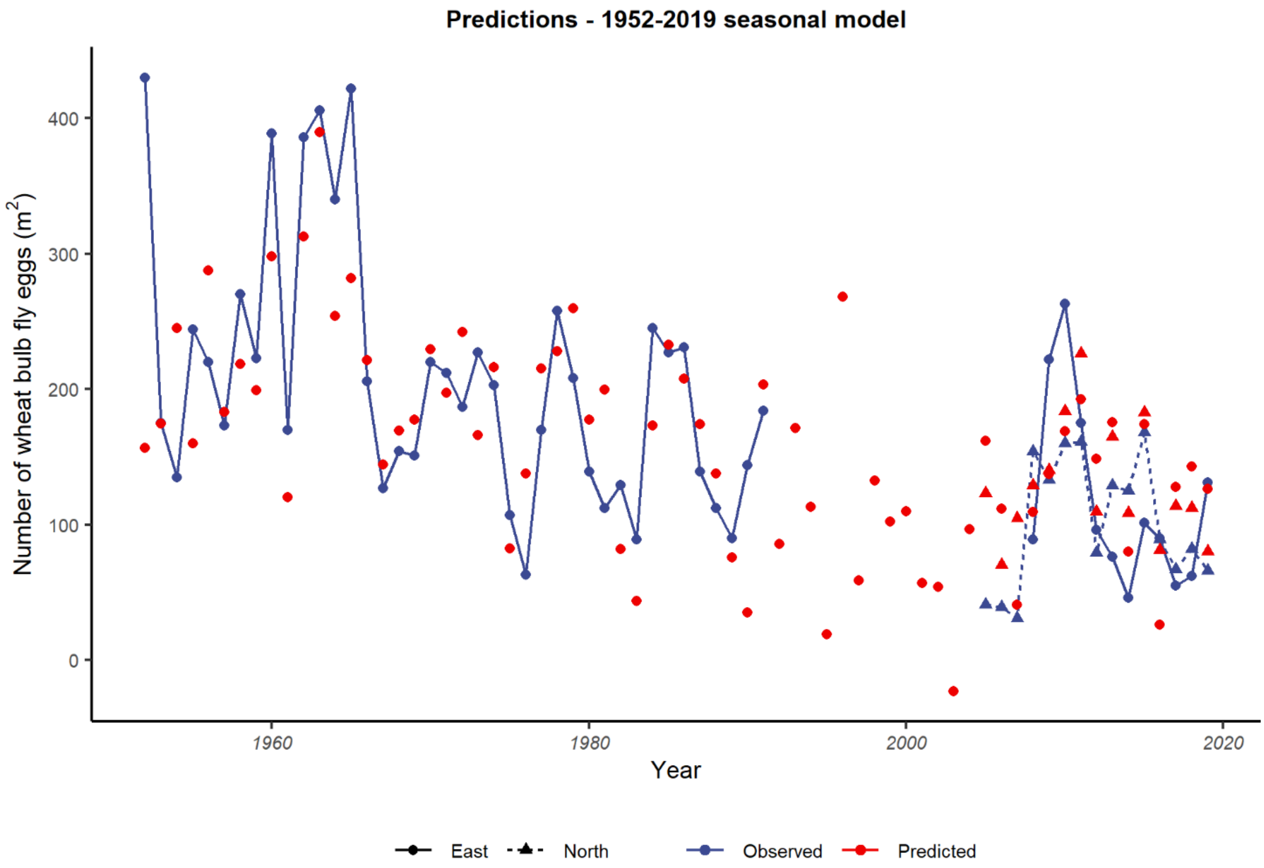

Figure 3: Predicted and observed WBF egg density for 1952 – 2019 for north (triangle; dashed line) and east (circle; solid line) regions. Predictions based on the seasonal 1952 – 2019 model (red) are plotted alongside the mean observed value per region per year (blue). Model predictions are included for years 1992 – 2004. For clarity, trendlines are included for the observed values only.

Correlations between these seasonal meteorological parameters and the observed WBF egg density data are: preceding autumn rain days ($t = -1.83$; $p = 0.071$; $r = -0.22$; Figure 4A), the minimum winter temperature ($t = -3.80$;$p = <0.001$; $r = -0.43$; Figure 4B), spring mean temperature ($t = -1.95$; $p = 0.055$; $r = -0.24$; Figure 4C, spring maximum temperature ($t = -2.26$; $p = 0.027$; $r = -0.27$; Fig. 4D), spring rainfall ($t = -0.56$; $p = 0.578$; $r = -0.07$; Figure 4E), and summer minimum temperature ($t = -5.45$; $p = <0.001$; $r = -0.56$; Figure 4F).

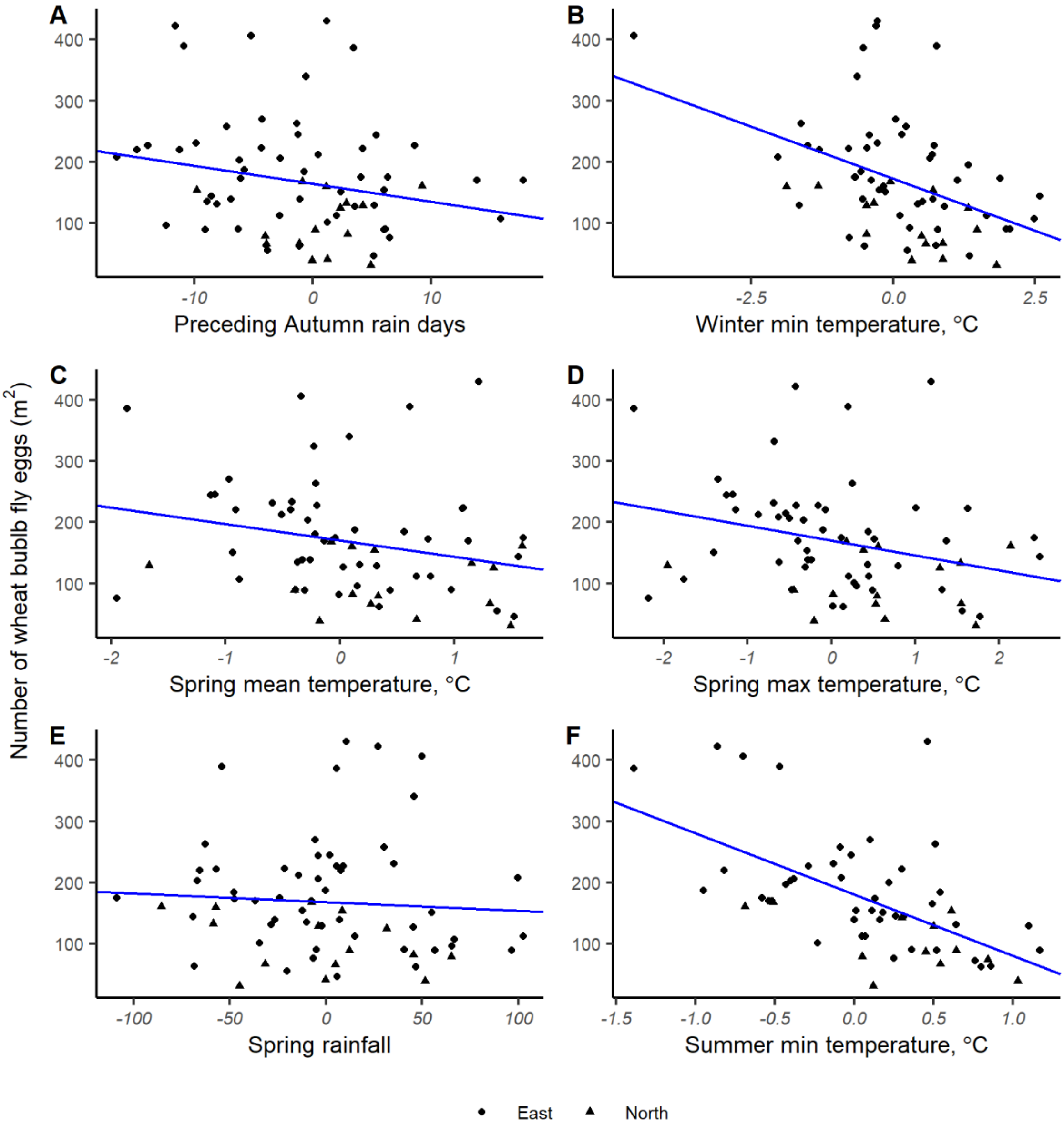

Figure 4: Correlations between WBF egg density (eggs m^2) and departure from long-term average for meteorological parameters included in the seasonal 1952 – 2019 model.

In order to identify the months which influence WBF egg abundance the meteorological parameters included in the seasonal 1952 – 2019 model were assessed on a monthly basis for the highlighted seasons: preceding September – preceding November for preceding autumn months, preceding December – February for winter months, and June – August for summer months. Linear regression modelling indicated that the most important monthly meteorological parameters for predicting WBF density 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 = <0.001; adjusted R^2 = 0.49). The monthly meteorological parameters listed above were used as inputs for the predictive model. The predictions of this model, compared with the observed values, are shown in Figure 5.

