Potential Impacts of projected warming scenarios on winter wheat in the U.K.

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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, 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 on 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 Global Climate Models, with two cultivars and five planting dates were simulated the end of the century. Results of this study showed that the UK potential wheat yield will increase by 2 to 8% under projected climate. Farmers will need to close such gap in the future because it will have implications in terms of food security. Future climatic conditions might increase such

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.

Key words: Climate change, crop models, climate impacts

Introduction

Wheat is among one of the largest cultivated crops worldwide, second, in millions of hectare 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 a 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 & Gawith 1999; Semenov 2008; Ferrise et al. 2014; Semenov & Stratonovitch 2014; Trnka et al. 2014; Asseng et al. 2015; Asseng et al. 2019). In a study where statistical and process-based models were compared, it has been found that global wheat production will fall by 4 to 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 an 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; Asseng et al. 2015; Asseng et al. 2019; Cammarano et al. 2019a; Müller et al. 2019; Cammarano et al. 2020; 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 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 problem can be minimized by using an ensemble of GCMs, because the uncertainty associated with the climate projection can be quantified (Cammarano & 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; Basso et al. 2011; Cammarano et al. 2019a; Maestrini & 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 assumption (Evans & 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 proxy for evaluating projected impacts of temperature changes on crop development and potential yield (Asseng et al. 2011; Asseng et al. 2015; Asseng et al. 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 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, twenty-seven crop models and sixteen 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 a wheat and maize and on two contrasting soils. The authors calculated sixteen climate indices finding that climate impacts differ depending on the soil type and the growth stage at which extreme climate events happens. 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 the 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. 2019a; 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 the 2015 stated that the World needs to achieve a maximum 2.0°C or an ambitious 1.5°C. Global wheat production can be significantly impacted by raising temperature (Asseng et al. 2013; Asseng et al. 2015; Asseng et al. 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 quantifying 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; Foulkes et al. 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; Foulkes et al. 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^{-1} 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 crop growth models used in this study were the CSM-CERES-Wheat (Ds), the CSM-Nwheat (Nw) and the WheatGrow (Wg) (Cao & Moss 1997; Hoogenboom et al. 2019) and were selected because of the different temperature response functions impacting developmental processes. These three crop growth models require a set of weather (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; Foulkes et al. 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; Asseng et al. 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 temperature (Asseng et al. 2015). The main differences 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 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 423ppm) and 2.0°C (CO_2 concentration of 487ppm) 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 360ppm; the CO_2 concentrations correspond to centre of the 1980-2010, and the 1.5 and 2.0°C global warming level as highlighted in Ruane et al. (2018a). 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 details in other studies (Ruane et al. 2015; Ruane et al. 2018b). Four Global Climate Models (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 concentration (360ppm 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:

$$RMSE = \sqrt{\frac{\sum_{i=1}(O_i - S_i)^2}{n}} \qquad [1]$$

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 cross-comparison method between models (Wilmott 1982; Martre et al. 2015; Cammarano et al. 2019b).

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

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

$$RC = \frac{S_{f,i} - S_{b,i}}{S_{b,i}} * 100 \qquad [3]$$

$S_{f,i}$ was the simulated (S) value as predicted by any combination of factors (*f*) for a 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. Eeach 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:

$$CV\% = \frac{\sigma}{\bar{x}} * 100 \qquad [4]$$

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).

Results

The results of model calibration of the models are shown in Figure 3. Overall, the simulated data showed good agreement with the observed data (Fig. 3). The simulated anthesis dates had a RMSE of 10 days and a D-Index of 0.70, while maturity dates had a RMSE of 4 days and a D-Index of 0.97. Aboveground biomass and grain yield had a 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 Supplemental 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 Figure 5. Overall, under baseline weather data the simulated potential yield ranged from 10,000 to 14,500 kg DM ha^{-1} with lower values in the north and higher in the south (Fig. 5a). The standard deviation of the simulations (size of the dots in Figure 5) at each point was due to the planting date, GCM, cultivar, and the crop model used (Fig. 5a) and it was about 1500 kg DM ha^{-1} with lower values in the south and higher in the north (Fig. 5a). 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^{-1} (Fig. 5a).

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 to -1% under scenario 1 and 2. However, the simulated impacts of increased CO_2 caused the simulated yield potential to increase 7 to 10% for scenario 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 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 (Supplemental 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 Figure 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 toward 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 was 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 Figure 9. The relationship between simulated anthesis date and daily minimum temperature differs slightly among the two cultivars, but there was less disagreement from the crop growth models. For later sowing dates, the Wg model tends to simulate anthesis dates that plateaued at about 3ºC.

