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Climate Change

Likelihood of Extreme Early Flight of *Myzus persicae* (Hemiptera: Aphididae) Across the UK

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Abstract

Myzus persicae (Sulzer, Hemiptera: Aphididae) is a major global crop pest; it is the primary aphid vector for many damaging viruses and has developed resistance to most insecticides. In temperate regions, the risk of widespread crop infection and yield loss is heightened following warm winters, which encourage rapid population growth and early flight. Estimates of the frequency and magnitude of warm winters are, therefore, helpful for understanding and managing this risk. However, it is difficult to quantify the statistical distribution of climate events, particularly extremes, because climate observations represent just a small sample of the possible climate variations in a region. The purpose of this study was to establish a large-scale relationship between temperature and *M. persicae* observations across the UK and apply this to a very large ensemble of climate model simulations, which better sample the variability in climate, to quantify the current likelihood of extreme early *M. persicae* flight across the UK. The timing of *M. persicae* flight was shown to be significantly related to January-February mean temperature, where a 1°C warmer/cooler temperature relates to about 12 d earlier/later flight. Climate model simulations predict 40% likelihood of experiencing a year with unprecedented early *M. persicae* flight during the next decade in the UK. Results from this method can help crop managers assess the long-term viability of crops and management practices across the UK and provide early warning information for targeting pest surveillance activities on the locations and timings at highest risk of early *M. persicae* flight.

Key words: biosecurity, pest risk management, climate variability, UNSEEN method

Pests and pathogens pose a major risk to the integrity of natural ecosystems and the security of food supplies worldwide (Savary et al. 2019, Yadav et al. 2019). Aphids are among the foremost global plant pests and are responsible for serious economic damage to a wide range of agricultural crops and commodities (van Emden and Harrington 2017). In the UK, potential crop losses of £70 million per year have been estimated for an average aphid infestation, and £120 million per year, on wheat alone, for a severe widespread outbreak (Tatchell 1989), with similar losses estimated for France and Australia (Dedryver et al. 2010, Valenzuela and Hoffmann 2015).

Only about 100 of the over 5,000 species of aphid in the world are of significant economic importance for agricultural crops (Blackman and Eastop 2000). One of the most widespread and damaging crop pest species is *Myzus persicae* (Sulzer, Hemiptera: Aphididae), also known as the peach-potato or green peach aphid after its primary winter host peach *Prunus persica* [(Linnaeus) Batsch, Rosales: Rosaceae] (Kwon 2017). It has been recorded in all crop-growing countries and is particularly prevalent in the temperate northern hemisphere (Blackman and Eastop 2000). Like other aphids, *M. persicae* causes damage to foliage through sap feeding

and secretion of honeydew, a sugar-rich liquid that attracts other insects and fungal spores. However, the most negative economic impacts of *M. persicae* are caused by virus transmission (Devonshire et al. 1998, Blackman and Eastop 2000, CABI 2021). *M. persicae* has also shown widespread resistance to many classes of insecticide, including organophosphates, carbamates, and pyrethroids (Field et al. 1988, IRAC 2021), due to their extensive use over recent decades (Devonshire et al. 1998, Foster et al. 1998, Margaritopoulos et al. 2009, Bass et al. 2015).

In the UK, *M. persicae* is the primary vector for many prominent crop viruses, including Virus Yellows, a complex of three viruses that cause severe damage to sugar beet (Qi et al. 2004; Hull 2007, Ribbands 2009), *Turnip yellows virus* (Sobelivirales: Pisoniviricetes) which significantly limits the yield of oilseed rape in UK (AHDB 2019, Asare-Bediako et al. 2020), *Potato virus Y* and *A* (Patatavirales: Stelpaviricetes), which are the most commonly intercepted potato viruses in growing crop inspections (Fox et al. 2017), and *Potato leafroll virus* (Pisoniviricetes: Sobelivirales), a persistent virus that has contributed to declining potato productivity over the last century (Radcliffe and Ragsdale 2002, Chatzivassiliou et al. 2008, Alford, 2010). The most effective insecticides for *M. persicae* control, neonicotinoids (Nauen and Denholm 2005), have been severely restricted or banned across the EU since 2013 to protect honeybees and other pollinators. Consequently, many farmers have experienced increased crop loss, even with the use of alternative postemergence sprays (Bass and Field 2018).

