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Combining historical agricultural and climate datasets sheds new light on early 20th century barley performance

Joanna Raymond[1] | Ian Mackay[2] | Steven Penfield[3] | Andrew Lovett[1] | Haidee Philpott[4] | Stephen Dorling[1]

[1]School of Environmental Sciences, University of East Anglia, Norwich, UK
[2]Principal's Academic Team, Scotland's Rural College (SRUC), Edinburgh, UK
[3]Crop Genetics, John Innes Centre, Norwich, UK
[4]Cambridge Crop Research, National Institute for Agricultural Botany, Cambridge, UK

Correspondence
Joanna Raymond, School of Environmental Sciences, University of East Anglia, Norwich, UK.
Email: joanna.raymond@kit.edu

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Abstract

Barley (*Hordeum vulgare* ssp. *vulgare*) is cultivated globally across a wide range of environments, both in highly productive agricultural systems and in subsistence agriculture and provides valuable feedstock for the animal feed and malting industries. However, as the climate changes there is an urgent need to identify adapted barley varieties that will consistently yield highly under increased environmental stresses. Our ability to predict future local climates is only as good as the skill of the climate model, however we can look back over 100 years with much greater certainty. Historical weather datasets are an excellent resource for identifying causes of historical yield variability. In this research we combined recently digitised historical weather data from the early 20th century with published Irish spring barley trials data for two heritage varieties: *Archer* and *Goldthorpe*, following an analysis first published by Student in 1923. Using linear mixed models, we show that interannual variation in observed spring barley yields can be partially explained by recorded weather variability, in particular July maximum temperature and rainfall, and August maximum temperature. We find that while *Archer* largely yields more highly, *Goldthorpe* is more stable under wetter growing conditions, highlighting the importance of considering growing climate in variety selection. Furthermore, this study demonstrates the benefits of access to historical trials and climatic data and the importance of incorporating climate data in modern day breeding programmes to improve climate resilience of future varieties.

KEYWORDS
breeding, climate variability, Spring barley, statistical modelling, Student

1 | INTRODUCTION

Spring barley (*Hordeum vulgare* ssp. *vulgare*) is the most widespread spring crop in Ireland and approximately 120,000 ha are sown each year (TEAGASC, 2020). It has been grown in Ireland since the 1800s and is well suited to the Irish soils and long growing season, which offer high yield potential (TEAGASC, 2017). As the climate changes and extreme weather events become more frequent, identification of spring barley varieties that prosper and consistently produce high yields is a priority.

Within barley's germplasm there are genotypes that can tolerate abiotic stresses such as drought and heat (Bindereif et al., 2021;

Ivandic et al., 2000; Wu et al., 2017). Barley landraces can also grow well in biogeographical zones with reduced soil fertility in which modern elite barley varieties fail to reach maturity (Schmidt et al., 2019). As environmental stresses become more frequent and there is a need for varieties demanding fewer resource inputs, heritage varieties may provide valuable genetic variation and a possible resource for these wild-type traits.

A well-documented set of spring barley trials data for 1901–1906 exists, comparing two heritage spring barley varieties: *Archer* and *Goldthorpe*. *Archer* is a two-row narrow-eared variety that originated in East of England and outperformed the long-running favourite *Chevalier* in yield, quality and straw strength (Hunter, 1913). *Goldthorpe* is a two-row wide-eared barley known for its high malting quality. In 1889 a single wide ear was found in a field of *Chevalier* near Goldthorpe, Yorkshire and was selected and propagated to become *Goldthorpe* (Gothard et al., 1983; Malcolm, 1983; Reid et al., 1929).

Analysis of these trials data by William Gosset in Student (1923) concluded that the chief difficulty in comparing variety performance was that differences between varieties are small compared with variations due to weather. While weather was recorded during this period at various locations across Ireland (Section 2.1), these data were not accessible to Student at that time.

On the approach to its centenary, Student's, 1923 paper "On testing of Cereal Varieties" remains noteworthy. It was published in the early days of establishing methods of variety testing and lists reasons why yield trials are necessary which have not changed—environmental conditions 'evoke different responses in strains'; 'the soil on which plants are grown is never uniform'; and 'the effects of soil and weather are far greater than the differences [between varieties] which we have to investigate'.