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 cultivar was also showing higher uncertainty but much lower than the crop models. The GCM showed the least of the 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 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. Global wheat yield projection of Ruane et al. (2018a) 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 highlight 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 temperature. 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), 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 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 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 tends to be, especially in the northern part, around the values of the base temperature. Therefore, any increase of air temperature will not cause significant reductions of 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. (2018a) 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. 2018a).

The results of variability of the crop models in terms of phenology and yield response as 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) and

Asseng et al. (2015). Ruane et al. (2018a) reported values of global wheat yield uncertainty analysis finding that uncertainty of climate models is smaller than the 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 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 use 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 model 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 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, projected potential wheat yield in the UK will increase by 2 to 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.

Financial Support

Royal Society of London Exchange Program

Conflicts of Interest

The authors declare there are no conflicts of interest.

Ethical Standards

Not applicable

Acknowledgment

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.

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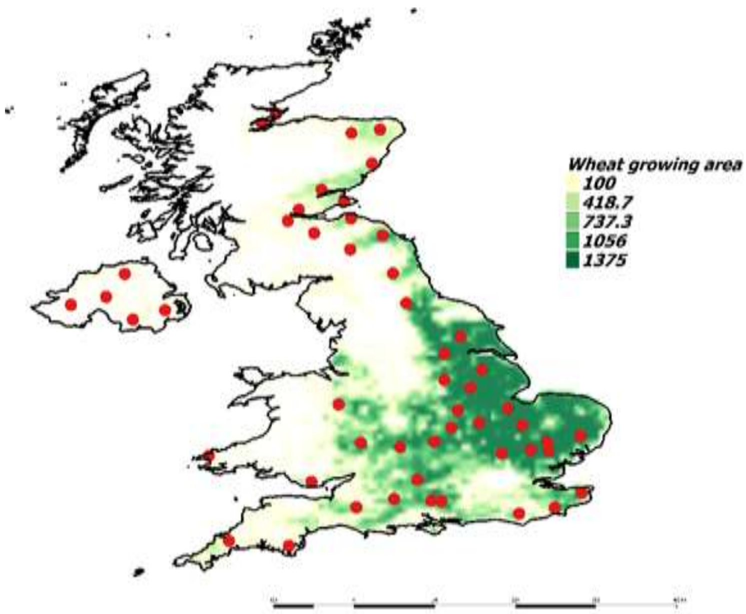

Figure 1. United Kingdom (UK) wheat growing area and points used in the simulation study.