Unlike most aphid species, *M. persicae* is highly polyphagous; it is able to feed on over 400 host plant species, including several major crop types (Blackman and Eastop 2000, Cocu et al. 2005). The life cycle of the *M. persicae* is rapid and flexible, enabling populations to grow quickly and respond to changing environmental conditions. With suitable climate and habitat, it can develop to maturity in 8–10 d. In locations where the primary winter host is available and sub-zero temperatures are experienced, *M. persicae* can reproduce sexually and lay cold-hardy eggs for the winter (Guillemaud et al. 2003). However, in the absence of a primary host and where a mild climate permits, it is also able to switch its reproductive mode and produce offspring parthenogenetically (anholocyclicly, where females give birth to live young) throughout the year. *Myzus persicae* is able to overwinter on a wide range of secondary host (mostly crop and weed) species (Margaritopoulos et al. 2002, Vorburger et al. 2003). Wingless (apterous) young are produced until the population growth becomes limited by high aphid densities or poor host plant conditions, at which point winged (alate) morphs are produced that can migrate hundreds of kilometers in search of new hosts (Cocu et al. 2005). Survival, development, and reproduction of most aphid species, including *M. persicae*, is strongly regulated by temperature (e.g., Cocu et al. 2005, Harrington et al. 2007, Bell et al. 2015). Significant relationships have been noted between earlier/later annual onset of *M. persicae* migration and warmer/cooler winter temperatures in the UK (Harrington 2002, Harrington and Clark 2010, Bell et al. 2015, Thackeray et al. 2016). Early emergence is likely a combination of reduced mortality and increased development (Harrington 2002).

Managing the risks to crops from *M. persicae* is challenging. As most host plants are colonized by flying aphids, the annual timing of flight is important for assessing the potential severity of *M. persicae* damage and planning suitable management strategies, such as the choice of crop variety, timing and locations of surveillance inspections, or timing of approved insecticide application (Taylor 1977). Seasonally early flight is a particular concern for young, developing crop plants, as these are more vulnerable to damage and disease than mature plants, and *M. persicae* is able to feed on other host species before crop emergence (Petitt and Smilowitz 1982, Harrington 2002, Katis et al. 2007, Harrington and Clark 2010, Bell et al. 2015).

In the UK, agricultural research and advisory organizations, such as the Rothamsted Insect Survey (RIS), Agriculture and Horticulture Development Board (AHDB), and Science and Advice for Scottish Agriculture (SASA) include annual forecasts of the timing of *M. persicae* flight based on prior winter temperatures (https://ahdb.org.uk/aphid-forecasts). To help farmers prepare for extreme early *M. persicae* flight it would also help to understand the current likelihood of experiencing extreme warm winters. Winter temperatures show large year-to-year variability across the UK, due to internal climate fluctuations, and these are superimposed on a long-term warming trend. Climate observations represent only a small sample of the variability in climate that is possible, and they therefore cannot be used alone to quantify the current likelihood of extreme events. Here, we address this problem by applying the UNSEEN (UNprecedented Simulated Extremes using ENsembles) method (Thompson et al. 2017, Kay et al. 2020, Kent et al. 2022) to estimate the current likelihood of experiencing extreme warm winter temperatures and associated early *M. persicae* flight across the UK. The method uses a large ensemble of climate model runs to simulate 2,320 realizations of plausible UK winters, providing at least an order of magnitude more samples and a wider range of temperatures than are available from observations.

Materials and Methods

Aphid Data

Observations of *M. persicae* are from the RIS suction-trap network (Harrington 2014). Migrating aphids are collected at each RIS site using a 12.2 m-high suction-trap, which is emptied daily (weekly in winter) and all aphids are identified to species level by experts at Rothamsted Research or SASA (Science and Advice for Scottish Agriculture), Edinburgh. The timing of appearance in a suction-trap provides an integrated signal of local changes in aphid phenology and abundance that is considered representative of the landscape scale. The trap height of 12.2 m is based on mathematically derived estimates of the 'logarithmic mean height of aphid flight' (Taylor 1974a, b), which reflect the lowest height at which the landscape, rather than the local sample of the population, can be derived. For this study, *M. persicae* records from 13 RIS sites across England and Scotland for the period 1980–2018 were selected. While longer records are available for individual RIS sites, the selection used here provides a consistent time period of *M. persicae* count data for sites covering a large geographic area. As well as species counts, RIS calculate a range of phenology indicators to characterize the annual timing of aphid activity. We focus on the indicator for day-of-year when 5% of the total annual catch was observed, DOY_5. The initiation of *M. persicae* flight across the UK is significantly related to air temperature during the preceding winter (Harrington 2002; Thackeray et al. 2010, 2016) and is a useful indicator for informing pest control measures such as early warning systems or crop surveillance practices (Harrington 2014). Minor gaps in the annual records of DOY_5 at individual sites (see Table 1 for details) were filled using the relationship between T_{JF} and DOY_5 at the site.