A recent data rescue project has extended the temporal coverage of digitally available daily maximum and minimum air temperature and rainfall observations to include this early 20th century period (Mateus et al., 2020; Ryan et al., 2021). Historical climate data has been shown to be valuable for identifying the climatic influence on crops (e.g. Kahiluoto et al., 2019; Lopes, 2022; Rezaei et al., 2015; Trnka et al., 2010) as well as the impact of the interaction between genotype and the environment (G × E) on yield (e.g. de los Campos et al., 2020; Fabio et al., 2017). Understanding how crops respond to weather and climate variability is vital for identifying crops and varieties that will perform well in our rapidly changing climate. Despite this, few studies take advantage of the benefits of combining historical crop trials data with historical weather data in barley (Gillberg et al., 2019).

In this study we show that by combining spring barley trials data with climate data, interannual variation in early 20th century spring barley yields can be partially explained by recorded weather variability. We demonstrate the relative stabilities of *Archer* and *Goldthorpe* varieties and show the importance of considering the growing climate in variety selection. We also explore a range of variable selection methods and modelling tools to identify the most suitable modelling techniques for highly correlated, multi-dimensional yield and climate data. Finally, we discuss the benefits of access to trials data and the importance of incorporating climate data in modern day breeding programmes to improve the climate resilience of future varieties.

2 | MATERIALS AND METHODS

2.1 | Datasets

The barley trials dataset analysed by Student (1923) consists of two spring varieties—*Archer* and *Goldthorpe*—in unreplicated 2-acre plots at 18 distinct farm locations across the barley-growing districts in Ireland (Figure 1a,b). Locations for each trial site are recorded by the town and district, from which a latitude and longitude has been estimated. The number of trial sites increases each year from four in 1901 to 12 in 1906. Yield data was recorded in barrels and stones per acre and price was recorded in pounds, shillings and pence (£sd) per acre. To give the values modern context, these have been converted to tonnes/ha and £/ha, respectively.

Each trial site was paired with weather data for the 1901–1906 growing seasons from the nearest weather station open during the period (Table 1 and Figure 1b). Here growing season is defined as 1 March to 31 August, based on current spring barley growing practices. Daily temperature data was obtained from the recently released Ireland Long-term Maximum and Minimum Air Temperature dataset (ILMMT), for which raw daily observations from 12 long-term and 21 short-term maximum and minimum air temperature series were rescued from archives (Mateus et al., 2020). Daily rainfall data was obtained for the period 1901–1906 from Met Éireann and forms part of Ireland's pre-1940 rainfall records (Ryan et al., 2021).

Both daily climate datasets are the product of a large data rescue project by Met Éireann and Maynooth University, which also forms part of the worldwide data rescue effort I-DARE (https://www.idare-portal.org/). Part of this project involves digitising Met Éireann's pre-1960s rainfall and climate station records, including manuscripts and daily weather reports (Mateus et al., 2020; Ryan et al., 2021).

To enable long term localised climate analysis, daily temperature data for the weather stations closest to the trial sites (Table 1) from the digitised ILMMT data was combined with data from the Met Éireann website for the duration of opening of each station (https://www.met.ie/climate/available-data/historical-data). Monthly rainfall totals for 1850–2010 for these weather stations (Table 1) were also downloaded where available (https://www.met.ie/climate/available-data/long-term-data-sets) (Noone et al., 2016).

In addition to weather station data, the European Centre for Medium-Range Weather Forecasts (ECMWF) twentieth century reanalysis dataset (ERA-20C) (Poli et al., 2016) was used to add a gridded and regional context to the weather stations and as a further quality control check. ERA-20C is a gridded dataset spanning 1900–2010, with a resolution of 125 km × 125 km. Here we used the monthly means of daily means for 2 m (i.e. air temperature at 2 m height) temperature (*K*) and total precipitation (*m*) was downloaded from http://apps.ecmwf.int/datasets/data/era20c-daily/. Monthly means of daily means for photosynthetically active radiation (PAR) at the surface

