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PAPER

Climate data integration into wheat performance evaluation reveals large inter-varietal responses

Joanna Raymond[1,*], **Steven Penfield**[2], **Andrew Lovett**[1], **Ian Mackay**[3,6], **Haidee Philpott**[4], **Conor John Christopher Simpson**[5] and **Stephen Dorling**[1]

[1] School of Environmental Sciences, University of East Anglia, Norwich, United Kingdom
[2] John Innes Centre, Norwich Research Park, Norwich, United Kingdom
[3] Scotland's Rural College (SRUC), Kings Buildings, West Mains Road, Edinburgh EH9 3JG, United Kingdom
[4] National Institute of Agricultural Botany, Lawrence Weaver Road, Cambridge, United Kingdom
[5] Institute of Meteorology and Climate Research, Atmospheric Environmental Research (IMK-IFU), Karlsruhe Institute of Technology, Kreuzeckbahnstraße 19, 82467 Garmisch-Partenkirchen, Germany
[6] deceased.
[*] Author to whom any correspondence should be addressed.

E-mail: joanna.raymond@kit.edu

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Abstract

There is an urgent need to adapt crop breeding strategies to boost resilience in the face of a growing food demand and a changing climate. Achieving this requires an understanding of how weather and climate variability impacts crop growth and development. Using the United Kingdom (UK) as an example, we evaluate changes in the UK agroclimate and analyse how these have influenced domestic wheat production. Here we quantify spatial and temporal variability and changes in weather and climate across growing seasons over the last four decades (1981–2020). Drawing on variety trial data, we then use statistical modelling to explore the interaction between genotype and agroclimate variation.

We show that changes in the UK agroclimate present both risks, and opportunities for wheat growers, depending on location. From 1981–2020, in Wales, the West Midlands, large parts of the North West, and Northern Ireland, there was an overall increase in frost risk in early spring of 0.15 additional frost days per year, whilst in the east early frost risk decreased by up to 0.29 d per year. Meanwhile, over the period 1987–2020, surface incoming shortwave radiation during grainfill increased in the east by up to 13% but decreased in Western areas by up to 15%. We show significant inter-varietal differences in yield responses to growing degree days, heavy rainfall, and the occurrence of late frost. This highlights the importance of evaluating variety-climate interactions in variety trial analyses, and in climate-optimised selection of crops and varieties by growers. This work provides guidance for future research on how climate change is affecting the UK agroclimate and resulting impacts on winter cereal production.

1. Introduction

Climate change presents a major challenge for agriculture, both in terms of climate change mitigation and climate adaptation (Parolini 2022). Climate change has already altered the distributions of viable cropping areas, the ranges of pests and diseases, and increased weather and climate variability (Falloon *et al* 2015, Skendžić *et al* 2021). There is an ongoing need to assess the effects of climate variability on crop and individual variety yields (Bathiany *et al* 2023) to improve climate resilience in agriculture. Indeed, in the most recent UK Food Security Report (DEFRA 2021), the largest medium to long-term risk to domestic production was identified as climate change, and other environmental pressures, such as soil degradation.

Interannual climate variability can lead to high production variability (Ray *et al* 2015), which in turn contributes to instability in farmer incomes, consumer prices and local food security (Frieler *et al* 2017, Zhao *et al* 2021). This was exemplified in the UK by recorded rainfall variability in the 2007 and 2020 cereal harvest years: in July 2007, waterlogging saw regional yields decrease by up to 40% (Posthumus *et al* 2009), whilst in 2020, a very wet preceding autumn sowing season followed by a very dry spring contributed to the lowest winter wheat production in 30 years and sharp increases in bread prices (Rowlatt 2020, Tasker 2020). There are many points within the growing season when a crop is vulnerable to climate variability. Historical analysis has shown that climate impacts on wheat yields are strongest in years with compound weather extremes across multiple growth stages (Slater *et al* 2022). Figure 1 shows the multiple stages of winter wheat development when anomalous weather is most likely to impact production. The mechanisms of their influence are explained in greater detail in supplementary material 1.

Agroclimate indicators have been shown to be useful for quantifying the effect of changes in weather and climate on agriculture, and can significantly improve crop model performance over simpler raw weather data (Mathieu and Aires 2018). They provide valuable information for supporting specific farm management decisions. In the UK, one particular use of these indicators has focussed on future climate change impacts on agriculture (Semenov 2009, Harkness *et al* 2020, Arnell and Freeman 2021). A report by the Climate Change Committee provides a synthesis of the literature on potential UK agricultural risks associated, for example, with future exceedance of extreme temperature thresholds (Jones *et al* 2020). This also highlights the need to breed, and grow, crop varieties that can cope with such extremes.

A range of indices has also been used to analyse the observed UK agroclimate, including growing degree days (GDD) and agricultural drought risk (Rivington *et al* 2013, Harding *et al* 2015, Arnell and Freeman 2021). Whilst these provide a useful summary of the agroclimate over 30 year periods, they mask the inter-annual and more recent variability that is critical for understanding short-term impacts. Few studies have investigated how observed UK climate has affected historical yields, and the focus of these has largely been on specific sub-national areas (Addy *et al* 2020, Addy *et al* 2021, Slater *et al* 2022) or relied on national and regional average yield and climate data which can mask significant local variability (Knight *et al* 2012, Slater *et al* 2022). In contrast, we make use of high-resolution gridded climate datasets and site-specific yield data to capture the complex effects of climate on historical yields across diverse UK environments, thereby addressing the limitations of broader-scale analysis.

Thus far, the agroclimate metrics used in these analyses have mostly been based on temperature and precipitation data, with some studies also incorporating sunshine hour data (e.g. Addy *et al* 2020, Arnell and Freeman 2021, Slater *et al* 2022). The availability of high-quality satellite solar radiation data, such as satellite-derived daily surface incoming solar radiation (SIS) (Pfeifroth *et al* 2018b), now provides an excellent opportunity to also explore the effect of solar radiation on important stages of the growing season and on final yields. Such data also enables more extensive spatial and temporal analysis than field experiments have been capable of (Kirkegaard *et al* 2018).

Historical multi-environment multi-variety trials provide an exceptionally valuable source of high-quality, site-specific yield data (Smith *et al* 2005, Brown *et al* 2019) and are therefore useful for understanding the interaction of genotypes with the environment (G $\times$ E). The wide array of environments and varieties represented in trials can be used to assess the impact of biotic and abiotic stresses on variety performance (Pidgeon *et al* 2006, Raymond *et al* 2023a). There are also a number of high resolution and highly accurate gridded observational and reanalysis weather and climate datasets that now exist for the UK (e.g. Hollis *et al* 2019). Gridded observational weather datasets are interpolated from historical weather station data and have been used for climate monitoring and assessments of trends and variability (Hollis *et al* 2019). They hold many advantages over weather station data, including their coverage of areas far from weather stations and their completeness over time. There is a great opportunity to combine these datasets with variety trial data to quantify variety climate sensitivity and support improved variety suitability assessment. Here we explore changes in the UK's agroclimate and how these have impacted the production of wheat (the most widely grown arable crop). Crucially, we showcase methods to identify location-specific climate resilient wheat varieties that could be instrumental in supporting climate-adaptive agriculture.

2. Materials and methods

2.1. Climate

There are regional variations in climate, with the east and south of the UK tending to be drier, warmer, less windy, and sunnier than the north and west (Met Office 2022), while arable farming is typically focussed in the east (figure 2) and livestock farming is more common in the west (DEFRA 2020).

2.1.1. UK temperature and precipitation data

After evaluating multiple daily gridded weather datasets against weather station data, we chose to use HadUK (Hollis *et al* 2019) air temperature and precipitation data to input into our crop model due to its high correlation (>0.99) with observed data and its low bias. HadUK is an open-access daily gridded weather

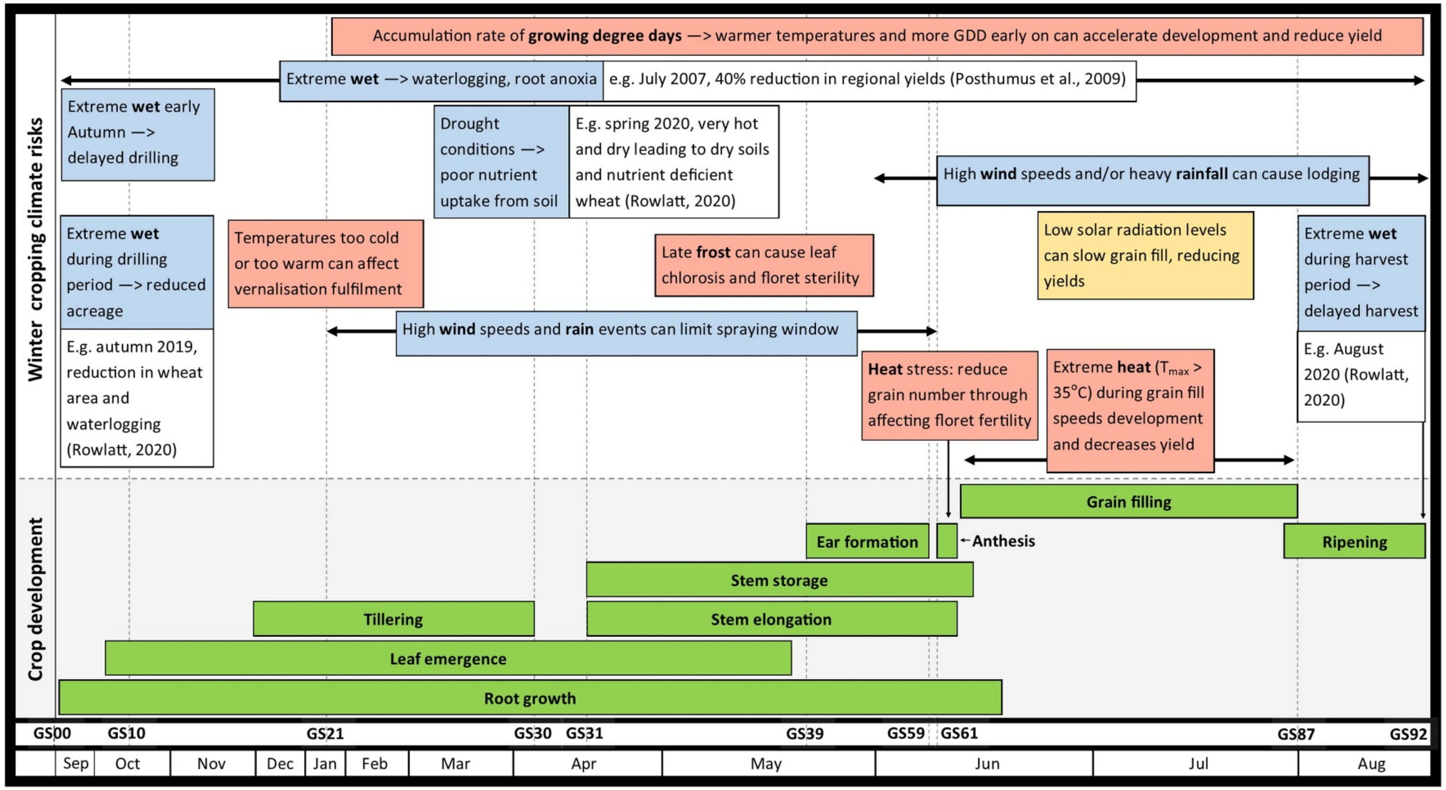

Figure 1. The major weather and climate risks to winter wheat yields across the stages of the UK growing season. Growth stages from AHDB Cereals and Oilseeds (2018b).