Air Temperature Data

Temperature data are from the UK 1km^2 gridded climate dataset, HadUK-Grid (Hollis et al. 2019), available from the Met Office's Integrated Data Archive System (MIDAS) (Met Office 2012). This

dataset is derived from the UK network of meteorological station observations and provides a range of monthly and daily climate variables, including continuous monthly mean temperature data from 1884 to present. January–February mean air temperatures, T_{JF}, for 1 km^2 grid boxes covering each of the RIS sites are used to estimate site relationships with *M. persicae* DOY_5 observations. The HadUK-Grid UK mean T_{JF} is also used to estimate UK mean DOY_5 for comparison with model estimates.

Sensitivity of Aphid Flight to Temperature

The sensitivity of *M. persicae* DOY_5 to T_{JF} is defined as the number of days change in DOY_5 per 1°C change in T_{JF}. This is estimated for individual sites as the slope of a least-squares linear regression relationship between observations of DOY_5 and T_{JF} from 1980 to 2018. The large-scale sensitivity across all 13 sites used in this study is estimated from the regression between the 13-site mean DOY_5, $MDOY_5$, and the corresponding 13-site mean T_{JF}, MT_{JF}.

Model Ensemble and Reliability Tests

The UNSEEN method – UNprecedented Simulated Extremes using ENsembles (Thompson et al. 2017), is used to represent a plausible distribution of UK mean T_{JF} values for the current climate. This method uses an ensemble of relatively high resolution (60 km atmosphere and 0.25° ocean) runs of the Met Office Hadley Centre's 3rd Decadal Prediction System, DePreSys3, initialized with atmospheric, oceanic, and sea-ice observations, and forced with current anthropogenic and natural forcings (Dunstone et al. 2016). DePreSys3 was coded in FORTRAN and run on the Met Office Cray XC40 supercomputing system. Forty model simulations (ensemble members) were run for the period 1960–2018 and UK mean T_{JF} values were calculated for each model year, providing a total of 2,320 individual simulated years.

To represent the variability in recent UK temperature ensuring series stationarity, the long-term trend was removed with a linear regression through the ensemble mean time series (following Kay et al. 2020), and the anomalies were added to the 2018 value of the regression line (4.05°C). Thus, the model data have a mean T_{JF} that is equivalent to the 2018 value on the regression line, with variation around this mean based on the simulated climate variability between 1960 and 2018.

Statistical tests, coded in Python, were conducted to check that the model simulations are realistic representations of the current climate across the UK. To provide more robust statistics, 10,000 proxy time series of UK mean T_{JF} were produced by randomly resampling across all ensemble members for each year. Statistical moments for standard deviation, skewness, and kurtosis of the proxy T_{JF} series were compared with the same statistics for UK mean T_{JF} from the observation-based HadUK-Grid series (Hollis et al. 2019). The test for the model was at the 5% level, i.e., whether the observed statistic falls within the 2.5–97.5 percentile of the proxy ensemble distribution.

Extreme Early Aphid Flight

To assess the likelihood of extreme early DOY_5 flight across the UK, DOY_5 values were estimated between 1980 and 2018 using the large-scale regression relationship between MT_{JF} and $MDOY_5$ together with UK mean T_{JF} values from the modeled and observed time series. Model values were based on the ensemble mean T_{JF} (UK mean) and observation values were based on UK mean T_{JF} from the HadUK-Grid dataset from 1980 to 2018. Frequency distributions of the model- and observation-based DOY_5 estimates were compared, and the likelihood of experiencing a year with extreme early *M. persicae* flight was calculated as the percentage of model-based DOY_5 estimates that were earlier than any of the observation-based estimates.

Relevance to UK Agriculture

To demonstrate a potential application of our results for informing local crop management decisions, we compare UK 1km resolution estimates of DOY_5 for the year with the warmest observed UK mean T_{JF}, 1990, with DOY_5 estimates for an extreme year (1% warmest) estimated from modeled T_{JF}. The primary locations of a vulnerable UK crop, potato, across England and Scotland was included as a map layer using data from the 2017 Crop Map of England (CROME) (Defra 2017) and SASA (J. Pickup, personal communication, March 2021).

Results

Temperature Sensitivity of *M. persicae* Flight Date

The seasonal timing of *M. persicae* flight in the UK is closely associated with mean winter temperatures. For the 1980–2018 period, significant positive relationships ($p < 0.05$) were noted between DOY_5 and T_{JF} at each of the 13 RIS sites used in this study (Table 1). Earlier/later DOY_5 dates were associated with warmer/cooler T_{JF}. The sensitivity of the DOY_5 to T_{JF} relationship (regression slope) varies between about 10 d per °C at Starcross to 15 d at Kirton, and 12.5 d per °C for the 13-site mean series (Table 1). The strongest relationships were at sites in central and south-eastern England (Broom's Barn, Wye, Writtle, Hereford, and Rothamsted), where T_{JF} explains up to 69% of the inter-annual variation in DOY_5. The weakest relationships were at Starcross in south-west England and the three sites in Scotland, where T_{JF} explains less than 34% of the variance in DOY_5. Sites with the strongest relationships also experience the lowest annual T_{JF} values (≤2.0°C, see Discussion).