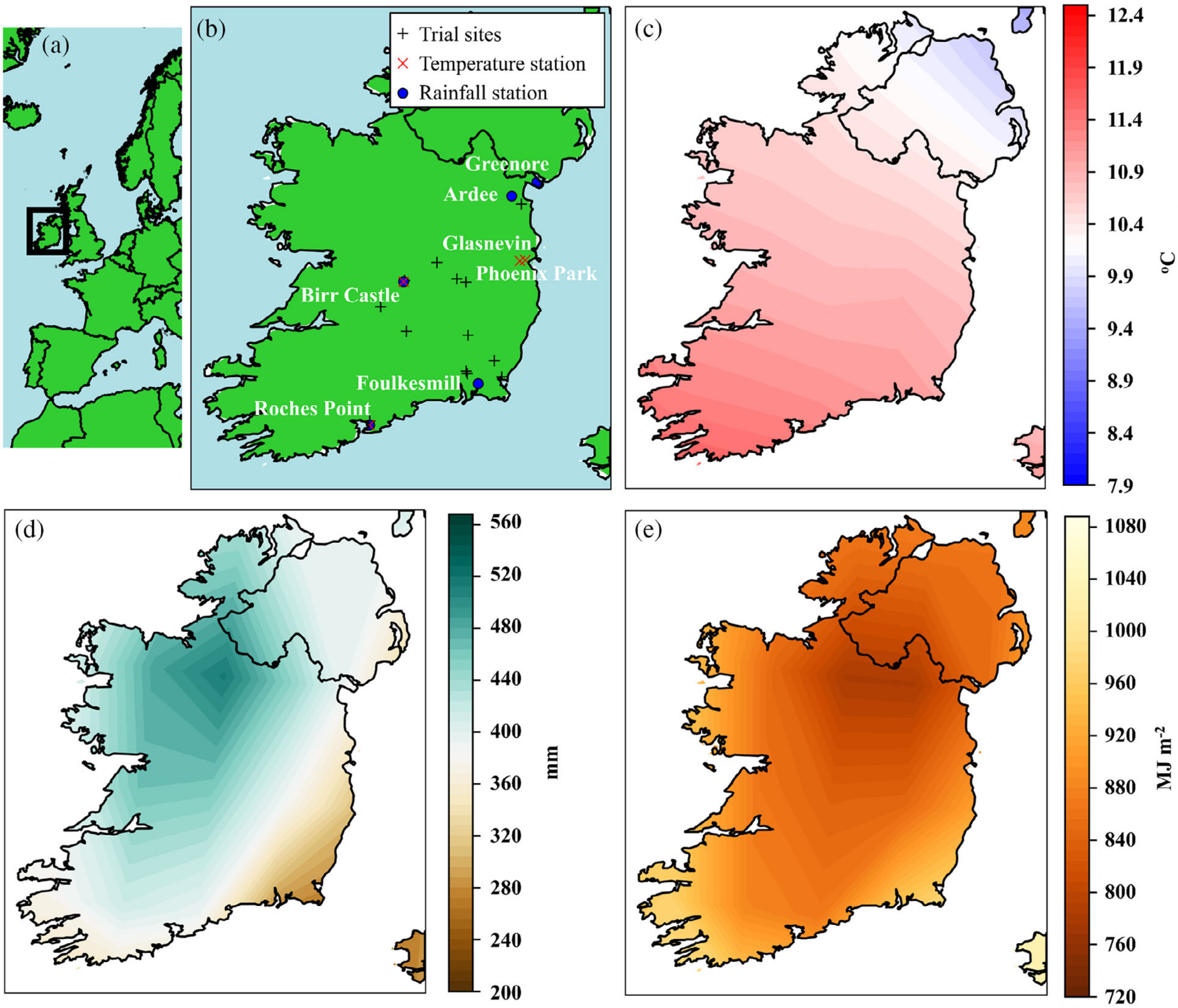

FIGURE 1 1901–1930 growing season climate for Ireland. (a) The location of Ireland relative to Europe and North Africa. (b) Weather stations open between 1901 and 1906 and closest to barley trial sites (+). Stations with rainfall only (blue circle), temperature only (red ×) and both rainfall and temperature data are shown. Growing season (March–August) average temperature (°C) (c) total rainfall (mm) (d) and surface photosynthetically active radiation (MJ/m^2) (e) for 1901–1930, calculated using ERA-20C (Poli et al., 2016).

TABLE 1 The closest weather stations to the barley trials sites with daily data for 1901–1906.

Station number	Station name	County	Daily rainfall data availability (Ryan et al., 2021)	Monthly rainfall data availability (Noone et al., 2016)	Daily temperature data availability (Mateus et al., 2020)
438	Ardee (Lisrenny)	Louth	1886–1913		
119	Birr Castle	Offaly	1875–1951; 1954–2009	1850–2010	1880–2009
1823	Dublin (Glasnevin)	Dublin			1834–1958; 1961–2020
108	Foulkesmill (Longraigue)	Wexford	1874–1906; 1914–1940; 1941–2020	1850–2010	
338	Greenore	Louth	1876–1940		
175	Phoenix Park	Dublin		1850–2010	1831–1959; 1961–2012
1004	Roches Point	Cork	1873–1940; 1941–1996; 2008–2016	1850–2010	1872–1999; 2009–2020

Note: The period of daily rainfall and temperature data is given for each station, along with monthly rainfall.

