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Impacts of climate change on wheat anthesis and fusarium ear blight in the UK

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Abstract Climate change will affect both growth of agricultural crops and diseases that attack them but there has been little work to study how its impacts on crop growth influence impacts on disease epidemics. This paper investigates how impacts of climate change on wheat anthesis date will influence impacts on fusarium ear blight in UK mainland arable areas. A wheat growth model was used for projections of anthesis dates, and a weather-based model was developed for use in projections of incidence of fusarium ear blight in the UK. Daily weather data, generated for 14 sites in arable areas of the UK for a baseline (1960–1990) scenario and for high and low CO_2 emissions in the 2020s and 2050s, were used to project wheat anthesis dates and fusarium ear blight incidence for each site for each climate change scenario. Incidence of fusarium ear blight was related to rainfall during anthesis and temperature during the preceding 6 weeks. It was projected that, with climate change, wheat anthesis dates will be earlier and fusarium ear blight epidemics will be more severe, especially in southern England, by the 2050s. These projections, made by combining crop and disease models for different climate change scenarios, suggest that improved control of fusarium ear blight should be a high priority in industry and government strategies for adaptation to climate change to ensure food security.

Keywords Climate change adaptation · Crop-disease-climate models · Food security · Fusarium head blight (*Fusarium culmorum*/*F. graminearum*) · Wheat growth model · Weather-based disease forecast

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Introduction

Across the world, climate change is affecting growth of agricultural crops (Metz et al. 2007; Stern 2007) and the severity of epidemics of diseases that attack them (Chakraborty 2005; Garrett et al. 2006). Whilst there has been much work on the impact that climate change will have on crop yields, little has been done to project how climate change impacts on crop growth will affect impacts on diseases (Gregory et al. 2009). Although elevated CO_2 concentrations under climate change may improve photosynthetic activity and increase crop yields in parts of Europe, including the UK (Ewert et al. 2002), this may be counteracted by increased stress on plants, for example heat or drought stresses (Semenov 2009), or by the increased severity of diseases as a result of climate change (Gregory et al. 2009). As changing temperature and rainfall patterns may produce serious disease epidemics (Chakraborty et al. 2000; Evans et al. 2008), detailed analysis of future crop production in relation to projected effects on the pathogens and their hosts is vital to allow strategic government planning relating to food security and to enable industry to plan ahead for adaptation to climate change (Barnes et al. 2010). This requires quantitative crop-disease-climate models, although much previous work has focused on qualitative impacts of climate change on crop diseases (Coakley et al. 1999; Anderson et al. 2004) and there have been few attempts to produce combined crop-disease-climate models (Butterworth et al. 2010; Luo et al. 1995).

Climate change is predicted to impact on the growth of arable crops, including winter (autumn-sown) wheat (Semenov 2009), the most important arable crop grown in the UK, grown over 2 Mha in 2008, with a value of £2.2 billion (www.ukagriculture.com). Its importance continues to grow, as wheat grain is a potential future source of UK-grown bio-fuels (Tuck et al. 2006). The crop, sown in September/October and harvested the following August, is mostly grown on arable land in the east of England, due to poor terrain and soil conditions for arable agriculture in the west (Fig. 1). The wheat crop growth model Sirius (Jamieson et al. 1998; Jamieson and Semenov 2000), used to estimate impacts of climate change on wheat yields (Semenov 2009), can also be used to estimate impacts on crop growth parameters such as anthesis date. However, it assumes that diseases are controlled and does not take into account effects of diseases on yield and grain quality.

The timing of wheat anthesis greatly influences the severity of wheat fusarium ear blight (also known as fusarium head blight or scab), since the disease is monocyclic (one disease cycle per cropping season) because the wheat is susceptible to infection only for a short period around anthesis, when weather is warm and wet (Xu et al. 2007). The disease is caused by a number of pathogens (Xu and Nicholson 2009); of particular concern in the UK are *Fusarium graminearum* and *F. culmorum* of which some chemotypes produce mycotoxins that are hazardous to human health if affected grain is consumed (www.hgca.com; Goswami and Kistler 2004; Xu et al. 2008; Madden and Paul 2009). The disease symptoms include ear bleaching, formation of pink/orange conidial masses and dark necrotic lesions on spikelets. Severe fusarium ear blight epidemics have occurred in the USA (Windels 2000; Madden and Paul 2009), China (Yang

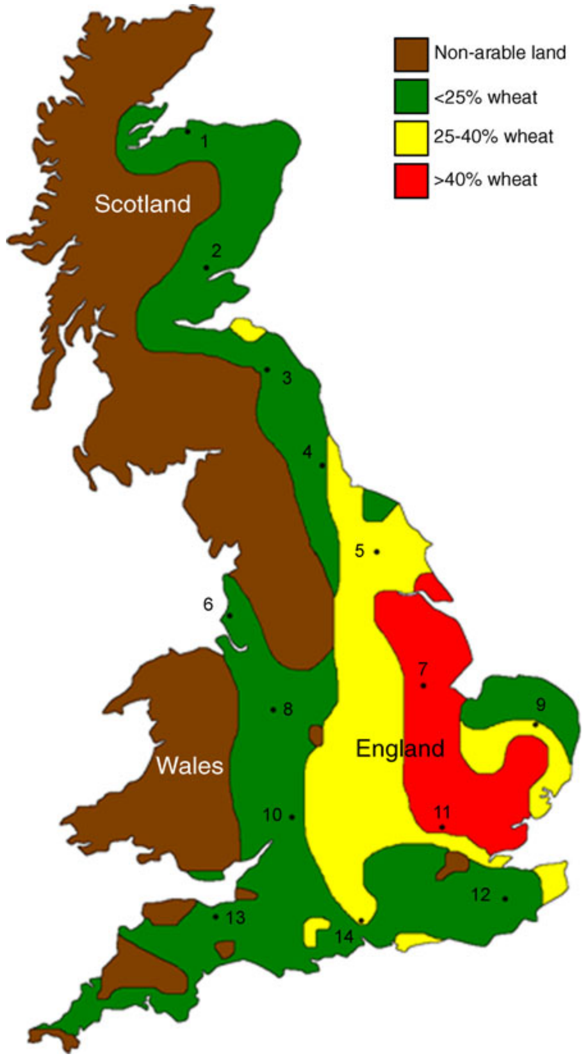

Fig. 1 Areas of arable land on the UK mainland, indicating areas where <25% (■), 25–40% (■) and >40% (■) of the area is currently sown to wheat. The majority of UK wheat is grown in east England, although some is grown in east Scotland or west England. None is grown in west Scotland, northwest England or Wales, because the terrain is unsuitable for arable agriculture (■). Also shown are the 14 sites located within the arable area included in the modelling exercise for which weather data were generated for the different climate scenarios. The sites, selected from UK synoptic weather stations (further information at www.bits.bbsrc.ac.uk/metweb) to give representative weather in different arable regions, are labelled in order of decreasing latitude (Table 4). Wheat and arable area information were from www.hgca.com/cerealsmap/version9.swf