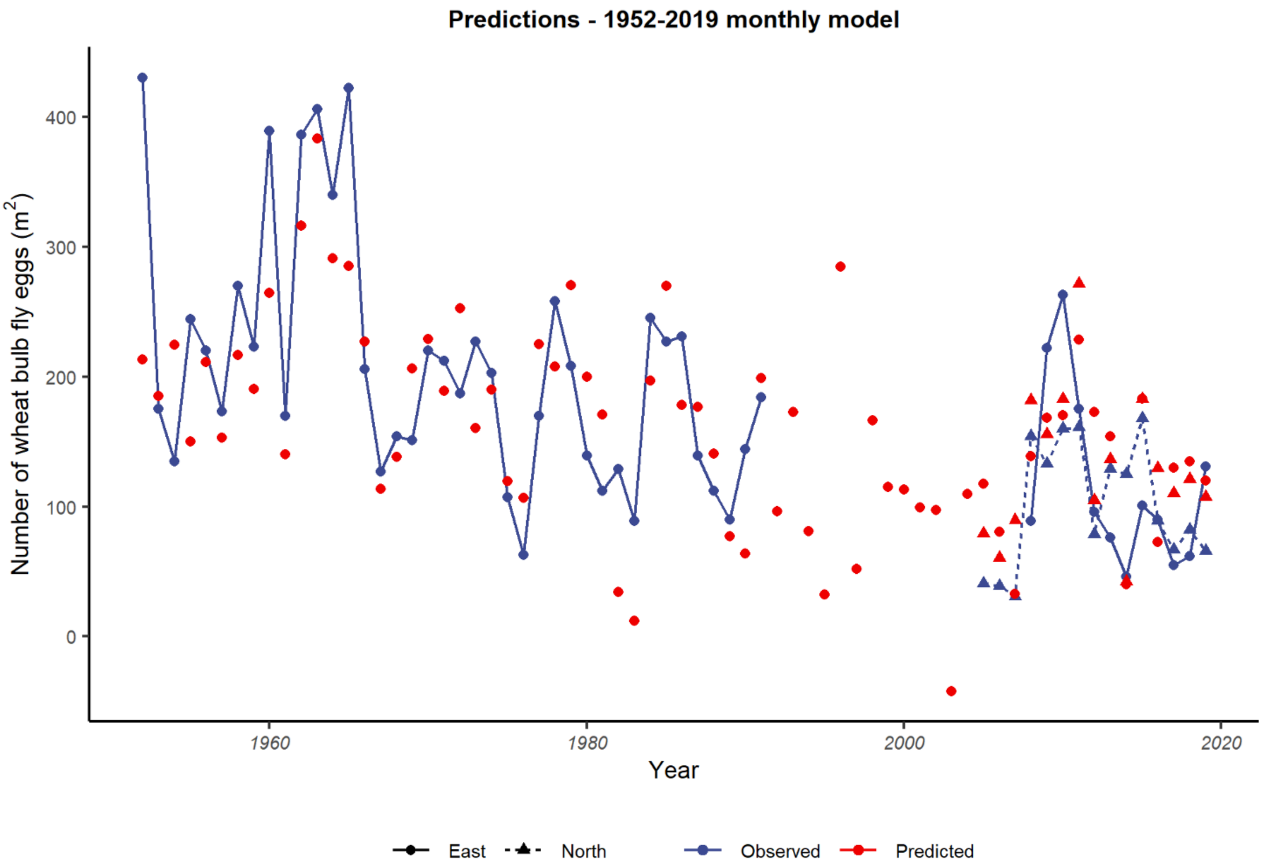

Figure 5: Predicted and observed WBF egg density for 1952 – 2019 for north (triangle; dashed line) and east (circle; solid line) regions. Predictions based on the monthly 1952 – 2019 model (red) are plotted alongside the mean observed value per region per year (blue). Model predictions are included for years 1992 – 2004. For clarity, trendlines are included for the observed values only.

Correlations between these monthly meteorological parameters and the observed wheat bulb fly egg density data are: preceding October rain day ($t = -2.42$; $p = 0.018$; $r = -0.29$; Figure 6A), preceding December minimum temperature ($t = -2.07$; $p = 0.043$; $r = -0.25$; Figure 6B), January minimum temperature ($t = -3.31$; $p = 0.002$; $r = 10.38$; Figure 6C), March mean temperature ($t = -1.82$; $P = 0.073$; $r = -0.22$; Figure 6D), May mean temperature ($t = -0.82$; $P = 0.418$; $r = -0.10$; Figure 6E), March maximum temperature ($t = -1.96$; $p = 0.056$; $r = -0.23$; Figure 6F), May maximum temperature ($t = -1.02$; $p = 0.311$; $r = -0.13$; Figure 6G), May rainfall ($t = -0.41$; $p = 0.116$; $r = -0.19$; Figure 6H), June minimum temperature ($t = 2.81$; $p = 0.006$; $r = -0.33$; Figure 6I), July minimum temperature ($t = -4.34$; $p = <0.0001$; $r = -0.47$; Figure 6J), and August minimum temperature ($t = -2.65$; $p = 0.010$; $r = -0.31$; Figure 6K).

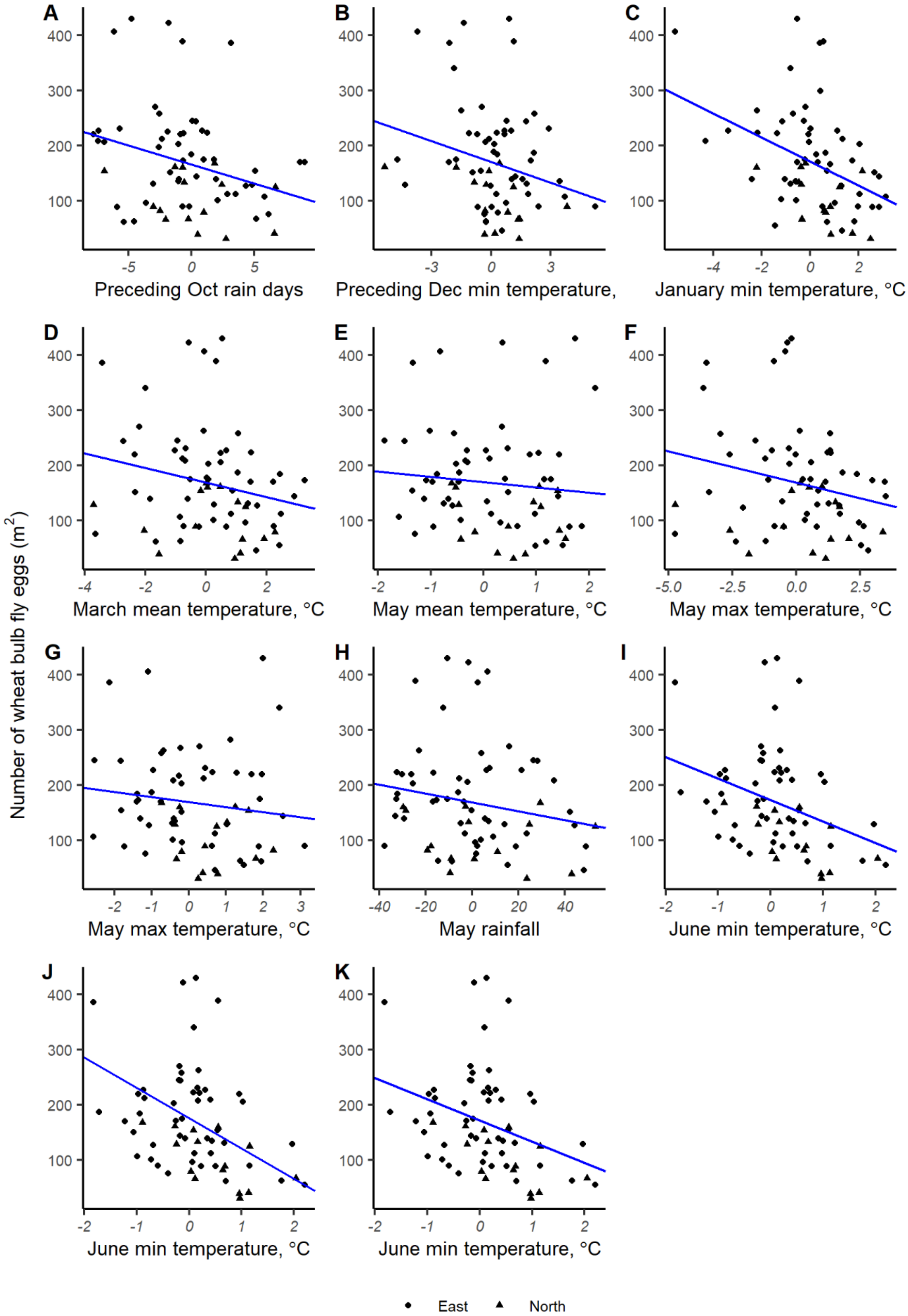

Figure 6: Correlations between WBF egg density (eggs m^2) and departure from long-term average for meteorological parameters included in the monthly 1952 – 2019 model.

4.3. Introducing air frost into predictive models increases predictive power

One key factor that might influence WBF egg density is air frost. The UK meteorological office began long-term monitoring of air frost in 1960. In order to incorporate air frost into the data models WBF egg abundance data from 1971 – 2019 were used, allowing at least 10-years of data to be included in the departure from long-term average calculations. A seasonal model was produced, comprising all meteorological parameters listed above as well as the departure from long-term average for the 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 (adjusted R^2 = 0.59, $F_{9,38}$ = 842; p = <0.001) and comprised departure for 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 seasonal meteorological parameters listed above were used as inputs for the predictive model. The predictions of this model, compared with the observed values, are shown in Figure 7.