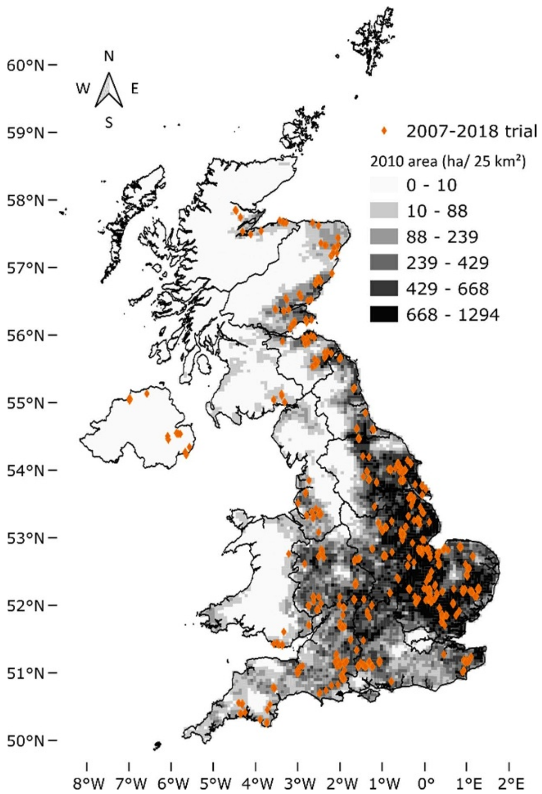

Figure 2. Trial locations (orange diamonds) for 2007–2018 for winter wheat relative to its growing areas (ha/25 km^2) in the 5 km 2010 Agricultural Census (EDINA 2022). Data on growing areas in Wales and Northern Ireland were not available. Reproduced from Raymond (2023). CC BY 4.0.

dataset obtained from interpolation of ground-based station data and has a 1 km horizontal resolution for the UK land surface. Daily maximum air temperature (T_{max}), minimum air temperature (T_{min}) and precipitation (P) were downloaded for 1981–2020 from the Met Office (www.metoffice.gov.uk/research/climate/maps-and-data/data/haduk-grid/datasets) via the CEDA data archive (Hollis *et al* 2019).

2.1.2. UK surface incoming shortwave radiation data

Daily surface incoming shortwave radiation (SIS) data was downloaded from the EUMETSAT CM-SAF website (https://wui.cmsaf.eu/safira/action/viewDoiDetails?acronym=SARAH_V002) for the 1987–2020 period. At the time of accessing the data, 1987 was the first year available. CM-SAF SIS data is derived from Meteosat satellite observations of cloud parameters and is available for the region $\pm 65°$ longitude and $\pm 65°$ latitude, with a resolution of approximately 8 km over the UK (Pfeifroth *et al* 2018b).

2.2. National crop yield data

National annual UK wheat yield, production and area data for 1981–2020 was downloaded from FAOSTAT (www.fao.org/faostat/en/#data/QCL). Regional annual wheat yield data was also downloaded for the available period (1999–2019) from the Department for Environment, Food and Rural Affairs (Defra) Food and Farming website (www.gov.uk/government/statistical-data-sets/structure-of-the-agricultural-industry-in-england-and-the-uk-at-june).

2.3. Variety trials data

Winter wheat yield data was extracted from the UK National List/Recommended List (NL/RL) variety trials dataset for the period 1982–2018, including data across the UK's wheat growing area (figure 2). The Agriculture and Horticulture Development Board (AHDB) Recommended List is managed by a project consortium of AHDB, the British Society of Plant Breeders (BSPB), Maltsters' Association of Great Britain (MAGB) and the United Kingdom Flour Millers (UKFM). Full data for 2002 onwards is available at ahdb.org.uk/rl, whilst the previous years are available upon request to AHDB-BSPB. After at least 2 years in the NL trials, the Recommended List committee reviews variety performance and, if successful, a variety will then move into the RL trials until outclassed, which is typically after 6 years, but can be over 20 years (Austin 1999, Mackay *et al* 2011, Berry *et al* 2015). We only included data from 1982 onwards as this marks the year the variety trials process was reformed and was the first year cereal trials were split into fungicide untreated and treated trials. Sowing and harvest dates were only available in this dataset from 1988 onwards. Prior to statistical analysis, we applied several pre-processing and quality control steps to the trials data to amalgamate data from different databases, including checking for duplicates, trial site locations, sowing and harvest dates, and consistency of variety names. These are described in more detail in Raymond *et al* (2023b).

2.4. Agroclimate metrics

A list of agroclimate metrics were compiled following a review of the literature (table 1). These encompass national and regional climate-based metrics, as well as site-specific agricultural metrics, such as sowing date, extracted from the trials data. Regional metrics were calculated for government regions for England, combined with Met Office regions for Scotland (figure S1). A description of how these agroclimate metrics were calculated can be found in supplementary material 2.

Due to a lack of phenological dates available for winter wheat in the UK, it was not possible to define a dynamic anthesis and grain fill period that varied from year to year and across the country. In the UK, anthesis in wheat typically occurs in early- to mid-June at a thermal time of 2100 °C days after sowing (AHDB Cereals and Oilseeds 2018a). Hence the 'anthesis' period defined here (table 1) is 1st May–15th June as it also encompasses the ∼20 d period before anthesis, during which time increased temperatures have been shown to cause significant reduction of grain numbers (Yang *et al* 2017, Jones *et al* 2020). Meanwhile, grain fill is defined as the ∼6 week period following on from this, 16th June–31st July. Attempts were made to use thermal time after sowing to define a more dynamic period, however this resulted in anthesis dates within the same week as recorded harvest dates, indicating a lack of suitability of the metric, resulting in the use of static periods instead.

Vernalisation is the chilling period required to trigger reproductive growth in winter annual crops. While vernalisation requirements can vary, Wu *et al* (2017) defined vernalisation degree days (VDD) as the number of days from planting date to anthesis. In the UK, vernalisation is most crucial during the colder months, therefore we modified the VDD to be within the period of November to February, in accordance with recommendations from British crop breeders.

2.5. Statistical modelling

2.5.1. Isolating the contribution of climate to winter wheat yields

To analyse the impact of climate on winter wheat yields, climate data underpinning each agroclimate metric (table 1) was downloaded for each variety trial location. Given the very low occurrence of the two extreme heat metrics, 32 °C during anthesis (anthesis32) and 35 °C during the grain fill period (grainfill35) (see Results section 3.5), these were not included in the models as, thus far, they have not occurred frequently enough to be able to isolate their yield impacts in the UK.

Prior to modelling the yield relationship with agroclimate metrics, a base model (1) was developed on the variety trials data to allow a comparison of fit with the agroclimate crop model (2):

$$y_{ijk} = \mu + r_j + v_i + vr_{ij} + s_{jk} + e_{ijk} \quad (1)$$

where y_{ijk} is the yield of variety i in growing season j at site k. The overall mean is μ, with r_j as the effect of season j, v_i as the effect of variety i, and vr_{ij} is their interaction. The effect of site k in season j is s_{jk}, and e_{ijk} is the residual error term (Mackay *et al* 2011).

The growing season effect, r_j was modelled as a fixed factor to account for significant non-linear year effects and to maintain consistency with previous studies (Mackay *et al* 2011, Raymond *et al* 2023b). r_j captures additional influences on crop yield, such as unaccounted agroclimatic factors, changes in management practices, like fertilizer application, widespread disease outbreaks (e.g. Fusarium ear in 2007 and 2014 (Turner *et al* 2021)), and longer-term trends like climate change or technological advancements. The variety effect v_i was also treated as a fixed effect due to the historical nature of the data and interest in individual varietal performance. Interaction terms vr_{ij} (varieties × growing seasons) and s_{jk} (sites within growing seasons), were modelled as random effects because the data is discontinuous; varieties and sites vary over time, as such the same ones are not consistently used each year. To identify the multivariate model in the simplest form and to find the equation which generated the best predictor of yield given the variables included, we then used the *step* function from the ***lmerTest*** package (Kuznetsova *et al* 2017) in R. *step* automatically performs backward selection of both the fixed and random effects in the mixed model, thus removing non-significant effects from the agroclimate model.

The modelling was then split into two phases, as in Hakala *et al* (2012). During the first phase, all varieties with at least 3 years of data and location information were included to establish the general relationship between specific agroclimate variables and winter wheat as a species under UK climatic conditions. In this univariate climate analysis, each agroclimate metric and its interaction with variety were iteratively added to

Table 1. Summary of selected agroclimate metrics used in analysis of changes in the UK's agroclimate. The description provides the definition of the metrics. Equations (S1) and (S2) can be found in the supplementary material.

Variable	Description	Data source	Motivation	Reference
Sowing day of year	—	NIAB/AHDB	Sowing date influences the number of growing degree days (GDD) available to the crop. Sowing date is affected by autumn rainfall, as well as non-weather factors such as ploughing/direct sowing and weed pressure.	
Harvest day of year	—	NIAB/AHDB	Harvest date is affected heavily by weather events in the growing season and by other factors such as agronomic decisions.	
Growing degree days *gdd*	Sum $T_{mean} > 5.6$ °C for September to August (S1)	HadUK	GDD allows predictions of development stages.	(Arnell and Freeman 2021, Harding *et al* 2015, Kendon *et al* 2023)
Vernalisation degree days *vdd*	Sum of vernalisation function (S2) × daily mean temperature from November to February	HadUK	Vernalisation is an important process for triggering reproductive growth for many winter crops. Climate change could affect the vernalisation fulfilment.	(Wu *et al* 2017)
Spring air frost days *frost03* *frost04* *frost05*	Days $T_{min} < 0$ °C per spring month	HadUK	Rather than focussing on total frosts across the year, the focus is on frosts during spring when the winter crop is more vulnerable. After loss of winter-hardiness frost can cause leaf chlorosis, lower stem damage and floret sterility (Barlow *et al* 2015, Gusta and Fowler 1976).	(Arnell and Freeman 2021, Harding *et al* 2015, Harkness *et al* 2020, Kendon *et al* 2023)
Heavy rainfall *<month>_rain10* *<month>_rain20*	Days per month with >10 mm or >20 mm rainfall from September to August	HadUK	Heavy rain events can lead to delays in getting heavy machinery on the land to complete important jobs, such as spraying and sowing. Looking at changes in the number of days with rainfall >10 mm and >20 mm is important to see if there have been any significant changes at critical times of growing season.	(Peltonen-Sainio *et al* 2009)
Extreme heat around anthesis *anthesis32*	The number of days $T_{max} \geqslant 32$ °C between 1st May–15th June	HadUK	Several studies categorise 32 °C as the threshold above which heat stress during the period prior to anthesis can be detrimental, causing sterility and reproductive damage.	(Arnell and Freeman 2021, Cammarano *et al* 2020)

(Continued.)