et al. 2008) and Australia (Chakraborty et al. 2005). In the UK, incidence of fusarium ear blight has increased recently, with widespread epidemics in 2007 and 2008 (80% and 60%, respectively, of crops sampled at GS 75 with symptoms, by comparison with 20–30% in the previous few seasons, www.cropmonitor.com) but it is not clear whether climate change will continue to increase the severity of epidemics, with implications for food safety if mycotoxin production is also increased (Xu et al. 2008; Miraglia et al. 2009). Since associated global threats to food security will mean that there is a need to maximise cereal production in the UK (Stern 2007; Mahmuti et al. 2009; Hughes et al. 2011), it is essential to project the impact of climate change on severity of epidemics.

For projecting climate change impacts on fusarium ear blight, it is necessary to have a simple weather-based model that predicts fusarium ear blight incidence or severity using only a few weather variables as inputs (e.g. temperature, rainfall), in a similar way to the statistical model used to describe the disease cycle of another monocyclic disease, phoma stem canker of oilseed rape (Evans et al. 2008). Such a fusarium model can then be combined with the Sirius model predicting wheat anthesis date and with local-scale weather for future climate scenarios to project impacts of climate change on the disease. The weather-based models developed to predict severity of fusarium ear blight epidemics to guide use of fungicides for disease control in Europe, North America and South America (e.g. Moschini et al. 2001; De Wolf et al. 2003; Rossi et al. 2003; Del Ponte et al. 2005; De Wolf and Isard 2007; Prandini et al. 2009; Table 1) all use as an input relative humidity, a parameter that is not always measured by UK synoptic weather stations and not easily included in projected weather for different climate change scenarios. This paper describes work to combine a simple, UK temperature/rainfall-based model for predicting fusarium ear blight with a wheat crop model and local-scale climate scenarios to project the direct impact of climate change on wheat anthesis date and incidence of fusarium ear blight epidemics. It does not assess direct impacts of changes in concentrations of CO_2 (Chakraborty and Newton 2011) or indirect impacts of climate change (e.g. through changes in cropping practice such as increasing maize production) on the severity of fusarium ear blight epidemics.

Materials and methods

Collation of the weather, winter wheat date of anthesis and fusarium ear blight severity data

To project the impacts of climate change on the severity of fusarium ear blight epidemics, observed weather data (daily minimum and maximum temperature (°C), total rainfall (mm) and solar radiation (MJ d^{-1})) from synoptic weather stations around the UK (Fig. 2; Table 2) were collated. Observed weather data were supplied by the UK Meteorological Office and Rothamsted. Rothamsted meteorological data were used for the development of the fusarium ear blight model. The other weather data, used for validation of the wheat anthesis date and fusarium ear blight incidence predictions, were from the synoptic weather stations closest to the locations of trials from which observed data for date of anthesis or fusarium ear blight incidence were collected.

Data for dates of anthesis for winter wheat cultivar (cv.) Consort were collated from HGCA Recommended List trials, wheat water use efficiency trials and a few other sources (Table 3) for many locations throughout the UK. Sowing date data for these trials were also collated. These anthesis date and sowing date data were used for validation of the predictions of anthesis date made by the wheat crop growth model Sirius for cv. Consort for harvest years 2004–2008. The model Sirius predicts growth stage 65 (this is mid-anthesis; anthesis starts at growth stage 60 and ends at growth stage 69 on the Zadoks scale, Lancashire et al. 1991), but the data sets often differed in the exact growth stage measured (often it was growth stage 61 which is usually 2-3 days before growth stage 65) and how often the measurements were taken (some were taken daily, some every 2-3 days and some weekly). Cv. Consort was selected for use since it is one of the three cultivars available on the 2009/10 HGCA Recommended List (available from www.hgca.com) for which Sirius has been calibrated and its resistance rating (ranging from 1–9, where 1 is susceptible and 9 is resistant) to fusarium ear blight (rated a score of 6) is intermediate between that of the other two available cultivars (Claire, rated 7, and Soissons, rated 5).

Fusarium ear blight severity data were collated from the CropMonitor disease survey of mainly

Table 1 Models produced in Argentina, the USA and Italy to predict the severity/risk of fusarium ear blight (FEB) from observed weather variables at critical crop growth stages; relative humidity (RH), daily rainfall, temperature and solar radiation. These three[a] models can be used to determine the optimum timing of fungicide sprays for control of FEB

Reference country	Factor predicted	Weather inputs	Critical weather period (crop growth dependent)	Equations[g]
Argentina[d] (2 models)	Percentage of ears with FEB[b]	RH[c], daily rainfall, daily temperature	From 8 days before ear emergence (growth stage 50) until 550° days have elapsed	$PI\% = 20.37 + 8.63\,NP_2 - -0.49\,DD_{926}$
				$DD_{926} = \sum[(MaxT - -30)] + (9 - -MinT)]$
				$PI\% = 18.34 + 4.12NP_{12} - -0.49DD_{1026}$
				$DD_{1026} = \sum[(MaxT - -30)] + (10 - -MinT)]$
USA[e] (4 models)	Risk of a FEB epidemic (field disease severity≥10%)	RH[c], daily rainfall, daily temperature	From 7 days before the start of anthesis (growth stage 60) to 10 days after the start of anthesis	$RFE = -3.38 + 6.81\,TRH9010$
				$RFE = -3.73 + 10.5\,T15307\,TRH9010$
				$RFE = -1.06 - 14.2\,T15307\,DPPT7 + 39.5\,T15307\,DPPT7\,TRH9010$
				$RFE = -1.54 + 31.8\,T15307\,DPPT7\,TRH9010 - 5.81\,DPPT7$
Italy[f]	Risk of a FEB epidemic (field disease severity)	RH[c], daily rainfall, daily max./min. temperature,	From ear emergence (heading) until harvest	$FHB\_risk = \sum SPO\,DIS\,INF\,GS^h$

[a] There is an additional model from Brazil (Del Ponte et al. 2005) that was investigated but it is very complex and requires the calculation or knowledge of many additional factors such as anther extrusion rate (to calculate the area of available tissue for infection), spore cloud density and infection frequency to produce an overall risk of FEB infection

