The Journal of Agricultural Science

cambridge.org/ags

Climate Change and Agriculture Research Paper

Cite this article: Cammarano D, Liu B, Liu L, Ruane AC, Zhu Y (2021). Potential impacts of projected warming scenarios on winter wheat in the UK. *The Journal of Agricultural Science* **159**, 511–522. https://doi.org/10.1017/S0021859621000903

Received: 18 June 2021
Revised: 18 October 2021
Accepted: 3 November 2021

Key words:
Climate change; climate impacts; crop models

Author for correspondence:
Davide Cammarano,
E-mail: dcammar@purdue.edu

Potential impacts of projected warming scenarios on winter wheat in the UK

Davide Cammarano[1], Bing Liu[2,3], Leilei Liu[2,3], Alexander C. Ruane[4] and Yan Zhu[2,3]

[1]James Hutton Institute, Invergowrie, DD25DA, UK; [2]National Engineering and Technology Center for Information Agriculture, Key Laboratory for Crop System Analysis and Decision Making, Ministry of Agriculture, Jiangsu, China; [3]Key Laboratory for Information Agriculture, Nanjing Agricultural University, Nanjing, China and [4]NASA Goddard Institute for Space Studies, New York, NY, 10025, USA

Abstract

The goals of this study are to analyse the impacts of 1.5 and 2.0°C scenarios on UK winter wheat using a combination of Global Climate Models (GCMs), crop models, planting dates and cultivars; to evaluate the impact of increased air temperature on winter wheat phenology and potential yield; to quantify the underlying uncertainties due to the multiple sources of variability introduced by climate scenarios, crop models and agronomic management. The data used to calibrate and evaluate three crop models were obtained from a field experiment with two irrigation amounts and two wheat cultivars that have different phenology and growth habit. After calibration, the model was applied to fifty locations across the wheat-growing area of the UK to cover all the main growing regions, with most points located in the main growing areas. Four GCMs, with two cultivars and five planting dates, were simulated at the end of the century. Results of this study showed that the UK potential wheat yield will increase by 2–8% under projected climate. Farmers will need to close such a gap in the future because it will have implications in terms of food security. Future climatic conditions might increase such a gap. Adaptation measures (e.g. moving the optimal planting time), along with climate-ready varieties bred for future conditions and with precision agriculture techniques can help to reduce this gap and ensure that the future actual UK wheat production will be close to the potential.

Introduction

Wheat is among one of the largest cultivated crops worldwide, second, in millions of hectares only to rice (FAOSTAT 2021). In the UK, wheat is the main cultivated arable crop, sown on approx. 1.9 million hectares (UK Flour Millers, 2020). Most of the UK production is in the eastern parts of England. The annual UK production averaged about 14 million tonnes over a period of 10-years (2000–2019), with a variability of 11–16 million tonnes (UK Flour Millers, 2020; FAOSTAT 2021).

The current climate patterns are causing gradual warming of Earth, with the last 5 years (2015–2019) being among the world's warmest while 9 out of 10 warmest years that have been recorded since 2005 (NOAA 2020). The impacts of increased temperature on crop development, yield and quality has been well documented (Porter and Gawith, 1999; Semenov, 2008; Ferrise *et al.*, 2014; Semenov and Stratonovitch, 2014; Trnka *et al.*, 2014; Asseng *et al.*, 2015, 2019). In a study where statistical and process-based models were compared, it has been found that global wheat production will fall by 4–6% per °C of air temperature increase (Liu *et al.*, 2016). However, the impacts of increased air temperature will vary over space and time (Asseng *et al.*, 2015).

The temperature trend in the UK over the past 30 years (1989–2019) has shown unequivocal warming with the top ten warmest years recorded since 1884 happening from 2002 (UK Met Office, 2019). It has been found that the most recent decade (2009–2018) is about 1°C warmer than the pre-industrial era (1850–1900) and agrees with findings observed at global scale (UK Met Office, 2019). Future projections indicate that the UK temperatures will increase with an uneven warming trend in summer and winter.

Global Climate Models (GCMs) have been used in many studies to quantify the impacts of projected climate for a given crop (Asseng *et al.*, 2013, 2015, 2019; Cammarano *et al.*, 2019*a*, 2020; Müller *et al.*, 2019; Ruane, 2021; Ruane *et al.*, 2021). Given their coarse resolution, the GCMs have been downscaled at finer scales before using them for any impact study on the agricultural area. However, due to the different downscaling methods, the GCMs might have biases in representing temperature extremes or rainfall patterns (Cammarano *et al.*, 2013; Harkness *et al.*, 2020). Such a problem can be minimized by using an ensemble of GCMs, because the uncertainty associated with the climate projection can be quantified (Cammarano and Tian, 2018; Harkness *et al.*, 2020).

The impacts of climate on agricultural crops can be quantified using crop growth models (CSM). Such models simulate the daily growth, development and final yield as influenced by weather, soil, crop and agronomic management (Jones *et al*., 2003). Those models have been used to extrapolate the abovementioned interactions beyond a single year and a single experimental site (Basso *et al*., 2001, 2011; Cammarano *et al*., 2019*a*; Maestrini and Basso, 2021). Potential yield is defined as the maximum yield that can be obtained by a crop in a given environment and determined using CSM with plausible physiological and agronomic assumptions (Evans and Fischer, 1999). Potential yield is mainly impacted by air temperature and atmospheric CO_2 concentration and crop genetic. Therefore crop phenology, defined as the timing of life cycle events (Ritchie, 1991), can be used as a proxy for evaluating projected impacts of temperature changes on crop development and potential yield (Asseng *et al*., 2011, 2015, 2017; Zhao *et al*., 2017).

Harkness *et al.* (2020) assessed ten weather indices using a range of GCM ensemble and two greenhouse gas emissions (RCP 4.5 and 8.5) on winter wheat in the UK. The authors found that hotter and drier summers improve sowing and harvesting conditions. They also analysed the impact of rainfall and found that wetter winter and spring could pose waterlogging problems (Harkness *et al*., 2020). But, drought stresses during the reproductive phase will remain low by mid-century. The use of multiple GCM was important for quantifying the uncertainty between their projections and they found that such variation was greater than between the two emissions scenarios (Harkness *et al*., 2020). In another study, 27 crop models and 16 GCMs were used to quantify the main source of uncertainty and crop models shared a greater amount of uncertainty than the GCMs (Asseng *et al*., 2013). Cammarano and Tian (2018) used both an ensemble of CSM and GCMs to quantify the impacts of climate projection and extremes on wheat and maize and on two contrasting soils. The authors calculated16 climate indices finding that climate impacts differ depending on the soil type and the growth stage at which extreme climate events happen. The use of a multi-CSM and -GCM ensemble has been used to quantify the climate impacts on soil carbon and the source of uncertainty (Asseng *et al*., 2013; Martre *et al*., 2015; Wallach *et al*., 2021).

Another factor that might affect the simulated impacts of projected climate on crop yield using CSM is agronomic management. The shifting of sowing date can be considered as an agronomic adaptation measure that might help to offset the negative impact of climate change (Cammarano *et al*., 2019*a*; Rodríguez *et al*., 2019; Ojeda *et al*., 2021). Semenov (2008) using a climate model and a CSM to assess the impacts of climate change on wheat production in England, found that heat stress around flowering might cause considerable yield losses. Recent studies highlighted how drought conditions during the growing season and around flowering cause a projected decline in wheat yield up to 20% of the potential yield levels in the UK and across Europe (Clarke *et al*., 2021; Putelat *et al*., 2021; Senapati *et al*., 2021).

To avoid the negative and irreversible impacts from global temperatures, the Paris Agreement of 2015 stated that the World needs to achieve a maximum of 2.0°C or an ambitious 1.5°C. Global wheat production can be significantly impacted by raising the temperature (Asseng *et al*., 2013, 2015, 2019) but quantifying such impacts on regional wheat production can help to point out the local adaptation and related uncertainties.

An assessment of 1.5 and 2.0°C scenarios on UK winter wheat using a combination of GCM and CSM, planting dates, and cultivars is lacking. The goal of this study is to analyse all those factors together to evaluate the impact of increased air temperature on winter wheat phenology and potential yield, and to quantify the underlying uncertainties due to the multiple sources of variability introduced by climate scenarios, crop models and agronomic management. Therefore, the objectives of this study are to (i) evaluate the impacts of projected temperature by the different GCMs and atmospheric CO_2 concentration on winter wheat phenology and potential yield; (ii) determine the main source of uncertainty among the different factors.

Materials and methods

Observed data

The data used to calibrate and evaluate the crop models were obtained from a field experiment with two irrigation treatments and two wheat cultivars that have different phenology and growth habit (Foulkes *et al*., 2001, 2002). The field experiments were located at ADAS Gleadthorpe (53°13′N, 1°6′W) and were conducted during three growing seasons: 1993–1996. The experimental design was a randomized block, split-plot experiment with two irrigation treatments, full irrigation and no irrigation and six cultivars. All the details of the experimental design are reported elsewhere (Foulkes *et al*., 2001, 2002). Two cultivars were chosen for calibration, Haven and Maris Huntsman. The former is a late-developing, photoperiod sensitive cultivar. The latter is an old, tall cultivar. They were chosen for the difference in their growth and phenology response to environmental conditions. Sowing dates, phenology, aboveground biomass and grain yield were provided for each growing season. The soil information available from the experimental site (e.g. soil texture) were integrated with the Land Information System soil data (Hallett *et al*., 2017) purchased from the soil data's portal.

The observed wheat data for wheat yield for the UK yield (1984–2009), and the database with variety trials (2002–2009) results were obtained from the Agriculture and Horticulture Development Board (AHDB) and the Department for Environment, Food & Rural Affairs (DEFRA), respectively (AHDB 2021; DEFRA 2021).

To simulate the impacts of temperature changes on wheat yield fifty locations were selected across the wheat-growing area of the UK to cover all the main growing regions, with most points located in the main growing areas (Fig. 1). The soil and weather information from these 50 locations across the UK were downloaded from the Land Information System soil data (Hallett *et al*., 2017) and NASA AgMERRA for the baseline period 1980–2010 (Ruane *et al*., 2015), respectively. Daily incident solar radiation ($MJ/d/m^2$), maximum and minimum air temperature (°C) and precipitation (mm) were used as input to the crop models. Soil texture (clay, silt, sand content), organic carbon (%), pH, lower limit, drain upper limit and saturation were the soil input for the model.