Table 1. (Continued.)

Mild heat stress during grain fill *grainfill31*	The number of days $T_{\max} \geqslant 31$ °C between 16th June–31st July	HadUK	This has already been used as an index (Bönecke *et al* 2020, Ceglar *et al* 2019). Significant association between number of days above 30 °C during grain filling, grain number and yield (Dreccer *et al* 2018, Rezaei *et al* 2018).	(Bönecke *et al* 2020, Ceglar *et al* 2019, Dreccer *et al* 2018, Rezaei *et al* 2018)
Extreme heat stress during grain fill *grainfill35*	The number of days $T_{\max} \geqslant 35$ °C between 16th June–31st July	HadUK	Extreme heat shortens the development period and decreases yield (Nasehzadeh and Ellis 2017, Savill *et al* 2018). It has been linked to yield stagnation in France (Knight *et al* 2012).	(Harkness *et al* 2020, Jones *et al* 2020, Yang *et al* 2017)
Total surface incoming shortwave radiation during grain fill *grainfillSIS*	Total surface incoming shortwave radiation (SIS) during the period 16th June–31st July (MJ m^{-2})	CM-SAF SIS	June sunshine shown to be important in determining wheat yield (Knight *et al* 2012). Solar radiation during grain fill is rarely quantified.	(Knight *et al* 2012)

the base crop model (1) to test the significance of each variable's relationship with yield, as in:

$$y_{ijk} = \mu + \sum C_{jk} + v_i + r_j + vr_{ij} + \sum vC_{jk} + s_{jk} + e_{ijk} \quad (2)$$

where y_{ijk} is the yield of variety i in growing season j at site k, μ is the overall trial series mean, C_{jk} is the effect of the selected climate variable(s) in growing season j at site k, v_i is the effect of variety i, r_j is the effect of growing season j, vr_{ij} is the effect of the interaction between variety i and growing season j, vC_{jk} is the interaction between variety v_i and climate variable C_{jk}, s_{jk} is the effect of site k in growing season j and e_{ijk} is the residual term. Here, the variety effects v_i, year effects r_j and climate × variety interaction terms vC_{jk} were fitted as fixed effects, whilst variety × growing seasons vr_{ij} and sites within growing seasons s_{jk} were fitted as random effects.

The significant climate variables and their interactions with variety were then combined in a multivariate agroclimate analysis, using equation (2). The first phase test data included 30 473 yield records. In the second phase, popular cultivars with at least 10 years of data were used (table S1) which consisted of 7062 yield records.

2.5.2. Identifying climate-resilient varieties

To explore individual varietal responses to the significant agroclimate variables, the climate covariates were classified into three categories (low, medium and high) of equal numbers of variety trials, using a similar method to Hakala *et al* (2012). Specifically, each agroclimate covariate was ordered by its magnitude, and split into the lowest, middle and highest terciles to define the three category value ranges. For each agroclimate category, the average yield across all variety trials in each category was calculated. This was then compared with the average national yield for each variety across the period 1988–2017 (table S1) to calculate the average yield response of each variety to low, medium and high agroclimate events.

3. Results

3.1. Wheat yield potential and instability have increased

From 1981 to 2020, wheat production in the UK demonstrated significant variability in yield, harvested area, and total production (figure 3). The harvested area fluctuated, starting at 1.49 Mha in 1981 and reaching over 2 Mha in 1989, before undergoing large decreases and increases over the following three decades. Wheat yields increased rapidly in the first 15 years, from 5.8 t ha^{-1} in 1981 to 8.1 t ha^{-1} in 1996. 2000 onwards saw yields fluctuating around 8 t ha^{-1}, with notably low average yields in 2012 (6.7 t ha^{-1}) and 2020 (7.0 t ha^{-1}), and the highest yields on record in 2015 (9.0 t ha^{-1}) and 2019 (8.9 t ha^{-1}). The standard deviation in yield for the four decades was 0.6 t ha^{-1} in 1981–1990, 0.4 t ha^{-1} in 1991–2000, 0.4 t ha^{-1} in 2001–2010 and 0.8 t ha^{-1} in 2011–2020. The combination of increased yields and variable harvested areas resulted in substantial changes in total production, with an initial rise from 8.7 million tons in 1981 to 16.7 million tons by 1996.

3.2. The UK agroclimate has changed

3.2.1. Sowing date has been brought forward but harvest dates are unchanged

Analysis of variety trials data shows that since 1988, winter wheat trial sowing day of year has been getting earlier by 1 d every 3 years ($p < 0.001$) (figure S3(a)). Harvest dates showed considerable variation from year to year with minimal change over time ($\beta = -0.02$, $p < 0.001$) (figure S3(b)). Overall, the growing season length (from sowing to harvest) increased on average by 1 d every 2 years since 1988 ($p = 0.003$).

3.2.2. The available growing degree days has increased

Annual GDD (calculated from 1st September–31st August; table 1) for each decade within 1982–2020 was highest in the South-East of England and East Anglia, at over 1800 °C days, compared to less than 1000 °C days in parts of Scotland (figure S4). When GDD was calculated at variety trial sites from sowing to harvest, GDD significantly ($p < 0.001$) increased from 1988 to 2018 by ∼5%, on average 3 °C days per year (figure 4). This increase was significantly correlated with the trend towards earlier sowing dates (figure S3(a)); sowing 2 d earlier was associated with an increase in GDD by 1 °C day ($p < 0.001$).

VDD (as calculated in supplementary material 2) also showed widespread increases over the period. In each decade, it was highest in the southern half of England, the coastal areas of Wales, and parts of Northern Ireland (figure S5).

3.3. Widespread decrease in April air frost days

March had the highest number of spring air frost days from 1981–2020, with an average of 8 frost days each year. Nationally, there is a clear geographic divide in the change over time, with frost days decreasing in

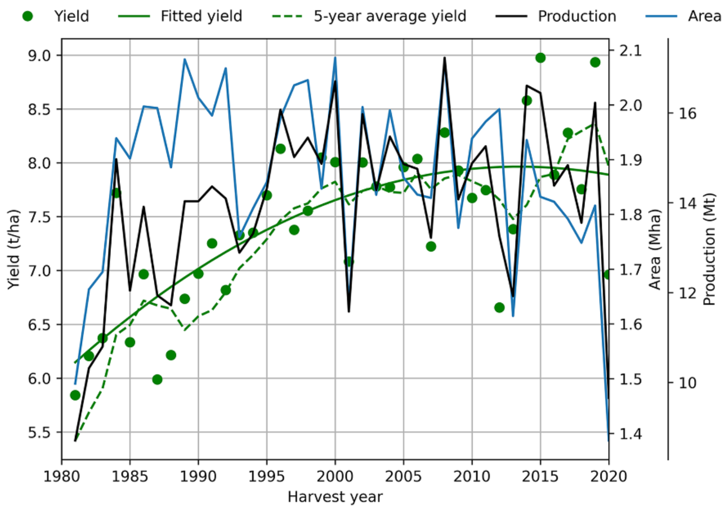

Figure 3. National annual wheat yields (green dots), harvested area (blue line), and production total (black line) for 1981–2020. The 5 year running mean yield (green dash) and quadratic (green line) give an indication of long-term UK wheat yield trends. Data from FAOSTAT.

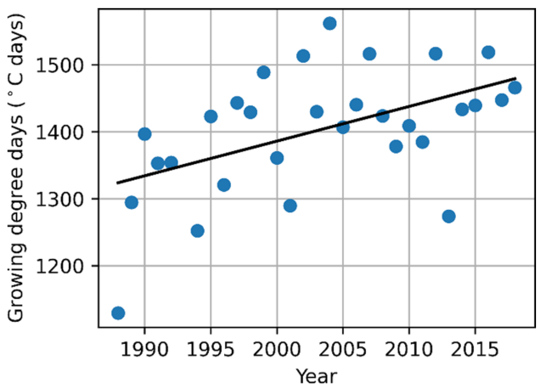

Figure 4. Median growing degree days (GDD) (°C days) at winter wheat trial sites from sowing date to harvest date for 1988–2018. The increase in growing degree days is significant ($p < 0.001$) (black).

eastern regions and increasing in western regions (figure 5(b)). This is not reflected in April, where the national average number of frost days decreased from 6.3 in 1981 to 2.9 in 2020. In May less change was observed from a low baseline of 1.8 frost days in 1981, with an average change of −0.007 frost days across 1981–2020.

3.4. Increased rainfall coincides with key growth stages in winter wheat

The distribution of heavy rain days (>10 mm) across the UK from 2011 to 2020 shows notable seasonal and regional differences compared to the 1981–1990 baseline (figure 6). February had the largest increase in heavy rain days, with parts of eastern England experiencing over a 500% rise, while March demonstrated widespread decreases, particularly in northern regions. September exhibited reductions in heavy rainfall of up to 50%, compared to the 1981–1990 average, especially across Scotland and northern England. June and July presented more consistent increases in heavy rain days (both >10 mm and >20 mm, see also figure S9), particularly across southern and central England, whereas August shows a patchier increase in rainfall, especially in parts of northern England and western Scotland. Overall, these trends highlight significant shifts in the seasonal distribution of heavy rainfall, with increases in winter and summer, and reductions in early spring and autumn.

3.5. Heat stress during anthesis and grain fill is still rare

Across the 40 year period, extreme heat ($T_{max} > 32$ °C) during the defined anthesis period (1st May–15th June) was very rare, occurring only twice in 1996 and 2005 at trial sites in East Anglia and the South East England. Similarly, extreme heat ($T_{max} > 35$ °C) during grain fill period (16th June–31st July) only occurred on 1 d in each of 2006, 2015 and 2019 and 2 d in 2018, in East Anglia and South East England.