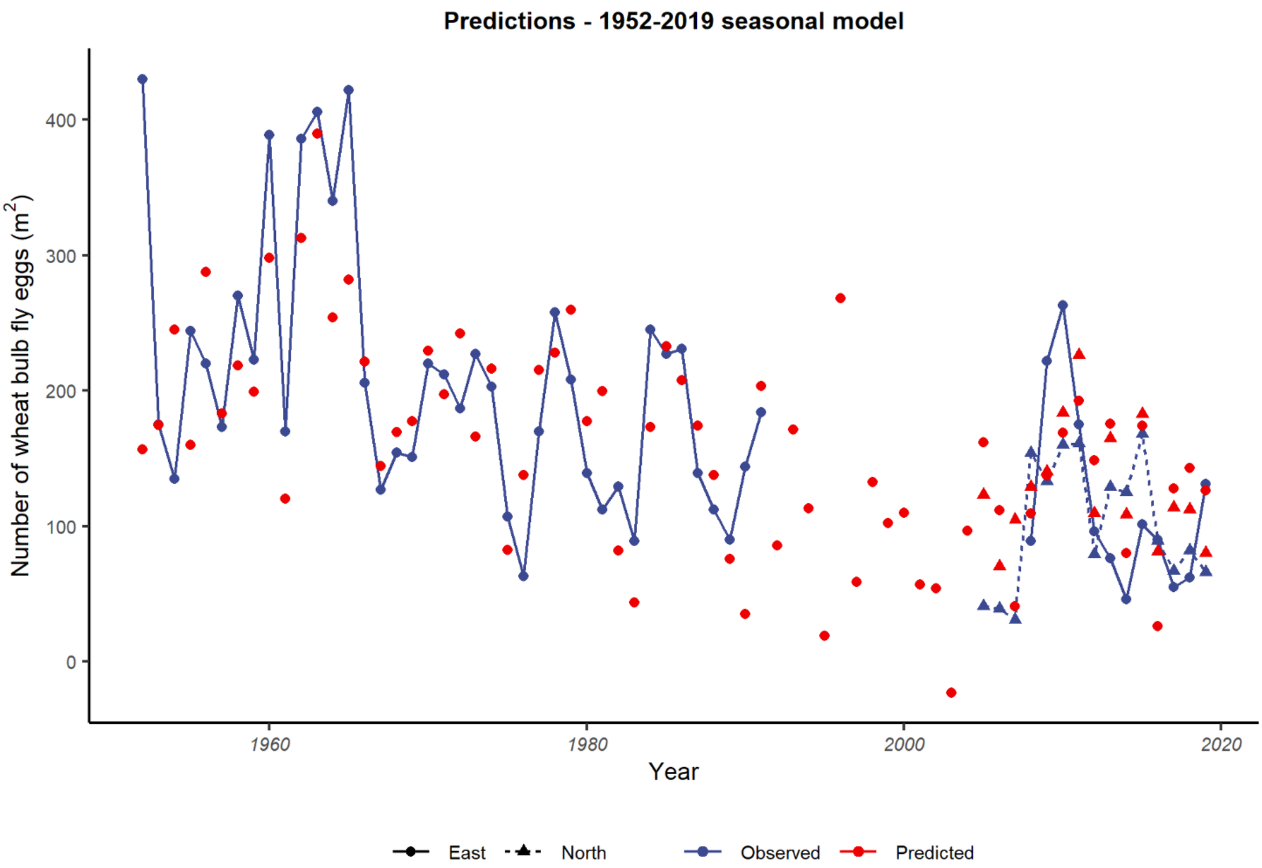

Fig. 7: Predicted and observed WBF egg density for 1971 – 2019 for north (triangle; dashed line) and east (circle; solid line) regions. Predictions based on the seasonal 1971 – 2019 model (red) are plotted alongside the mean observed value per region per year (blue). Model predictions are included for years 1992 – 2004. For clarity, trendlines are included for the observed values only.

Correlations between these seasonal meteorological parameters and the observed WBF egg density data are: preceding autumn rain days (t = -1.34; p = 0.188; r = -0.19; Figure 8A), preceding Autumn sun days (t = -0.97; p = 0.339; r = -0.14; Figure 8B), winter mean temperature (t = -3.17; p = 0.002; r = -0.42; Figure 8C), winter air frost days (t = 2.12; p = 0.039; r = 0.30; Figure 8D), spring maximum temperature (t = -1.41; p = 0.167; r = -0.20; Figure 8E), spring rainfall (t = -1.44; p = 0.156; r = -0.21; Figure 8F), summer minimum temperature (t = -4.18; p = <0.001; r = -0.52; Figure 8G), summer mean temperature (t = -3.51; p = 0.001; r = -0.46; Fig 8H), and Summer maximum temperature (t = -2.86; p = 0.006; r = -0.39; Figure8I).

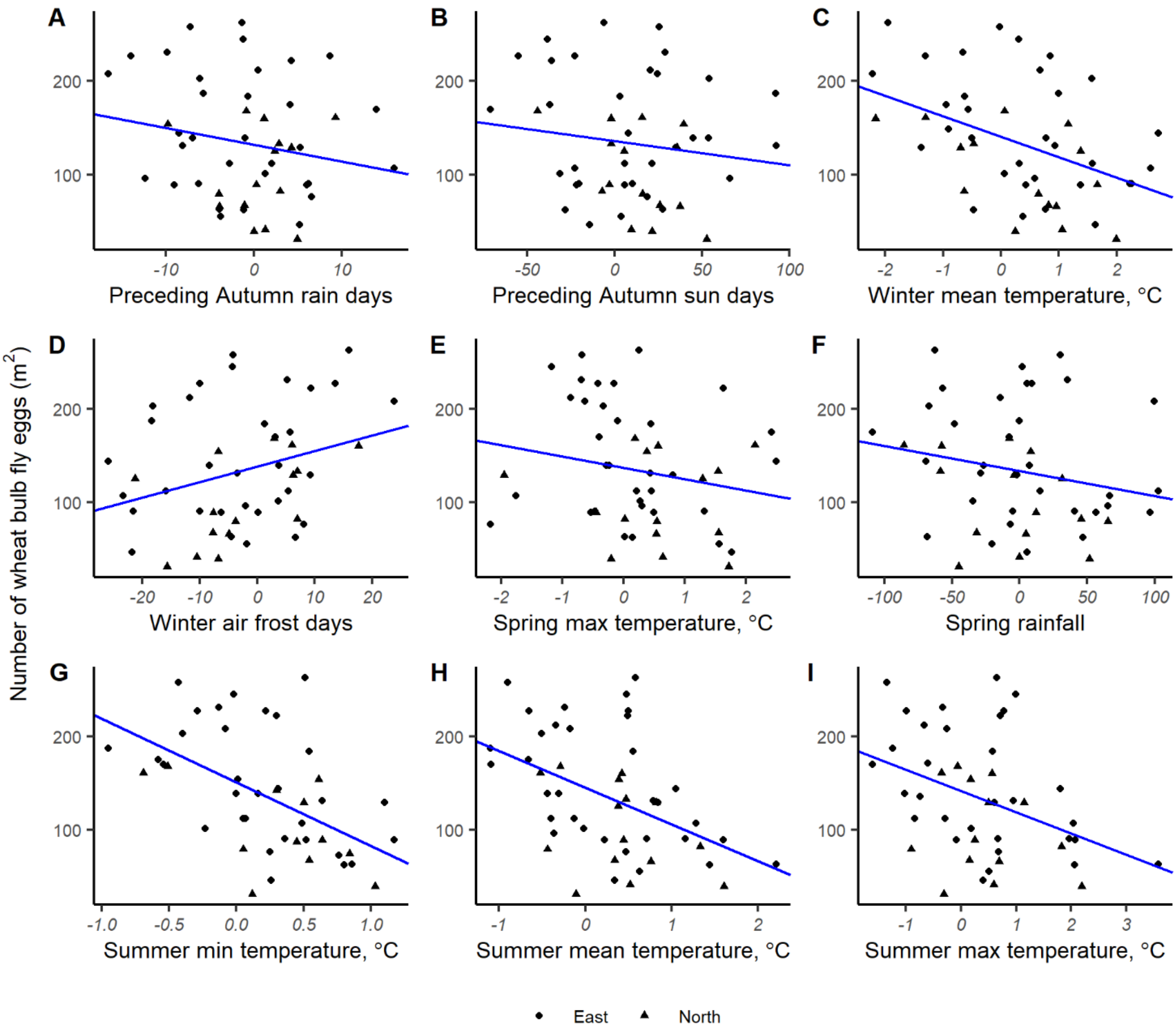

Fig. 8: Correlations between WBF egg density (eggs m^2) and departure from long-term average for meteorological parameters included in the seasonal 1971 – 2019 model.

A refined 1971 – 2019 model was created using monthly average data for the seasons shown to be important in the seasonal model: preceding September – preceding November for preceding autumn months, preceding December – February for winter months, March – May for spring months, and June – August for summer months. The meteorological inputs for this refined monthly model were: 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 a higher predictive power than previous models (adjusted R^2 = 0.70, $F_{8,39}$ = 14.88; p = <0.001). The monthly meteorological parameters listed above were used as inputs for the predictive model. The predictions of this model, compared with the observed values, are shown in Figure 9 with the correlative relationship displayed in Appendix Figure 1.