(J/m^2) were also downloaded to supplement the lack of solar radiation observations from the weather stations. Analysis of this data for the growing season for the first 30-year period (1901–1930) shows that the driest and sunniest region in Ireland is in the south-east (Figure 1a–c), where the majority of trial sites are focussed (Figure 1b).

Growing degree days (GDD) were calculated for of each weather station closest to trial sites (Table 1) across their period of opening using daily temperature data for growing season months March to August and the following equation:

$$GDD(0) = \begin{cases} \sum \frac{T_{\min} + T_{\max}}{2}, & \frac{T_{\min} + T_{\max}}{2} > 0 \\ 0, & \frac{T_{\min} + T_{\max}}{2} \leq 0 \end{cases}, \quad (1)$$

where $T_{\min}$ is daily minimum temperature and $T_{\max}$ is daily maximum temperature. $GDD(0)$ gives a day-by-day sum of the number of degrees by which the mean temperature exceeds 0°C (Baron et al., 2012; Bauer et al., 1992; Juskiw et al., 2001). To ensure that missing data did not incorrectly reduce the final GDD value, growing seasons with at least 1 day of missing maximum and/or minimum temperature data were dropped. Roches Point was missing data from 18 years (1872, 1994–2008, 2010, 2015), Dublin was missing 9 years (1959, 1960, 1963, 1965–1967, 1969, 1988, 2020) and Birr Castle 3 years (1952–1954). None of the years in 1901–1906 study period were missing data.

In the climate analysis two averaging periods were used: the full record of selected weather datasets, to provide context for extreme events, and the relevant 30-year period, as the basis for the calculation of anomalies. For the weather station data, the 30-year period used was 1891–1920, however for the gridded reanalysis dataset ERA-20C, which begins in 1900, this was 1901–1930.

2.2 | Modelling Irish spring barley and climate data

The spring barley variety trials are located across different sites, creating a clustered dataset where trial yields are not independent and not all farms were used each year. At a given site, the yields are all dependent on the same environmental factors such as rainfall and soil type, as well as the same farmer and agronomy. Therefore, the following linear mixed-effect model was used so that both farm and year could be included as random effects, using REML through *lmer* from ***lme4*** (Bates et al., 2020) in R:

$$y_{ijk} = \mu + T_{jk} + P_{jk} + v_i + r_j + vT_{ijk} + vP_{ijk} + s_{jk} + e_{ijk} \quad (2)$$

where y_{ijk} is the yield of variety i in year j at farm k, μ is the overall trial series mean, T_{jk} is the effect of monthly temperature in year j at farm k, P_{jk} is the effect of monthly precipitation in year j at farm k, v_i is the effect of variety i, r_j is the effect of year j, with year included as a factor variable, vT_{ijk} is the interaction between variety i, monthly temperature T_{ijk} in year j at farm k, and vP_{ijk} is the interaction between variety i and monthly precipitation P in year j at farm k and e_{ijk} is the residual term. s_{jk} is the effect of site (farm) within years, representing the interaction between year term r_j and farm term f_k. This term means each farm is treated as different each year, which is a more accurate representation given the exact location of fields is unknown and may have varied.

The monthly variables T_{jk} and P_{jk} encompass the growing season (March–August) monthly precipitation and temperature. The site term s_{jk} and year term r_j are fitted as random effects. The two genotype-by-environment terms (G×E) variety × temperature vT_{ijk} and variety × rainfall vP_{ijk} terms are fitted as fixed effects as the specific reaction of individual varieties (genotype) with the climate covariates (environment) is of interest.

2.2.1 | Variable selection methods

To reduce the dimensionality of the data and identify the most significant monthly temperature and precipitation variables in determining yield to include in (2), best subset selection, forwards and backwards stepwise selection, the lasso (Tibshirani, 1996) and elastic net (Zou & Hastie, 2005) were used on the linear model run using *lm* in R:

$$y_{ijk} = \mu + T_{jk} + P_{jk} + e_{ijk} \quad (3)$$

These were implemented in R using the functions and arguments detailed in Table S1. Significant variables ($p < .05$) in each of the selected models were identified using an analysis of variance (ANOVA). For each method, the root mean squared error (RMSE) and adjusted R^2 were calculated for the selected model. Residuals from the models were checked and found to conform to the assumptions of the analysis.