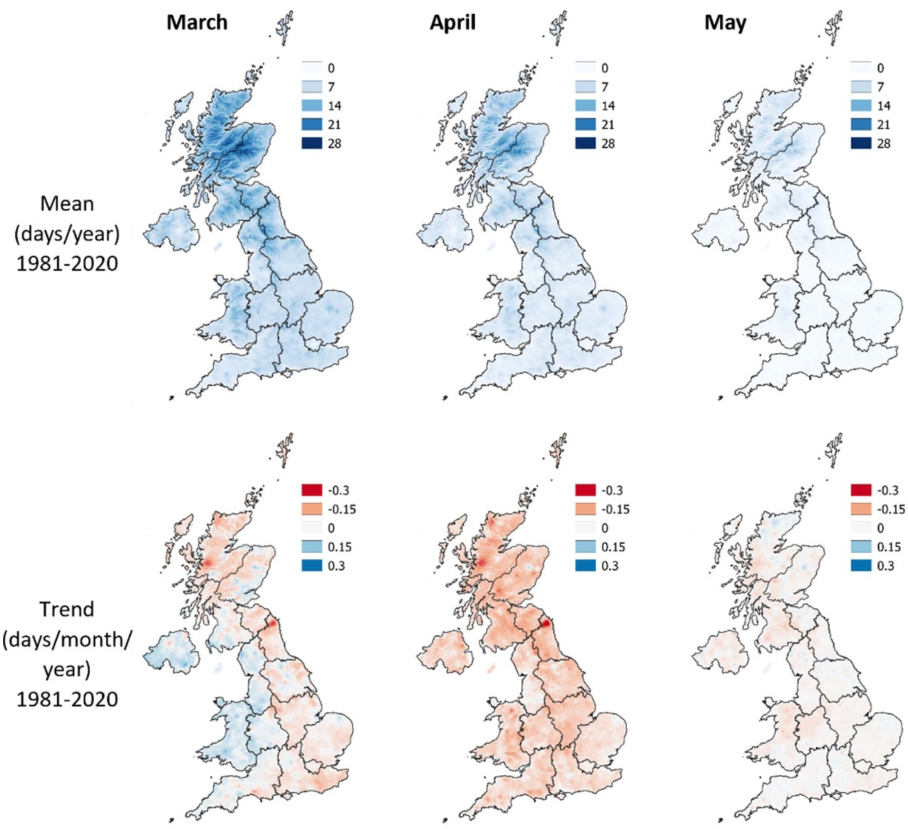

Figure 5. The mean and rate of change in number of air frost days in the UK for 1981–2020 for March, April and May. The trend is calculated using the 1981–1985 and 2016–2020 periods. Created using 1 km × 1 km gridded HadUK temperature data (Hollis *et al* 2019).

The frequency of mild heat stress ($T_{max} > 31$ °C) during the defined grain fill period was much higher. An anomalous year within the period 1981–2020 was 2006, which recorded the hottest July on record (Met Office 2024) and saw the grain fill threshold exceeded 10 times at several locations in Cambridgeshire, in East Anglia (see example site figure S6). Whilst less detrimental than extreme heat, mild heat stress has been shown to affect grain size and yields (Dreccer *et al* 2018), however 2006 had a positive yield anomaly across most regions, including East Anglia and South East England (figure S7).

3.6. Total solar radiation received during grain fill has increased in the East of the UK

For the period 1987–2020, SIS accumulated during grain fill (16th June–31st July) decreased with increasing latitude (figure 7). The south of the UK received the most solar radiation during grain fill with over 800 MJ m^{-2} on average received in South West England, South East England and East Anglia. In Scotland, particularly in the north, crops received on average over 25% less grain fill SIS than southern England during this period, despite longer daylengths. This spatial pattern of greater SIS in the South of the UK has not only been seen during grain fill but also across the year (Pfeifroth *et al* 2018a). However, the change in grain fill SIS between 1987 and 2020 across the UK was highly dependent on longitude; regions in the east saw increases in grain fill SIS of 5%–13%, whereas those in the West saw decreases of up to 15%.

Regression analysis between grain fill SIS and yield averaged at the regional level showed no significant relationships in all regions (the South West had the lowest p-value of 0.19) However, when site specific grain fill SIS data was paired with winter wheat variety trial yield data (figure S8), significant positive correlations existed between grain fill SIS and winter wheat yield in North East England ($r = 0.41$), Northern Ireland ($r = 0.29$), Eastern Scotland ($r = 0.22$), South East England ($r = 0.20$), and most significantly in Wales ($r = 0.79$), highlighting the value of localised climate information and the need for more thorough statistical modelling.

3.7. Growing degree days account for most winter wheat yield variation

Agroclimate metrics (table 1) were combined individually with the winter wheat NL/RL yield data in the crop model (2). April frost (frost04), May frost (frost05), total surface incoming shortwave radiation during

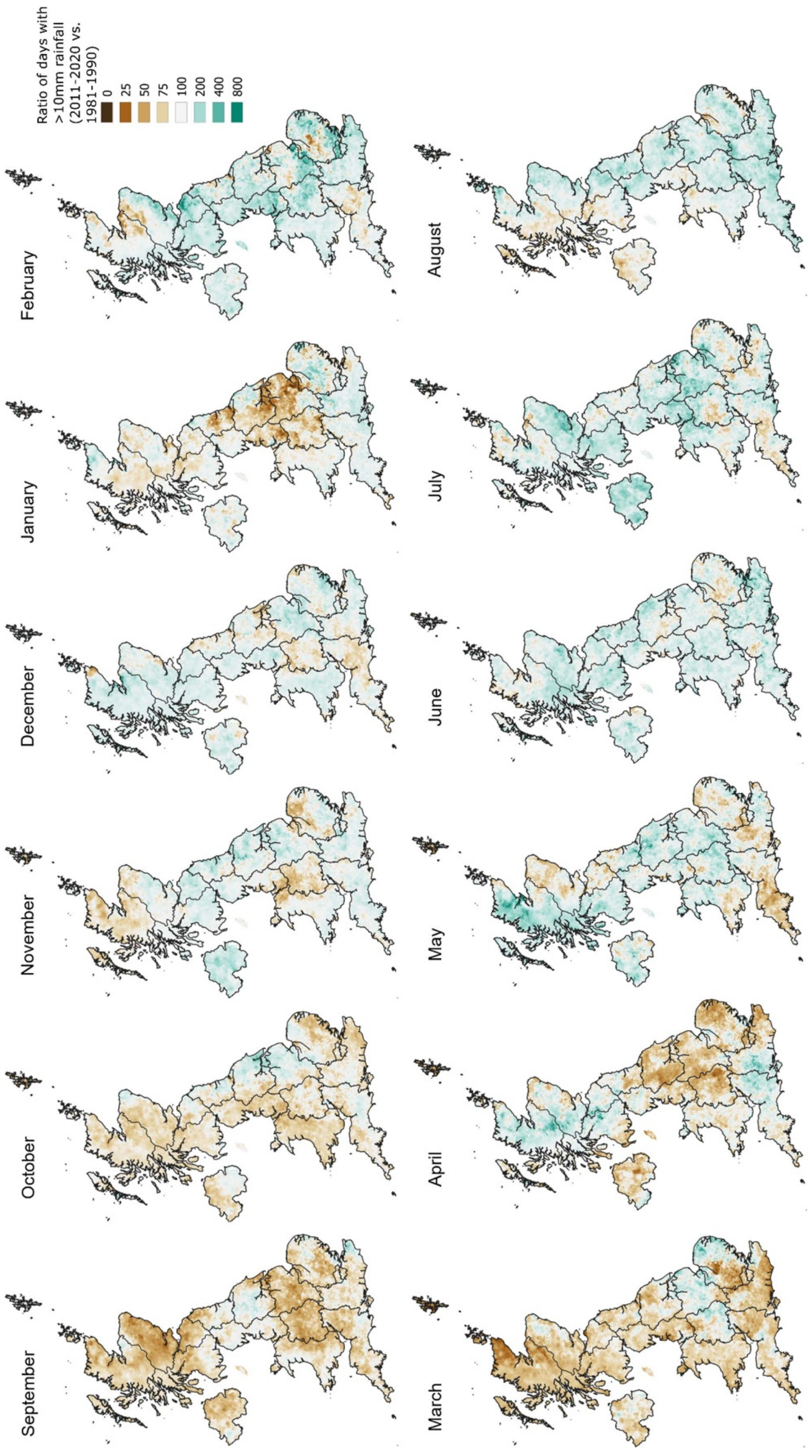

Figure 6. The monthly number of heavy rain (>10 mm) days in the 2011–2020 decade relative to the 1981–1990 (%). An increase in heavy rain days is indicated in blue, a decrease in brown. Data from HadUK 1 km × 1 km gridded precipitation dataset (Hollis *et al* 2019).

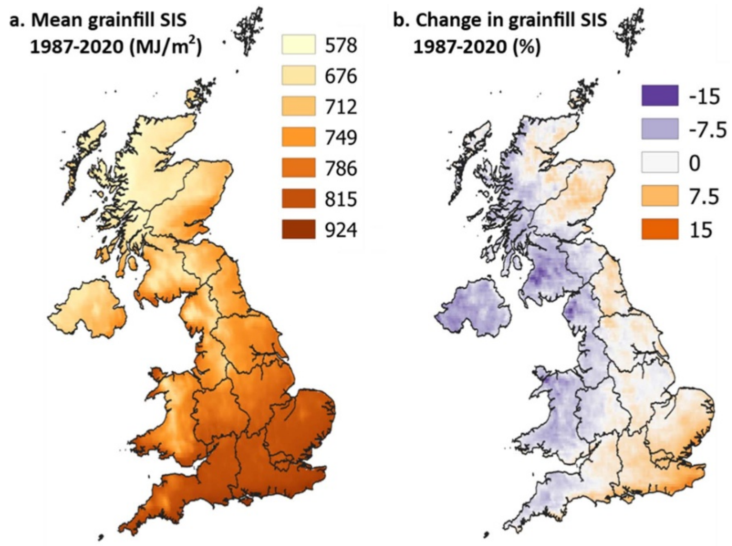

Figure 7. Mean total grain fill surface incoming solar (SIS) radiation (MJ m^{-2}) (a.) and percentage change in grain fill SIS from 1987–1991 to 2016–2020 (b.). Grain fill incorporates the period 16th June–31st July. Created using gridded 0.05° × 0.05° degree CMSAF-SIS data (Pfeifroth *et al* 2018b).