Inter-annual variations in UK mean T_{JF} from the HadUK-Grid dataset (Hollis et al. 2019), were significantly correlated with T_{JF} series at each of the sites ($r > 0.95$, $p < 0.001$), and with the 13-site mean T_{JF} (MT_{JF}, $r > 0.99$, $p < 0.0001$), indicating that variations in site temperatures are closely related to the large-scale UK climate. Inter-annual variations in MT_{JF} explain 76% of the variation in the 13-site mean DOY_5 ($MDOY_5$, $r^2 = 0.76$, $p = 0.0008$), which is higher than the variation in DOY_5 explained by T_{JF} at any of the individual sites. The sensitivity of this large-scale relationship is 12.5 d earlier (or later) $MDOY_5$ per 1°C warmer (or cooler) MT_{JF} (Equation 1, Table 1, Fig. 1). Uncertainty in the MT_{JF} versus $MDOY_5$ relationship is represented by the 95% confidence interval around the regression line.

$$MDOY_5 = -12.5 \times MT_{JF} + 222.1 \quad (1)$$

Model Reliability

Before using the modeled winter temperature values to estimate the initiation of *M. persicae* flight, it was necessary to test if the climate model simulations are a faithful representation of the real-world winter climate. This was done by comparing the frequency distributions of T_{JF} from model simulations and observations to assess whether the modeled temperatures are statistically different from the observations. Fig. 2 shows a comparison of the statistical moments of the modeled versus observed T_{JF}. For each of the statistics tested (standard deviation, skewness, and kurtosis) the observed value lies within the 95% range of the modeled distribution and so we conclude that the simulated T_{JF} values over the UK are statistically indistinguishable from the observations.

Table 1. Summary information for 13 Rothamsted Insect Survey (RIS) sites used in the study and the 13-site mean over the 1980 to 2018 period, including (from south to north) latitude, longitude, mean day of year of 5% *M. persicae* catch (DOY_5), mean and minimum January–February temperatures (T_{JF}), and linear regression parameters (slope, intercept and r^2) between annual T_{JF} and DOY_5 time series (all are significant, $p < 0.05$). Note, the 13-site mean regression parameters are for the relationship between annual 13-site mean T_{JF} (MT_{JF}) and DOY_5 ($MDOY_5$) time series (see Equation 1 and Fig. 1). Footnote shows years with missing DOY_5 data

RIS site			Day of year of 5% *M. persicae* catch (DOY_5)	Jan-Feb mean temperature (T_{JF}, °C)		Regression parameters		
E – England S - Scotland	Latitude	Longitude	Mean	Mean	Minimum	Slope	Intercept	r^2
Starcross, E	50.630	−3.455	151	6.0	0.3	−9.7	209.5	0.26
Wye, E	51.186	0.945	156	4.7	−2.1	−12.5	214.3	0.69
Silwood, E	51.409	−0.643	144	4.7	−1.7	−11.3	197.5	0.58
Writtle, E	51.734	0.429	154	4.5	−2.0	−12.0	208.1	0.68
Rothamsted, E	51.807	−0.360	158	4.0	−2.2	−12.5	208.2	0.64
Hereford, E	52.124	−2.638	164	4.4	−2.1	−13.7	224.0	0.65
Broom's Barn, E	52.261	0.568	163	4.3	−2.1	−12.3	215.9	0.69
Kirton, E	52.937	−0.071	168	4.2	−1.7	−15.1	231.2	0.62
Preston, E	53.854	−2.767	162	4.8	−1.1	−11.8	218.7	0.48
Newcastle, E	55.213	−1.685	178	4.0	−1.1	−14.8	237.2	0.58
Ayr, S	55.477	−4.568	182	4.6	−1.2	−10.9	232.3	0.31
Dundee, S	56.457	−3.074	183	3.8	−1.5	−10.3	221.6	0.34
Elgin, S	57.645	−3.366	199	4.0	−1.5	−15.0	258.1	0.31
13-site mean			**166**	**4.5**	**−1.5**	**−12.5**	**222.1**	**0.76**

Missing years: Silwood 1990–1999, 2010; Ayr 2011–2012; Dundee 2007, 2009; Elgin 2001, 2011, 2017–2018.