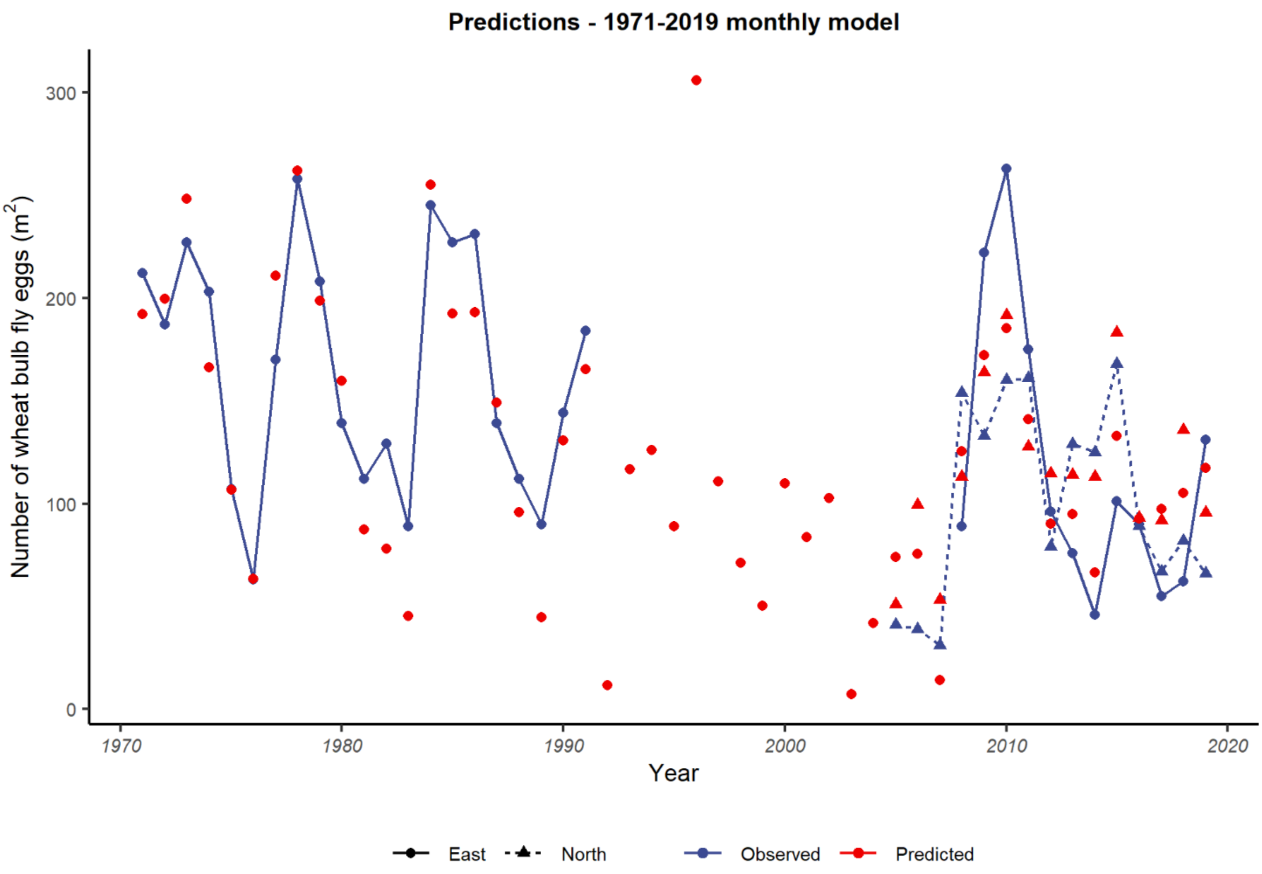

Fig. 9: Predicted and observed WBF egg density for 1971 – 2019 for north (triangle; dashed line) and east (circle; solid line) regions. Predictions based on the monthly 1971 – 2019 model (red) are plotted alongside the mean observed value per region per year (blue). Model predictions are included for years 1992 – 2004. For clarity, trendlines are included for the observed values only.

Correlations between these monthly meteorological parameters and the observed WBF egg density data are: preceding September sun days (t = -3.03; p = 0.004; r = -0.41; Figure 10A), preceding October rain days (t = -1.87; p = 0.068; r = -0.27; Figure 10B), January mean temperature (t = -3.09; p = 0.003; r = -0.41; Figure 10C), January frost (t = -2.10; p = 0.041; r = 0.30; Figure 10D), April maximum temperature (t = -0.77; p = 0.445; r = -0.38; Figure 10E), May maximum temperature (t = -2.41; p = 0.020; r = -0.56; Figure 10F), April rainfall (t = -0.84; p = 0.405; r = -0.12; Figure 10G), and July minimum temperature (t = -2.59; p = 0.013; r = -0.36; Figure 10H).

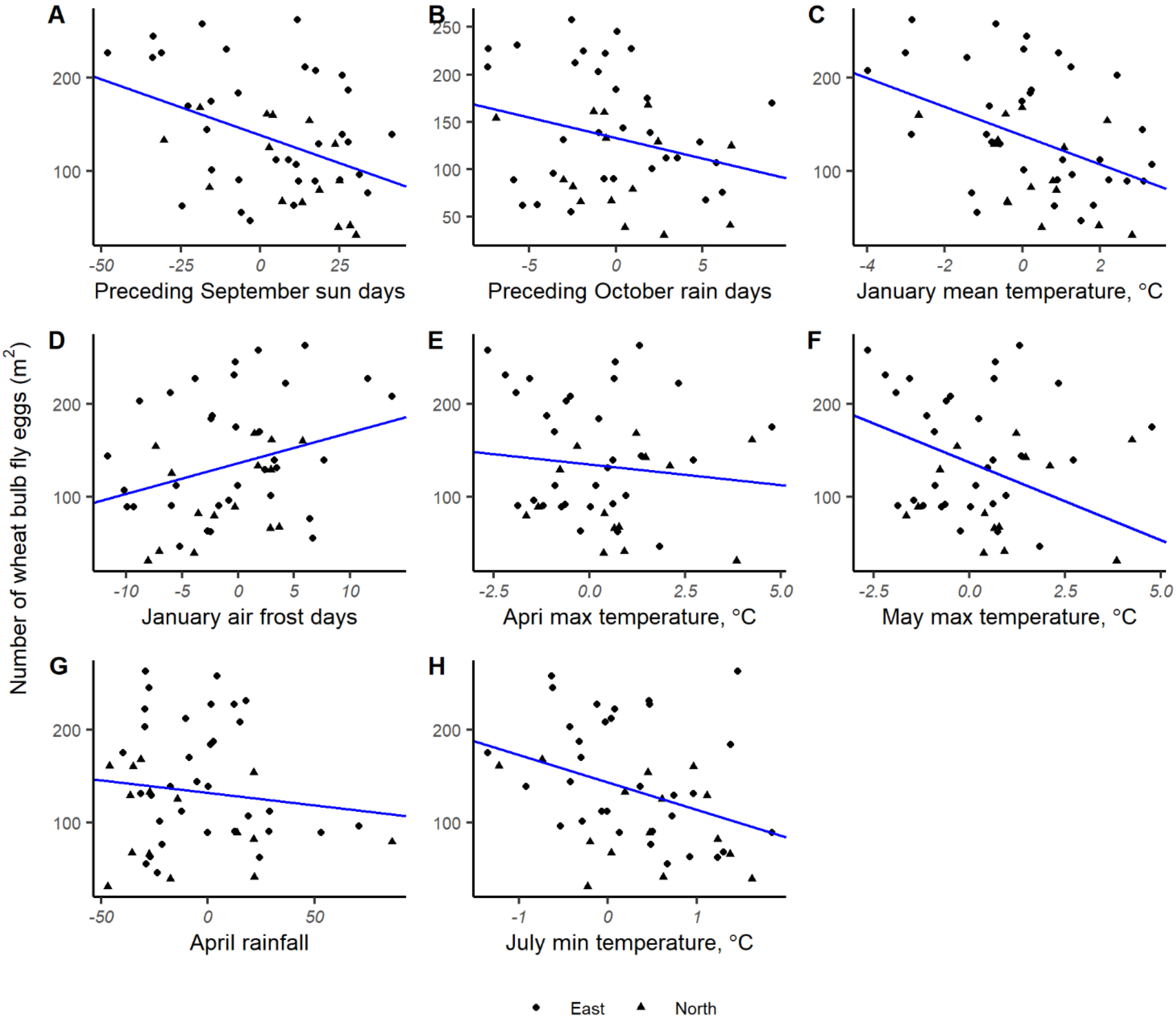

Fig. 10: Correlations between WBF egg density (eggs m[2]) and departure from long-term average for meteorological parameters included in the monthly 1970 – 2019 model.