Table 2. Univariate climate model sum of squares (SS), p-value and significance for each climate variable and the respective climate × variety interaction term, calculated using (2) on each single climate variable C_{jk} paired with the treated variety trials data for 1988–2018. frost03, frost04 and frost05 correspond to the number of frost days in March, April and May, respectively. grainfill31 is the number of days with $T_{max} > 31$ °C in the grain fill period (16th June–31st July), grainfillSIS is the total incoming surface shortwave radiation received during the grain fill period, and rain10 and rain20 are the number of days in the growing season with at least 10 mm, and 20 mm, of rainfall, respectively. vdd_novfeb is the vernalisation degree days calculated from November to February and gdd is the growing degree days.

C_{jk}	Coefficient	SS clim	p clim (sig.)	SS var × clim	p var × clim (sig.)
frost03	0.022	0.010	0.8	88.4	<0.001 ([a])
frost04	−0.006	5.060	<0.001 ([a])	78.8	<0.001 ([a])
frost05	−0.103	1.976	0.004 ([a])	99.9	<0.001 ([a])
grainfill31	−0.042	0.056	0.6	71.6	0.007 ([a])
grainfillSIS	0.003	0.885	0.05 ([a])	205.4	<0.001 ([a])
rain10	−0.023	1.042	0.04 ([a])	121.3	<0.001 ([a])
rain20	−0.065	0.385	0.2	137.0	<0.001 ([a])
vdd_novfeb	0.002	4.485	<0.001 ([a])	237.4	<0.001 ([a])
gdd	−0.002	10.072	<0.001 ([a])	243.0	<0.001 ([a])

[a] Significant at the 95% level.

grain fill (grainfillSIS), the number of >10 mm rain days from sowing to harvest (rain10), vernalisation degree days (vdd_novfeb) and growing degree days from sowing to harvest (GDD) all had significant effects on yields (table 2).

Significant variables in the univariate analysis (table 2) were combined in a single model to identify the most influential climate variables. Whilst 41.0% of yield variation was attributed to the growing season and variety, significant yield variation was also attributed to variation in grain fill SIS (1.0%), the number of >10 mm rainfall days throughout the growing season (1.8%), GDD (3.5%), and the range in responses of each variety to the different climatic conditions (table S2).

To obtain the multivariate model in the simplest form, backwards elimination using *step* from ***lmerTest*** (Kuznetsova *et al* 2017) was used (see Methods 2.5.1). The selected model can be found in supplementary material 7 (table S3) and the results of the model and coefficients in table 3. Comparisons between this agroclimate model and the simpler base model (1) that did not include any climate terms showed that the agroclimate model (S1) provided a significantly better fit to the data, as indicated by a likelihood ratio test ($\chi^2 = 291.4$, Df = 61, $p < 0.001$).

Analysis of variance of the model covariates shows that of the four climate covariates, GDD accounts for the most variation in yield (sum of squares, SS = 4.123) (table 3). This was accompanied by a very small negative model coefficient ($\beta = -0.000\,050$), indicating that a big increase in GDD was associated with small decreases in yield. There was large varietal variation in yield responses to GDD, accounting for ∼18% in

Table 3. Sum of squares for fixed effects in the multivariate agroclimate model of winter wheat, using the optimised model (S1). grainfillSIS is the total surface incoming shortwave radiation received during the grain fill period (16th June–31st July), rain10 is the number of days in the growing season with at least 10 mm of rainfall, vdd_novfeb is the vernalisation degree days calculated from November to February and gdd is the growing degree days.

	SS	Df	F value	p (sig.)	coef	coef SE
grainfillSIS	1.043	1	4.071	0.04 ([a])	0.0030	0.001
rain10	1.987	1	7.753	0.005 ([a])	−0.013	0.008
gdd	4.123	1	16.086	<0.001 ([a])	−0.000 050	0.0004
vdd_novfeb	0.676	1	2.637	0.1	0.000 49	0.001
Growing season	26.709	28	3.722	<0.001 ([a])		
Variety	36.927	19	7.584	<0.001 ([a])		
rain10:Variety	14.16	19	2.908	<0.001 ([a])	*See table S4*	
gdd:Variety	20.968	19	4.306	<0.001 ([a])		
vdd_novfeb:Variety	11.838	19	2.431	0.001 ([a])		

[a] Significant at the 95% confidence level. Coefficient estimates and standard error (SE) are given for the climate variables. The marginal R^2 and conditional R^2 for this model were 0.22 and 0.92, respectively and RMSE was 0.92.

overall yield variation in this model (calculated by dividing SS for GDD by the total SS of the model, from table 3). To check for issues caused by multicollinearity, the correlation between variables within the model was examined, which showed the highest correlation was only 0.5 (between VDD and GDD) (see figure S10).

Increases in the number of >10 mm rain days were associated with a yield decrease of ~0.13 t ha^{-1} per 10 extra >10 mm rain days. Higher SIS during grain fill increased yields by ~0.3 t ha^{-1} per extra 100 MJ m^{-2}. However, the interaction term with variety was dropped in the backwards elimination process, indicating the yield responses of individual varieties to solar radiation during grain fill were not significantly different, rather they largely respond in a similar, positive way. VDD from November to February was included in this final model but proved not to significantly affect yield ($p = 0.1$).

3.8. Statistical modelling can be used to identify climate-resilient varieties

When analysing the response of individual varieties to variation in agroclimate conditions, it must be acknowledged that varieties are only tested in a subset of the growing seasons and sites, and do not all experience the same conditions. By only including varieties present for at least 10 years we increase the range of conditions experienced by each variety to strengthen robustness of conclusions on their agroclimatic sensitivity. Despite the grainfill SIS × variety interaction term not being significant in the final agroclimate model (S1), this agroclimate metric was included here to explore individual varietal responses to SIS variation. There was a range in yield responses (figures 8, S11) each winter wheat variety to the tiered agroclimate conditions (low/medium/high; table S5). The majority of varieties yielded higher under high GDD, for example *Gallant* yielded 6% more than average in years with high GDD and 7% lower than average in years with low GDD. However, there were several exceptions, such as *Mercia* and *Soissons* which yielded highest in years of low GDD.

Varietal yield responses to the number of >10 mm rain days suggest that between 12–17 >10 mm rain days across the growing season is preferable for winter wheat (figure 8). All 20 varieties, except *Mercia, Soissons* and *Savannah* produced their highest yields in this 'medium' rainfall category, whilst these three varieties performed best when there were fewer of these events. *Mercia* also produced higher yields during growing seasons with fewer rain days of >20 mm (figure S11). Several varieties had a strong positive response to high SIS during grain fill, particularly *Claire, Cordiale, Deben* and *XI19* which yielded at least 5% higher than average.

Most varieties saw a distinct yield penalty as a result of 'low' VDD from November to February. Exceptions to this were *Robigus* and *Deben*, which had similar yields regardless of VDD. These inter-varietal differences are in contrast to the overall effect of VDD, which was insignificant in the final model (table 3). Yield responses for medium and high levels of VDD were very similar across varieties.

Given the low frequency in occurrence of mild heat stress during grain fill ($T_{max} > 31$ °C) and air frost days in May, the yield response to these climate variables was split into whether they occurred or not. The influence of grain fill heat stress on yield was minimal, however late spring frost was more detrimental (figure 9). Across all varieties, the occurrence of at least one May frost day was associated with yield losses, with *Mercia* showing the smallest yield loss (<2%) and *XI19* the largest (>10%). Earlier air frosts in spring (frost03 and frost04 in figure S11) resulted in much smaller detrimental yield impacts.

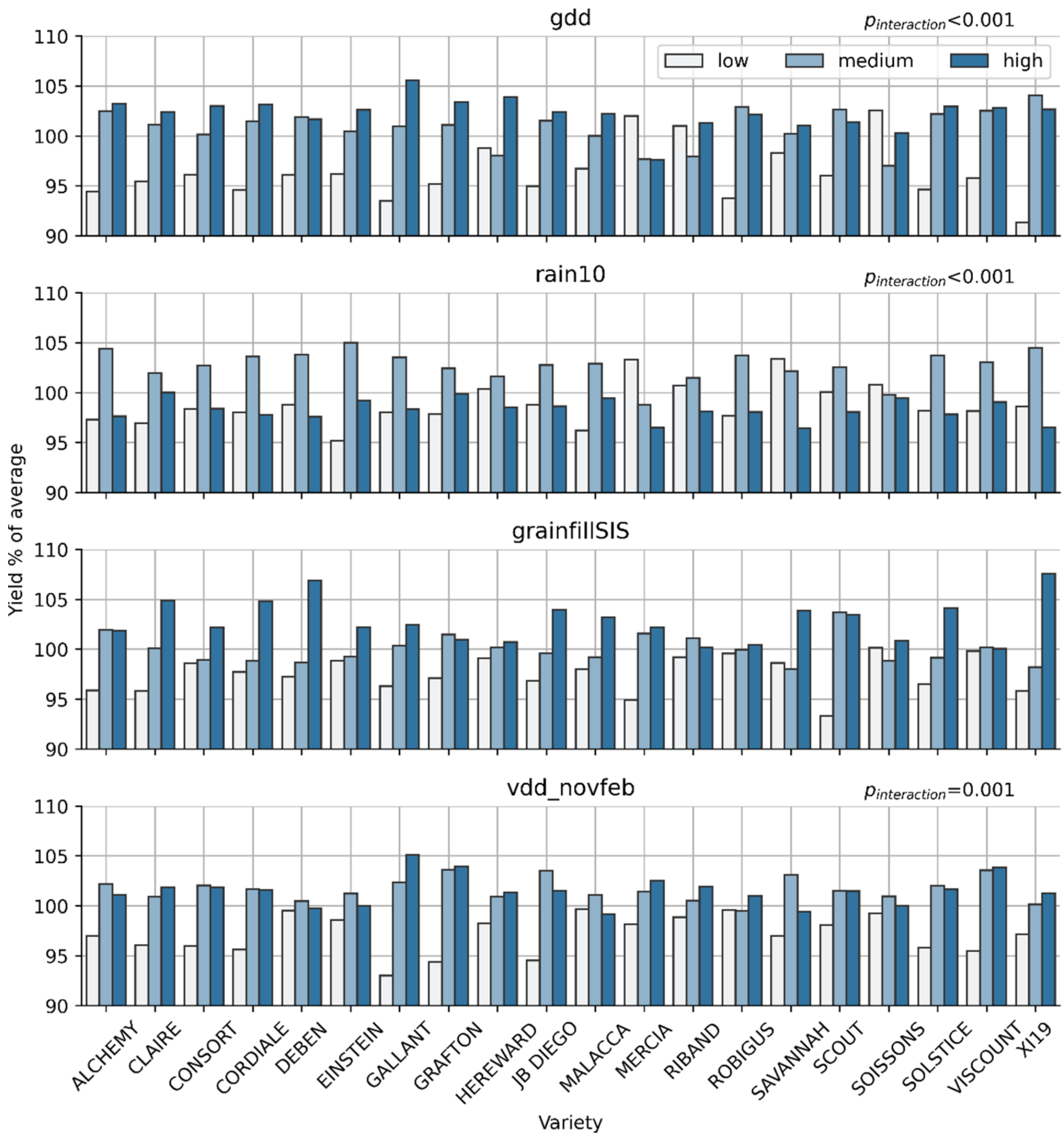

Figure 8. Yield responses (% of average) of each winter wheat variety to low, medium and high growing degree days (gdd), number of >10 mm rainfall days in the growing season (rain10), total surface incoming shortwave radiation during grain fill (grainfillSIS) and vernalisation degree days from November to February (vdd_novfeb). Varieties included here are those present for at least 10 years in the variety trials dataset from 1988–2017 (table S1). The statistical significance of the interaction between variety and the agroclimate metric is given, except for grainfillSIS due to the interaction term not being included in the final model.