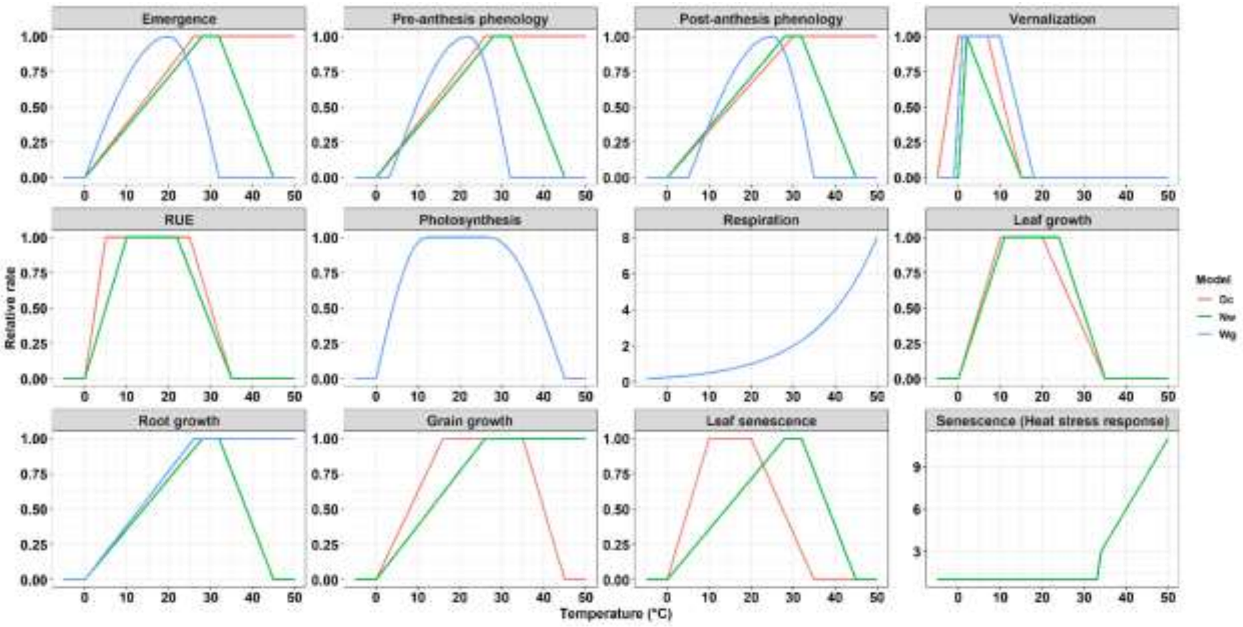

Figure 2. Temperature response functions for different simulated processes by the CSM-CERES-Wheat (Dc, red line), the CSM-Nwheat (Nw, green line), and the WheatGrow (Wg, blue line).

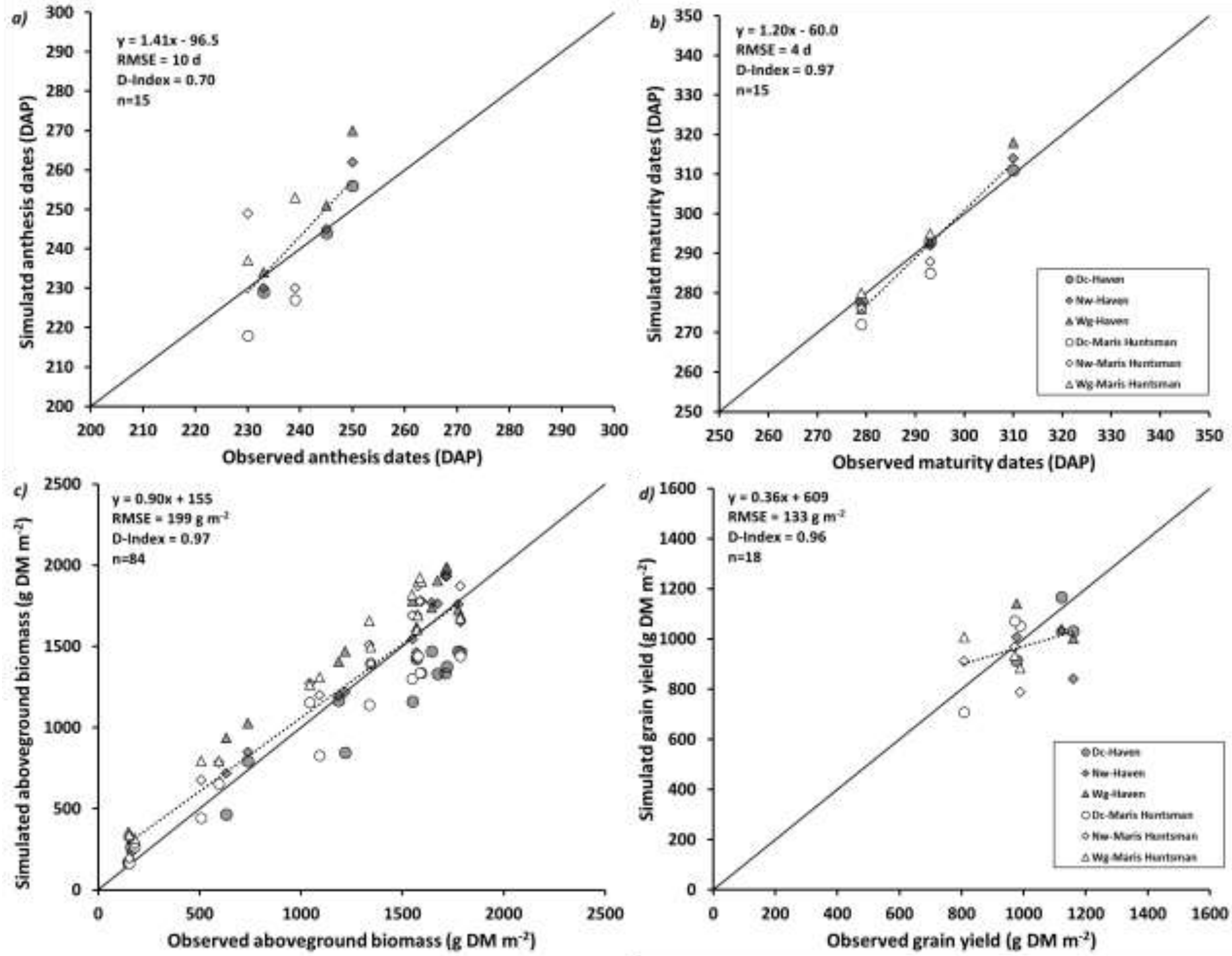

Figure 3. Calibration of the CSM-CERES-Wheat (Dc, dots), CSM-NWheat (Nw, diamonds), and WheatGrow (Wg, triangles) models for two wheat cultivars Haven (grey) and Maris Huntsman (white) for (*a*) anthesis dates; (*b*) maturity dates; (*c*) aboveground biomass; and (*d*) grain yield.