Mixed-effect model backwards elimination was also carried out using *step* in Equation (2) modelled using *lmer* from ***lmerTest*** package (Kuznetsova et al., 2017).

2.2.2 | Pearson's correlation and principal component analysis

Pearson's correlation analysis was used to identify the climate covariates with the highest correlation with yield as well as the degree of correlation between the climate covariates.

A principal component analysis (PCA) was implemented using the *ggcorr* function from ***GGally*** (Schloerke et al., 2021) and *prcomp* function from ***stats***. A PCA approach was adopted to test whether linear combinations of the monthly climate variables, rather than the individual climate variables themselves, could be used to model yield.

2.2.3 | Akaike information criterion

Each climate variable was input into Equation (2) iteratively and the significance of that variable and accompanying model Akaike information

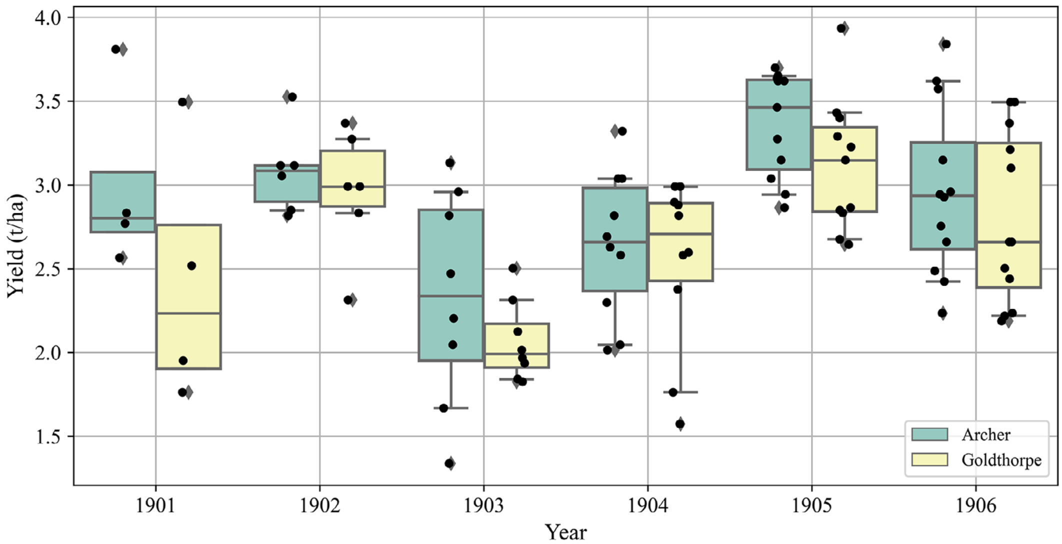

FIGURE 2 Barley trials yields (t/ha) (black dots) for 51 trials across 18 farms between 1901 and 1906, for two varieties: Archer (blue) and Goldthorpe (yellow). The box forms the interquartile range in yield and the middle line in the box is the median yield. Outliers (diamonds) represent trial yields in the 5th and 95th percentiles. There were 51 trials per variety, increasing from 4 in 1901 to 12 in 1906. Data from Student (1923). A dot and a diamond side-by-side and partially overlapping are the same data point.

citerion (AIC) was calculated. The AIC was then compared with (2) without any climate variables to see if the additional variable improved the fit, using *anova*(*model1*,*model2*) in R. Additional climate variables were iteratively added and their significance and model AIC inspected.

2.3 | Comparison of standard error of difference between means

Student (1923) calculates the standard error of the mean difference in variety means. To understand if the models run in this analysis can improve on this value, this was first repeated using the equation $SE(d) = \frac{s_d}{\sqrt{n}}$, where s_d is the standard deviation of the differences and n is the number of paired trials. After checking this against Student (1923), the value was then converted to t/ha.

To find an estimate of the standard error of difference between the varieties in the selected model, the *emmeans* function in R was used. The model and variable of interest, variety v_i, were specified. The *contrast* function was then applied to this, using *method* = '*pairwise*'. This calculates the estimate of difference, standard error, degrees of freedom, t ratio and p value for the variety pair. The statistical significance of the difference in mean values was then checked by calculating the t-statistic.