4. Discussion

As the climate changes and the weather becomes more variable, it is important to regularly evaluate the influence of climate on crop and variety performance in different environments to increase the resilience of crop production. We have shown how the UK agroclimate has changed in recent decades, and by combining linear mixed modelling, variety trial yields and site-specific weather data, we have isolated the yield impact of several agroclimate variables on winter wheat in general, and on a subset of individual varieties in particular. There is great potential for this work to be done on a more regular basis, with an array of agroclimate variables, to help growers and breeders identify more climate-resilient varieties to grow in their area, as well as to mainstream monitoring of the changing agroclimate in the UK and elsewhere.

During the 1981–2020 period, the rapid increase in yields until the late 1990s (figure 3) has been associated with genetic improvement of cultivars, improved agronomic management, and intensification of chemical fertilizers and pesticides (Mackay *et al* 2011, Lin and Huybers 2012 , Raymond *et al* 2023b). The subsequent decades were characterised by high yield variability, which may be partly explained by widespread extreme weather events that took place, particularly in low yielding years. For example, 2012 saw the wettest

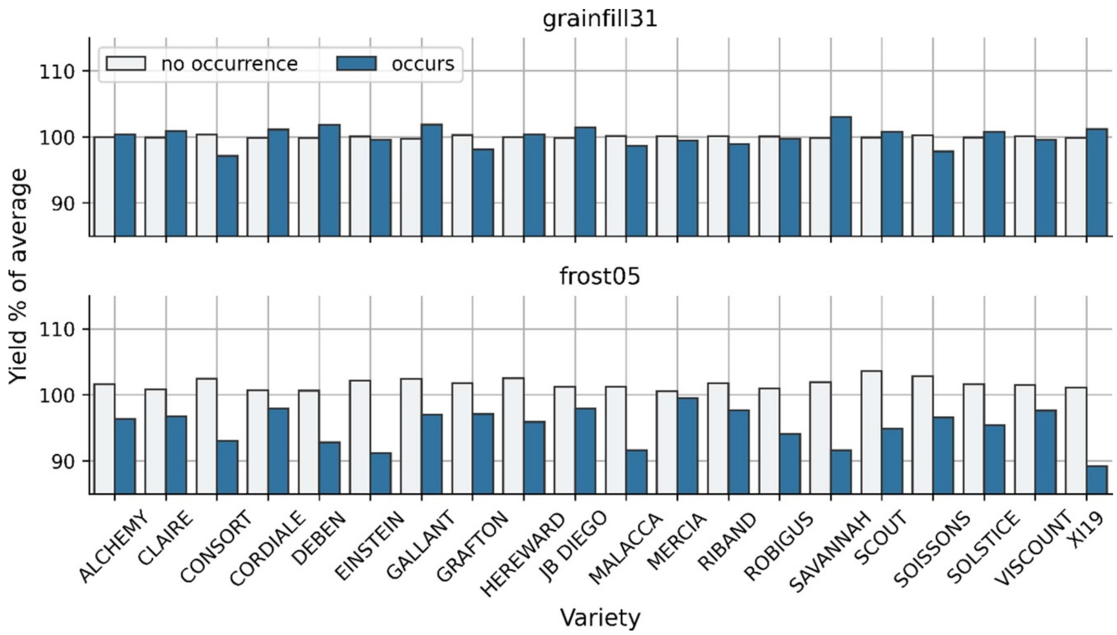

Figure 9. Yield responses (% of average) of each winter wheat variety to zero (white) or at least one (dark blue) occurrence of mild heat stress during grain fill (grainfill31) and air frost in May (frost05). Grain fill corresponds to the period 16th June–31st July.

April and June (since 1836) and lowest June sunshine on record (since 1910), and 3rd lowest summer sunshine (Met Office 2024), the latter likely having a large impact on photosynthesis during grain fill.

The trend in earlier sowing date (figure S3(a)) has also been documented on-farm (Turner *et al* 2021). Changes in the climate, such as the reduction in heavy rainfall days in September (figure 6), and changes in agronomy have contributed to this trend. In contrast, the substantial increase in heavy rain days in February has interrupted the preparation of land ahead of the first T0 round of winter crop spraying in March. Delays due to waterlogging can also have affect later in the season, through delaying growth stages (Berry and Brown 2021). Likewise, the increase in heavy summer rainfall and accompanying clouds can limit photosynthesis, whilst mild conditions with high relative humidity can also encourage diseases such as Fusarium ear blight to spread (Bayer 2020) and prevent the grain from drying, delaying harvest.

The spatial patterns shown in VDD, change in frost days and change in grainfill SIS present important considerations for growers. As expected for a coastal climate, fewer extreme cold or warm days from autumn to spring were likely responsible for coastal areas in Scotland having higher VDD (figure S5) than the more mountainous areas further inland, making these areas more suitable for varieties with higher vernalisation requirements (McKnight and Hess 2008). The increase in grainfill SIS in the eastern regions of the UK could increase suitability for cereals and soft fruit production, whilst those based in the west may want to consider crops less dependent on solar radiation during this important development period. Meanwhile, the frost risk increase in March in Wales and western England indicates a need for careful selection of frost-resilient varieties.

4.1. Combining observed changes in the agroclimate with variety responses

The influence of subtle and local year-to-year weather variability on agricultural production is much more difficult to isolate than the impact of large spatial scale and sustained weather anomalies, since yields are a product of many confounding climatic and non-climatic factors. Statistical modelling using site-specific weather data can help isolate these weather factors in combination with agroclimate analyses. Univariate agroclimate analysis identified the most important agroclimate yield drivers (table 2), whilst multivariate analysis quantified the relative importance of these variables when simultaneously accounting for multiple factors (table 3). In this large-scale analysis, it was also possible to detect the genotype-by-environment interaction (G $\times$ E), which was subsequently dissected to reveal variety sensitivity to individual metrics, enabling localised variety recommendations. Furthermore, identifying varietal resilience to different agroclimatic conditions has also generated a resource which supports selection of parent varieties to create new, better adapted and more resilient varieties.

Differences between varietal responses to monthly frost days exemplifies the importance of evaluating variety responses to specific climate variables alongside changes in the variables. Whilst there was variation in yield responses to March frost amongst cultivars (table 2, SS var $\times$ clim = 88.4), winter wheat yields were not significantly sensitive to early spring air frost, which is perhaps unsurprising given the high frequency of air frost days in March across the UK (figure 5). This contrasts with the results for later in spring, when more April and May frost days had significant detrimental effects on yield, with May frost decreasing yields by 0.1 t ha^{-1} per frost day. In the UK, May is typically when the reproductive growth of winter wheat occurs and is therefore when the yield impact from frost damage is greatest (Frederiks *et al* 2012). Yield impact of late spring frost was substantial across all varieties except for *Mercia* (figure 9).

In the context of a warming climate and therefore increased GDD availability (figure S4), the significant negative relationship between GDD and yield reported both by us (table 3) and Kukal and Irmak (2018), could be detrimental for future food production. A follow up study should assess the specific GDD periods within the growing season that are contributing most to this yield relationship, (as in e.g. Li *et al* 2021). A warming climate and increased risk of low chilling years also raises concerns around vernalisation fulfilment, given the low VDD yield penalty (figure 8).

Introduction of varieties with lower vernalisation demands could be an effective adaptation strategy (Zhang *et al* 2013), given the lack of yield benefit beyond a certain VDD threshold, and there is evidence that some newer cultivars already have lower vernalisation requirements (Grogan *et al* 2016a, 2016b, Rezaei *et al* 2018). As the climate warms, the risk of extreme heat events to crop yields in the UK is increasing (Kendon *et al* 2023). Whilst the low frequency of such events within the period of this research meant they could not be included in our model, it should be acknowledged that they would be important to include in future analysis of weather impacts on yield. This should also reveal which varieties are more resilient to extreme heat stress, an assessment which is currently restricted to controlled-environment experiments

Given the demonstrated increase in grain fill SIS in the South East of England and East Anglia (figure 7), the varieties identified as responding particularly positively to high levels of SIS during this period (figure 8), such as *Deben* and *XI19,* could be adopted to good effect more commonly in this area. Varieties such as *Soissons* showed less yield sensitivity to SIS and could be considered for growing in western parts of the UK where decreased SIS was recorded and negative trends observed over the period 1987–2020 (figure 7). Although little wheat is currently grown in western UK, there may be big changes to cropping and farming systems in the near future as a function of several factors, including climate change mitigation, carbon sequestration demands, land use, and dietary change. Alongside agroclimate, these drivers will also influence crop species and variety allocation.

Our analysis utilised linear mixed models to quantify these relationships: this approach was selected both to maintain consistency with Mackay *et al* (2011), and for its clarity and interpretability, especially when making practical agronomic recommendations. However, there is growing potential for artificial intelligence (AI)-based models to complement these findings by capturing more complex, non-linear relationships, as highlighted in Akkem *et al* (2023). However, the strength of linear models lies in their ability to provide transparent, actionable insights, which are crucial for informing decisions in breeding programs and climate-resilient crop selection.

4.2. Greater data sharing and collaboration between growers, modellers, crop physiologists and plant breeders is required

Our analysis has highlighted several gaps in knowledge and data that could facilitate improved agroclimate modelling. Whilst it is known that chilling is very important for winter crops, the threshold vernalisation time required is not well understood. Different varieties also have different vernalisation requirements (figure 8), therefore using one metric across varieties is simplistic. Given vernalisation in winter wheat typically takes place in late Autumn and Winter in the UK (Steve Penfield, *pers. comm.*), it is likely the modification adopted to the time period for VDD, November-February, is a better representation of the available VDD to winter crops than that previously used by Wu *et al* (2017). Furthermore, we found that despite the warming climate, VDD increased each decade (figure S5), due to the precise vernalisation function used, raising doubts about the validity of this measure. Evidently, there is a need for crop modellers and physiologists to work together to define a more suitable vernalisation metric. Further investigations could also look at changing the upper temperature limit T_{amp} on VDD, and the change in the number of non-vernalisation days.