Crop modelling

The CSM used in this study were the CSM-CERES-Wheat (Ds), the CSM-Nwheat (Nw) and the WheatGrow (Wg) (Cao and Moss, 1997; Hoogenboom *et al*., 2019) and were selected because of the different temperature response functions impacting developmental processes. These three CSM require a set of weather

https://doi.org/10.1017/S0021859621000903 Published online by Cambridge University Press

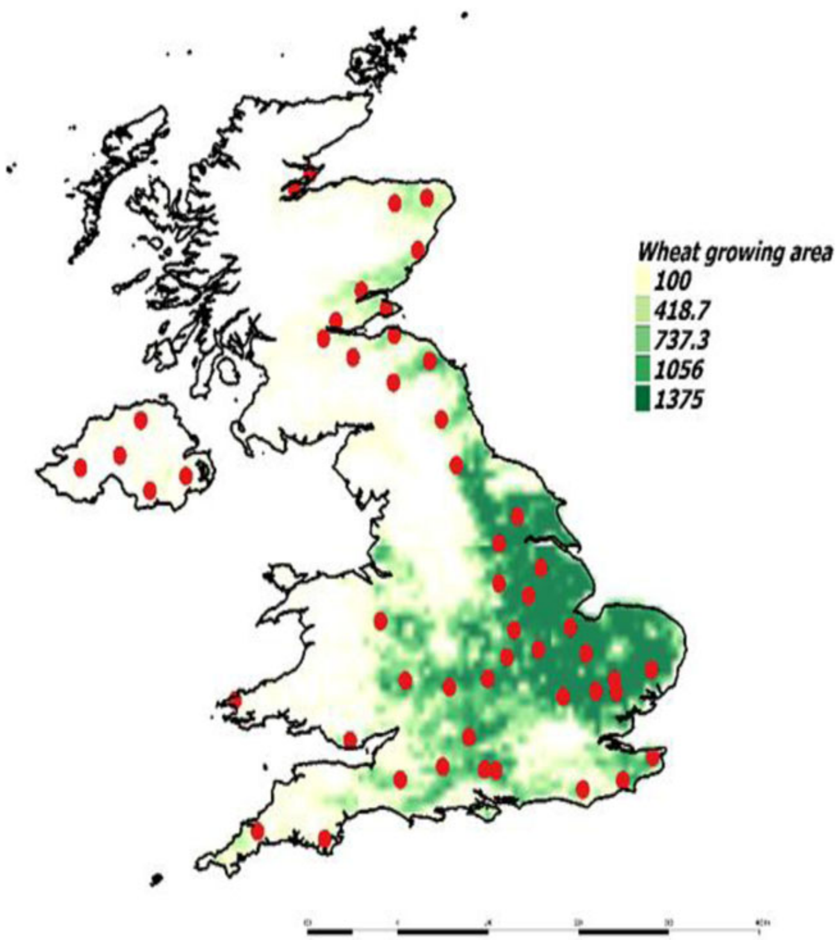

Fig. 1. Colour online. United Kingdom (UK) wheat-growing area and points used in the simulation study.

(e.g. daily air minimum and maximum temperature, solar radiation, precipitation), soil (e.g. texture, bulk density, organic matter) and agronomic input data (e.g. planting date) for running. In addition, they require observations, such as main phenological events (flowering, maturity), grain yield to calibrate for a crop and an independent dataset for evaluating the results of the calibration.

The two cultivars, Maris Huntsman and Haven were calibrated using the irrigated experiment described in the section above (Foulkes *et al*., 2001, 2002). The main aim of the cultivars' calibration was to parameterise the models' for simulating the observed phenology and yield levels and to adjust the growth and yield parameters for simulating aboveground biomass and grain yield.

Since the main aim of this study was to simulate the impacts of rising temperature on potential yield, the models were evaluated on their ability to simulate values higher than the observed yield as recorded in the reported databases. For simulating yield potential, the models were set with optimal water and nitrogen input so that that abiotic stresses were minimized. This procedure has been used in other temperature-related modelling studies so that other agronomic management practices such as fertilization will not impact simulated yield (Asseng *et al*., 2015, 2019). In addition, the effect of raised CO_2 concentration is considered in the CSMs routines as it is an input to the models and modifies several processes. In Ds and Nw the elevated CO_2 modifies the Radiation Use Efficiency (RUE) and Transpiration Efficiency (TE), while in Wg the elevated CO_2 modifies leaf photosynthesis rate.

These three crop models have differences in their temperature response functions for the different growth and development processes (Fig. 2). Wang *et al*. (2017) described in details the differences and similarities among those temperature response functions. These three models have been extensively compared against datasets comprising wheat response to varying temperatures (Asseng *et al*., 2015). The main difference among the models is that Wg simulated photosynthesis and transpiration while Nw and Ds use the concept of RUE to simulate the accumulation aboveground biomass as a function of the intercepted radiation (Monteith, 1972). Respiration is indirectly considered by using only net photosynthesis in the RUE estimation. Nw simulated the effects of heat stress on leaf senescence where the increase in maximum air temperature causes a hastening in leaf senescence (Asseng *et al*., 2011).

Long-term simulations

To set up the long-term simulations, the climate scenarios for 1.5 (CO_2 concentration of 423 ppm) and 2.0°C (CO_2 concentration of 487 ppm) above pre-industrial level was obtained from the Half a degree Additional warming, Prognosis and Projected Impacts project (HAPPI) (Mitchell *et al*., 2017). The time period for projected climate scenarios that were 1.5 and 2.0C warmer than the pre-industrial level was 2106–2115. The baseline CO_2 concentration for the 1980–2010 period was 360 ppm; the CO_2 concentrations correspond to the centre of 1980–2010 and the 1.5 and 2.0°

https://doi.org/10.1017/S0021859621000903 Published online by Cambridge University Press

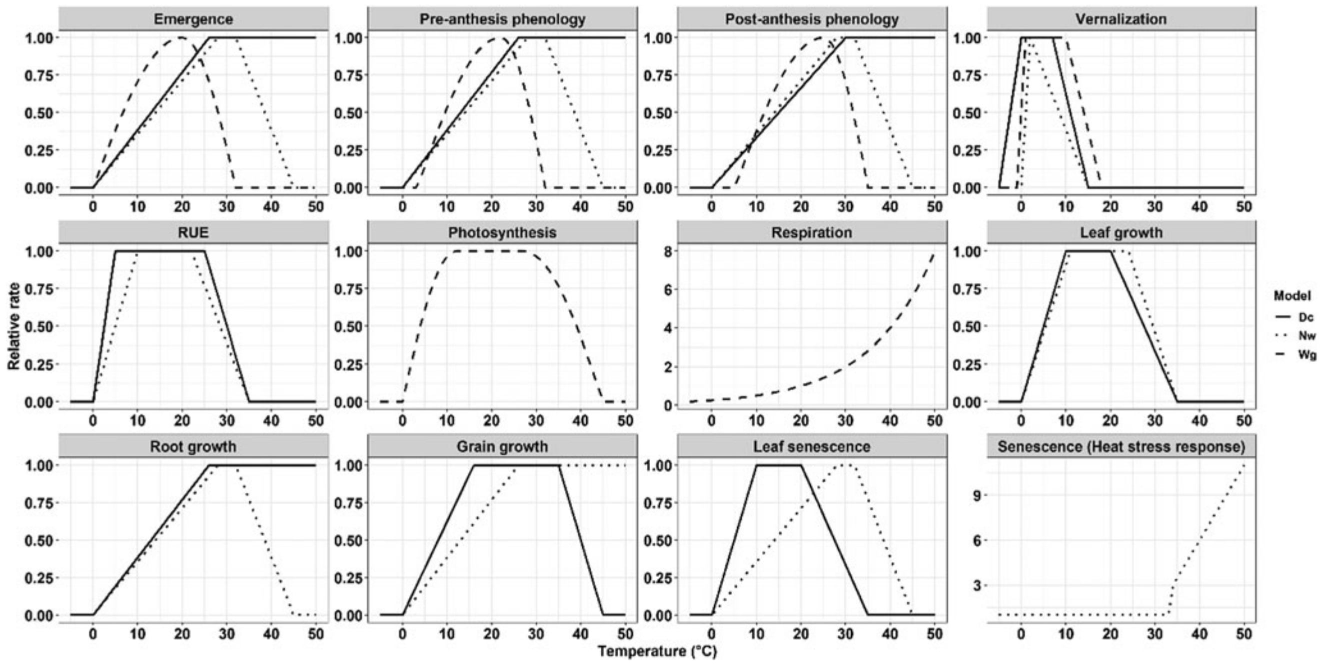

Fig. 2. Temperature response functions for different simulated processes by the CSM-CERES-Wheat (Dc, red line), the CSM-Nwheat (Nw, green line) and the WheatGrow (Wg, blue line).

C global warming level as highlighted in Ruane *et al.* (2018*a*). For each of the 50 weather stations, and for each scenario, the daily climate data were generated using the pattern-scaling approach employed and described in detail in other studies (Ruane *et al.*, 2015, 2018*b*). Four GCMs were used for each scenario. The GCMs selected were the CanAM4, CAM4, MIROC5, NorESM1-M. The reason for choosing those GCMs was because they were used in a previous global study on wheat to quantify the impacts of 1.5 and 2.0 C above pre-industrial warming where also the same crop models were used (Liu *et al.*, 2019).

The three crop models were run in a factorial combination, with four GCMs used (CanAM4, CAM4, MIROC5 and NorESM1); two CO_2 concentrations (360 ppm and the respective CO_2 concentration of each climate scenario as reported above); five planting dates (from Mid-Sep to Mid-Nov); and three scenarios (Baseline; 1.5 and 2.0°C). This combination was run for the 50 locations and for 30 years of daily weather data, for a total of 76 500 000 simulations. Since the target was the simulation of potential yield the models were re-set every year and no water or nitrogen stress was simulated.