4.4. Validating the 1971–2019 monthly model

The 1971 – 2019 monthly model had the highest predictive power (adjusted R^2 = 0.70; Figure 9). The predictive power of the model was validated by removing a series of years from the model, rerunning the model, and observing the effect the removal of these years had on the ability of the model to predict WBF egg density for all years (1971 – 2019). Eight validation models were developed in total. The first four were developed by removing a specified range of five-year periods: the first five years (validation 1: years 1971 – 1975 removed; Figure 11A), the last five years (validation 2: years 2015 – 2019 removed; Figure 11B), the five years with the highest recorded WBF density (validation 3: years 1978, 1984, 1985, 1986, 2010 removed; Figure 11C), and the five years with the lowest recorded WBF density (validation 4: years, 2005, 2006, 2007, 2014, 2017 removed; Figure 11D). A second round of validation was done out by removing four sets of five randomly selected years (validations 5 - 8; Figure 12). These validations had no observable detrimental effect on the predictive power of the validation models (Figure 9 vs. Figure 11; Figure 9 vs. Figure 12).

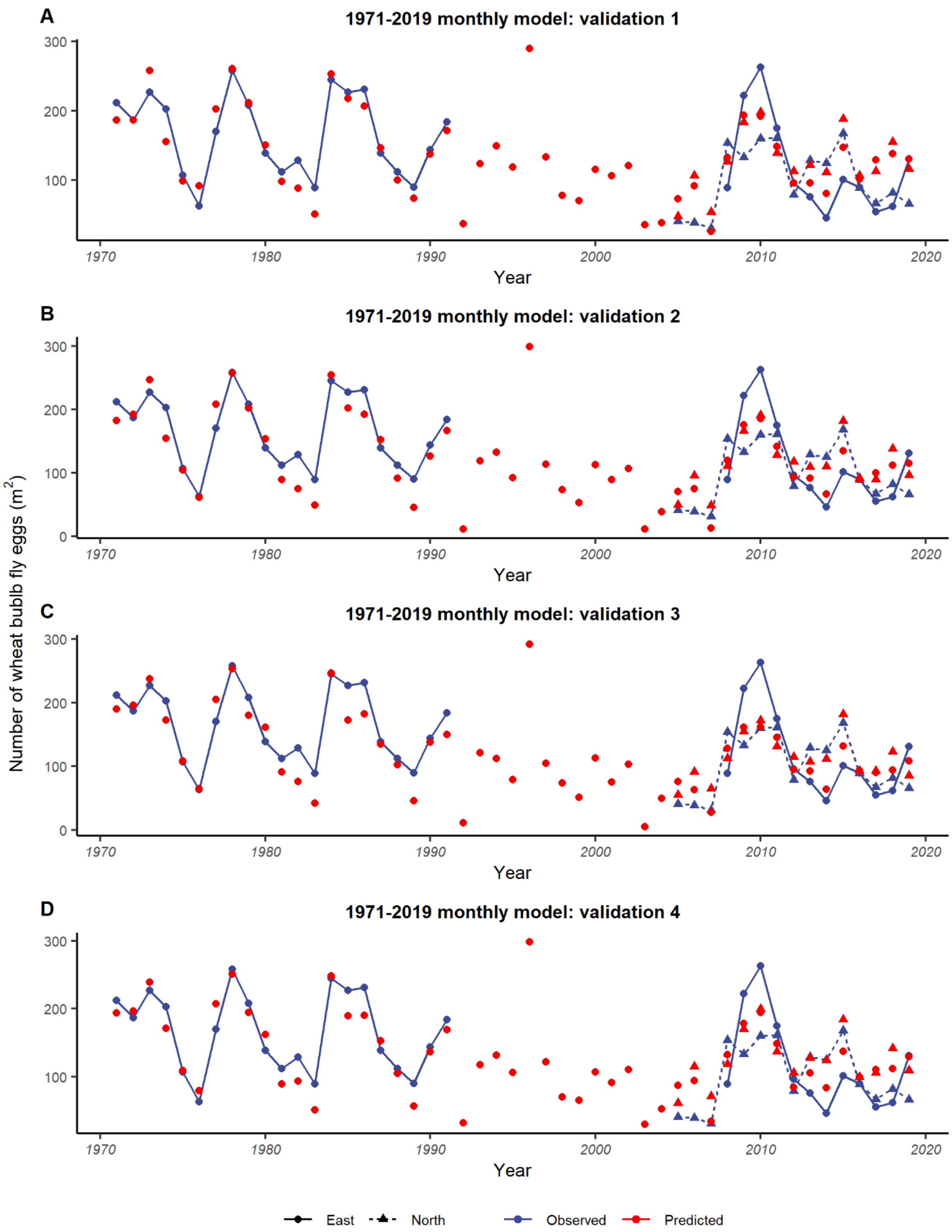

Fig. 11. Validation 1 (removal of specific years) of the 1971 – 2019 monthly model. Graphs show the predicted and observed WBF egg density for 1971 – 2019 for north (triangle; dashed line) and east (circle; solid line) regions. A) Validation 1 excluding years 1971 – 1975. B) Validation 2 excluding years 2015 – 2019. C) Validation 3 excluding years 1978, 1984 - 1986, 2010. D) Validation 4 excluding years, 2005 - 2007, 2014, 2017. For clarity, trendlines are included for the observed values only.

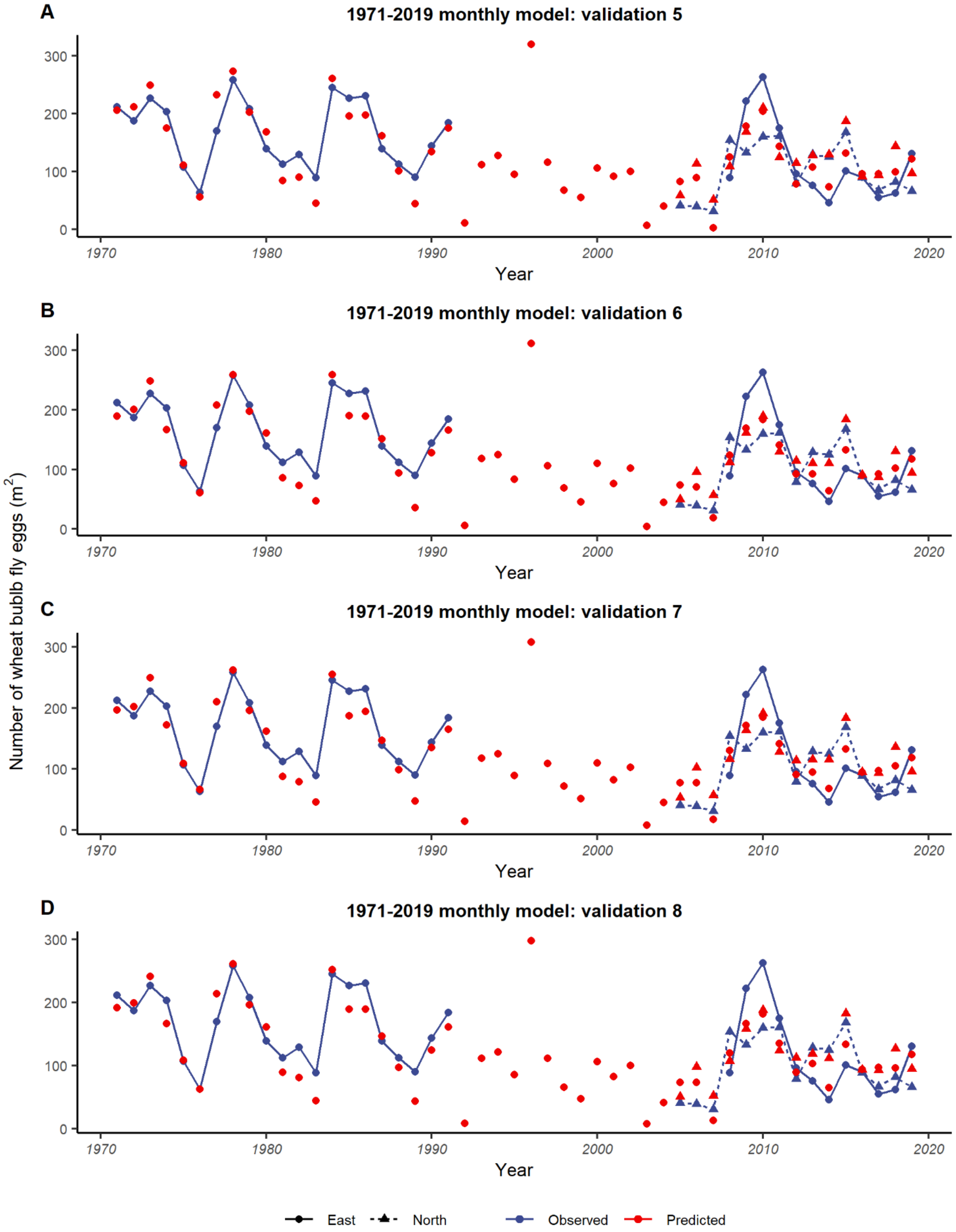

Fig. 12. Validation 2 (removal of random years) of the 1971 – 2019 monthly model. Graphs show the predicted and observed WBF egg density for 1971 – 2019 for north (triangle; dashed line) and east (circle; solid line) regions. A) Validation 5. B) Validation 6. C) Validation 7. D) Validation 8. For clarity, trendlines are included for the observed values only.