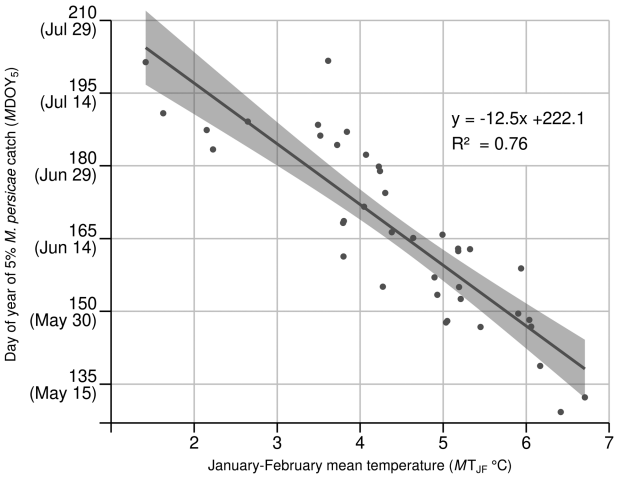

Fig. 1. Aphid flight dates depend linearly on late winter temperature. The regression relationship (black line and equation) is between the 13-site mean day of year of 5% *M. persicae* catch ($MDOY_5$) and January–February mean temperature (MT_{JF}). Each point is the annual mean of 13 RIS sites across the UK from 1980 to 2018 (see Table 1). The shaded area shows the 95% confidence interval around the regression line.

Likelihood of Extreme Early *M. persicae* Migration

Comparison of frequency distributions of UK mean *M. persicae* DOY_5 estimated with the modeled and observed T_{JF} (UK mean) series (Fig. 3), showed that the likelihood of experiencing a year with unprecedented early DOY_5 flight across the UK is ~5% (shaded red), or ~40% over the coming decade. To assess the timing of early flight we focused on modeled DOY_5 estimates spanning a range of likelihoods from 15 to 0.1% (Fig. 4). The dashed line on Fig. 4 highlights that there is currently a 1% likelihood of experiencing unprecedented *M. persicae* DOY_5 flight dates that are 10–15 d earlier than those estimated for 1990, the warmest observed T_{JF} year. There is also about 15% likelihood of experiencing DOY_5 flight dates that are as early as the top 6 yr in the observational record.

Relevance for UK Agriculture

While UK-wide estimates of the timing of flight are useful for understanding potential large-scale risks posed by early flight, practical management of pest risk is usually implemented at local scales and targeted at specific crops. Fig. 5 demonstrates an output of these large-scale results that can be useful for managing crop risk at local scales. It compares spatial variations in DOY_5 across the UK estimated using climate observations for 1990 (the year with the warmest observed UK mean T_{JF}) with DOY_5 estimates for an extremely warm, 1% warmest, T_{JF} year, as simulated by the climate model ensemble. In this example, the spatial details of the results for UK potato crops are highlighted with a map layer showing the main areas of potato cultivation. For the modeled 1% warmest T_{JF} estimates parts of southern England could experience DOY_5 dates between late-March and early-April, which are about one month earlier than the DOY_5 dates for 1990. Also, for the main areas of potato cultivation in eastern England (Lincolnshire, Cambridgeshire, Norfolk), and western and central England (Herefordshire, Shropshire, and Warwickshire), DOY_5 dates in late-April and early-May are possible, compared with mid- to late-May for 1990. Here, we have demonstrated the potential for a 1% likelihood of unprecedented early DOY_5 dates across the UK. However, the UNSEEN method enables similar maps to be produced for any % likelihood, and map layers can be included to highlight the spatial distributions of other vulnerable crops.

Discussion

We have demonstrated an approach for estimating the likelihood of extreme early flight of a priority UK plant pest in the current climate by combining historical observations of winter temperature and aphid catch with estimates of winter temperature from a large ensemble of climate model simulations applied with the UNSEEN method. Extreme early flight of *M. persicae* is particularly important because it has many host species in the wider environment and is, therefore, able to build up in large numbers even before the appearance of vulnerable young plants. The UNSEEN method was originally applied to assess

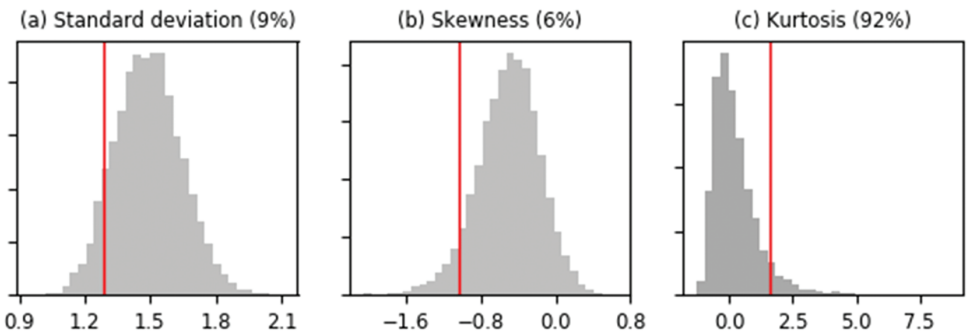

Fig. 2. Observed winter temperatures are indistinguishable from modeled temperatures. Results of the fidelity tests performed on the ensemble hindcast dataset for (a) standard deviation, (b) skewness, and (c) kurtosis. The grey histograms show the calculated statistics of 10,000 resampled 'proxy' observed time series from ensemble climate model simulations. The thick red line shows the observed value and the number in brackets in the plot title is the percentile of the modeled distribution represented by the observed value.