[b] As these models were produced outside the UK, the disease is referred to as fusarium head blight in the original papers (not fusarium ear blight)

[c] From a statistical viewpoint, the relative humidity is difficult to work with since it cannot be greater than 100%, so that any formula developed using relative humidity as an input would need to take this into account

[d] Moschini et al. 2001

[e] De Wolf et al. 2003. Field disease severity is the mean percentage of ear area with FEB symptoms in the crop (including all plants with/without symptoms)

[f] Rossi et al. 2003. Field disease severity is the mean percentage of ear area with FEB symptoms (www.ext.nodak.edu)

[g] Notation used in the equations:

DD_{926} 926° days accumulated, $DD_{1,026}$ 1026° days accumulated, *DPPT7* Duration of precipitation (hours) in the 7 days before anthesis, *MaxT* Maximum daily temperature >26°C, *MinT* Minimum daily temperature <9°C or <10°C, NP_2 Number of 2 day periods with precipitation≥0.2 mm and RH >81%, NP_{12} Number of NP_2 periods plus the total number of days with precipitation≥0.2 mm and RH >83%, *PI%* Predictive index, *RFE* Risk of a FEB epidemic (epidemic if FEB field disease severity≥10%), *T15307* Duration (hours) of 15≤T≤30°C in the 7 days before anthesis, *TRH9010* Duration (hours) 15≤T≤30°C and RH≥90% during anthesis

[h] FHB risk is calculated daily and accumulated until harvest; equations for each of the components (SPO, sporulation rate; DIS, dispersal rate; INF, infection rate; GS, empirical weight) are given in Rossi et al. (2003). The model assumes that inoculum is always present

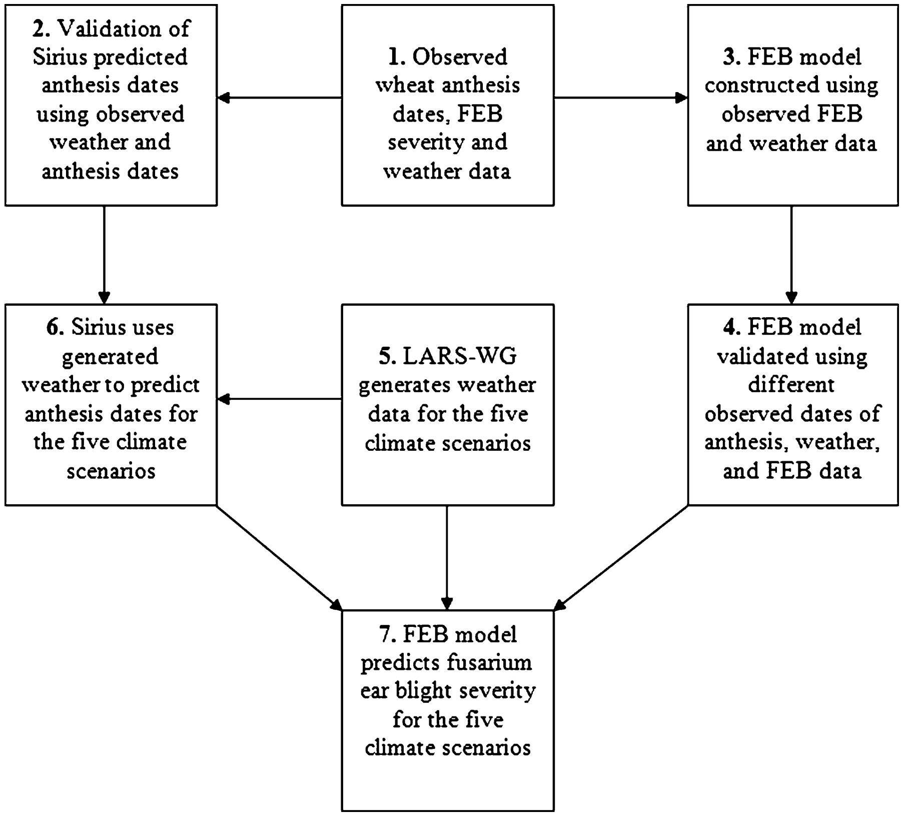

Fig. 2 An illustration of how the different models were combined to produce projections of date of winter wheat anthesis (growth stage 65) and fusarium ear blight (FEB) incidence (% plants affected) for different climate change scenarios. (1) Observed data for weather (daily minimum and maximum temperature (°C), total rainfall (mm) and solar radiation (MJ day^{-1})), date of anthesis and fusarium ear blight incidence were collated from a number of sources for different regions of the UK for the years 1994–2008. (2) The dates of anthesis predicted using the wheat growth model Sirius were validated by comparing predicted anthesis dates for winter wheat cv. Consort, generated by Sirius using observed weather data, with observed anthesis dates for the same sites for the period 1997–2004. (3) A fusarium ear blight model was developed from data for fusarium ear blight incidence from sites within 80 km of Rothamsted and observed weather for Rothamsted for the period 1994–2008; the model related fusarium ear blight incidence to average May temperature and rainfall in the second week of June (time of observed anthesis dates for Rothamsted) (Eq. 1). (4) Predictions of average percentage of plants affected by fusarium ear blight were validated by comparing predictions made using observed weather to observed fusarium ear blight incidence data for the period 1994–2008 for different regions of the UK (northeast, southwest and east England) which were plotted as north (northeast) and south (southwest and east) England on the validation graph (Fig. 5). (5) Weather data were generated using LARS-WG for each of the 14 sites (Fig. 1) for each climate scenario; baseline (based on the statistical variability (or patterns) in observed weather variables in the period 1960–1990) and high CO_2 and low CO_2 emissions scenarios for the 2020s and 2050s (2020LO, 2020HI, 2050LO and 2050HI). (6) The dates of anthesis for cv. Consort were projected for each site for each climate scenario using Sirius, allowing maps to be generated to show the effect of climate change on date of anthesis (Fig. 5). (7) Using the weather generated by LARS-WG and average date of anthesis projected using Sirius for each of the sites for each of the five climate scenarios, the fusarium ear blight model was used to project fusarium ear blight incidence for each site for each of the five climate scenarios (Fig. 6)

commercial crops and HGCA Recommended List trials, for up to 30 different winter wheat cultivars (www.cropmonitor.co.uk, Table 2). These data were recorded as percent plants affected by fusarium ear blight approximately 3 weeks after anthesis. CropMonitor data over the period with harvest years 1994–2008 for sites within 80 km of Rothamsted were used in model construction and CropMonitor data from other areas and HGCA data for 2004–2008 were used for model validation.