4.5. Building a revised model from 2005–2019 observations

The 2005 – 2019 seasonal model had a predictive power similar to the previous seasonal models developed ($F_{8,18}$ = 6.88; p = <0.001; adjusted R^2 = 0.64; Figure 13A), with preceding autumn minimum temperature, winter maximum temperature, winter rain days, spring minimum temperature, spring mean temperature, spring rainfall, spring rain days, and summer sun days used as inputs to predict WBF egg density in the final model. When refined on a monthly basis this model had the highest predictive power when compared with all preceding models ($F_{13,13}$ = 11.62; P = <0.001; adjusted R^2 = 0.84; Figure 13B), with final monthly model parameters including January maximum temperature, March minimum temperature, April minimum temperature, May minimum temperature, May mean temperature, March rainfall, April rainfall, March rain days, April rain days, May rain days, Jun sun days, July sun days, August sun days. The correlative relationship between the predictions of the final monthly model and the observed values is displayed in Appendix Figure 2.

Validation of the final monthly model was done as above for the 1971 – 2019 monthly model. Eight validation models were developed in total. The first four were developed by removing a specified range of five-year periods: first five years (validation 1: years 2005 – 2009 removed; Figure 14A), the last five years (validation 2: years 2015 – 2019 removed; Figure 14B), the five years with the highest recorded WBF density (validation 3: years 2008, 2009, 2010, 2011, 2019 removed; Figure 14C), and the five years with the lowest recorded WBF density (validation 4: years 2005, 2006, 2007, 2014, 2017 removed; Figure 14D. A second round of validation was done by removing four sets of five randomly selected years (validations 5 - 8; Figure 15). Validations 1, 3, 4, 5, 6, 7, and 8 had no observable detrimental effect on the predictive ability of the validation models. However, validation 2 (removal of the years 2015 – 2019) showed a reduction in the ability of the model to successfully predict WBF egg density for 2016 – 2018.

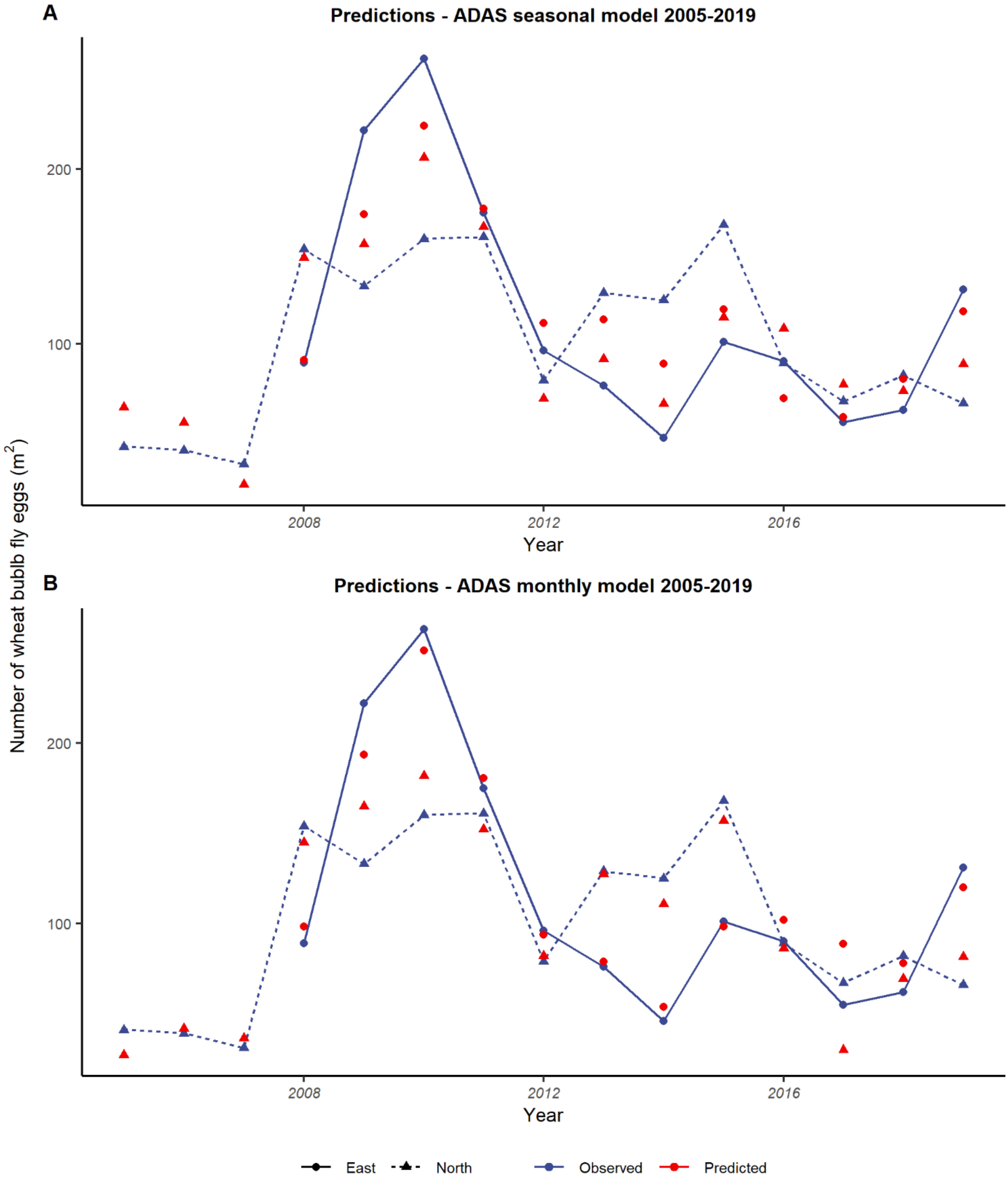

Figure 13: Predicted and observed WBF egg density for 2005 - 2019 for north (triangle; dashed line) and east (circle; solid line) regions. Model predictions are based on the seasonal 2005 - 2019 model (A) and the monthly 2005 – 2019 model (B). For clarity, trendlines are included for the observed values only.

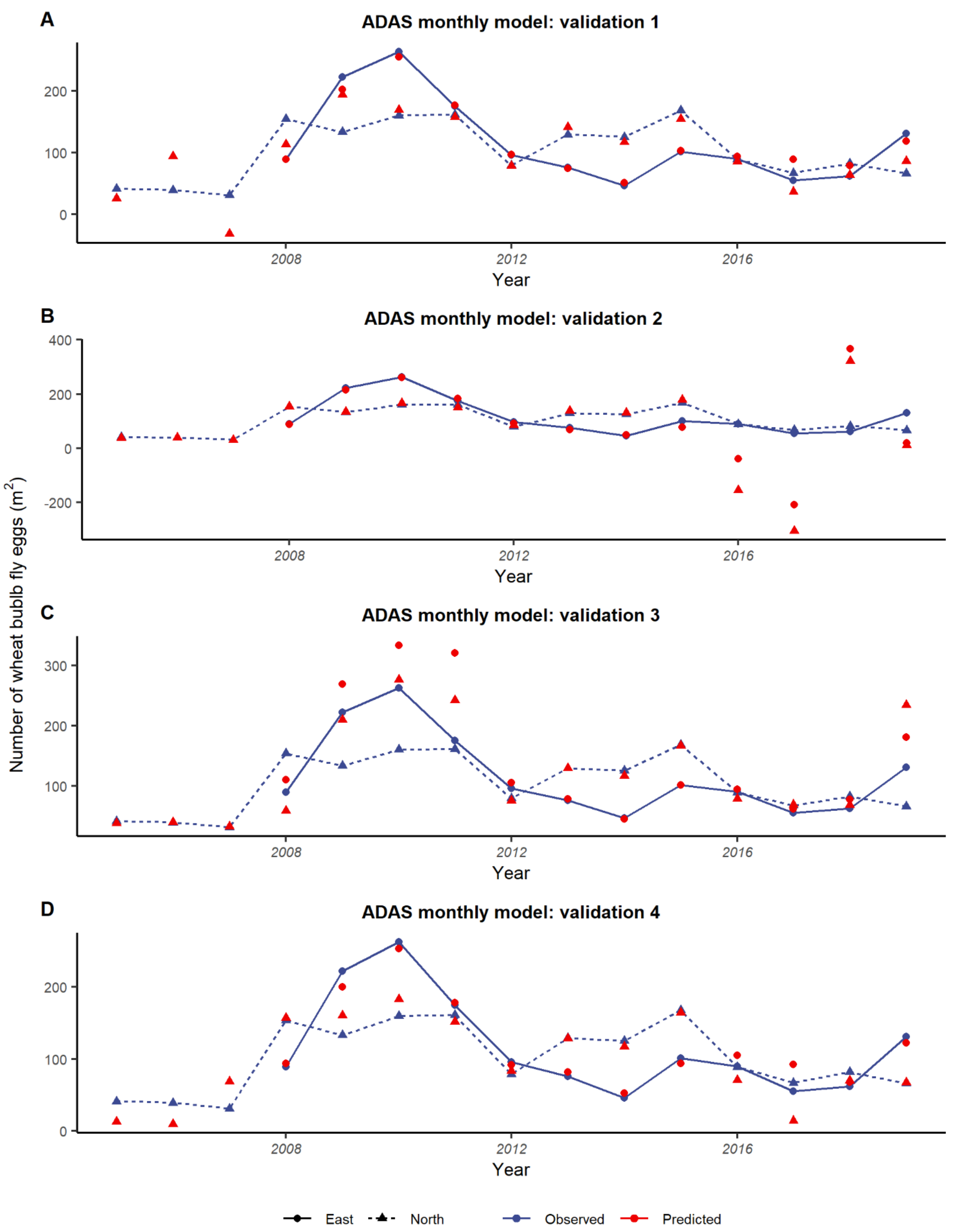

Figure 14: Validation of the 2005 - 2019 monthly model. Graphs show the predicted and observed WBF egg density for 2005 – 2019 for north (triangle; dashed line) and east (circle; solid line) regions. A) Validation 1 excluding years 2005 – 2009. B) Validation 2 excluding years 2015 – 2019. C) Validation 3 excluding years 2008 – 2011, 2019. D) Validation 4 excluding years, 2005 - 2007, 2014, 2017. For clarity, trendlines are included for the observed values only.