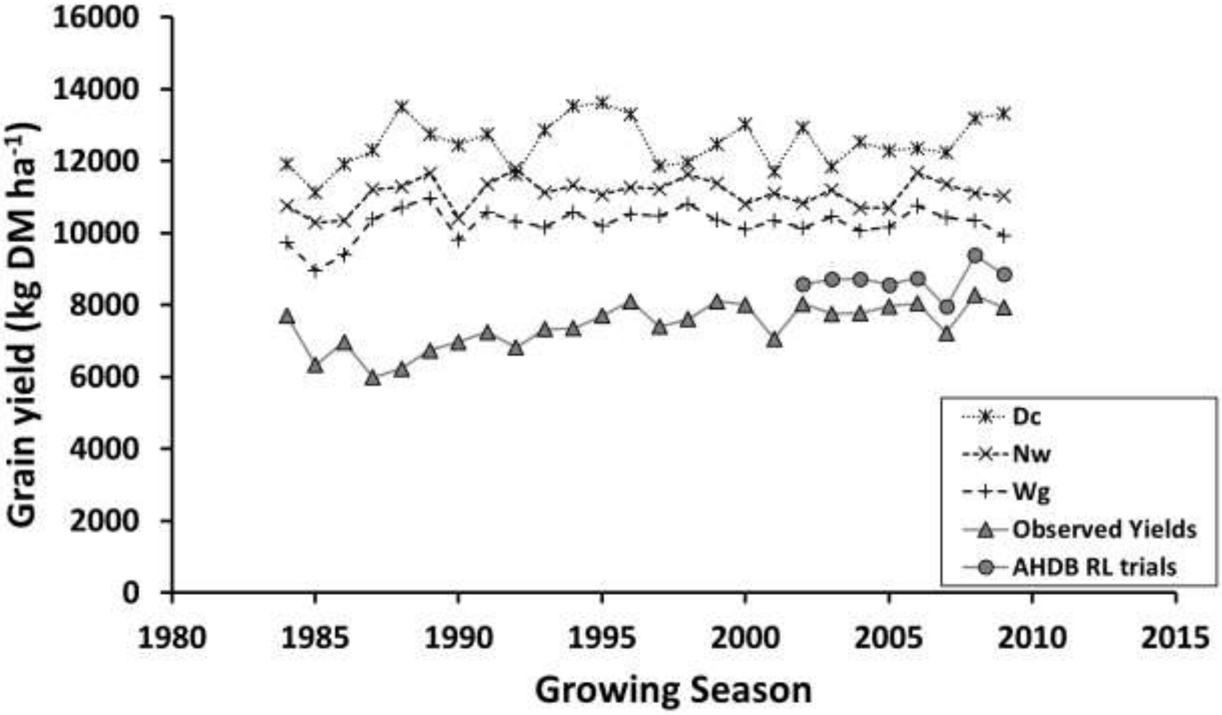

Figure 4. Patterns of simulations of potential wheat yield as simulated, from 1984 to 2009, by the CSM-CERES-Wheat (Dc, stars and dotted line), CSN-NWheat (Wg, cross and short dash line), and WheatGrow (Wg, plus and long dot line). In addition, observed data from the UK national statistics (grey triangles),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