Table 2 Sources of the observed fusarium ear blight incidence (% plants affected) data used to construct and validate the weather-based model for predicting the incidence of wheat fusarium ear blight equation. Separate sets of CropMonitor data were used for construction and validation of the model and the HGCA recommended list trial data were used only in model validation. For validation see Fig. 4. The observed data were averaged for areas near each weather station for each year to smooth out the very high and very low levels recorded, even near the same weather station

Location	Harvest year(s)[d]	No. of points	Source of data	Reference
Data used for model construction:				
Various sites[a]	1994–2008	322	CropMonitor[e]	www.cropmonitor.co.uk
Independent data used for model validation:				
Various sites[b]	2004–2008	165	CropMonitor[e]	www.cropmonitor.co.uk
Various sites[c]	2004–2008	65	HGCA Recommended List trials[f]	www.hgca.com

[a] Disease data for sites in a region within 80 km of Rothamsted in south England were averaged for groups of sites in areas near each of the synoptic weather stations at Andrewsfield, Bedford, Benson, Bracknall, Brize Norton, Charlwood, High Wycombe, South Farnborough, Wittering, Redhill and Heathrow (i.e. 11 weather stations and 15 years, 165 data sets). For each set of disease data, daily total rainfall and average temperature for April, May and June were collated

[b] Data for sites in southwest and northeast England for which the nearest synoptic weather station was given. Sites in southwest England were near St Mawgan, Dunkeswell Aerodrome, Yeovilton, Chivenor, Camborne, Plymouth and Hurn. Sites in northeast England were near Linton on Ouse, Leeming, Church Fenton, Fylingdales, Bridlington, Boulmer and Loftus

[c] Sites are Cranwell and Binbrook in Lincolnshire

[d] Fusarium ear blight incidence (% plants affected) was assessed approximately 3 weeks after the start of anthesis on a range of winter wheat cultivars

[e] CropMonitor survey sites are mostly commercial farms but some are dedicated trial sites. The survey is coordinated by Fera, with funding provided by Defra, HGCA and Bayer Crop Science

[f] The trials are funded by HGCA for the purpose of selecting cultivars most suitable for planting for the UK Recommended List

Table 3 Sources of the observed date of anthesis and sowing date data for winter wheat cv. Consort used to validate predictions made using observed weather and sowing date data with the wheat growth model Sirius[a]. Some of the observed values were for growth stage 61 rather than growth stage 65 that the model predicts for

Location	Harvest year(s)[d]	No. of points	Source of data	Reference
Various sites[b]	2003–2007	25	HGCA Recommended List trials[e]	www.hgca.com
Rothamsted	2006–2007	12	PhD thesis, EU project BioExploit	Sarah Holdgate (2009)[g]
Rothamsted	2008	1		Rohan Lowe, personal communication
Various sites[c]	2006–2008	10	Water use efficiency trials (Defra-funded Sustainable Arable LINK project)	www.defra.gov.uk
Rosemaund	2006	1	CropMonitor[f]	www.cropmonitor.co.uk

[a] For validation of the Sirius wheat growth model see Fig. 3. The data used for validation of Sirius anthesis data were independent of the data used for model construction

[b] Sites are Dunmow and Stebbing in Essex and Bramham in West Yorkshire, for several different sowing dates

[c] Sites are Shelford, Grantchester and Trumpington in Cambridgeshire, Clopton in Suffolk, Malden in Essex and Riseholme in Lincolnshire

[d] To determine anthesis dates, trials were assessed regularly in late May and June (daily, every 2-3 days or weekly)

[e] The trials are funded by HGCA for the purpose of selecting cultivars most suitable for planting for the UK Recommended List

[f] CropMonitor survey sites are mostly commercial farms but some are dedicated trial sites. The survey is coordinated by Fera, with funding provided by Defra, HGCA and Bayer Crop Science

[g] Holdgate, S. (2009).

Validation of Sirius for prediction of dates of anthesis

Predictions of anthesis date (for growth stage 65) were made with the wheat crop growth model Sirius using observed weather. To predict dates of anthesis using Sirius, it was necessary to input data for the cultivar, sowing date, minimum and maximum daily temperature, total daily rainfall and daily solar radiation. Further parameters such as fertiliser treatment and soil nitrogen distribution were set at default values. The anthesis dates generated by Sirius for cv. Consort were adjusted to fit observed data by adjusting input parameters (e.g. the phyllochron and thermal times between different stages in crop development). To validate anthesis date predictions produced by Sirius, predictions were compared to anthesis dates observed in trials in different areas of England that comprised a data set independent of data used in model construction (Table 3). The predictions were made with observed weather (daily data for minimum and maximum temperature (°C), total rainfall (mm), solar radiation (MJ d^{-1})) and sowing dates as inputs to the model. The deviation of predicted against observed validation data from the 1:1 line was analysed statistically.

Construction of a UK fusarium ear blight model

The CropMonitor data used in model construction were for incidence (%) of plants affected by fusarium ear blight for wheat crops located within an region up to 80 km from Rothamsted (Hertfordshire, England, that accounted for c. 15% of the UK mainland arable area and c. 33% of the arable land where >25% is sown to wheat) for harvest years from 1994–2008 (varying from 13–32 sites per year; total of 322 data points). Disease data for all crops within an area near each of 11 synoptic weather stations (Table 2) were averaged for each year to decrease the overall variability in the data. Daily weather data from these 11 synoptic weather stations for the months April, May and June were summarized as were, separately, data for the first 2 weeks in June. These data were average temperature and total rainfall and these periods were chosen as those in which the weather was most likely to affect subsequent fusarium ear blight incidence (Xu et al. 2007). This gave a set of 10 weather variables [average temperature for April, May and June, average rainfall for April, May and June and the corresponding weather measurements for the first and second weeks of June] to be tested alone or in combination in relation to disease incidence over the 15 year period.

The main problem with the weather data from the individual stations was that some data sets were incomplete; consequently disease data for some station/year combinations were excluded. With 11 stations and 15 years, there were potentially a maximum of 165 weather/fusarium data sets. When data sets with missing disease or weather data were excluded, it reduced the size of the data available to 88 data sets. However, by using weather data from Rothamsted that were complete over the period, the number of data sets increased to 117 (disease data associated with the synoptic weather stations were missing from 48 data sets). One simplification made was to assume that the same relationship between the weather variables and disease incidence was appropriate for all data sets. It was much easier to justify the same form of relationship if data from a single weather station were used. Therefore Rothamsted weather data were selected, since the data were complete and Rothamsted was central to the region used for constructing the model.