In evaluating varietal responses to agroclimate variability, it is important to acknowledge that each response was dependent on the range of conditions experienced by that variety. Given that varieties are trialled across different sites in different years, no two varieties experience the same range of weather and climate variability. To counter this, we have improved upon the method used by Mackay *et al* (2011) who used varieties with just 3 years of data or more. Here the assessed varieties had at least 10 growing seasons, ensure they had experienced a wider range of weather and climate variability, increasing the chances of the rarer agroclimate events occurring e.g. May frost.

An additional metric that would be valuable is the change in the number of suitable spraying days during key development periods—the timely application of fungicides and pesticides to the crop depends upon the availability of low wind and dry periods.

4.3. The need for climate information in variety performance evaluation and selection: recommendations

The UK variety trials system currently lacks a regular, systematic evaluation of variety performance that takes into account the widespread spatial and temporal variation in climate, meaning that there is insufficient information available to growers to select varieties based on their local climatic conditions. Our results contribute to the growing body of literature (Falloon *et al* 2015, Van Etten *et al* 2019, Born *et al* 2021, Toreti *et al* 2022) recommending targeted climate services in agriculture and plant breeding. Simulation of the combined effect of optimal farm management, and the breeding and growing of well-adapted varieties, suggests that crop-level management adaptations could increase global yields in a 2 °C warmer world by an average of 7%–15% relative to no-adaptation scenarios (Challinor *et al* 2014). To maximise crop yield resilience in the rapidly changing climate, there needs to be greater collaboration between crop scientists and geneticists, and meteorologists and climate scientists, in variety trial planning and evaluation, and when making localised variety recommendations. The methods used here can be used with different agroclimate variables, crops and crop traits. Based on our research findings we make the following recommendations for use of results using these methods:

1. **Use agroclimate information in variety selection tools**. Given the heterogeneity of farming environments (Van Etten *et al* 2019), highlighted in part here by the differing trends across a range of agroclimate variables (see figures 5 and 7), variety selection should incorporate local climate information. Indeed, introducing a climate service supporting variety selection was shown to reduce the impacts of climate change on yields of durum wheat in the Euro-Mediterranean region (Toreti *et al* 2022). While the current AHDB Variety Selection Tool (https://ahdb.org.uk/variety-selection-tool) has successfully incorporated disease resistance ratings, agronomic features and market options to help growers identify the best varieties for their farm, climate data is not currently included. Regular evaluation of observed performance of varieties in these different growing environments using the mixed modelling methods described here could be used in conjunction with data on the changes in the agroclimate to help recommend growing climates for each available variety, such that if a grower inputs their location into the tool, historical climate records could be used to indicate which varieties may be most climate-smart at their farm location, complementing the disease resistance ratings and agronomic factors.
2. **Make large-scale multi-environment field trial location data more accessible.** Significant work was required to access and combine the various sources that made up the NL/RL variety trials dataset for 1988–2018 in this analysis. Today's large-scale field trial datasets should be made more easily accessible, with all historical data records quality controlled and in one location, ideally with variety trial site location data to facilitate evaluation of variety trial performance alongside localised agroclimate data, to enhance our knowledge of crop-climate interactions and enable analysis of individual variety performance across different agroclimates.
3. **Publish variety trials which do not make it to harvest.** As in much of Europe (Kahiluoto *et al* 2019), large yield losses due to weather events are currently not recorded in the UK variety trials. This makes it difficult to assess the full range of responses to past weather variability. For example, it can mask the significant impact of localised heavy rainfall causing waterlogging and crop abandonment, overstating resilience to climate variability. Documenting these major yield losses and sharing this information with users of multi-environmental trials data provides additional context and may help to better explain observed yield variation.
4. **Create a national database for crop phenological dates**. The sharing of widespread records of on-farm planting, harvest, anthesis and grainfill dates would deliver many benefits. Firstly, it would enable a similar analysis to that completed in this research, but optimised for real on-farm conditions. Secondly, given the observed range in sowing dates (figure S3(a)), climate and GDD experienced by winter wheat in variety trials across the country, we know that the actual anthesis and grain fill periods will have varied spatially and temporally across the study period. This confirmation of the start date of anthesis and the grain fill period would make the agroclimate metrics more representative, supporting a more accurate analysis of changes in cereal phenology. To minimise any grower concerns concerning anonymisation, data could be summarised at a county level and still be a significant improvement over estimation methods using thermal degree days and using UK-wide fixed date ranges.
5. **Create a regular State of the UK Agroclimate report.** The Met Office release a comprehensive State of the UK Climate report (Kendon *et al* 2023) each year, however this is very much focussed on calendar years, with variables such as GDD calculated from 1st January to 31st December. To make climate information

more relevant to breeders and growers, we recommend regular (e.g. 2–3 years) analysis of crop specific variables, including those studied here for winter wheat, to monitor the changing state of the UK agroclimate. In addition, this should encompass additional crops and corresponding agroclimate metrics, such as Ontario Heat Units for maize (FWI 2018) and Growing Season Temperature for grapes (Nesbitt *et al* 2016). This agroclimate data can then be regularly updated and made accessible to the agriculture community, complementing the data on future projected changes in Climate Risk Indicators at uk-cri.org.

6. **Incorporate disease and soil data into the multivariate analysis to create variety suitability mapping.** In addition to weather, pests and disease lead to significant yield impacts and are themselves weather-dependent. For example, Fusarium ear blight is an emerging threat to grain quality (AHDB Cereals and Oilseeds 2018b, Turner *et al* 2021) and there have been several epidemics in the last two decades, such as in 2007 and 2014 (Turner *et al* 2021). Risk factors include warm dry springs allowing spore production followed by rain-splash events in June which spread the spores onto ears. We recommend a detailed multi-variate analysis accounting for the interaction between climate, soil type and crop diseases to optimise variety suitability further. By overlaying the distribution of soils, the agroclimate and disease risk, suitability maps could be developed for each variety.
7. **Increase international multi-environment variety trials.** The rapidly changing climate will give rise to novel climates in the UK; therefore, incorporation of a greater range of international variety trial sites outside of the UK in regions already experiencing similar climates to those projected for the UK should be a priority. International, transdisciplinary collaboration is essential for achieving future food security.

5. Conclusion

The effects of climate change are already being observed across all aspects of society including agriculture. Understanding the climatic conditions and extreme weather events plant breeders should consider and prepare for when looking for desirable traits to breed into crops is key to maximising future crop yields. Variety trials data is an underexploited industrial resource which we have shown can be combined with crop-specific agroclimate data to reveal how past crop yields have been affected by interannual weather and climate variability. To enhance future food security in a changing climate, we recommend a greater integration of crop-specific weather and climate data into both variety trials and breeding programs. This will help identify climate-resilient traits in existing varieties and guide crop and variety selection, enabling more locally relevant and climate-adapted farming practices.

Data availability statement

The Agriculture and Horticulture Development Board (AHDB) Recommended List is managed by a project consortium of AHDB, the British Society of Plant Breeders (BSPB), Maltsters' Association of Great Britain (MAGB) and the United Kingdom Flour Millers (UKFM). The data that support the findings of this study are available upon reasonable request from AHDB-BSPB, subject to AHDB-BSPB's Materials Transfer Agreement.

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ORCID iDs

Joanna Raymond https://orcid.org/0000-0002-8815-528X
Conor John Christopher Simpson https://orcid.org/0000-0001-7055-3186

References

Addy J W G, Ellis R H, Macdonald A J, Semenov M A and Mead A 2020 Investigating the effects of inter-annual weather variation (1968–2016) on the functional response of cereal grain yield to applied nitrogen, using data from the Rothamsted Long-Term Experiments *Agric. For. Meteorol.* **284** 107898

Addy J W G, Ellis R H, Macdonald A J, Semenov M A and Mead A 2021 Changes in agricultural climate in South-Eastern England from 1892 to 2016 and differences in cereal and permanent grassland yield *Agric. For. Meteorol.* **308–309** 108560

AHDB Cereals and Oilseeds 2018a *Wheat Growth Guide* (Agriculture and Horticulture Development Board)

AHDB Cereals and Oilseeds 2018b *Wheat and Barley Disease Management Guide* (Agriculture and Horticulture Development Board)

Akkem Y, Biswas S K and Varanasi A 2023 Smart farming using artificial intelligence: a review *Eng. Appl. Artif. Intell.* **120** 105899

Arnell N W and Freeman A 2021 The effect of climate change on agro-climatic indicators in the UK *Clim. Change* **165** 1–26

Austin R B 1999 Yield of wheat in the United Kingdom: recent advances and prospects *Crop Sci.* **39** 1604–10

Barlow K M, Christy B P, O'Leary G J, Riffkin P A and Nuttall J G 2015 Simulating the impact of extreme heat and frost events on wheat crop production: a review *Field Crops Res.* **171** 109–19

Bathiany S, Belleflamme A, Zohbi J E, Ney P, Goergen K and Rechid D 2023 Increasing interannual climate variability during crop flowering in Europe *Environ. Res. Lett.* **18** 044037

Bayer 2020 *Wheat Diseases* (Crop Science) (available at: https://cropscience.bayer.co.uk/threats/diseases/wheat-diseases/)

Berry P M, Kendall S, Rutterford Z, Orford S and Griffiths S 2015 Historical analysis of the effects of breeding on the height of winter wheat (Triticum aestivum) and consequences for lodging *Euphytica* **203** 375–83

Berry P and Brown I 2021 National environment and assets *The Third UK Climate Change Risk Assessment Technical Report* ed R A Betts, A B Haward and K V Pearson (Climate Change Committee)

Bönecke E, Breitsameter L, Brüggemann N, Chen T W, Feike T, Kage H, Kersebaum K C, Piepho H P and Stützel H 2020 Decoupling of impact factors reveals the response of German winter wheat yields to climatic changes *Glob. Change Biol.* **26** 3601–26

Born L, Prager S, Ramirez-Villegas J and Imbach P 2021 A global meta-analysis of climate services and decision-making in agriculture *Clim. Serv.* **22** 100231

Brown J K M, Beeby R and Penfield S 2019 Yield instability of winter oilseed rape modulated by early winter temperature *Sci. Rep.* **9** 6953

Cammarano D *et al* 2020 Integrated assessment of climate change impacts on crop productivity and income of commercial maize farms in northeast South Africa *Food Secur.* **12** 659–78

Ceglar A, Zampieri M, Toreti A and Dentener F 2019 Observed northward migration of agro-climate zones in Europe will further accelerate under climate change *Earth's Future* **7** 1088–101