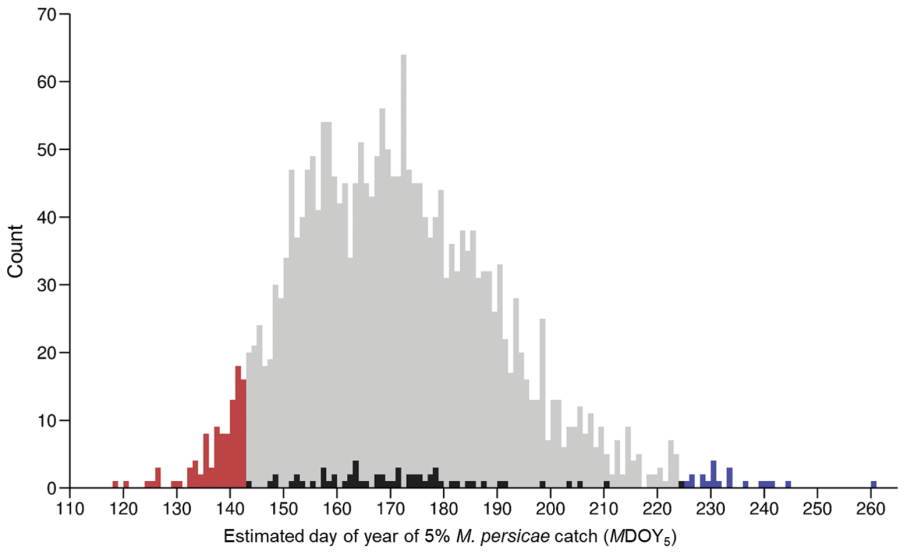

Fig. 3. Climate variability and extreme *M. persicae* flight dates. Frequency distributions for the 13-site mean day of year of 5% *M. persicae* catch ($MDOY_5$) estimated with January–February mean UK temperatures from the model ensemble (grey) and the observation-based HadUK-Grid dataset (black). Both the model and observation data cover the period 1961 to 2018. Red (early) and blue (late) shading highlight model-based estimates of $MDOY_5$ that are outside the range of the observation-based estimates.

the current risk of unprecedented UK rainfall (Thompson et al. 2017), and used in the UK government National Flood Resilience Review. Subsequently, the method has been applied to assess the likelihood of unprecedented hot summers (Kay et al. 2020) and extreme daily summer rainfall events (Kent et al. 2022). Here, we show how the method can be extended to secondary, climate-related risks, in this case temperature-sensitive pests. We focus on the seasonal timing of *M. persicae* flight in the UK because long and near-continuous records of *M. persicae* catch are available from the UK RIS network, and the relationship between the seasonal timing of *M. persicae* flight and winter temperatures in the UK is well established (Harrington and Clark 2010, Bell et al. 2015).

Our results support previous findings for a clear and large-scale response of ~12 d earlier/later *M. persicae* DOY_5 per 1°C warmer/cooler T_{JF} across the UK (Harrington and Clark 2010). This large-scale signal is related to a close coupling between inter-annual variations in T_{JF} at individual RIS sites and UK mean T_{JF}, and it helps explain why data from the RIS sites could be used to generate a regional flight model for the species (Cocu et al. 2005). Spatial differences in the relationship between T_{JF} versus DOY_5 for *M. persicae* among the 13 RIS sites in this study are most likely caused by local influences on aphid productivity, including availability of host plant species and land management practices (Bell et al. 2019). It is interesting to note that the strongest relationships occur consistently at sites with the coldest minimum T_{JF} values close to 0°C, in central and south-eastern England. The mechanism for this observation is not straightforward as there are multiple factors and timescales of influence. While aphids have a super-cooling point of around −25°C (the point at which body fluids freeze), they experience prefreeze mortality such that persistent minimum temperatures close to 0°C can cause chilling injury that severely affects the survival of *M. persicae* (Howling et al. 1994). Furthermore, the accumulation of degree days above a base temperature (approximately 4°C, Walton and Smilowitz 1979) influences the ability of overwintering populations to sustain themselves and develop before flight. Understanding this causal mechanism is an important consideration for estimating future *M. persicae* risk as freezing winter temperatures become less likely with future climate warming.