Since disease incidence was expressed as a percentage, the association was investigated using a generalized linear model where the logit-transformed incidence was related to a linear combination of the weather variables using principles of step-wise regression. This meant that predictions were naturally evaluated to be between 0 and 100. Weather variables were selected for inclusion in the model on the basis of the percentage of 'deviance' accounted for. The single best weather variable was total rainfall from the second week in June, the week at the end of which anthesis was observed, according to data for Rothamsted for 2006–2008. The next best variable was average temperature in May (i.e. from 6 to 2 weeks before anthesis).

Validation of a UK fusarium ear blight model

Validation was done using independent data for other regions of the UK mainland. Since crops in these areas have different anthesis dates from those near Rothamsted, it was necessary to express the model in a form related to anthesis date. Therefore, incidence of fusarium ear blight was related to rainfall for the week leading up to anthesis and to average temperature for the 4-week period from 6 to 2 weeks before anthesis. It was tested whether the same relationship was reasonable for different arable areas in the UK mainland. This was necessary because there was insufficient information at some weather stations to form separate relationships for different areas. Since the model was going to be used for extrapolation, a model based on averages was likely to be more robust.

Predictions of fusarium ear blight incidence were validated using observed weather data and mean observed dates of anthesis (from trials in corresponding areas of the UK to allow the appropriate weather to be used when producing predictions, Table 3) as inputs to the fusarium ear blight model. As much of the weather data were incomplete, data from several weather stations in a region were collated to estimate missing information. Predictions, in terms of average % plants affected, were compared to observed fusarium ear blight incidence data, from several regions of the UK (Table 2). Data used for model validation were independent of data used for model construction. It was not appropriate to analyse the deviation of validation data from the 1:1 line statistically since the logit transformation used gives a non-homogeneous scale.

Local-scale daily weather for climate change scenarios

Daily weather data (minimum and maximum daily temperature, total daily rainfall and daily solar radiation) specific to the 14 sites located in UK mainland arable areas (altitude, latitude and longitude, Table 4) were generated using LARS-WG stochastic weather generator (Semenov 2007), for each of the 14 sites selected from within the UK mainland arable area, for each of the five climate scenarios; baseline, 2020LO, 2020HI, 2050LO and 2050HI. The baseline scenario is based on LARS-WG site parameters derived from observed weather for the period 1960–1990. The other four climate scenarios relate to high (HI) and low (LO) CO_2 emissions for the 2020s and 2050s, based on the UKCIP02 projections (Semenov 2007). The values used for the CO_2 concentration in the UK atmosphere were 334 ppm (baseline), 422 ppm (2020LO), 437 ppm (2020HI), 489 ppm (2050LO), 593 ppm (2050HI), taken from the IPCC emission scenarios. These projections are in turn based on the IPCC global emissions scenarios (Nakicenovic 2000) and the HadCM3 global climate model (Collins et al. 2001; Hulme et al. 2002). For each of the 14 sites used and for each climate scenario, 50 yearly simulations of synthetic daily

Table 4 Site location information for each of the 14 sites selected for generation of simulated weather for the five climate change scenarios, distributed around the UK mainland in arable areas. Sites were chosen at the location of synoptic weather stations and altitude, latitude and longitude data from each site were obtained from http://www.bits.bbsrc.ac.uk/metweb/

Site[a]		Altitude (metres above sea level)	Latitude (degrees)	Longitude (degrees)
1	Kinloss	5	57.646	-3.562
2	Mylnefield	31	56.457	-3.072
3	Haddington	41	55.580	-2.450
4	Durham	102	54.768	-1.585
5	Askham Bryan	34	53.950	-1.080
6	Crosby	10	53.776	-3.037
7	Cranwell	62	53.031	-0.501
8	Newport Salop	66	52.779	-2.428
9	Morley St Botolph	48	52.550	1.050
10	Cheltenham	65	51.900	-2.050
11	Rothamsted	128	51.806	-0.358
12	East Malling	33	51.287	0.451
13	Cannington	28	51.090	-3.040
14	Porton	111	51.070	-1.420

[a] The locations of sites

weather data (minimum and maximum temperature, rainfall and solar radiation) were produced. These data were then used as inputs for the wheat crop growth model Sirius and as inputs for the fusarium ear blight model, to allow average anthesis dates and average fusarium ear blight incidence to be generated for each site under each climate scenario. Only the arable area was included since it is unnecessary to produce projected fusarium ear blight incidence for areas of the UK where no wheat will ever be grown, for example in mountainous regions like the English Pennines or Scottish Highlands.

Projection of wheat anthesis dates for the 2020s and 2050s

Projected dates of anthesis were generated using projected weather from LARS-WG for all five of the climate change scenarios for each of the 14 sites as inputs into the Sirius model. Maps were drawn to illustrate how anthesis dates will change under the different climate change scenarios by spatial interpolation between the 14 sites. The changes in the dates of anthesis under climate change were used to define the specific time periods for which simulated weather (from 6 to 2 weeks before anthesis for average temperature and week of anthesis for total rainfall) was required to input into the fusarium ear blight model.

Projections of fusarium ear blight incidence for the 2020s and 2050s

Using the LARS-WG generated weather for each of the five climate scenarios and the average anthesis date calculated (averaged over 50 dates projected from the generated weather data) for each site and each climate scenario, fusarium ear blight incidence projections were made for each site under each of the five climate scenarios. Maps were produced by spatial interpolation between the 14 sites.

Results

Validation of Sirius for prediction of dates of anthesis

The predicted anthesis dates produced by Sirius with observed weather data and sowing dates as inputs were plotted against observed anthesis dates to show the relationship between them (Fig. 3). For predicting anthesis dates, since many sets of weather data were incomplete, data from several weather stations in a region were collated to estimate missing information. Thus the trial sites (for anthesis dates) and nearest synoptic weather stations were grouped into three regions; east England, southwest England and north-east England, for use in the validation. To illustrate the validation data, the east and southwest were then combined into south England. Although the observed dates of anthesis were not always for growth stage 65, no correction was made to equivalent predicted values, since the correction needed varied from site to site and year to year. Generally, the anthesis dates for south England were earlier than those for north England and there was a reasonable relationship between predicted and observed values. The root mean squared value of