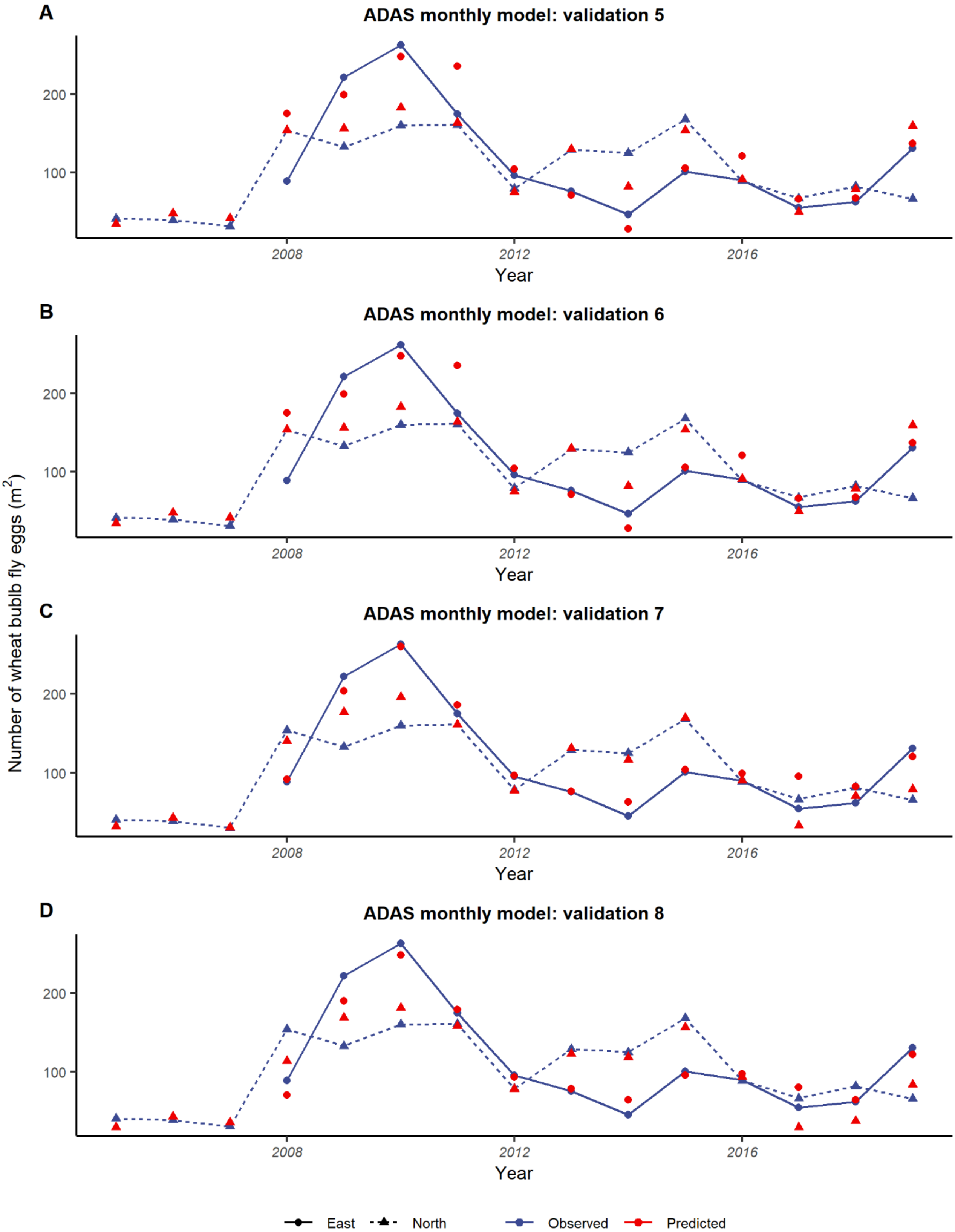

Figure 15: Validation of the 2005 - 2019 monthly model. Graphs show the predicted and observed WBF egg density for 2005 – 2019 for north (triangle; dashed line) and east (circle; solid line) regions. A) Validation 5. B) Validation 6. C) Validation 7. D) Validation 8. For clarity, trendlines are included for the observed values only.

4.6. The previous crop in the rotation influences WBF abundance

The previous crop in the rotation significantly influenced the number of WBF eggs laid following crop harvest ($\chi^2 = 59.68$; p = < 0.001; Figure 16A). From the previous crops reported in the 2005 – 2019 dataset, potatoes had the highest average WBF egg counts, followed by leeks & onions and beet, with a preceding crop of cereals or oilseeds having the lowest WBF risk (Figure 16A). Soil type did not significantly influence the number of WBF eggs laid ($\chi^2 = 6.59$; p = 0.143; Figure 16B).

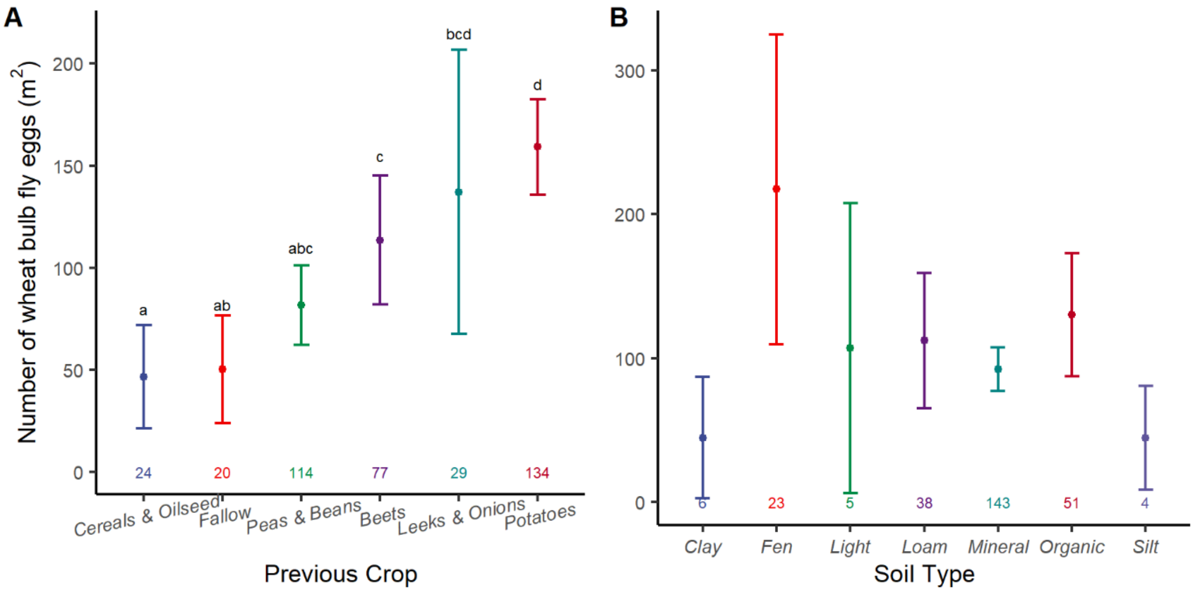

Fig. 16: WBF eggs m2 across all years categorised by the previous crop (A) and the soil type (B) at each site. Plots indicate the mean and the 95% confidence intervals. The values at the bottom of each line indicate the replication number and the letters above each line show which factors are significantly different based on post-hoc analysis (estimated marginal means with Tukey adjustment for multiple comparisons; threshold for significance α = 0.05).

5. Discussion

5.1. Predicting WBF risk to inform control measures

A WBF risk prediction model, developed by Young & Cochrane (1993), represents an alternative avenue to time consuming soil sampling for predicting pest risk. However, there has been little if any testing of the precision of this model in the years since it was developed.

In this study, the effectiveness of the Young & Cochrane WBF risk prediction model was tested by using it to predict the average level of WBF risk across two regions of the UK and comparing these predictions with survey data collected by ADAS between 2005 and 2019. The Young & Cochrane model did not accurately predict the level of WBF risk observed between 2005 and 2019, indicating that it needs updating if it is to remain an effective predictive tool. To update the model, the ADAS WBF survey data were combined with the Young & Cochrane (1993) data and an updated risk prediction model was developed. The most accurate model developed, the 1971 – 2019 monthly model, had a predictive power of 70%, an 11% increase in predictive power when compared with the Young & Cochrane model (Young & Cochrane, 1993). Validation of this updated 1971 – 2019 monthly model, achieved by removing a series of five-year periods, re-running the model, and comparing the predictions of these validation models with the full model, indicated that the 1971 – 2019 monthly model could still adequately predict wheat bulb fly risk when data were removed from the model. A further refined WBF prediction model, using the 2005 – 2019 data, was developed. Although this model had the highest predictive power of all the models developed (84%), validation resulted in a decrease in its ability to predict accurately risk in the omitted years for one of these validation models. Therefore, the 1971 – 2019 monthly model likely represents the most stable model developed in this study.