This study has demonstrated how a large ensemble of climate model simulations can be used together with historic observations to

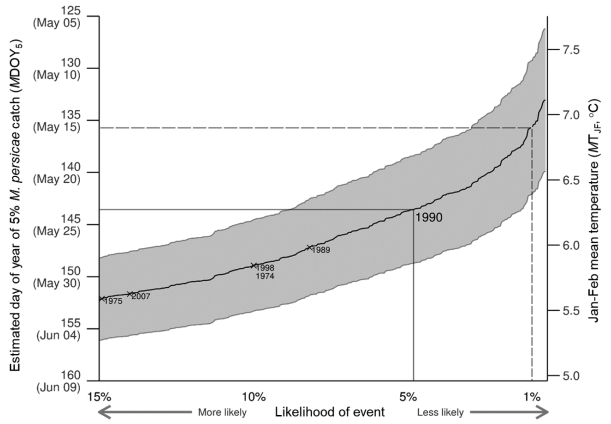

Fig. 4. Likelihood of a year with extreme early *M. persicae* flight. Showing the relationship between the 1980 to 2018 observations of mean day of year of 5% aphid catch for 13 sites across the UK ($MDOY_5$) and the ensemble of modeled UK mean January-February temperature (MT_{JF}) (Equation 1). Grey shading represents the 95% confidence interval around the regression (Fig. 1). The current likelihood of the warmest observed UK mean T_{JF}, 1990, occurring in any year is about 5% as highlighted by the grey lines, and the 1% extreme year, characterized by MT_{JF}, is highlighted by grey dashed lines. Other recent warm T_{JF} years are shown for reference.

quantify the current likelihood of climate-related risks, in this case the risk posed by a major agricultural pest. We focus on the current risks in this study, but the approach could be extended to include an assessment of future climate-related risks utilizing climate change projections (e.g., UKCP18, Gohar et al. 2018).

The results of this study have a range of practical applications relevant for managing risks to UK crops. Estimates of the likelihood of extremely early DOY_5 dates across the UK can be used by crop managers to assess the economic viability of specific crops and management techniques or make contingency plans for managing such events in future years. For example, in 2020, sugar beet crops in the UK were hit by exceptional weather, including the wettest February since 1914, the driest May since 1868 and one of the warmest winters in recent decades (Tandon and Schultz 2020). Aphid vectors were early, and the farmers could not get onto the fields due to waterlogging to manage the crop. One farmer lost £640,000 (US$850,000) from the 2020 harvest alone and there are many examples where losses have been so extreme that growers will not consider sugar beet anymore (see Financial Times article https://www.ft.com/content/f521ffae-2c1d-41e3-a9ce-0406d5ef5591). By quantifying the likelihood of specific climate extremes in advance, farmers would be able to prepare for different events based on their anticipated damage and current resilience to extremes.