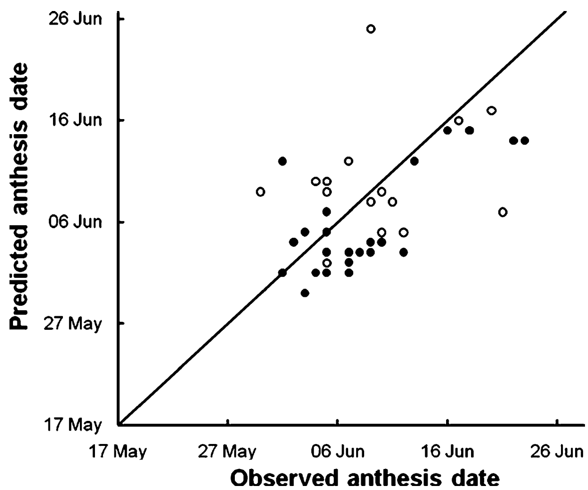

Fig. 3 Validation of winter wheat (cv. Consort) dates of anthesis (growth stage 65) predictions made using the wheat growth model Sirius. The predictions made with observed weather (daily data for minimum and maximum temperature (°C), total rainfall (mm) and solar radiation (MJ day^{-1})) and sowing dates as inputs to the model were compared to observed anthesis dates for harvest years 2003–2008 for two regions of the UK; south England (●) and north England (○). As many sets of weather data were incomplete, data from several stations in a region were collated to estimate missing information for use in the validation. Predicted anthesis date (y axis) was plotted against observed anthesis date (x axis) and the line predicted anthesis date = observed anthesis date is shown for comparison. Sources of data for the date of anthesis and sowing date are listed in Table 3. The root mean squared value of deviation from the 1:1 line was 5.75 days, which can be accounted for by variability in the observed data (differences in the exact growth stage (GS 61–65) at which observations were made, some observations were taken daily, some every 2-3 days and some weekly)

deviation of validation data from the 1:1 line was 5.75 days. This value is a result of several factors, including variation in the frequency of observations (some daily, some at 2-3 day intervals, some weekly) and in the observed growth stage at which anthesis date was measured (from GS 61 to GS 65, generally about 2–4 days in the UK) when compared to the Sirius model predictions for growth stage 65.

Construction of a UK fusarium ear blight model

When weather variables were selected for inclusion in the model on the basis of the percentage of 'deviance' accounted for, the single best weather variable was total rainfall from the second week in June (i.e. time of anthesis at Rothamsted) while the next best variable was average temperature in May; they accounted for 22.5% and 19.0% of the deviance, respectively. Regression coefficients were 0.93 (0.199) and 0.08 (0.0133). The remaining 8 variables accounted for much less of the deviance and related to periods of weather that were considered less important to the development of the disease. The final model including these two variables accounted for 36.0% of the deviance and the corresponding coefficients were 0.941 (0.201) and 0.069 (0.012), respectively. This represents a substantial proportion of the variation in fusarium ear blight incidence associated with weather factors (generally estimated at about 50%). The observation that the coefficients did not differ much if they were fitted separately or fitted in combination suggests that the variables were independent of each other. The relationship determined between the May average temperature (mayavt), rainfall in the second week of June (jwktotrn) and fusarium ear blight incidence (feb) is shown in Eq. 1, which applies to the region within 80 km of Rothamsted. Fusarium ear blight incidence is measured as percentage of plants affected. The right hand side of this expression is the back-transformation for the logit transformation used in the model construction.

$$feb = 100^* \frac{\exp(-15.3 + 0.941 mayavt + 0.069 jwktotrn)}{1 + \exp(-15.3 + 0.941 mayavt + 0.069 jwktotrn)} \quad (1)$$

Validation of a UK fusarium ear blight model

Validation was done using independent data from other regions of the UK mainland (Fig. 4). Predicted

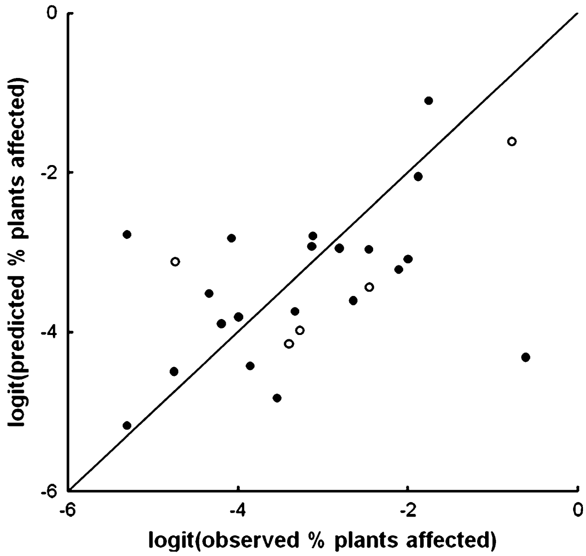

Fig. 4 Validation of wheat fusarium ear blight incidence (% plants affected) predictions. Predictions made using observed weather (daily data for minimum and maximum temperature (°C) and total rainfall (mm)) and observed anthesis dates (from trials in two regions of the UK, north England (○) and south England (●), to allow the appropriate weather to be used when producing predictions) were compared to observed fusarium ear blight incidence in the period 2004–2008. Crop fusarium data were divided into three regions, northeast, east and southwest England (the weather data from the nearest synoptic weather stations were combined for these regions in order to estimate missing information and these data were used to make predictions (the east and southwest were combined into south England for plotting the graph)). For each year/region, disease data available were averaged across all trials and cultivars to give one observed value for each year/region. Since the model was developed using approximately 30 cultivars, the validation was also done using an average of all trials and cultivars. The values have been transformed using a logistic function; the same method was used in the development of the model. Sources of fusarium ear blight incidence data used in the model construction and validation are listed in Table 2. It was not appropriate to analyse the deviation from the 1:1 line statistically as the logit transformation used gives a non-homogeneous scale

fusarium ear blight incidence, estimated using observed weather data and observed average dates of anthesis, was plotted against observed fusarium ear blight incidence. The values were transformed using a logistic function in the same way as the model was constructed. The relationship between predicted and observed values was influenced by the many factors contributing to variation in the observed data. For example, the outlying point was for southwest England in 2007, which was very wet in May, June and July (www.metoffice.gov.uk/climate/uk) in that region of the UK, accounting for the greater incidence of fusarium ear blight observed than was predicted by the model. However, this simple model, based on a few weather parameters, was suitable for use in work to project impacts of climate change on fusarium ear blight epidemics. Whilst other factors (e.g. previous crop, especially if it was maize, and use of fungicides; www.hgca.com) undoubtedly affected the incidence of fusarium ear blight, it is difficult to model the impact of climate change on such factors and outside the scope of this paper.