3 | RESULTS

3.1 | Spring barley yields show high variation

Median yields varied from year-to-year by up to 50% for *Archer* and up to 58% for *Goldthorpe* (Figure 2). For both varieties the lowest yields occurred in 1903 (combined mean 2.2 ± 0.5 t/ha), and highest in 1905 (combined mean 3.2 ± 0.4 t/ha). There was large variation in yields within years, in particular for *Archer* in 1903 (SD = 0.59 t/ha) and for *Goldthorpe* in 1901 (SD = 0.67 t/ha). This was despite the number of trials increasing each year.

Only three farmers were involved in all 6 years of the trials: Hawkins, McCarthy and Wolfe (Figure 3). There were clear differences from farm to farm in yields reflecting the differences in climate, soil type, topography, farm management practices and years. All three farms showed similar interannual variability: 1903 was the lowest yielding year while 1902 and 1905 were the highest. Yields fluctuated by up to 50% with average yields increasing approximately 45% (1.8 t/ha) between 1903 and 1905, indicating low stability in these varieties.

3.2 | Spring barley price shows similar variation to yield

Student used price as a measure of quality of the crop. The lowest quality of both varieties occurred in 1903 and highest in 1905 (Figure 4), as with yield (Figure 2). Student (1923) acknowledged that the value of the crop per acre was mostly dependent on the yield.

3.3 | Irish climate analysis

3.3.1 | Long-term climate reveals anomalous years

Growing season rainfall anomalies show large interannual variability, with differences of up to 300 mm between neighbouring years (Figure 5). Averaged across all stations, the lowest yielding year 1903 was the wettest of the 6 barley trial years 1901–1906, with a large

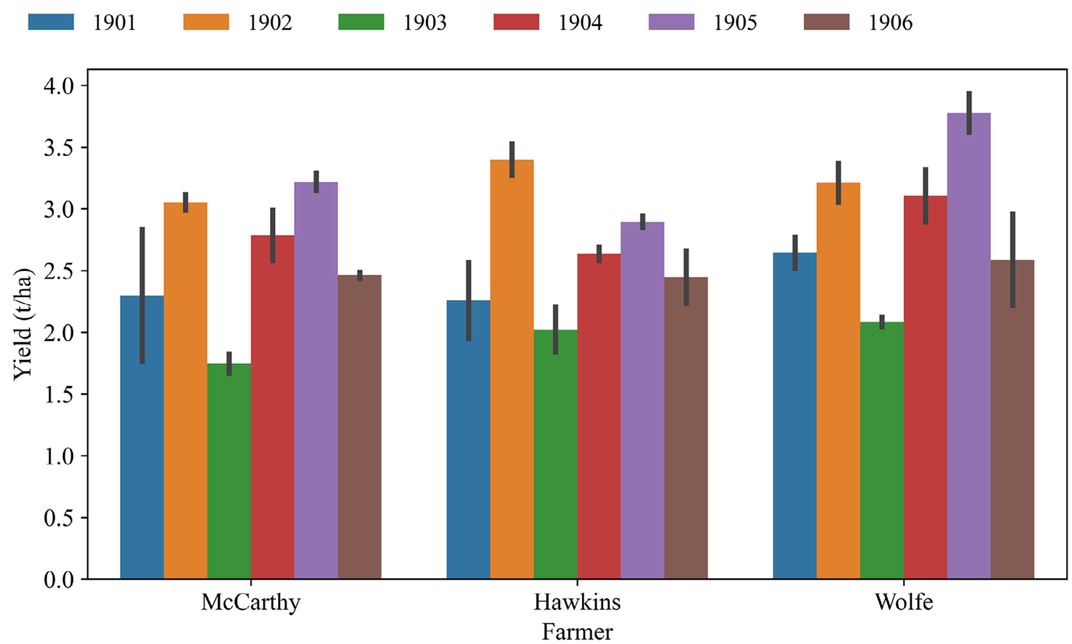

FIGURE 3 Interannual spring barley yield (t/ha) variability for three farms with data for the entire period 1901–1906. Error bars show the difference between Archer and Goldthorpe variety yields. Data from Student (1923).