Data analysis

The observed and simulated data were compared against two statistical indices to evaluate how well the models performed. The first index was the Root Mean Square Error (RMSE) and it was calculated as follows:

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1} (O_i - S_i)^2}{n}} \tag{1}$$

O_i, S_i, n were the observations, the simulations and the number of comparisons, respectively. The other index was the Wilmott index of agreement (D-Index), with values ranging between 0 (poor fit) and 1 (indicating a good fit). D-index values above 0.5 are to be considered acceptable. The D-Index expressed the measure of the goodness of fit and has been used as a cross-comparison method between models (Wilmott, 1982; Martre *et al.*, 2015; Cammarano *et al.*, 2019*b*).

$$D = 1 - \frac{\sum_{i=1}^{n} (O_i - S_i)^2}{\sum_{i=1}^{n} (|O_i - \bar{O}| + |S_i - \bar{O}|)^2} \tag{2}$$

$\bar{O}$ was the mean of the observed values. The relative change in terms of yield, respect to the baseline was calculated as follows.

$$\mathrm{RC} = \frac{S_{f,i} - S_{b,i}}{S_{b,i}} \times 100 \tag{3}$$

$S_{f,i}$ was the simulated (S) value as predicted by any combination of factors (f) for given growing season i, and $S_{b,i}$ was the baseline (b) value simulated for the growing season i.

To compare uncertainty among crop and climate models the approach described in Asseng *et al.* (2013). The coefficient of variation (CV%) was used to represent the uncertainty between a scenario of the A2 emission from 16 GCMs and 26 CSMs. Each CSM simulated the 16 GCM impacts plus a baseline scenario (1980–2010). Standard deviations were calculated for the simulated absolute yield impact for each CSM and across the GCMs. We also calculated the standard deviation across models for each GCM, across GCM for each model and for the different factors, the standard deviation was calculated across and for each model. The CV% was calculated as follows:

$$\mathrm{CV\%} = \frac{\sigma}{\bar{x}} \times 100 \tag{4}$$

where σ is the standard deviation of simulated yield for the different factors and $\bar{x}$ was the mean. All the Figures were made using GGPLOT2 (Wickham, 2016).

https://doi.org/10.1017/S0021859621000903 Published online by Cambridge University Press

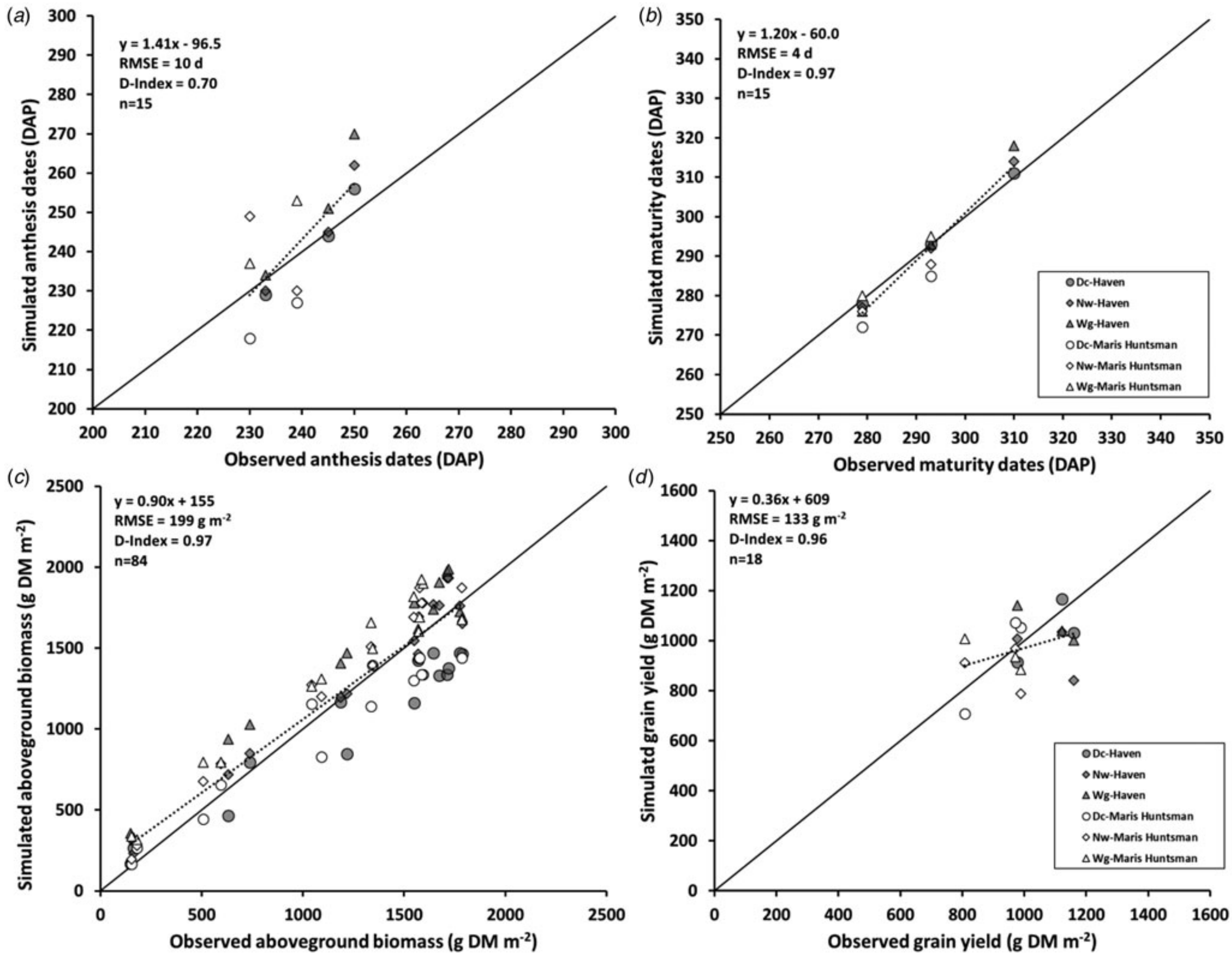

Fig. 3. Calibration of the CSM-CERES-Wheat (Dc, dots), CSM-NWheat (Nw, diamonds) and WheatGrow (Wg, triangles) models for two wheat cultivars Haven (grey) and Maris Huntsman (white) for (*a*) anthesis dates; (*b*) maturity dates; (*c*) aboveground biomass; and (*d*) grain yield.

Results

The results of model calibration of the models are shown in Fig. 3. Overall, the simulated data showed good agreement with the observed data (Fig. 3). The simulated anthesis dates had an RMSE of 10 days and a D-Index of 0.70, while maturity dates had an RMSE of 4 days and a D-Index of 0.97. Aboveground biomass and grain yield had an RMSE and D-Index of 199 and 133 g/DM/m^2 and 0.97 and 0.96, respectively (Fig. 3); the crop parameters for each of the models are presented in Supplementary Table 1.

The evaluation of potential yield simulation showed that models were simulating yield values higher than the national UK reported yields and the AHDB research trials (Fig. 4).

The results of the long-term simulations are shown in Fig. 5. Overall, under baseline weather data the simulated potential yield ranged from 10 000 to 14 500 kg/DM/ha with lower values in the north and higher in the south (Fig. 5(*a*)). The standard deviation of the simulations (size of the dots in Fig. 5) at each point was due to the planting date, GCM, cultivar and the crop model used (Fig. 5(*a*)) and it was about 1500 kg/DM/ha with lower values in the south and higher in the north (Fig. 5(*a*)). At 1.5C and 2.0°C the simulations considered where the ones with the elevated CO_2 concentration. Overall, the simulated potential yield increased for all the locations with higher increase in the south, but from 1.5 to 2.0°C the variability of the simulations increased to about 2500 kg/DM/ha (Fig. 5(*a*)).

When the overall change was split among the different components of the factorial simulations, the 2.0C scenario showed the highest yield increase ranging from −1 to 10% (Fig. 6). Under baseline CO_2 concentrations, the future potential wheat yield is projected to decrease between −1.6 and −1% under scenarios 1 and 2. However, the simulated impacts of increased CO_2 caused the simulated yield potential to increase 7–10% for scenarios 1 and 2, respectively (Fig. 6). Among the planting dates, later planting dates showed the highest yield increase with late-Oct/Mid-Nov having a higher increase in potential yield. Among the different GCM used there was a similar response under scenario 1, but under scenario 2 the simulated impact on potential wheat yield diverged. However, the simulated yield increase was more divergent among the three crop models, regardless of the scenario, the simulated yield increase ranging from 1.5 to 9% (Fig. 6).

Simulated potential wheat yield for both cultivars plateaued above 52°N and under baseline or future conditions. The simulated potential yield was different among the two cultivars, with

https://doi.org/10.1017/S0021859621000903 Published online by Cambridge University Press

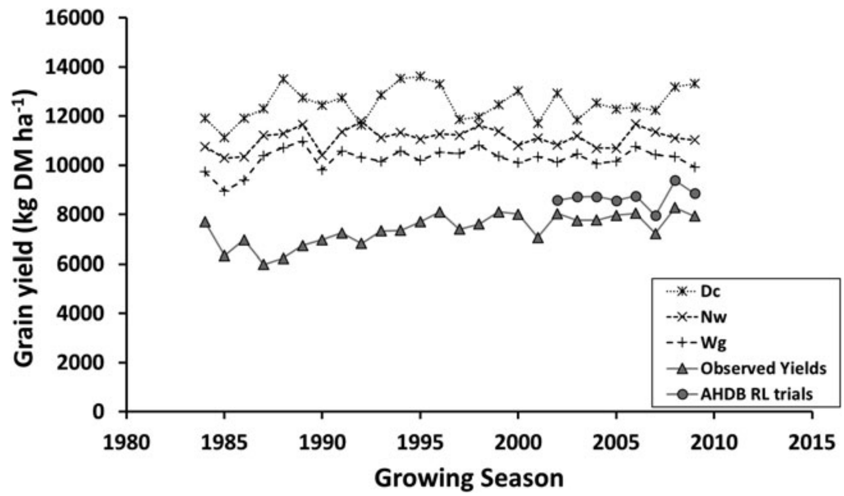

Fig. 4. Patterns of simulations of potential wheat yield as simulated, from 1984 to 2009, by the CSM-CERES-Wheat (Dc, stars and dotted line), CSN-NWheat (Wg, cross and short dash line) and WheatGrow (Wg, plus and long dot line). In addition, observed data from the UK national statistics (grey triangles), the AHDB research trials data (grey dots) are shown.