Projection of wheat anthesis dates for the 2020s and 2050s

The projections for anthesis dates suggest that as the weather in the UK changes, dates of anthesis will get progressively earlier, by about 11–15 days across the whole country (Fig. 5). This effect is slightly greater near the south coast of England than in the north of Scotland. The results suggest that the earliest dates of anthesis are expected in the southwest of England; c. 4 June in the 2020HI scenario and c. 28 May under the 2050HI scenario as opposed to c. 11 June in the baseline scenario. The results suggest that the latest anthesis dates are expected in the north of Scotland; c. 18 June for the 2020HI scenario, c. 13 June for the 2050HI scenario compared to c. 24 June in the baseline scenario. The anthesis dates are projected to be earlier in the high CO_2 scenarios when compared to the corresponding low CO_2 scenarios.

Projections of fusarium ear blight incidence for the 2020s and 2050s

The projections for changes in fusarium ear blight incidence (Fig. 6) are more complex than the projections for changes in anthesis dates, since the disease incidence is a function of both average temperature for the period from 6 to 2 weeks before anthesis and total rainfall for 1 week leading up to anthesis. Since the period of weather used to predict the disease incidence is related to the anthesis date and anthesis dates are

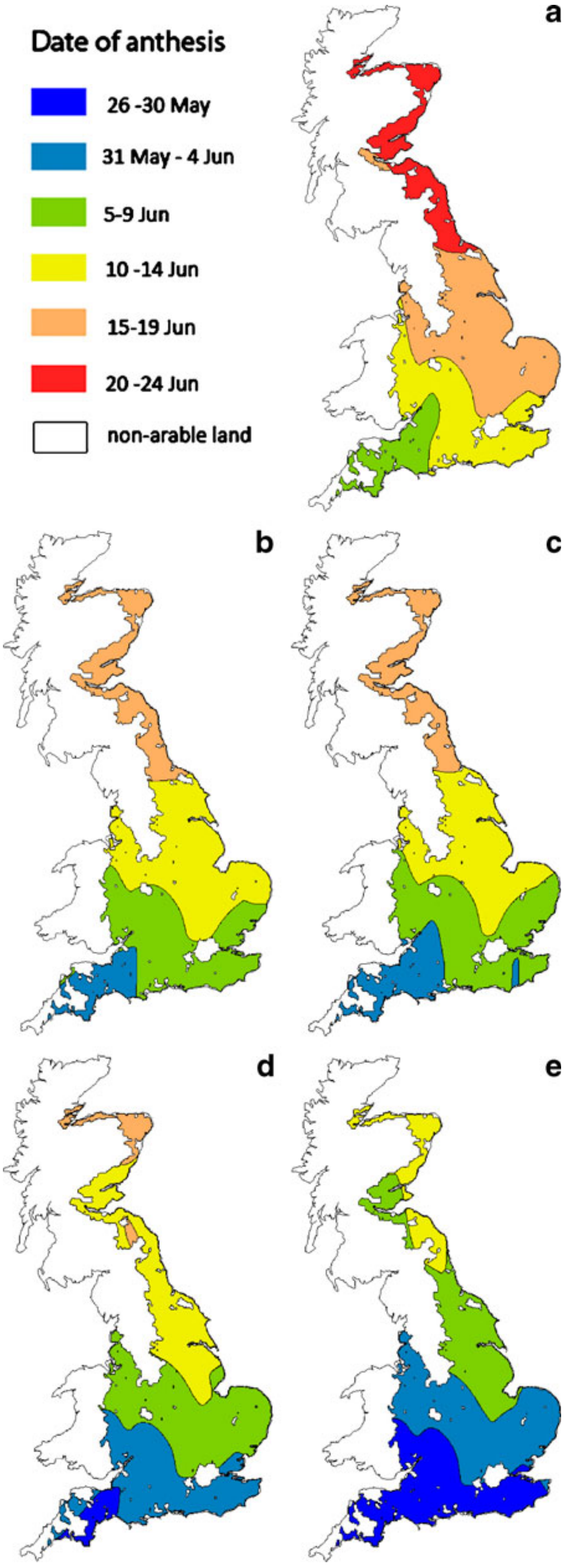

Fig. 5 Average dates of anthesis (growth stage 65), for winter wheat cv. Consort projected by the wheat growth model Sirius, for each of the five climate scenarios; **a** baseline, **b** 2020LO, **c** 2020HI, **d** 2050LO and **e** 2050HI. The baseline scenario is based on the patterns in observed weather factors from 1960–1990 and the other scenarios are high CO_2 (HI) and low CO_2 (LO) emissions scenarios for the 2020s and 2050s. The maps were produced by spatial interpolation between the 14 sites