A pre-drilling seed treatment is the only chemical control strategy for WBF in late sown crops (November onwards), and WBF risk can be mitigated further by sowing a higher seed rate to increase crop tolerance to the pest (Storer *et al.,* 2018). An accurate estimation of pest risk is therefore essential to ensure that seed treatments are applied when required and sowing rates are adjusted to produce a crop sufficiently robust to tolerate pest pressure. The model we have developed in this study represents a significant improvement on a previous WBF risk prediction model. Further validation and testing of the model is required, and this will be done by predicting the mean regional WBF risk and comparing this with the results of the annual ADAS WBF surveys in 2020 and 2021.

5.2. Meteorological factors influence WBF risk

The predictive models developed in this study incorporate a wider range of meteorological parameters than the Young & Cochrane model. The meteorological parameters included in the Young & Cochrane model were selected to include the factors hypothesised to have the greatest influence on WBF biology and phenology (Young & Cochrane, 1993). These included the departure from the long-term average for: the mean air temperature, total rainfall, number of rain days, and sunshine hours for June, July, and August, alongside mean air temperature, mean soil temperature, rainfall, and sunshine for the preceding September, preceding October, preceding November, preceding December, and January (Young & Cochrane, 1993). When developing the updated models, additional meteorological factors were included. Initially these were included on a seasonal basis, in order to identify which seasons and meteorological parameters have the greatest influence on WBF risk and then refined on a monthly basis for the highlighted seasons. 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 (from 1971 only). The benefits of building the model using open-access meteorological data are that the model inputs are standardised across the regions and freely available.

Previous correlations between WBF egg density and meteorological parameters by Young & Cochrane (1993) indicated that WBF egg density has a negative correlative relationship with increasing mean January and July temperature and a positive correlation with increasing August rain days. Correlations between WBF egg density and meteorological parameters were done here for the meteorological parameters included in the final 1952 – 2019 and 1971 – 2019 seasonal and monthly models. Meteorological factors that displayed a significant negative correlation with WBF egg density in the monthly models were: preceding September sun days, preceding October rain days, preceding December minimum temperature, January minimum temperature, January mean temperature, May maximum temperature, June minimum temperature, July minimum temperature, and August minimum temperature, with a positive correlation detected between egg density and January air frost days. The explanations behind these correlations are unclear and could be a result of one of many combinations of interactive factors from across the crop-pest-environment relationship. For example, negative correlations between WBF egg density and an increase in the preceding September sun days, preceding October rainfall, and preceding December minimum temperature could be due to the positive effects these increases are likely to have on crop growth and establishment. Furthermore, the correlation between a higher than average temperature and a reduction in WBF density could be caused by an increase in natural enemy activity, as has been reported for the natural enemies of other insect pest species (Romo & Tylianakis, 2013). Conversely, the positive correlation between a higher number of air frost days in winter and an increasing WBF egg density are likely due to the adverse effects of air frost on crop growth and natural enemy activity. Full elucidation of the drivers behind these observations would require comprehensive assessment of the relationship between weather, crop development, pest abundance, and natural enemy activity.

5.3. The preceding crop in the rotation influences WBF risk

From 2005, the majority of WBF surveys undertaken by ADAS have noted various agronomic factors at each site, including the soil type and the preceding crop in the rotation. Analysis of the 2005 – 2019 dataset indicated that WBF egg density is significantly influenced by the preceding crop in the rotation, with WBF risk highest following a wide rowed crop (potato, leek, onion, or beet), and lowest following a cereal or oilseed crop. This is probably because a wide rowed crop generally has a lower level of green canopy and provides easy access to bare soil for oviposition. Indeed, previous studies have reported that crops with higher soil exposure (i.e. root crops) experience significantly higher levels of WBF oviposition (Gough, 1947; Gough, 1949; Long, 1958; Young & Cochrane, 1993). Previous experimental work also suggested that fields following fallow have the highest WBF risk (Long, 1958); however, analysis of the survey results indicates that a previous fallow results in a low level of WBF risk. The contrasting findings between the historical observations (Long, 1958; Young & Cochrane, 1993) and the results reported here could be caused by a range of factors, including an overall decrease in WBF populations or a reduction in the number of farmers using bare fallow in their rotations.

Proximity to a previous cereal crop infested with WBF could also influence oviposition. The potential risk decreases the further away a site is from a cereal crop infested with the pest as reproductive adults only migrate up to 0.4 – 0.8 km from their emergence site (Bardner *et al.*, 1968). The proximity of sites to a preceding cereal crop was not reported in the extracted data, so this association could not be investigated in this analysis. The effect of soil type did not significantly affect the abundance of WBF eggs.

5.4. Conclusions

The Young & Cochrane 1993 WBF risk prediction uses rainfall during the preceding October, January air temperature, January soil temperature, and July air temperature to predict WBF egg density, and therefore determine the level of WBF risk. The predictive power (accuracy) of the Young & Cochrane model (developed using data from 1952 – 1991) is 59%, however the model has not been extensively tested or validated since it was developed. In this project we combined ADAS WBF survey data (2005 – 2019) with historical data (Young & Cochrane, 1993; data covering 1952 – 1991) to test and validate the Young & Cochrane 1993 risk prediction model. Following this, we developed an updated WBF risk prediction model which has a higher predictive power (70%). A brief summary of the project findings is reported below.

- The Young & Cochrane 1993 model was not able to accurately predict WBF egg densities in 2005 – 2019, indicating that it required further refinement if it is to be used effectively.
- A series of updated models were developed to attempt to improve the predictive power of the Young & Cochrane model.
- These updated models included a wider range of meteorological parameters and were initially developed on a seasonal basis; this was in order to identify the seasons and metrological factors which most significantly influence WBF egg density. Following this, models were refined on a monthly basis using the seasons and meteorological parameters identified in the seasonal models.
- The most accurate model developed was the 1971 – 2019 monthly model, this has a predictive power of 70% (an 11% increase compared with the original Young & Cochrane model).
- The 1971 – 2019 monthly model predicts WBF egg density from 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 updated WBF risk prediction model could be linked with a recently developed crop tolerance model (Storer *et al.,* 2018) to identify crops in high risk areas that should be drilled earlier and at higher seed rates in order to maximise WBF tolerance and minimise yield losses

- The 1971 – 2019 monthly model will be tested and validated during the 2020 and 2021 ADAS WBF surveys.
- Additional assessment of agronomic factors (previous crop and soil type) which were reported alongside the ADAS WBF surveys indicated that the previous crop influences WBF risk (higher risk for potatoes, leeks & onions, and beets compared with cereals & oilseeds) but soil type has no overall effect.

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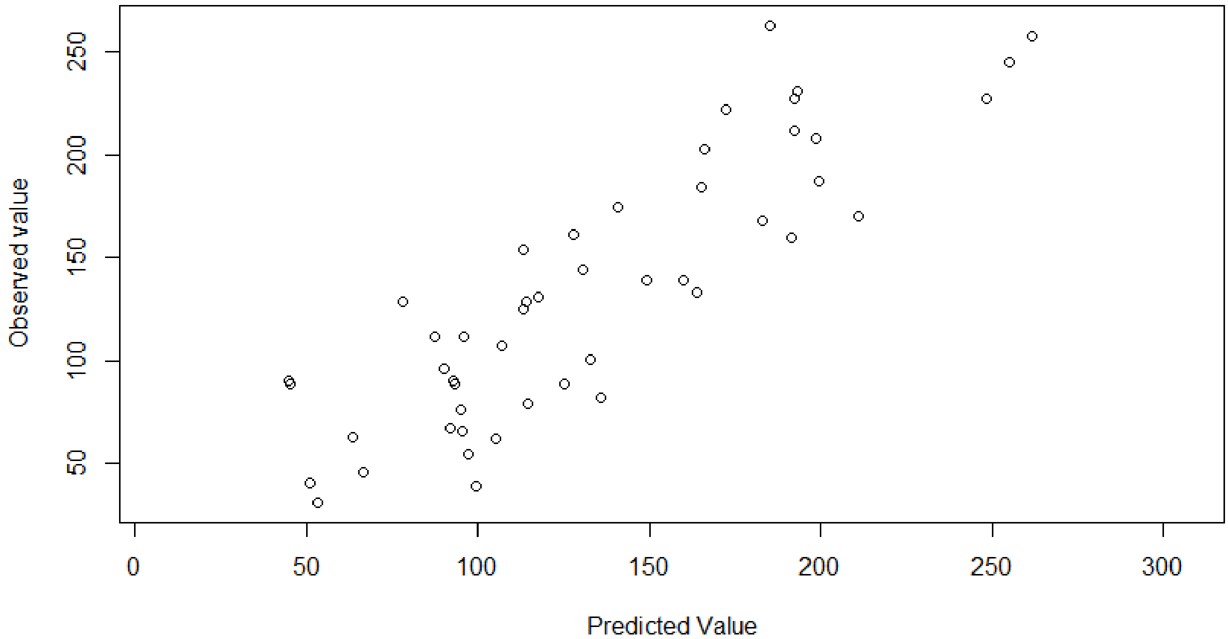
7. Appendix 1

Appendix Figure 1: Relationship between the Observed vs. Predicted values for the 1971 – 2019 Frost Monthly model



Appendix Figure 2: Relationship between the Observed vs. Predicted values for the 2005 – 2019 Monthly model