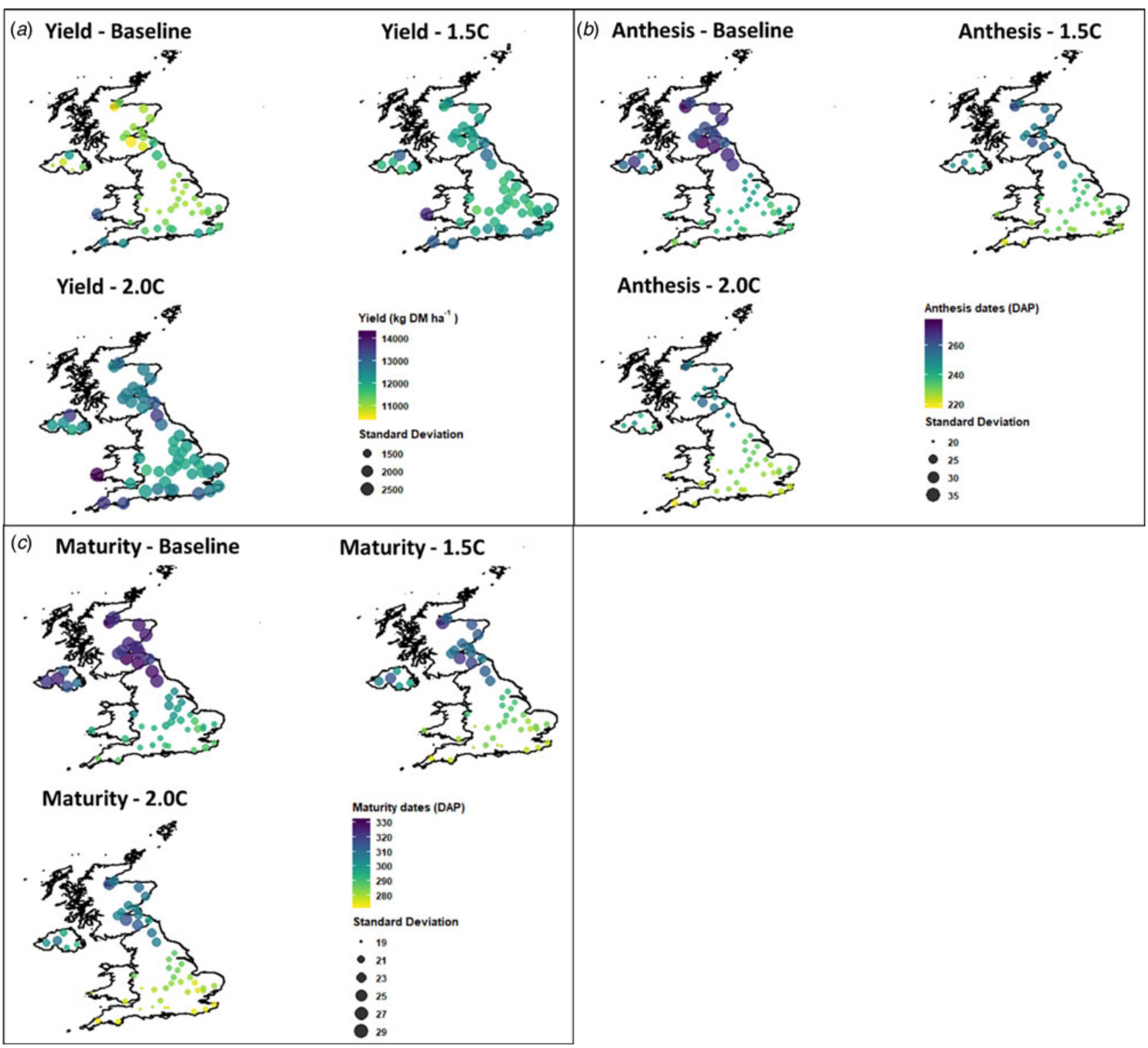

Fig. 5. Colour online. Simulated results as mean among two cultivars, four GCMs, five planting dates and three crop simulation models for (*a*) potential wheat yield; (*b*) anthesis; and (*c*) maturity dates for baseline, 1.5°C (Scenario 1) and 2.0°C (Scenario 2). The dots represent the standard deviation of the averaged values. For 1.5°C and 2.0°C conditions only the simulations with elevated CO_2 concentrations were used.

https://doi.org/10.1017/S0021859621000903 Published online by Cambridge University Press

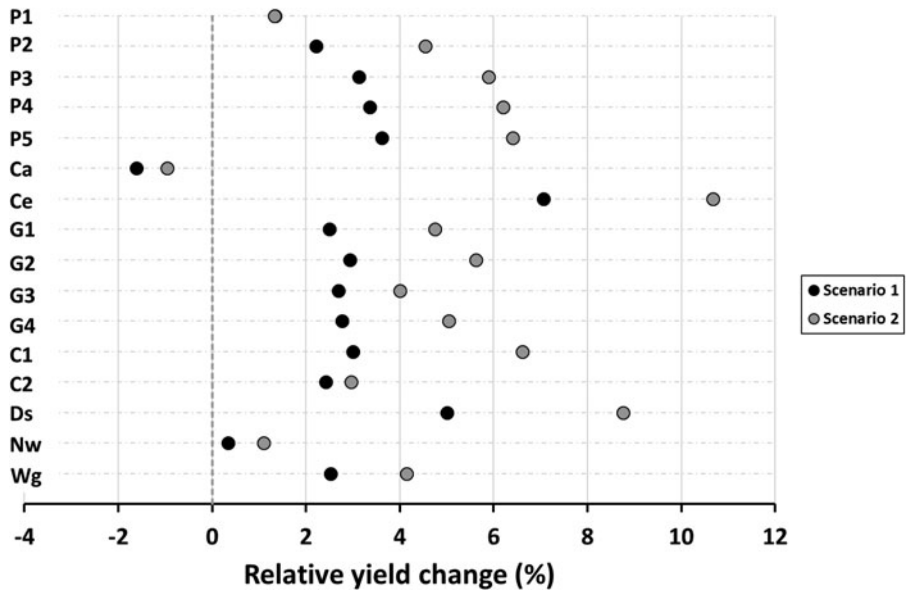

Fig. 6. Relative yield change, respect to the simulated baseline (1980–2010), for scenario 1 (black dots corresponding to 1.5°C) and scenario 2 (grey dots corresponding to 2.0°C) of different planting dates (P1: Mid-Sep; P2: Late-Sep; P3: Mid-Oct; P4: Late-Oct; P5: Mid-Nov), CO_2 concentrations (Ca: baseline CO_2 concentration of 360 ppm; C3: elevated CO_2 concentration of 423 ppm for the climate scenario 1.5°C and 487 ppm for the climate scenario 2.0°C), Global Climate Models (G1: CanAM4; G2: CAM4; G3: MIROC5; G4: NorESM1-M), wheat cultivars (C1: Haven; C2: Maris Huntsman) and different crop simulation models (Ds: CSM-CERES-Wheat; Nw: CMS-NWheat; Wg: WheatGrow).

Haven (C1) showing the higher simulated potential yield. The simulated anthesis dates linearly increased with the latitude, ranging from about 230 days after planting at 50°N to about 260 days after planting at 58°N (Supplementary Fig. 1). For the simulated anthesis dates, the cultivar Haven (C1) showed a slightly higher number of days from planting to anthesis because it has a higher photoperiod sensitivity with similar vernalization parameters. However, the simulated maturity date was similar among the two cultivars.

The relationship between simulated potential grain yield and mean growing season temperature is shown in Fig. 7. The response of the simulated yield differs greatly among crop models, with Ds showing distinct patterns for Haven and Maris Huntsman across the five planting dates. However, all the models agreed that the potential wheat yield shifts towards upper values under Scenarios 1 and 2 (Fig. 7).

The daily maximum temperature between anthesis to maturity does not reach values that will negatively hamper the grain-filling period. For this study, across the 50 locations, the higher values of daily maximum temperature were around 25°C and they were reached under Scenario 2 (2.0C; Fig. 8). The relationship between the anthesis date and the minimum temperature between sowing to anthesis is shown in Fig. 9. The relationship between simulated anthesis date and daily minimum temperature differs slightly among the two cultivars, but there was less disagreement from the CSM. For later sowing dates, the Wg model tends to simulate anthesis dates that plateaued at about 3°C.

Most of the uncertainty that impacts the simulated yield comes from the three crop simulation models, which had a coefficient of variability of 8% for baseline, increasing to 11% for Scenario 2 (Fig. 10). The increase in CO_2 concentration and the different cultivars was also showing higher uncertainty but much lower than the crop models. The GCM showed the least uncertainty with values below 1% (Fig. 10).

Discussion

The three models were able to represent the observed crop traits. The overestimation of anthesis date was mostly due to the Maris Huntsman cultivar while Haven showed a closer fit between observed and simulated data. However, the D-Index had values higher than 0.5 below which the results of the calibration should have been considered non-acceptable. Similar behaviour of spread between a multi-model comparison with observed phenology and yield were reported by Asseng *et al.* (2015).

The potential yield as defined by Evans and Fischer (1999) and van Ittersum *et al.* (2003) can be calculated with CSMs or with a simple but robust light-based approach (Monteith, 1972). The CSM-CERES-Wheat model simulates the potential yield conditions by disabling nitrogen and water simulated dynamics. In this way, the model's simulated yield was the only function of the calibrated cultivars, the environmental conditions and the atmospheric CO_2. This simulated yield potential approach is similar to what is used in the modelling community (van Ittersum *et al.*, 2003). However, the Nw model had to apply ample water and nitrogen in order to simulate potential yield which means that their results can still be affected by water and nutrient dynamics, like it could happen in field conditions. The results of the yield gap between the simulated potential and the observed UK wheat was about 25% for the DEFRA dataset and 45% for the UK census data, which is in line with the 39% reported by Senapati and Semenov (2019) in their study. The global wheat yield projection of Ruane *et al.* (2018*a*) also showed an increase of UK wheat yield but their results were based on generic wheat calibrations following the approach of Elliott *et al.* (2015) while in this study detailed crop physiological UK data were used to calibrate three wheat models. However, the reported wheat yield in both studies highlights an important point regarding the consistency and robustness of the obtained results.