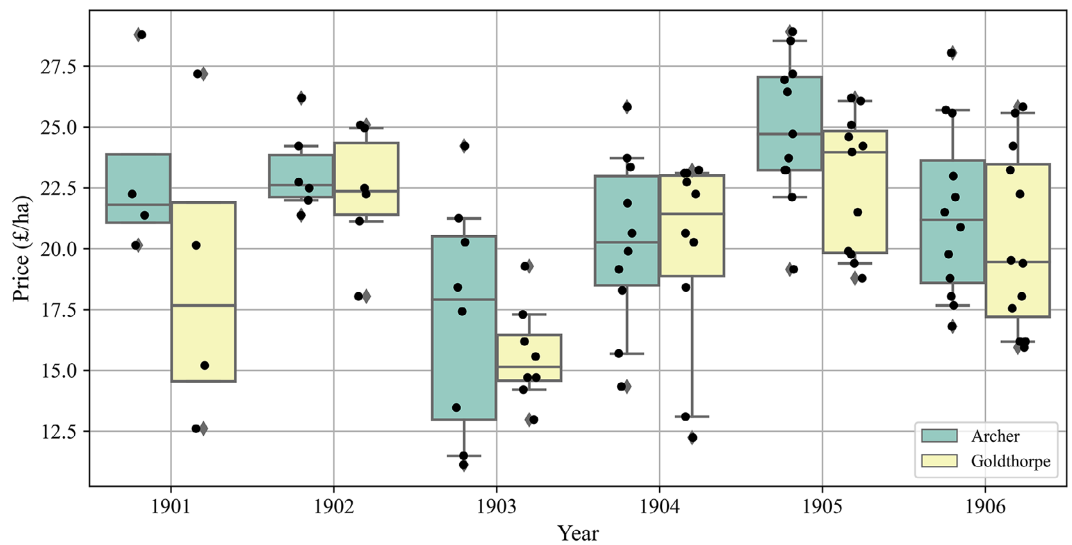

FIGURE 4 Barley trial price per hectare (£/ha) (black dots) for 1901–1906 for two varieties: Archer (blue) and Goldthorpe (yellow). The box forms the interquartile range in price and the middle line in the box is the median price. Outliers (diamonds) represent trial yields in the 5th and 95th percentiles. There were 51 trials per variety, increasing from 4 in 1901 to 12 in 1906. Data from Student (1923).

positive anomaly relative to the 1851–2010 average. Nationally the 1903 growing season received over 20% more rainfall than average. 1901 and 1902 were drier than average across the stations.

Over the 1874–2020 period, significant long-term increases in growing degree days of 0.76°C/year ($r = 0.26$, $p = 0.003$, t-test) and 2.3°C/year ($r = 0.66$, $p < .001$, t-test) have been seen at Birr Castle and Dublin respectively (Figure 6). The more extreme increase in seen at Dublin is likely due to increased urbanisation and industrialisation in the city (Dublin City Council, 2017), decreasing the city's albedo, increasing absorption of solar radiation and local temperatures. In addition to being the wettest of the 6 years, the 1903 growing season has the 11th lowest GDD recorded at both Birr Castle and Dublin stations across the period.

3.3.2 | 1891–1920 climatology reveals extreme wetness in 1903 and high temperature variability across the trials period

Comparing years 1901–1906 to the climate of 1891–1920 places the data in the context of the general climate at the time. The 6-year period showed some extreme wetness and temperatures.