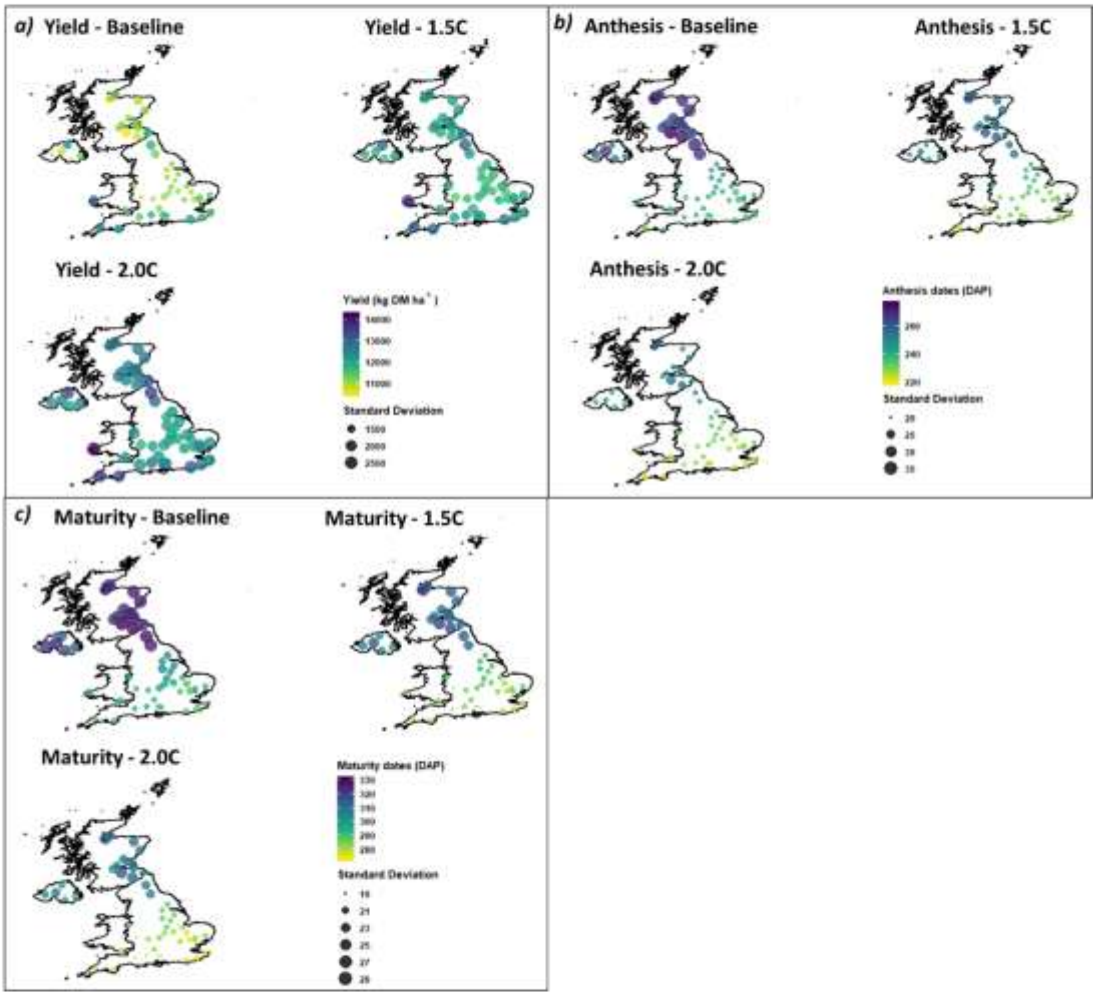

Figure 5. Simulated results as mean among two cultivars, four GCMs, five planting dates, and three crop simulation models for *(a)* potential wheat yield; (*b*) anthesis; and (*c*) maturity dates for baseline, 1.5°C (Scenario 1) and 2.0°C (Scenario 2). The dots represent the standard deviation of the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