Results of the projected warming on phenology and yield agree with the findings of Asseng *et al.* (2013) where crop models diverged in simulating phenology and yield at higher air temperatures. The simulated anthesis date for the baseline climate conditions (1980–2010) was 260 days after planting and showed higher simulated variability in the north than in the south in terms of mean air temperature. However, under 1.5 and 2.0°C the variability of the simulated anthesis decreased. This can be explained by the different temperature response functions for the vegetative stage of the different models. The temperature response function for vernalization has different shapes among models (Fig. 2),

https://doi.org/10.1017/S0021859621000903 Published online by Cambridge University Press

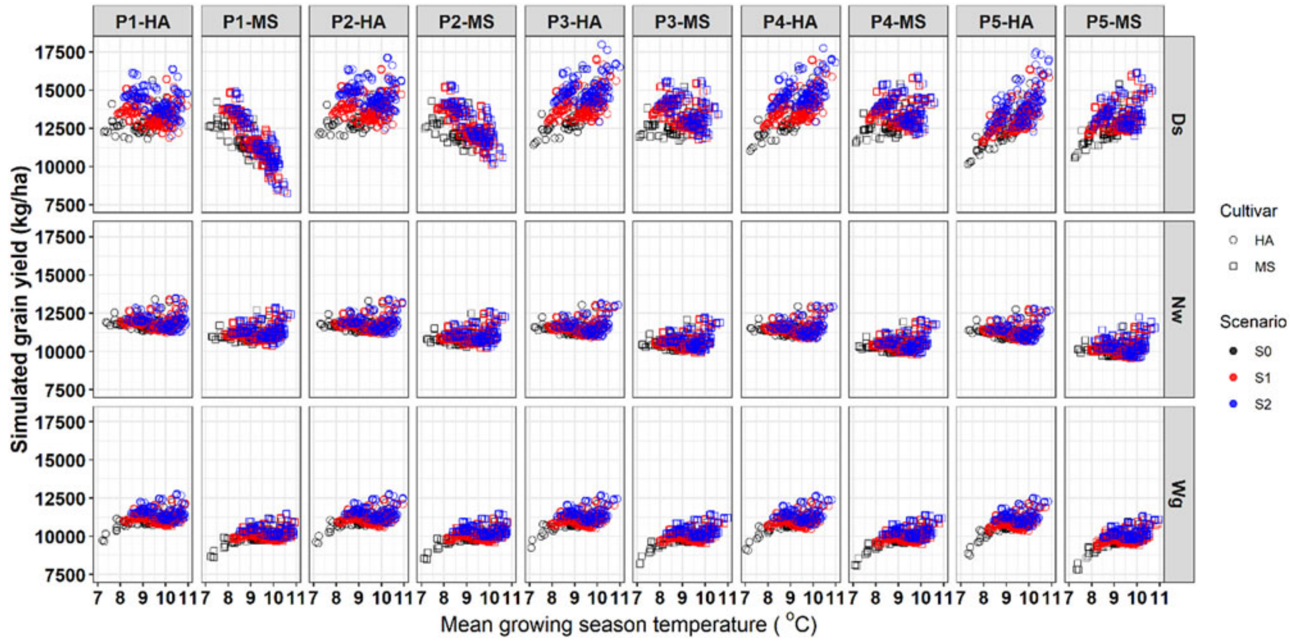

Fig. 7. Colour online. Relationship between mean growing season temperature and simulated potential wheat yield for the cultivar Haven (HA, open dots) and Maris Huntsman (MS, open squares) under baseline conditions (S0, black colour), 1.5°C (S1, red colour) and 2.0°C (S2, blue colour), for 5 different planting dates (P1: Mid-Sep; P2: Late-Sep; P3: Mid-Oct; P4: Late-Oct; P5: Mid-Nov) and different crop simulation models (Ds: CSM-CERES-Wheat; Nw: CSM-NWheat; Wg: WheatGrow).

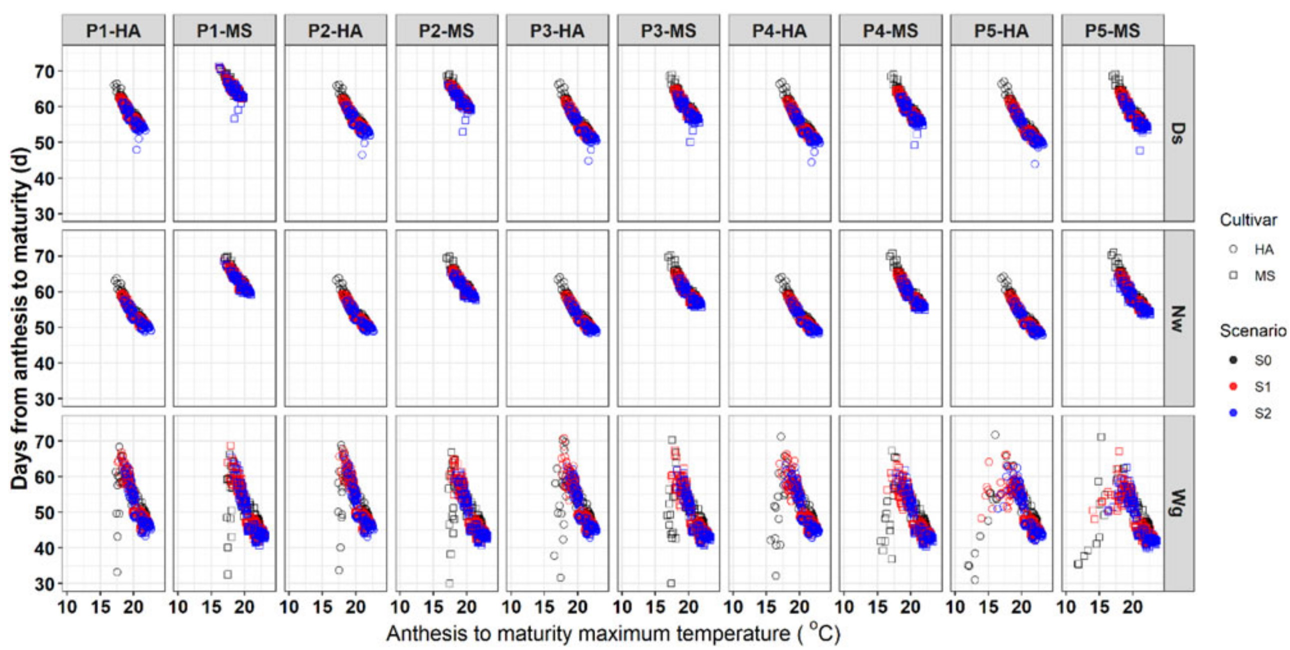

Fig. 8. Colour online. Relationship between daily maximum temperature averaged from anthesis to maturity and simulated days from anthesis to maturity for the cultivar Haven (HA, open dots) and Maris Huntsman (MS, open squares) under baseline conditions (S0, black colour), 1.5°C (S1, red colour) and 2.0°C (S2, blue colour), for 5 different planting dates (P1: Mid-Sep; P2: Late-Sep; P3: Mid-Oct; P4: Late-Oct; P5: Mid-Nov) and different crop simulation models (Ds: CSM-CERES-Wheat; Nw: CSM-NWheat; Wg: WheatGrow).

which means the number of days required to accumulate the vernalization requirement varies among models. Under baseline conditions, the air temperatures (2–5°C), especially in the northern UK, means that the accumulation of vernalization requirement varies among models because the slope and the cardinal temperature is rather different among models (Fig. 2). Under warming scenarios, the increase in air temperature causes the reaching of optimal vernalization rates for all the crop models (Fig. 2). This explains why under future conditions the variability among models in the northern UK decreases. These results agree

https://doi.org/10.1017/S0021859621000903 Published online by Cambridge University Press

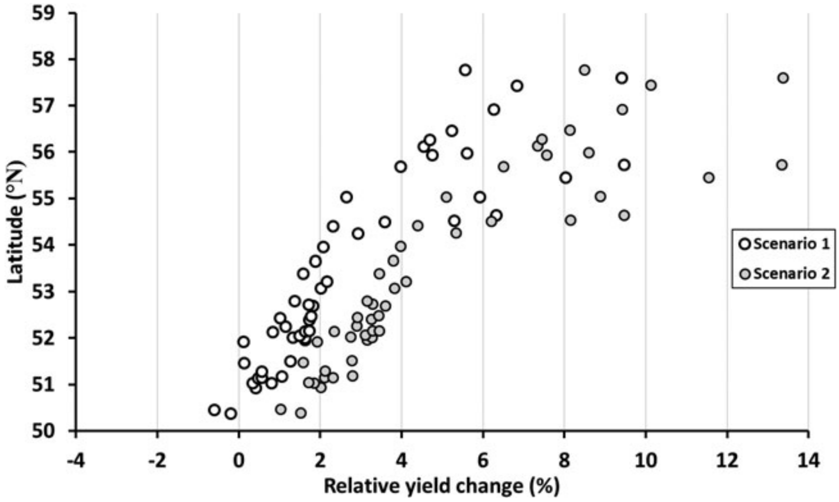

Fig. 9. Relative yield change at different latitudes for scenario 1 (white dots corresponding to 1.5°C) and scenario 2 (grey dots corresponding to 2.0°C) as mean across different planting dates (P1: Mid-Sep; P2: Late-Sep; P3: Mid-Oct; P4: Late-Oct; P5: Mid-Nov), CO_2 concentrations (Ca: baseline CO_2 concentration of 360 ppm; C3: elevated CO_2 concentration of 423 and 487 ppm for Scenario 1 and 2, respectively), Global Climate Models (G1: CanAM4; G2: CAM4; G3: MIROC5; G4: NorESM1-M), wheat cultivars (C1: Haven; C2: Maris Huntsman) and different crop simulation models (Ds: CSM-CERES-Wheat; Nw: CSM-NWheat; Wg: WheatGrow).

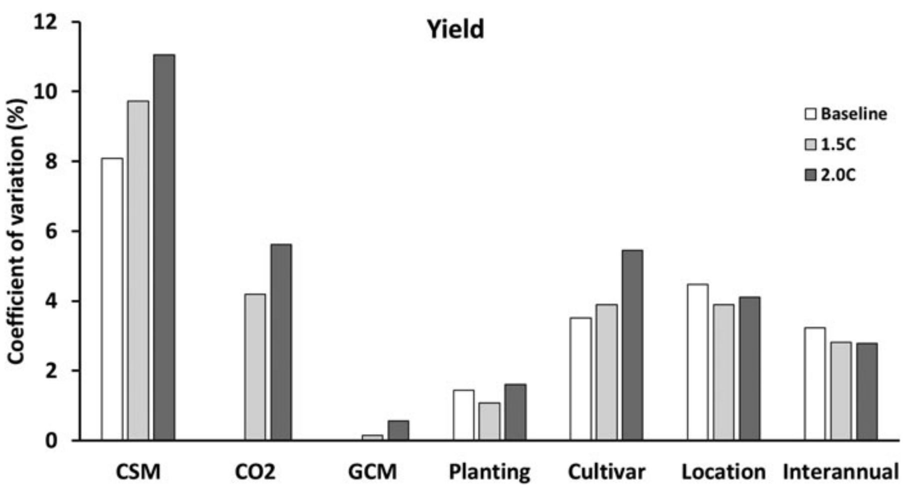

Fig. 10. Coefficient of variation of the different components (CSM: crop simulation models; CO_2: atmospheric CO_2 concentrations; GCM: Global Climate models used; Planting: five planting dates; Cultivar: two cultivars used; Location: fifty locations; Interannual: 30 years) affecting the simulated potential wheat yield under baseline (white bars), 1.5°C (light grey bars) and 2.0°C (dark grey bars).

with the findings of Ruiz-Ramos *et al.* (2018) and Rodríguez *et al.* (2019) who found, using many crop models, how the increase in air temperature reduces the time to vernalization.