Challinor A J, Watson J, Lobell D B, Howden S M, Smith D R and Chhetri N 2014 A meta-analysis of crop yield under climate change and adaptation *Nat. Clim. Change* **4** 287–91

DEFRA 2020 *Defra Statistics: Agricultural Facts, England Regional Profiles* 21

DEFRA 2021 *UK Food Security Report 2021, Presented to Parliament pursuant to Section 19 of the Agriculture Act 2020*

Dreccer M F, Fainges J, Whish J, Ogbonnaya F C and Sadras V O 2018 Comparison of sensitive stages of wheat, barley, canola, chickpea and field pea to temperature and water stress across Australia *Agric. For. Meteorol.* **248** 275–94

EDINA 2022 *Agricultural Census 2010* (AgCensus) (available at: https://agcensus.edina.ac.uk/)

Falloon D P, Bebber D D, Bryant P J, Bushell D M, Challinor P A J, Dessai P S, Gurr P S and Koehler D A-K 2015 Using climate information to support crop breeding decisions and adaptation in agriculture *World Agric.* **5** 25–43

Frederiks T M, Christopher J T, Harvey G L, Sutherland M W and Borrell A K 2012 Current and emerging screening methods to identify post-head-emergence frost adaptation in wheat and barley *J. Exp. Bot.* **63** 5405–16

Frieler K *et al* 2017 Understanding the weather signal in national crop-yield variability: weather-signal in crop-yield variability *Earth's Future* **5** 605–16

FWI 2018 *How Maize Ontario Heat Units Can Help Variety Selection* (Farmers Weekly)

Grogan S M *et al* 2016a Phenotypic plasticity of winter wheat heading date and grain yield across the US Great Plains *Crop Sci.* **56** 2223–36

Grogan S M, Brown-Guedira G, Haley S D, McMaster G S, Reid S D, Smith J and Byrne P F 2016b Allelic variation in developmental genes and effects on winter wheat heading date in the U.S. Great Plains *PLoS One* **11** 1–23

Gusta L V and Fowler D B 1976 Dehardening and rehardening of spring-collected winter wheats and a winter rye *Can. J. Plant. Sci.* **56** 775–9

Hakala K, Jauhiainen L, Himanen S J, Rötter R, Salo T and Kahiluoto H 2012 Sensitivity of barley varieties to weather in Finland *J. Agric. Sci.* **150** 145–60

Harding A E, Rivington M, Mineter M J and Tett S F B 2015 Agro-meteorological indices and climate model uncertainty over the UK *Clim. Change* **128** 113–26

Harkness C, Semenov M A, Areal F, Senapati N, Trnka M, Balek J and Bishop J 2020 Adverse weather conditions for UK wheat production under climate change *Agric. For. Meteorol.* **282–283** 107862

Hollis D, McCarthy M, Kendon M, Legg T and Simpson I 2019 HadUK-Grid—a new UK dataset of gridded climate observations *Geosci. Data J.* **6** 151–9

Jones L *et al* 2020. Climate driven threshold effects in the natural environment *Report to the Climate Change Committee*

Kahiluoto H *et al* 2019 Decline in climate resilience of European wheat *Proc. Natl Acad. Sci.* **116** 123–8

Kendon M, McCarthy M, Jevrejeva S, Matthews A, Williams J, Sparks T and West F 2023 State of the UK climate 2022 *Int. J. Climatol.* **43** 1–82

Kirkegaard J A, Lilley J M, Brill R D, Ware A H and Walela C K 2018 The critical period for yield and quality determination in canola (Brassica napus L.) *Field Crops Res.* **222** 180–8

Knight S, Kightley S, Bingham I, Hoad S, Lang B, Philpott H, Stobart R, Thomas J, Barnes A and Ball B 2012 (AHDB) Desk study to evaluate contributory causes of the current "yield plateau" in wheat and oilseed rape

Kukal M S and Irmak S 2018 U.S. agro-climate in 20th century: growing degree days, first and last frost, growing season length, and impacts on crop yields *Sci. Rep.* **8** 6977

Kuznetsova A, Brockhoff P B and Christensen R H B 2017 **lmerTest** package: tests in linear mixed effects models *J. Stat. Softw.* **82** 26

Li X *et al* 2021 An integrated framework reinstating the environmental dimension for GWAS and genomic selection in crops *Mol. Plant* **14** 874–87

Lin M and Huybers P 2012 Reckoning wheat yield trends *Environ. Res. Lett.* **7** 024016

Mackay I, Horwell A, Garner J, White J, McKee J and Philpott H 2011 Reanalyses of the historical series of UK variety trials to quantify the contributions of genetic and environmental factors to trends and variability in yield over time *Theor. Appl. Genet.* **122** 225–38

Mathieu J A and Aires F 2018 Assessment of the agro-climatic indices to improve crop yield forecasting *Agric. For. Meteorol.* **253–254** 15–30

McKnight T L and Hess D 2008 *Physical Geography: A Landscape Appreciation* 9th edn (Pearson Prentice Hall)

Met Office 2022 UK regional climates (available at: www.metoffice.gov.uk/research/climate/maps-and-data/regional-climates/index) (Accessed 04 May 2022)

Met Office 2024 (available at: www.metoffice.gov.uk/research/climate/maps-and-data/uk-and-regional-series) (Accessed 04 May 2022)

Nasehzadeh M and Ellis R H 2017 Wheat seed weight and quality differ temporally in sensitivity to warm or cool conditions during seed development and maturation *Ann. Bot.* **120** 479–93

Nesbitt A, Kemp B, Steele C, Lovett A and Dorling S 2016 Impact of recent climate change and weather variability on the viability of UK viticulture—combining weather and climate records with producers' perspectives: climate and weather impacts on UK viticulture *Aust. J. Grape Wine Res.* **22** 324–35

Parolini G 2022 Weather, climate, and agriculture: historical contributions and perspectives from agricultural meteorology *WIREs Clim. Change* **13** 1–19

Peltonen-Sainio P, Jauhiainen L and Hakala K 2009 Are there indications of climate change induced increases in variability of major field crops in the northernmost European conditions? *Agric. Food Sci.* **18** 206

Pfeifroth U, Sanchez-Lorenzo A, Manara V, Trentmann J and Hollmann R 2018a Trends and variability of surface solar radiation in Europe based on surface- and satellite-based data records *J Geophys. Res. Atmos.* **123** 1735–54

Pfeifroth U, Trentmann J, Hollmann R, Selbach N, Werscheck M and Meirink J F 2018b ICDR SEVIRI radiation—based on SARAH-2 methods, satellite application facility on climate monitoring

Pidgeon J D, Ober E S, Qi A, Clark C J A, Royal A and Jaggard K W 2006 Using multi-environment sugar beet variety trials to screen for drought tolerance *Field Crops Res.* **95** 268–79

Posthumus H, Morris J, Hess T M, Neville D, Phillips E and Baylis A 2009 Impacts of the summer 2007 floods on agriculture in England *J. Flood Risk Manage.* **2** 182–9

Ray D K, Gerber J S, Macdonald G K and West P C 2015 Climate variation explains a third of global crop yield variability *Nat. Commun.* **6** 1–9

Raymond J 2023 Weatherproofing for a smarter, more resilient and sustainable agri-sector *PhD thesis* University of East Anglia

Raymond J, Mackay I, Penfield S, Lovett A, Philpott H and Dorling S 2023a Combining historical agricultural and climate datasets sheds new light on early 20th century barley performance *Ann. Appl. Biol.* **182** 381–96

Raymond J, Mackay I, Penfield S, Lovett A, Philpott H and Dorling S 2023b Continuing genetic improvement and biases in genetic gain estimates revealed in historical UK variety trials data *Field Crops Res.* **302** 109086

Rezaei E E, Siebert S, Hüging H and Ewert F 2018 Climate change effect on wheat phenology depends on cultivar change *Sci. Rep.* **8** 1–10

Rivington M, Matthews K B, Buchan K, Miller D G, Bellocchi G and Russell G 2013 Climate change impacts and adaptation scope for agriculture indicated by agro-meteorological metrics *Agric. Syst.* **114** 15–31

Rowlatt J 2020 *Bread Price May Rise after Dire UK Wheat Harvest* (BBC)

Savill G P, Michalski A, Powers S J, Wan Y, Tosi P, Buchner P and Hawkesford M J 2018 Temperature and nitrogen supply interact to determine protein distribution gradients in the wheat grain endosperm *J. Exp. Bot.* **69** 3117–26

Semenov M A 2009 Impacts of climate change on wheat in England and Wales *J. R. Soc. Interface* **6** 343–50

Skendžić S, Zovko M, Živković I P, Lešić V and Lemić D 2021 The impact of climate change on agricultural insect pests *Insects* **12** 440

Slater L J, Huntingford C, Pywell R F, Redhead J W and Kendon E J 2022 Resilience of UK crop yields to compound climate change *Earth Syst. Dyn.* **13** 1377–96

Smith A B, Cullis B R and Thompson R 2005 The analysis of crop cultivar breeding and evaluation trials: an overview of current mixed model approaches *J. Agric. Sci.* **143** 449–62

Tasker J, 2020 Cereal yields set to hit 30-year low as weather takes toll (Farmers Weekly)

Toreti A, Bassu S, Asseng S, Zampieri M, Ceglar A and Royo C 2022 Climate service driven adaptation may alleviate the impacts of climate change in agriculture *Commun. Biol.* **5** 1235

Turner J A, Chantry T, Taylor M C and Kennedy M C 2021 Changes in agronomic practices and incidence and severity of diseases in winter wheat in England and Wales between 1999 and 2019 *Plant Pathol.* **70** 1759–78

Van Etten J *et al* 2019 Crop variety management for climate adaptation supported by citizen science *Proc. Natl Acad. Sci. USA* **116** 4194–9

Wu X, Liu H, Li X, Tian Y and Mahecha M D 2017 Responses of winter wheat yields to warming-mediated vernalization variations across temperate Europe *Front. Ecol. Evol.* **5** 126

Yang X, Tian Z, Sun L, Chen B, Tubiello F N and Xu Y 2017 The impacts of increased heat stress events on wheat yield under climate change in China *Clim. Change* **140** 605–20

Zhang Y, Feng L P, Wang J, Wang E L and Xu Y L 2013 Using APSIM to explore wheat yield response to climate change in the North China Plain: the predicted adaptation of wheat cultivar types to vernalization *J. Agric. Sci.* **151** 836–48

Zhao X, Calvin K V, Wise M A, Patel P L, Snyder A C, Waldhoff S T, Hejazi M I and Edmonds J A 2021 Global agricultural responses to interannual climate and biophysical variability *Environ. Res. Lett.* **16** 104037