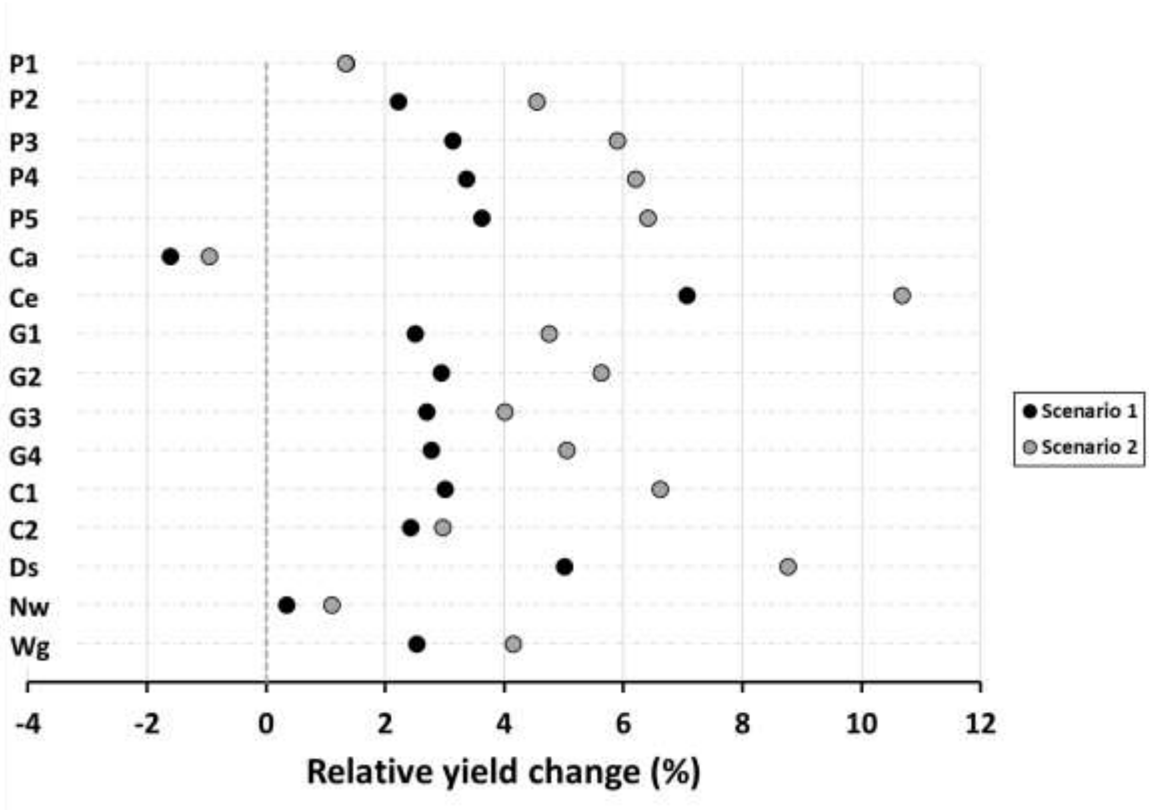

Figure 6. Relative yield change, respect to the simulated baseline (1980-2010), for scenario 1 (black dots corresponding to 1.5°C) and scenario 2 (grey dots corresponding to 2.0°C) of different planting dates (P1: Mid-Sep; P2: Late-Sep; P3: Mid-Oct; P4: Late-Oct; P5: Mid-Nov), CO_2 concentrations (Ca: baseline CO_2 concentration of 360ppm; C3: elevated CO_2 concentration of 423ppm for the climate scenario 1.5°C, and 487ppm 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).

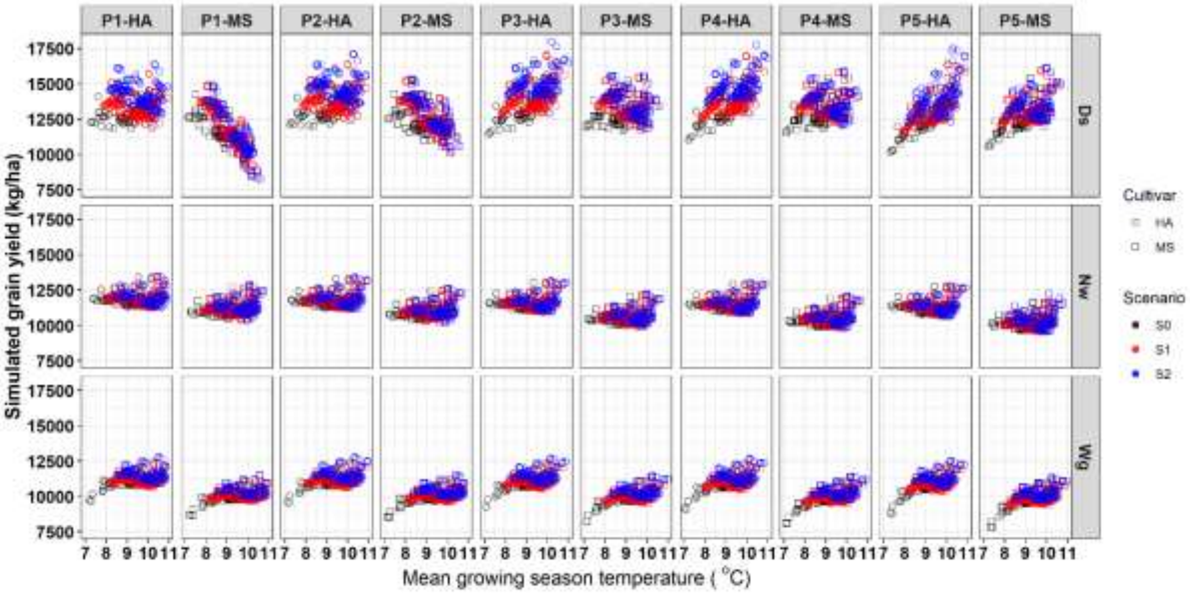

Figure 7. Relationship between mean growing season temperature and simulated potential wheat yield for the cultivar Haven (HA, open dots) and Maris Huntsman (MS, open squares) under baseline conditions (S0, black colour), 1.5°C (S1, red colour), and 2.0°C (S2, blue colour), for 5 different planting dates (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).