Among the planting dates, later planting dates (late-Oct/ Mid-Nov) showed the highest potential yield increase. In addition, the projected temperature changes are still within the optimal growth range for the winter wheat for several physiological processes. Fang *et al.* (2015) found that the increase of air temperature during the winter period does not cause any significant decrease in yield on winter wheat in northern environments where air temperatures are well below the wheat base temperature of 0°C. In the UK the mean air temperatures during winter times tend to be, especially in the northern part, around the values of the base temperature. Therefore, any increase in air temperature will not cause significant reductions in potential grain yield. Therefore, an increase in atmospheric CO_2 concentration at such latitudes boosts the potential wheat yield by an average of 3 and 6% for 1.5 and 2.0°C, respectively. Such behaviour, at northern latitudes, has been experimentally confirmed in northern China in the study of Fang *et al.* (2015).

Ruane *et al.* (2018*a*) reported a large CO_2 uncertainty in the crop model projections due to climate model projection. This means that different climate models need different levels of atmospheric CO_2 concentrations to reach a 2.0°C World leading to some substantial differences across the GCMs (Ruane *et al.*, 2018*a*).

The results of the variability of the crop models in terms of phenology and yield response as a function of air temperature showed that the spread is higher for the yield-temperature relationship than the phenology-temperature as also reported in Asseng *et al.* (2013, 2015). Ruane *et al.* (2018*a*) reported values of global wheat yield uncertainty analysis finding that uncertainty of climate models is smaller than one of five crop models used and results of this study agree with the magnitude of uncertainty for crop models, GCMs and CO_2 response of that study. This has led to several improvements in the model's sub-routines, such as the temperature response to phenology as shown in Alderman *et al.* (2013) and Asseng *et al.* (2015).

The overall uncertainty of the simulated system was mainly due to the multi-crop models used rather than the other factors. This same response has been observed in many multi-models' studies (Asseng *et al.*, 2013; Martre *et al.*, 2015; Cammarano *et al.*, 2016; Liu *et al.*, 2016; Ruane *et al.*, 2016; Wang *et al.*, 2017; Webber *et al.*, 2017). This high uncertainty among models is generally due to the fact the crop models have many different sub-routines simulating soil-plant-atmosphere interactions. In this study, the three CSM have an improved temperature response function but other processes impacting growth and development simulations such as evapotranspiration partitioning, and energy balance algorithms have not been improved yet. These two important sub-routines have been shown to cause a high variability in simulated yield among crop models (Cammarano *et al*., 2016; Webber *et al*., 2016). This is because to simulate yield potential models like Nw have to apply ample water and N meaning that other factors might still affect the simulated production.

Clarke *et al*. (2021) found that water limitation for UK wheat reduces yield depending on the timing and length of drought severity; and future projections of wheat yield losses to drought report negative impacts ranging between 5 to 20% (Putelat *et al*., 2021). The southeast of the UK, where most of the wheat is cultivated, showed greater uncertainties in simulated yield changes and this is in agreement with the findings of Putelat *et al*. (2021) in which the same region showed to be more sensitive to climate extremes. In addition, in their conclusions, Putelat *et al*. (2021) pointed out how the negative impacts of projected climates could also be offset by better choices of cultivar and planting dates. Those conclusions also hold in the current study which is based on the impact of temperature on potential wheat yield.

However, further issues that have to be addressed are how the impacts of rainfall changes would alter reduce such potential yield; and if grain protein is going to be affected negatively by such increase. In addition, ozone damage is another factor worth exploring that could potentially undermine potential yield. The highest uncertainty of this study is due to the differences among the crop models. This is not surprising because despite the temperature response functions have been improved in the past, other sub-routines, more complicated, such as the water and energy balances have not been subject to model's improvement. Since the simulation of yield potential, for some crop models, means that water and energy balances cannot be turned off their improvements would be needed to improve both potential and actual yield simulations.

The yield gap between potential and actual yield means that farmers have the chance to adopt agronomic management decisions (e.g. planting date, fertilization amount/timing, better genotypes) that can help reduce such gap. Digital technologies such as Precision/Digital agriculture can help in this sense. However, the question remains if farmers will be able to close such a gap in reality, despite the adoption of digital technologies. Adaptation and mitigation measures, along with climate-ready varieties bred for future conditions and with precision agriculture techniques can help to reduce this gap and ensure that the future actual UK wheat production will be close to the potential.

Conclusion

In conclusion, the projected potential wheat yield in the UK will increase by 2–8% depending on the location and the scenario considered. This is because an increase in air temperature is still within the limits of the optimal temperatures for wheat. This has important implications because in the UK it means that expectations for future higher potential yields are possible.

Supplementary material. The supplementary material for this article can be found at https://doi.org/10.1017/S0021859621000903

Acknowledgements. We appreciate the efforts of Dann Mitchell, Myles Allen, Peter Uhe, Mamunur Rashid and Carl-Friedrich Schleussner to process and make HAPPI data available for analyses. We thank the two anonymous reviewers for their constructive feedback that helped with improving the manuscript.

Financial support. Royal Society of London Exchange Program

Conflict of interest. The authors declare there are no conflicts of interest.

Ethical standards. Not applicable.

References

Agriculture and Horticulture Development (AHDB) (2021) *Recommended Lists for cereals and oilseeds (RL) harvest results*. Archive; https://ahdb.org.uk/ (Accessed 11 November 2021).

Alderman PD, Qulligan E, Asseng S, Ewert F and Reynolds MP (2013) *Proceedings of the Workshop Modelling Wheat Response to High Temperature*. El Batan, Mexico: CIMMYT.

Asseng S, Foster I and Turner NC (2011) The impact of temperature variability on wheat yields. *Global Change Biology* **17**, 997–1012.

Asseng S, Ewert F, Rosenzweig C, Jones JW, Hatfield JL, Ruane AC, Boote KJ, Thorburn PJ, Rötter RP, Cammarano D, Brisson N, Basso B, Martre P, Aggarwal PK, Angulo C, Bertuzzi P, Biernath C, Challinor AJ, Doltra J, Gayler S, Goldberg R, Grant R, Heng L, Hooker J, Hunt LA, Ingwersen J, Izaurralde RC, Kersebaum KC, Müller C, Naresh Kumar S, Nendel C, O'Leary G, Olesen JE, Osborne TM, Palosuo T, Priesack E, Ripoche D, Semenov MA, Shcherbak I, Steduto P, Stöckle C, Stratonovitch P, Streck T, Supit I, Tao F, Travasso M, Waha K, Wallach D, White JW, Williams JR and Wolf J (2013) Uncertainty in simulating wheat yields under climate change. *Nature Climate Change* **3**, 827–832.

Asseng S, Ewert F, Martre P, Rötter R.P, Lobell DB, Cammarano D, Kimball BA, Ottman MJ, Wall GW, White JW, Reynolds MP, Alderman PD, Prasad PVV, Aggarwal PK, Anothai J, Basso B, Biernath C, Challinor AJ, De Sanctis G, Doltra J, Fereres E, Garcia-Vila M, Gayler S, Hoogenboom G, Hunt LA, Izaurralde RC, Jabloun M, Jones CD, Kersebaum KC, Koehler A-K, Müller C, Naresh Kumar S, Nendel C, O'Leary G, Olesen JE, Palosuo T, Priesack E, Eyshi Rezaei E, Ruane AC, Semenov MA, Shcherbak I, Stöckle C, Stratonovitch P, Streck T, Supit I, Tao F, Thorburn PJ, Waha K, Wang E, Wallach D, Wolf J, Zhao Z and Zhu Y (2015) Rising temperatures reduce global wheat production. *Nature Climate Change* **5**, 143–147.

Asseng S, Cammarano D, Basso B, Chung U, Alderman PD, Sonder K, Reynolds M and Lobell DB (2017) Hot spots of wheat yield decline with rising temperatures. *Global Change Biology* **23**, 2464–2472.

Asseng S, Martre P, Maiorano A, Rötter RP, O'Leary GJ, Fitzgerald GJ, Girousse C, Motzo R, Giunta F, Babar MA, Reynolds MP, Kheir AMS, Thorburn PJ, Waha K, Ruane AC, Aggarwal PK, Ahmed M, Balkovič J, Basso B, Biernath C, Bindi M, Cammarano D, Challinor AJ, De Sanctis G, Dumont B, Eyshi Rezaei E, Fereres E, Ferrise R, Garcia-Vila M, Gayler S, Gao Y, Horan H, Hoogenboom G, Izaurralde RC, Jabloun M, Jones CD, Kassie BT, Kersebaum K-C, Klein C, Koehler A-K, Liu B, Minoli S, Montesino San Martin M, Müller C, Naresh Kumar S, Nendel C, Olesen JE, Palosuo T, Porter JR, Priesack E, Ripoche D, Semenov MA, Stöckle C, Stratonovitch P, Streck T, Supit I, Tao F, Van der Velde M, Wallach D, Wang E, Webber H, Wolf J, Xiao L, Zhang Z, Zhao Z, Zhu Y and Ewert F (2019) Climate change impact and adaptation for wheat protein. *Global Change Biology* **25**, 155–173.

Basso B, Ritchie JT, Pierce FJ, Braga RP and Jones JW (2001) Spatial validation of crop models for precision agriculture. *Agricultural Systems* **68**, 97–112.

Basso B, Ritchie JT, Cammarano D and Sartori L (2011) A strategic and tactical management approach to select optimal N fertilizer rates for wheat in a spatially variable field. *European Journal of Agronomy* **35**, 215–222.