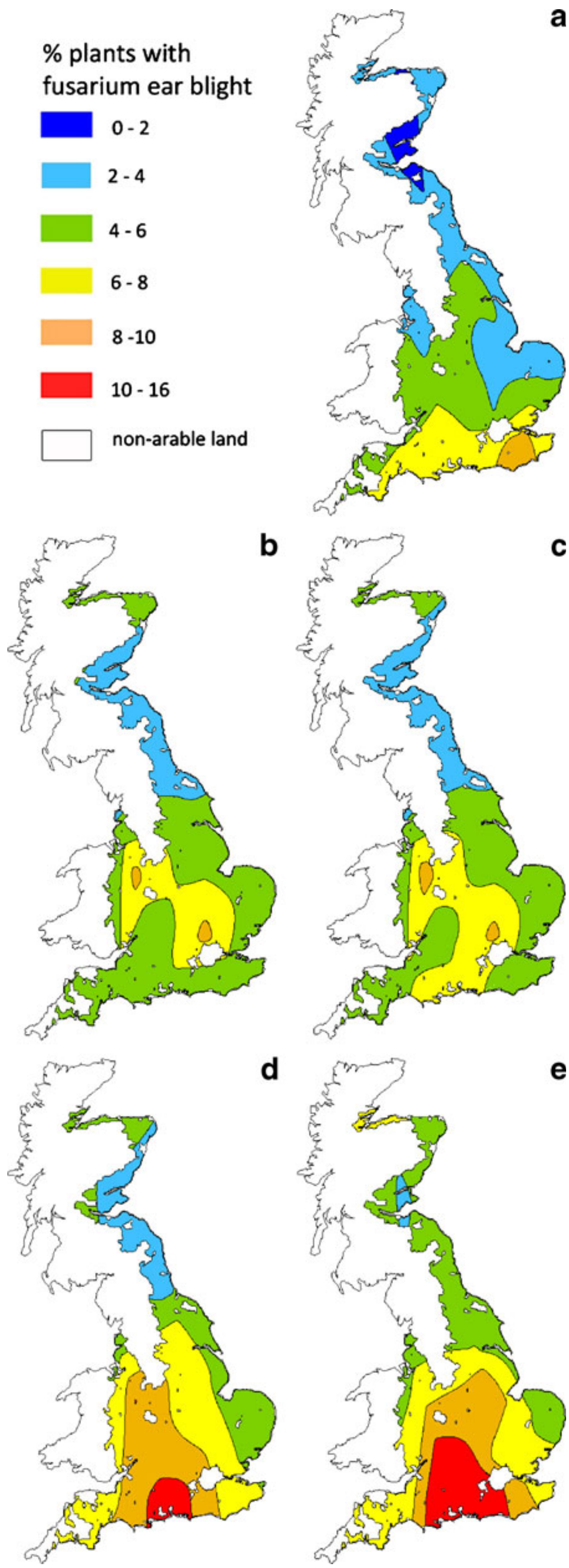

Fig. 6 Maps showing the projected average fusarium ear blight incidence (% plants affected) generated by the fusarium ear blight model using the average anthesis dates shown in Fig. 5 for each of the five weather scenarios; **a** baseline, **b** 2020LO, **c** 2020HI, **d** 2050LO and **e** 2050HI. The baseline scenario is based on the patterns in observed weather from 1960–1990, and the other scenarios are high CO_2 (HI) and low CO_2 (LO) emissions scenarios for the 2020s and 2050s. The maps were produced by spatial interpolation between the 14 sites

projected to be earlier under climate change, weather at different periods was then used to project fusarium ear blight incidence. For Scotland and northern and central England, there is projected to be a gradual increase in fusarium ear blight incidence with time, with little difference between the HI and LO emissions scenarios (Fig. 6). If the increase in disease incidence for each climate scenario is measured as a percentage of the baseline scenario, the greatest increase is for Scotland. For Scotland, where there is currently little fusarium ear blight, there is a projected 333% increase in incidence from the baseline to the 2050HI scenario, compared to an increase of 104% from the baseline to the 2050HI scenario on the south coast of England. The projected increases in incidence of fusarium ear blight are less for northern and central England. By contrast, across parts of southern England, fusarium ear blight incidence is projected to decrease slightly by the 2020s but then to increase from the 2020s to the 2050s, when compared to the baseline scenario. In both the 2020s scenarios, the areas with the greatest projected incidence of fusarium ear blight are in central southern England, rather than in the south coastal area of England that has the greatest incidence in the baseline scenario. At some sites, the projected incidence is less in the 2050HI scenario than the 2050LO scenario. Since the results are averaged over 50 runs of generated weather, what is not taken into account is the number of extreme values that affect the mean. Most runs have a projected fusarium ear blight incidence of less than 3%, but the mean values are greater because there are a few runs with much greater projected incidences that skew the data. For example, the percentage of runs with projections greater than 10% plants affected increases two-fold between the baseline and 2050HI scenarios across nearly the whole of the UK.

Discussion

The results suggest that climate change induced increases in temperature or rainfall during key periods in the disease cycle will directly increase risk of wheat fusarium ear blight epidemics across the whole of the UK by the 2050s. This suggests that there will be not only increased yield losses due to grain shrivelling but also an increased risk of mycotoxin contaminated grain (Xu et al. 2008; Miraglia et al. 2009). In the UK, there are currently strict limits on the amounts of mycotoxins that are acceptable in grain to be used for human consumption or animal feed, since they are hazardous to health if consumed (www.hgca.com). The results suggest that the number of crops for which permitted mycotoxin levels are exceeded will increase over the whole of the UK by the 2050s. In a world where more than one billion people do not have enough to eat (Anonymous 2009) and global food security means that there is a need to grow more food in northern Europe (Mahmuti et al. 2009; Stern 2007), strategies to decrease the future threat from fusarium ear blight (Goswami and Kistler 2004) should be a major priority for government and industry, as part of strategies for adaptation to climate change. There is a need to start programmes to breed new UK wheat cultivars that are more resistant to fusarium ear blight, and to optimise fungicide spray treatments to control the disease and decrease mycotoxin concentrations by developing for the UK fusarium and mycotoxin forecasting schemes like those that have been developed for North America (De Wolf et al. 2003; Schaafsma and Hooker 2007; De Wolf and Isard 2007; Prandini et al. 2009; http://www.wheatscab.psu.edu/) and some continental European countries (e.g. Rossi et al. 2003; Musa et al. 2007).

These projections for fusarium ear blight demonstrate that it is important to combine crop and disease models with climate scenarios to produce more accurate projections of the impacts of climate change. Whilst it is projected that the UK will have drier summer weather (Semenov 2009) that would not favour fusarium ear blight (Xu et al. 2007), use of the Sirius wheat model suggests that climate change will cause dates of wheat anthesis to occur earlier in the UK. This means that the critical time period when rainfall will favour fusarium ear blight infection (Xu et al. 2007) will be about 2 weeks earlier in the year, when weather is projected to be warmer and of similar wetness to the baseline (Semenov 2009). This work suggests that incidence of fusarium ear blight can be predicted from total rainfall at anthesis and average temperature for a four-week period before anthesis. The importance of rainfall at anthesis confirms predictions of models produced outside the UK (Table 1; Moschini et al. 2001; De Wolf et al. 2003; Del Ponte et al. 2005). The earlier effect of temperature may relate to production of pathogen inoculum, which probably limits epidemics more in the UK than it does in North America, South America and continental Europe where considerably more maize is grown (Paul et al. 2007). This work demonstrates that it is only when crop and disease models are combined that it is possible to project whether severity of epidemics will be increased (Luo et al. 1995), as for phoma stem canker on oilseed rape (Evans et al. 2008; Butterworth et al. 2010), or decreased, as for light leaf spot on oilseed rape in the UK (Evans et al. 2010).

To construct and validate such models, it is essential that long-term data sets for weather, crop growth and disease incidence are collated, as in the CropMonitor disease survey (www.cropmonitor.co.uk). Whilst there will inevitably be uncertainty in such projections of climate change impacts associated with uncertainty in projections of future weather and in the crop and disease models, that is no reason not to make them (Stern 2007, www.climatecongress.ku.dk). This work demonstrates the importance of assessing impacts of climate change on crop disease epidemics to guide government and industry strategies for adaptation to climate change to decrease future threats to global food security (Chakraborty 2005; Garrett et al. 2006; Gregory et al. 2009).

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