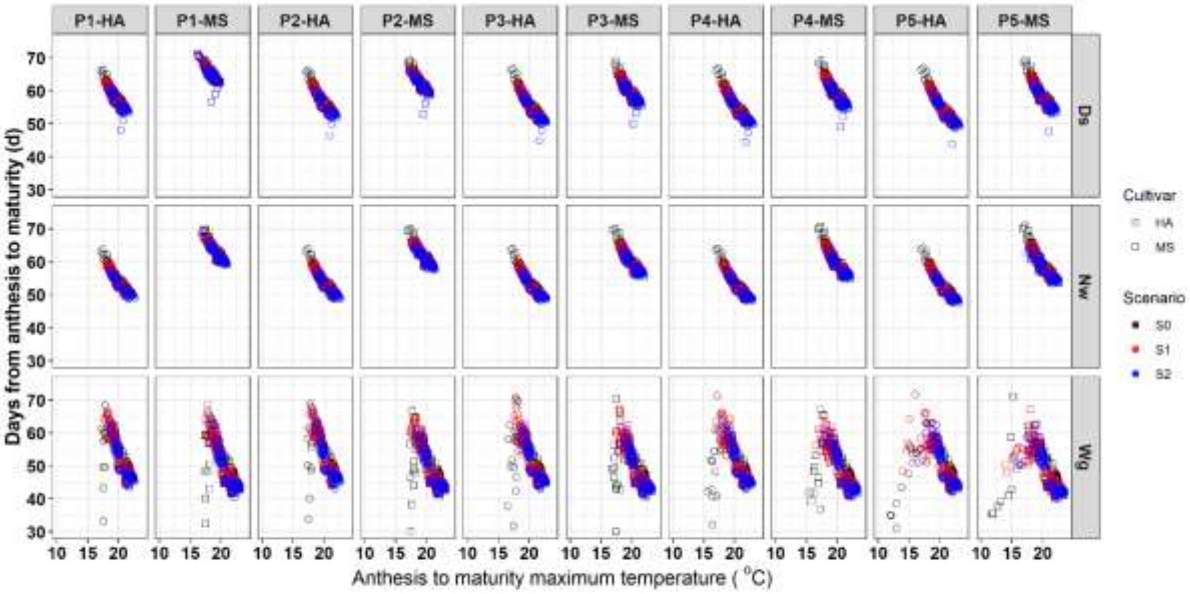

Figure 8. Relationship between daily maximum temperature averaged from anthesis to maturity and simulated days from anthesis to maturity for the cultivar Haven (HA, open dots) and Maris Huntsman (MS, open squares) under baseline conditions (S0, black colour), 1.5°C (S1, red colour), and 2.0°C (S2, blue 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).