Cammarano D and Tian D (2018) The effects of projected climate and climate extremes on a winter and summer crop in the southeast USA. *Agricultural and Forest Meteorology* **248**, 109–118.

Cammarano D, Stefanova L, Ortiz BV, Ramirez-Rodrigues M, Asseng S, Misra V, Wilkerson G, Basso B, Jones JW, Boote KJ and DiNapoli S (2013) Evaluating the fidelity of downscaled climate data on simulated wheat and maize production in the southeastern US. *Regional Environmental Change* **13**, 101–110.

Cammarano D, Rötter RP, Asseng S, Ewert F, Wallach D, Martre P, Hatfield JL, Jones JW, Rosenzweig C, Ruane AC, Boote KJ, Thorburn PJ, Kersebaum KC, Aggarwal PK, Angulo C, Basso B, Bertuzzi P, Biernath C, Brisson N, Challinor AJ, Doltra J, Gayler S, Goldberg R, Heng L, Hooker J, Hunt LA, Ingwersen J, Izaurralde RC, Müller C, Kumar SN, Nendel C, O'Leary GJ, Olesen JE, Osborne TM, Palosuo T, Priesack E, Ripoche D, Semenov MA, Shcherbak I, Steduto P, Stöckle CO, Stratonovitch P, Streck T, Supit I, Tao F, Travasso M, Waha K, White JW and Wolf J (2016) Uncertainty of wheat water use: simulated patterns and sensitivity to temperature and CO_2. *Field Crops Research* **198**, 80–92.

Cammarano D, Ceccarelli S, Grando S, Romagosa I, Benbelkacem A, Akar T, Al-Yassin A, Pecchioni N, Francia E and Ronga D (2019*a*) The impact of climate change on barley yield in the Mediterranean basin. *European Journal of Agronomy* **106**, 1–11.

Cammarano D, Hawes C, Squire G, Holland J, Rivington M, Murgia T, Roggero PP, Fontana F, Casa R and Ronga D (2019*b*) Rainfall and temperature impacts on barley (Hordeum vulgare L.) yield and malting quality in Scotland. *Field Crops Research* **241**, 107559.

Cammarano D, Valdivia RO, Beletse YG, Durand W, Crespo O, Tesfuhuney WA, Jones MR, Walker S, Mpuisang TN, Nhemachena C, Ruane AC, Mutter C, Rosenzweig C and Antle J (2020) Integrated assessment of climate change impacts on crop productivity and income of commercial maize farms in northeast South Africa. *Food Security* **12**, 659–678.

Cao W and Moss DN (1997) Modelling phasic development in wheat: a conceptual integration of physiological components. *The Journal of Agricultural Science* **129**, 163–172.

Clarke D, Hess TM, Haro-Monteagudo D, Semenov MA and Knox JW (2021) Assessing future drought risks and wheat yield losses in England. *Agricultural and Forest Meteorology* **297**, 108248.

Department for Environment, Food and Rural Affairs (DEFRA) (2021) *Agriculture in the United Kingdom data set*. Available at https://www.gov.uk/government/statistical-data-sets/agriculture-in-the-united-kingdom (Accessed 11 November 2021).

Elliott J, Müller C, Deryng D, Chryssanthacopoulos J, Boote KJ, Büchner M, Foster I, Glotter M, Heinke J, Iizumi T, Izaurralde RC, Mueller ND, Ray DK, Rosenzweig C, Ruane AC and Sheffield J (2015) The global gridded crop model intercomparison: data and modeling protocols for Phase 1 (v1.0). *Geoscientific Model Development* **8**, 261–277.

Evans LT and Fischer RA (1999) Yield potential: its definition, measurement, and significance. *Crop Science* **39**, 1544–1551.

Fang S, Cammarano D, Zhou G, Tan K and Ren S (2015) Effects of increased day and night temperature with supplemental infrared heating on winter wheat growth in North China. *European Journal of Agronomy* **64**, 67–77.

FAOSTAT (2021). *Food and Agriculture Organization of the United Nations Statics Division: Food and agriculture data*. Available at https://www.fao.org/faostat/en/#data (Accessed 11 November 2021).

Ferrise R, Moriondo M, Pasqui M, Toscano P, Semenov MA and Bindi M (2014) Using seasonal forecasts for predicting durum wheat yield over the Mediterranean Basin. *Climate Research* **65**, 7–21.

Foulkes MJ, Scott TLRK and Sylvester-Bradley R (2001) The ability of wheat cultivars to withstand drought in UK conditions: resource capture. *The Journal of Agricultural Science* **137**, 1–16.

Foulkes MJ, Scott RK and Sylvester-Bradley R (2002) The ability of wheat cultivars to withstand drought in UK conditions: formation of grain yield. *The Journal of Agricultural Science* **138**, 153–169.

Hallett SH, Sakrabani R, Keay CA and Hannam JA (2017) Developments in land information systems: examples demonstrating land resource management capabilities and options. *Soil Use and Management* **33**, 514–529.

Harkness C, Semenov MA, Areal F, Senapati N, Trnka M, Balek J and Bishop J (2020) Adverse weather conditions for UK wheat production under climate change. *Agricultural and Forest Meteorology* **282–283**, 107862.

Hoogenboom G, Porter CH, Boote KJ, Sheila V, Wilkens PW, Singh U, White JW, Asseng S, Lizaso JI, Moreno LP, Pavan W, Ogoshi R, Hunt LA, Tsuji GY and Jones JW (2019) The DSSAT crop modeling ecosystem. In Boote KJ (ed.), *Advances in Crop Modeling for A Sustainable Agriculture*. Cambridge, UK: Burleigh Dodds Science Publishing.

Jones JW, Hoogenboom G, Porter CH, Boote KJ, Batchelor WD, Hunt LA, Wilkens PW, Singh U, Gijsman AJ and Ritchie JT (2003) The DSSAT cropping system model. *European Journal of Agronomy* **18**, 235–265.

Liu B, Asseng S, Müller C, Ewert F, Elliott J, Lobell DB, Martre P, Ruane AC, Wallach D, Jones JW, Rosenzweig C, Aggarwal PK, Alderman PD, Anothai J, Basso B, Biernath C, Cammarano D, Challinor A, Deryng D, Sanctis GD, Doltra J, Fereres E, Folberth C, Garcia-Vila M, Gayler S, Hoogenboom G, Hunt LA, Izaurralde RC, Jabloun M, Jones CD, Kersebaum KC, Kimball BA, Koehler A-K, Kumar SN, Nendel C, O'Leary GJ, Olesen JE, Ottman MJ, Palosuo T, Prasad PVV, Priesack E, Pugh TAM, Reynolds M, Rezaei EE, Rötter RP, Schmid E, Semenov MA, Shcherbak I, Stehfest E, Stöckle CO, Stratonovitch P, Streck T, Supit I, Tao F, Thorburn P, Waha K, Wall GW, Wang E, White JW, Wolf J, Zhao Z and Zhu Y (2016) Similar estimates of temperature impacts on global wheat yield by three independent methods. *Nature Climate Change* **6**, 1130–1136.

Liu B, Martre P, Ewert F, Porter JR, Challinor AJ, Müller C, Ruane AC, Waha K, Thorburn PJ, Aggarwal PK, Ahmed M, Balkovič J, Basso B, Biernath C, Bindi M, Cammarano D, De Sanctis G, Dumont B, Espadafor M, Eyshi Rezaei E, Ferrise R, Garcia-Vila M, Gayler S, Gao Y, Horan H, Hoogenboom G, Izaurralde RC, Jones CD, Kassie BT, Kersebaum KC, Klein C, Koehler A-K, Maiorano A, Minoli S, Montesino San Martin M, Naresh Kumar S, Nendel C, O'Leary GJ, Palosuo T, Priesack E, Ripoche D, Rötter RP, Semenov MA, Stöckle C, Streck T, Supit I, Tao F, Van der Velde M, Wallach D, Wang E, Webber H, Wolf J, Xiao L, Zhang Z, Zhao Z, Zhu Y and Asseng S (2019) Global wheat production with 1.5 and 2.0°C above pre-industrial warming. *Global Change Biology* **25**, 1428–1444.

Maestrini B and Basso B (2021) Subfield crop yields and temporal stability in thousands of US Midwest fields. *Precision Agriculture* **22**, 1749–1767.

Martre P, Wallach D, Asseng S, Ewert F, Jones JW, Rötter RP, Boote KJ, Ruane AC, Thorburn PJ, Cammarano D, Hatfield JL, Rosenzweig C, Aggarwal PK, Angulo C, Basso B, Bertuzzi P, Biernath C, Brisson N, Challinor AJ, Doltra J, Gayler S, Goldberg R, Grant RF, Heng L, Hooker J, Hunt LA, Ingwersen J, Izaurralde RC, Kersebaum KC, Müller C, Kumar SN, Nendel C, O'Leary G, Olesen JE, Osborne TM, Palosuo T, Priesack E, Ripoche D, Semenov MA, Shcherbak I, Steduto P, Stöckle CO, Stratonovitch P, Streck T, Supit I, Tao F, Travasso M, Waha K, White JW and Wolf J (2015) Multimodel ensembles of wheat growth: many models are better than one. *Global Change Biology* **21**, 911–925.

Mitchell D, Achutarao K, Allen M, Bethke I, Beyerle U, Ciavarella A, Forster PM, Fuflestvedt J, Gillett N, Haustein K, Ingram W, Iversen T, Kharin V, Klingaman N, Massey N, Fischer E, Schleussner CF, Scinocca J, Seland Ø, Shiogama H, Shuckburgh E, Sparrow S, Stone D, Uhe P, Wallom D, Wehner M and Zaaboul R (2017) Half a degree additional warming, prognosis and projected impacts (HAPPI): background and experimental design. *Geoscientific Model Development* **10**, 571–583.

Monteith JL (1972) Solar radiation and productivity in tropical ecosystems. *Journal of Applied Ecology* **9**, 747–766.

Müller C, Elliott J, Kelly D, Arneth A, Balkovic J, Ciais P, Deryng D, Folberth C, Hoek S, Izaurralde RC, Jones CD, Khabarov N, Lawrence P, Liu W, Olin S, Pugh TAM, Reddy A, Rosenzweig C, Ruane AC, Sakurai, G, Schmid E, Skalsky R, Wang X, De Wit A and Yang H (2019) The global gridded crop model intercomparison phase 1 simulation dataset. *Scientific Data* **6**, 50.