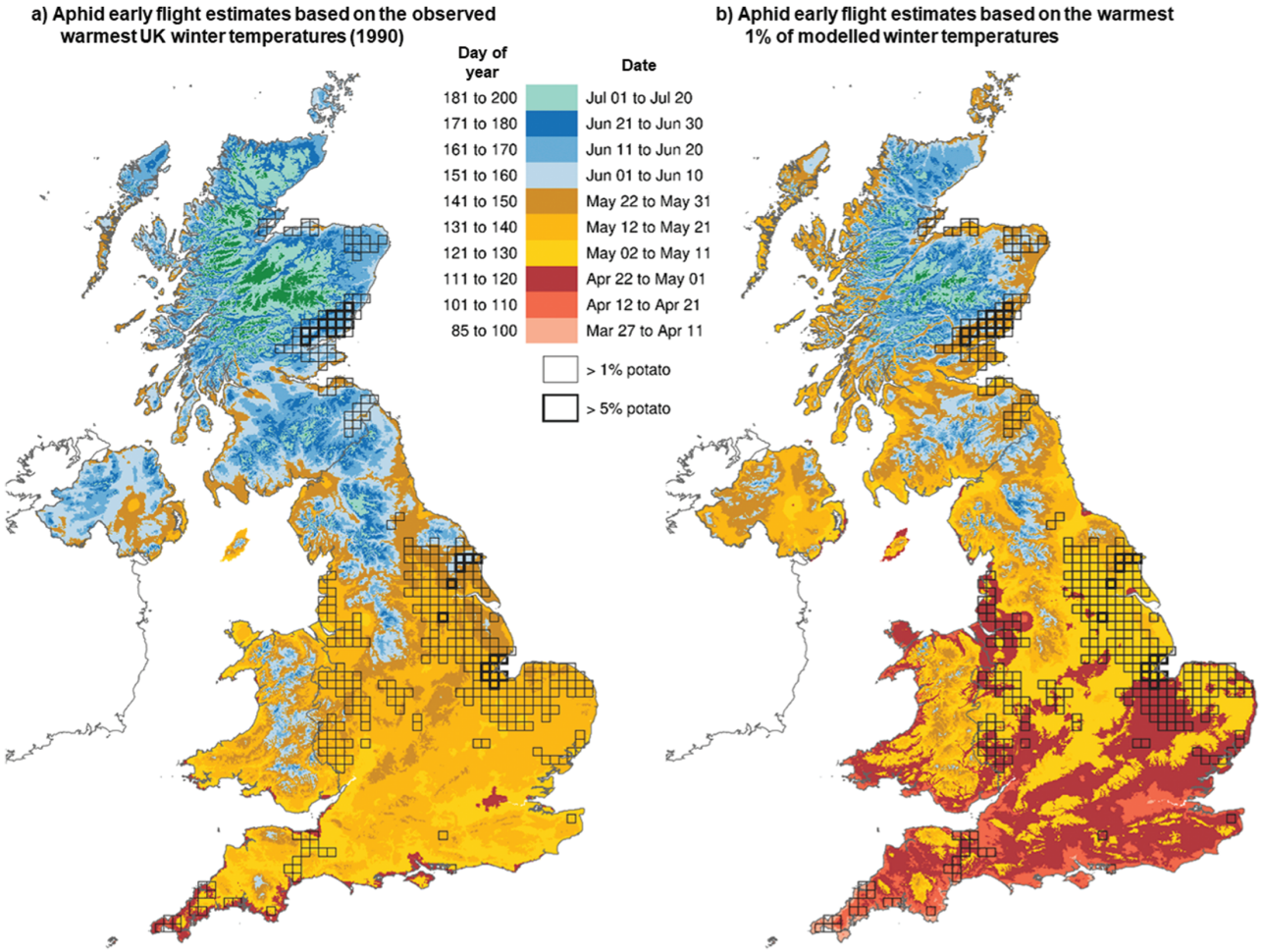

Fig. 5. Regional risk of extreme early *M. persicae* flight. Comparison of 1km gridded 'Day of year' and 'Date' of 5% *M. persicae* catch ($MDOY_5$) estimated using the relationship between January–February mean temperature (T_{JF}) and $MDOY_5$ (see Equation 1), and a) 1990 January–February mean temperature (T_{JF}) observations (HadUK-Grid dataset), where 1990 was the year with the warmest observed UK mean T_{JF}, and b) the warmest 1% of UK mean T_{JF} (99th percentile) from the model ensemble. Grid boxes show areas with >1% and 5% (bold) potato fields according to Defra's 2017 Crop Map of England (Defra 2017), and SASA (J. Pickup, personal communication).

At seasonal timescales, outputs from the method described here can be used to support early warnings for relevant UK growers. The leading edge of the observed aphid population is already widely communicated by RIS to growers in the UK who use this information to start surveillance for aphids in susceptible crops. Furthermore, there are several examples of where the aphid network observations have been used to drive forecasting models that relate to aphid numbers on the ground including *M. persicae*, *Rhopalosiphum padi* (Linnaeus, Hemiptera: Insecta), and *Phorodon humuli* (Schrank, Hemiptera: Insecta) (Heathcote et al. 1969, Tatchell and Woiwod 1990, Fabre et al. 2010), although the precision and accuracy of the forecasts can depend very much on within field, landscape, and environmental factors in addition to aphid biology. The approach detailed in this study could be used with the existing aphid observations and forecasts to communicate to growers the likely risk of early *M. persicae* flight during the upcoming crop season and highlight the timings and locations at highest risk across the UK. There is also potential to link our method with the UK seasonal climate forecast to provide a longer seasonal forecast window (e.g., Thornton et al. 2019). By combining the most up-to-date aphid and climate observations and models there is scope to provide further pest risk information to UK crop managers and help increase UK crop biosecurity.

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Data Availability

HadUK-Grid 1km gridded UK climate data are available from: https://www.metoffice.gov.uk/research/climate/maps-and-data/data/haduk-grid/haduk-grid. Rothamsted Insect Survey (RIS) data are available on request from: https://www.rothamsted.ac.uk/insect-survey. R code for the analyses and figures presented is available on GitHub: https://github.com/MetOffice/JEEpaperRcode2022. Due to intellectual property right restrictions, we cannot provide the source code or the documentation papers for HadGEM3-GC2. The Met Office Unified Model (MetUM) is available for use under license, see https://www.metoffice.gov.uk/research/approach/collaboration/unified-model/partnership.

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