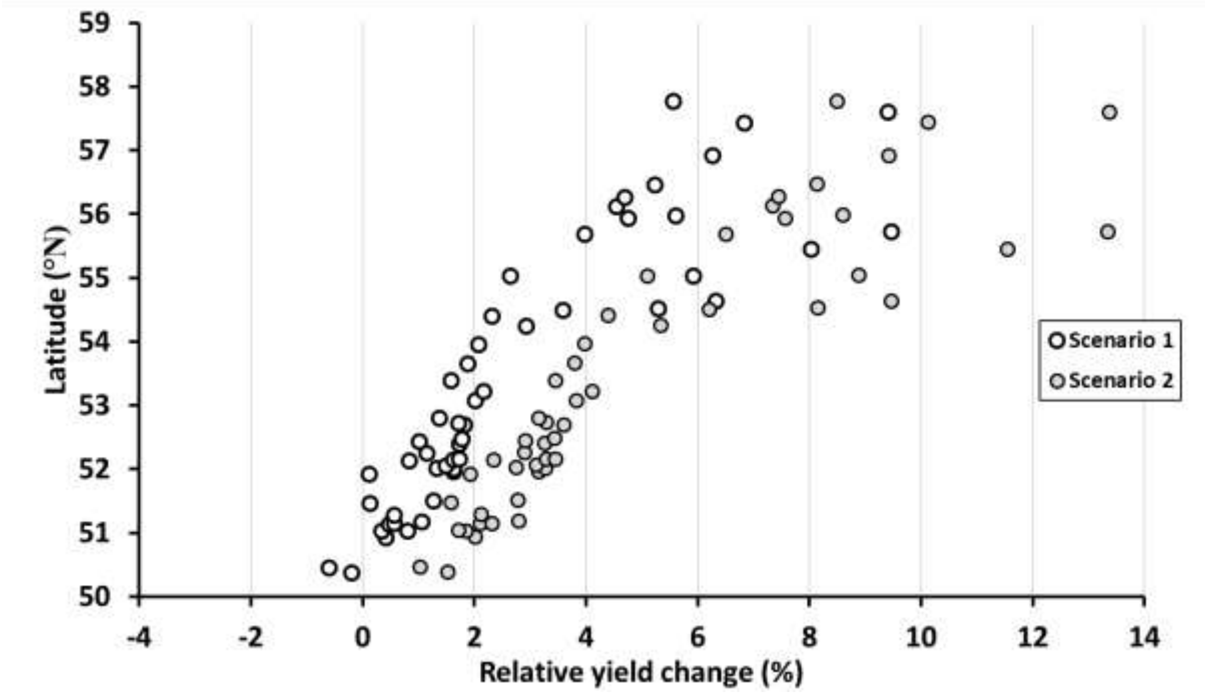

Figure 9. Relative yield change at different latitudes for scenario 1 (white dots corresponding to 1.5°C) and scenario 2 (grey dots corresponding to 2.0°C) as mean across different planting dates (P1: Mid-Sep; P2: Late-Sep; P3: Mid-Oct; P4: Late-Oct; P5: Mid-Nov), CO_2 concentrations (Ca: baseline CO_2 concentration of 360ppm; C3: elevated CO_2 concentration of 423 and 487ppm 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).

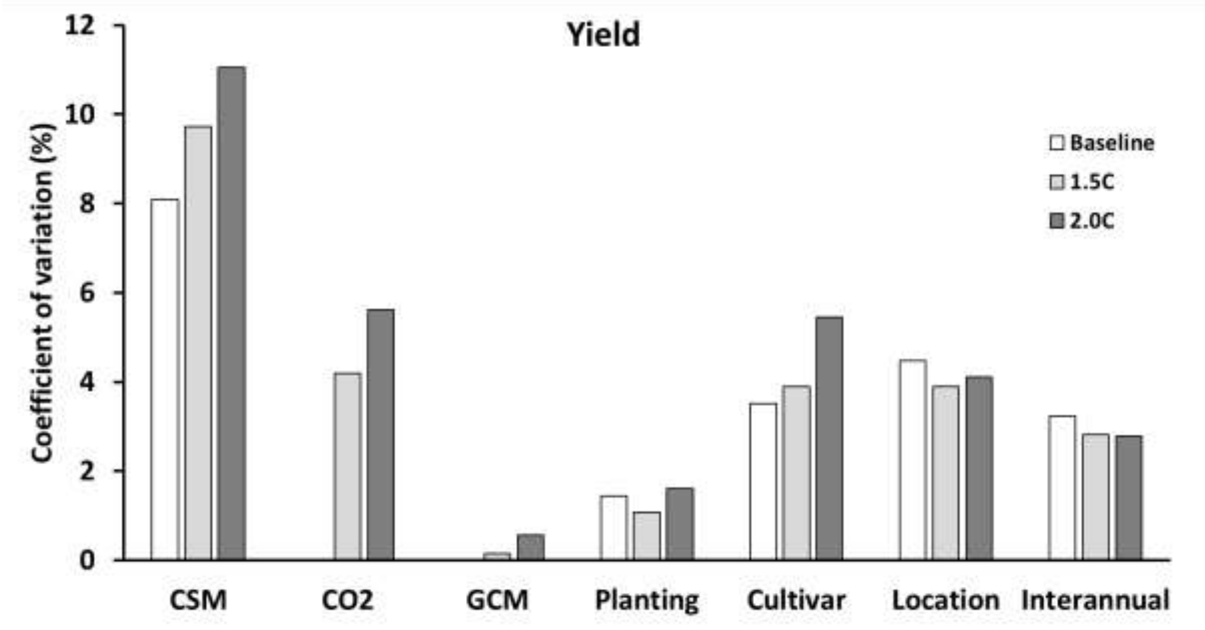

Figure 10. Coefficient of variation of the different components (CSM: crop simulation models; CO_2: atmospheric CO_2 concentrations; GCM: Global Climate models used; Planting: five planting dates; Cultivar: two cultivars used; Location: fifty locations; Interannual: Thirty years) affecting the simulated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