NOAA (2020) *National Oceanic and Atmospheric Administration: 2019 was 2nd hottest year on record for Earth say NOAA, NASA*. Available at https://www.noaa.gov/news/2019-was-2nd-hottest-year-on-record-for-earth-say-noaa-nasa (Accessed 11 November 2021).

Ojeda JJ, Rezaei EE, Kamali B, McPhee J, Meinke H, Siebert S, Webb MA, Ara I, Mulcahy F and Ewert F (2021) Impact of crop management and environment on the spatio-temporal variance of potato yield at regional scale. *Field Crops Research* **270**, 108213.

Porter JR and Gawith M (1999) Temperatures and the growth and development of wheat: a review. *European Journal of Agronomy* **10**, 23–36.

https://doi.org/10.1017/S0021859621000903 Published online by Cambridge University Press

Putelat T, Whitmore AP, Senapati N and Semenov MA (2021) Local impacts of climate change on winter wheat in Great Britain. *Royal Society Open Science* **8**, 201669.

Ritchie JT (1991) Wheat phasic development. In Hanks RJ and Ritchie JT (eds), *Modeling Plant and Soil Systems*. Agronomy Monograph #31. Madison, WI, USA: American Society of Agronomy, pp. 31–54.

Rodríguez A, Ruiz-Ramos M, Palosuo T, Carter TR, Fronzek S, Lorite IJ, Ferrise R, Pirttioja N, Bindi M, Baranowski P, Buis S, Cammarano D, Chen Y, Dumont B, Ewert F, Gaiser T, Hlavinka P, Hoffmann H, Höhn JG, Jurecka F, Kersebaum KC, Krzyszczak J, Lana M, Mechiche-Alami A, Minet J, Montesino M, Nendel C, Porter JR, Ruget F, Semenov MA, Steinmetz Z, Stratonovitch P, Supit I, Tao F, Trnka M, de Wit A and Rötter RP (2019) Implications of crop model ensemble size and composition for estimates of adaptation effects and agreement of recommendations. *Agricultural and Forest Meteorology* **264**, 351–362.

Ruane AC (2021). *AgMERRA and AgCFSR Climate Forcing Datasets for Agricultural Modeling*. Available at https://data.giss.nasa.gov/impacts/agmipcf/agmerra/ (Accessed 11 November 2021).

Ruane AC, Goldberg R and Chryssanthacopoulos J (2015). Climate forcing datasets for agricultural modeling: merged products for gap-filling and historical climate series estimation. *Agricultural and Forest Meteorology* **200**, 233–248.

Ruane AC, Hudson NI, Asseng S, Cammarano D, Ewert F, Martre P, Boote KJ, Thorburn PJ, Aggarwal PK, Angulo C, Basso B, Bertuzzi P, Biernath C, Brisson N, Challinor AJ, Doltra J, Gayler S, Goldberg R, Grant RF, Heng L, Hooker J, Hunt LA, Ingwersen J, Izaurralde RC, Kersebaum KC, Kumar SN, Müller C, Nendel C, O'Leary G, Olesen JE, Osborne TM, Palosuo T, Priesack E, Ripoche D, Rötter RP, Semenov MA, Shcherbak I, Steduto P, Stöckle CO, Stratonovitch P, Streck T, Supit I, Tao F, Travasso M, Waha K, Wallach D, White JW and Wolf J (2016) Multi-wheat-model ensemble responses to interannual climate variability. *Environmental Modelling & Software* **81**, 86–101.

Ruane AC, Antle J, Elliott J, Folberth C, Hoogenboom G, Mason-D'Croz D, Müller C, Porter CH, Phillps MM, Raymundo RM, Sands R, Valdivia RO, White JW, Wiebe K and Rosenzweig C (2018*a*). Biophysical and economic implications for agriculture of +1.5° and +2.0°C global warming using AgMIP coordinated global and regional assessments. *Climate Research* **76**, 17–39.

Ruane AC, Phillips MM and Rosenzweig C (2018*b*). Climate shifts within major agricultural seasons for +1.5 and+2.0°C worlds: HAPPI projections and AgMIP modeling scenarios. *Agricultural and Forest Meteorology* **259**, 329–344.

Ruane AC, Phillips M, Müller C, Elliott J, Jagermeyr J, Arneth A, Balkovic J, Deryng D, Folberth C, Iizum T, Izaurralde RC, Khabarov N, Lawrence P, Liu W, Olin S, Pugh TAM, Rosenzweig C, Sakurai G, Schmid E, Sultan B, Wang X, de Wit A and Yang H (2021) Strong regional influence of climatic forcing datasets on global crop model ensembles. *Agricultural and Forest Meteorology* **300**, 108313.

Ruiz-Ramos M, Ferrise R, Rodríguez A, Lorite IJ, Bindi M, Carter TR, Fronzek S, Palosuo T, Pirttioja N, Baranowski P, Buis S, Cammarano D, Chen Y, Dumont B, Ewert F, Gaiser T, Hlavinka P, Hoffmann H, Höhn JG, Jurecka F, Kersebaum KC, Krzyszczak J, Lana M, Mechiche-Alami A, Minet J, Montesino M, Nendel C, Porter JR, Ruget F, Semenov MA, Steinmetz Z, Stratonovitch P, Supit I, Tao F, Trnka M, de Wit A and Rötter RP (2018). Adaptation response surfaces for managing wheat under perturbed climate and CO_2 in a Mediterranean environment. *Agricultural Systems* **159**, 260–274.

Semenov MA (2008). Impacts of climate change on wheat in England and Wales. *Journal of the Royal Society Interface* **6**, https://doi.org/10.1098/rsif.2008.0285.

Semenov MA and Stratonovitch P (2014) Adapting wheat in Europe for climate change. *Journal of Cereal Science* **59**, 245–256.

Senapati N and Semenov MA (2019). Assessing yield gap in high productive countries by designing wheat ideotypes. *Scientific Reports* **9**, 5516.

Senapati N, Halford NG and Semenov MA (2021) Vulnerability of European wheat to extreme heat and drought around flowering under future climate. *Environmental Research Letters* **16**, 024052.

Trnka M, Rötter RP, Ruiz-Ramos M, Kersebaum KC, Olesen JE, Zalud Z and Semenov MA (2014) Adverse weather conditions for European wheat production will become more frequent with climate change. *Nature Climate Change* **4**, 637–643.

UK Flour Millers (2020). *Wheat*. Available at https://www.ukflourmillers.org/wheat#:~:text=Wheat%20is%20the%20most%20important,in%20a%20majority%20of%20countries.&text=In%20the%20UK%2C%20wheat%20is,1.9%20million%20hectares (Accessed 11 November 2021).

UK MET Office (2019) *UK Climate Projections: Headline Findings*. Exeter, Devon, UK: Met Office.

Van Ittersum MK, Leffelaar PA, Van Keulen H, Kropff MJ, Bastiaans L and Goudriaan J (2003) On approaches and applications of the Wageningen crop models. *European Journal of Agronomy* **18**, 201–234.

Wallach D, Palosuo T, Thorburn P, Hochman Z, Andrianasolo F, Asseng S, Basso B, Buis S, Crout N, Dumont B, Ferrise R, Gaiser T, Gayler S, Hiremath S, Hoek S, Horan H, Hoogenboom G, Huang M, Jabloun M, Jansson P-E, Jing Q, Justes E, Kersebaum KC, Launay M, Lewan E, Luo Q, Maestrini B, Moriondo M, Olesen JE, Padovan G, Poyda A, Priesack E, Pullens JWM, Qian B, Schütze N, Shelia V, Souissi A, Specka X, Kumar Srivastava A, Stella T, Streck T, Trombi G, Wallor E, Wang J, Weber TKD, Weihermüller L, de Wit A, Wöhling T, Xiao L, Zhao C, Zhu Y and Seidel SJ (2021) Multi-model evaluation of phenology prediction for wheat in Australia. *Agricultural and Forest Meteorology* **298–299**, 108289.

Wang E, Martre P, Zhao Z, Ewert F, Maiorano A, Rötter RP, Kimball BA, Ottman MJ, Wall GW, White JW, Reynolds MP, Alderman PD, Aggarwal PK, Anothai J, Basso B, Biernath C, Cammarano D, Challinor AJ, De Sanctis G, Doltra J, Dumont B, Fereres E, Garcia-Vila M, Gayler S, Hoogenboom G, Hunt LA, Izaurralde RC, Jabloun M, Jones CD, Kersebaum KC, Koehler A-K, Liu L, Müller C, Naresh Kumar S, Nendel C, O'Leary G, Olesen JE, Palosuo T, Priesack E, Eyshi Rezaei E, Ripoche D, Ruane AC, Semenov MA, Shcherbak I, Stöckle C, Stratonovitch P, Streck T, Supit I, Tao F, Thorburn P, Waha K, Wallach D, Wang Z, Wolf J, Zhu Y and Asseng S (2017) The uncertainty of crop yield projections is reduced by improved temperature response functions. *Nature Plants* **3**, 17102.

Webber H, Ewert F, Kimball BA, Siebert S, White JW, Wall G, Ottman MJ, Trawally DNA and Gaiser T (2016) Simulating canopy temperature for modelling heat stress in cereals. *Environmental Modelling & Software* **77**, 143–155.

Webber H, Martre P, Asseng S, Kimball B, White J, Ottman M, Wall GW, De Sanctis G, Doltra J, Grant R, Kassie B, Maiorano A, Olesen JE, Ripoche D, Rezaei EE, Semenov MA, Stratonovitch P and Ewert F (2017) Canopy temperature for simulation of heat stress in irrigated wheat in a semi-arid environment: a multi-model comparison. *Field Crops Research* **202**, 21–35.

Wickham H (2016) *ggplot2: Elegant Graphics for Data Analysis*. New York: Springer-Verlag.

Wilmott CJ (1982). Some comments on the evaluation of model performance. *Bulletin American Meteorological Society* **63**, 5.

Zhao C, Liu B, Piao S, Wang X, Lobell DB, Huang Y, Huang M, Yao Y, Bassu S, Ciais P, Durand J-L, Elliott J, Ewert F, Janssens IA, Li T, Lin E, Liu Q, Martre P, Müller C, Peng S, Penuelas J, Ruane AC, Wallach D, Wang T, Wu D, Liu Z, Zhu Y, Zhu Z and Asseng S (2017) Temperature increase reduces global yields of major crops in four independent estimates. *Proceedings of the National Academy of Sciences* **114**, 9326–9331.