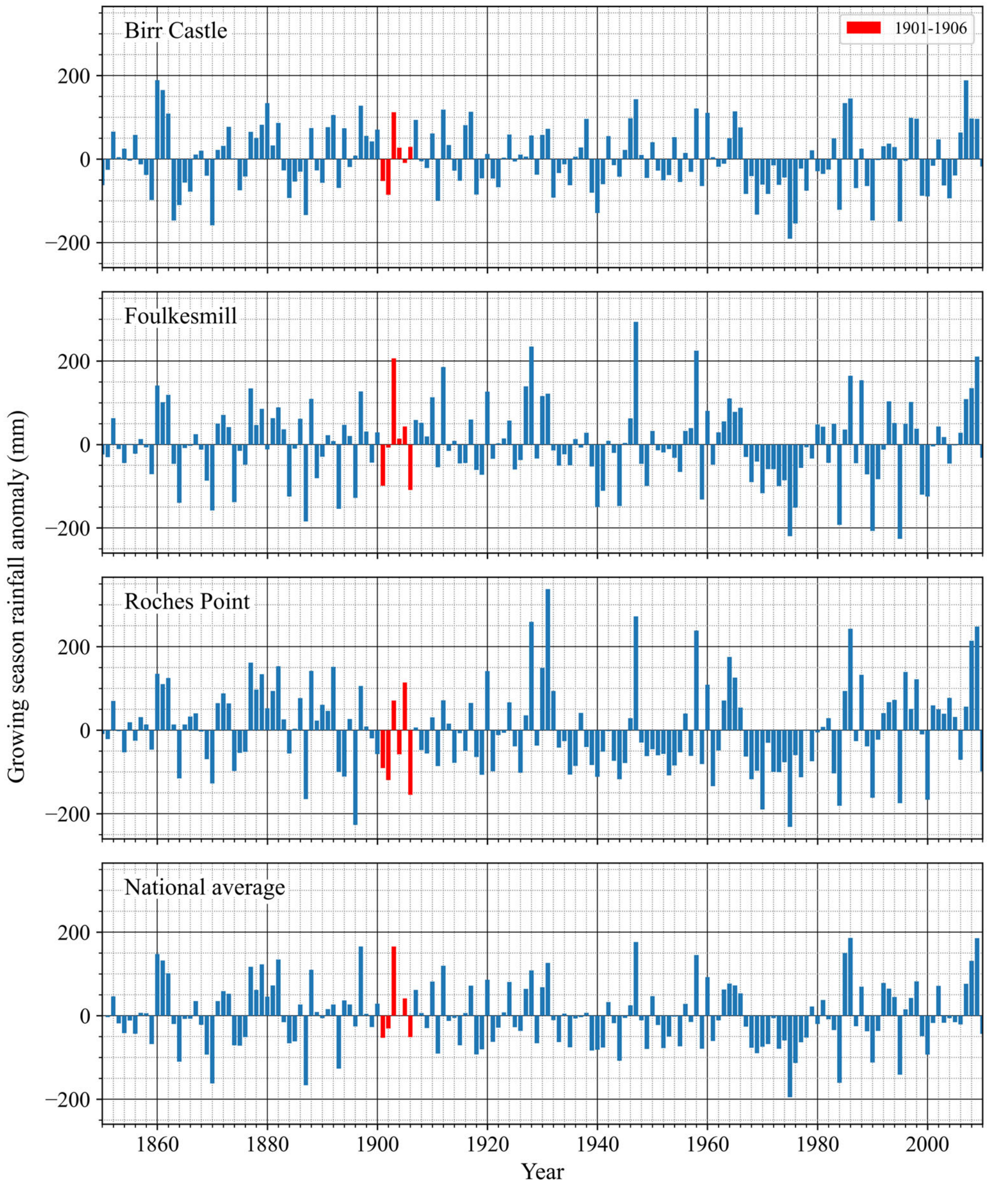

FIGURE 5 Growing season rainfall anomalies (mm) (March–August) for Birr Castle, Foulkesmill and Roches Point stations and nationally for 1850–2010. Years 1901–1906 are shown in red. The anomalies were calculated by subtracting the mean growing season rainfall for each station. The national average anomaly was calculated using the Island of Ireland precipitation series published by Noone et al. (2016).

March 1903 was the wettest March in the 1891–1920 30-year period for Ardee, Birr and Foulkesmill stations and nationally (Figure 7). The coastal stations Roches Point and Greenore saw more 'normal' rainfall amounts, with the former recording its highest March rainfall for the 30-year period in 1905. Cumulatively, 1903 was the wettest growing season in the 30-year period at Foulkesmill and nationally, recording over 600 mm rainfall. It was also the wettest growing season in the period 1901–1906 at Ardee, Birr and Greenore.

The less extreme temperature values seen at Roches Point are related to its coastal location, with higher mean minimum temperatures and lower mean maximum temperatures (Figures 8 and 9). 1906 saw extremely low monthly mean minimum temperatures in April at all three stations, as well as the highest mean minimum temperature for August in the 30-years at Dublin. The mean minimum temperatures at Roches Point and Birr Castle for this month were closer to the average highlighting that climate extremes vary spatially and can be localised, contributing to the range in observed yields. March 1902 saw relatively high mean minimum and maximum temperatures while May 1902 saw much lower than average mean maximum temperatures (Figure 9). July 1901 and 1905 both experienced particularly high mean minimum and maximum temperatures combined with low rainfall (Figures 7–10).

3.3.3 | Mapping climate anomalies

Analysis of growing season rainfall data from the gridded reanalysis dataset ERA-20C for 1901–1906 relative to the 1901–1930 averages (pre-1900 data was unavailable) shows that 1903 was much wetter than average across Ireland, the UK and much of Europe (Figure 10). 1906 was driest in the trials period. High rainfall is generally associated with a reduction in solar radiation and the 1903 growing season also received approximately 5% less PAR than the 1901–1930

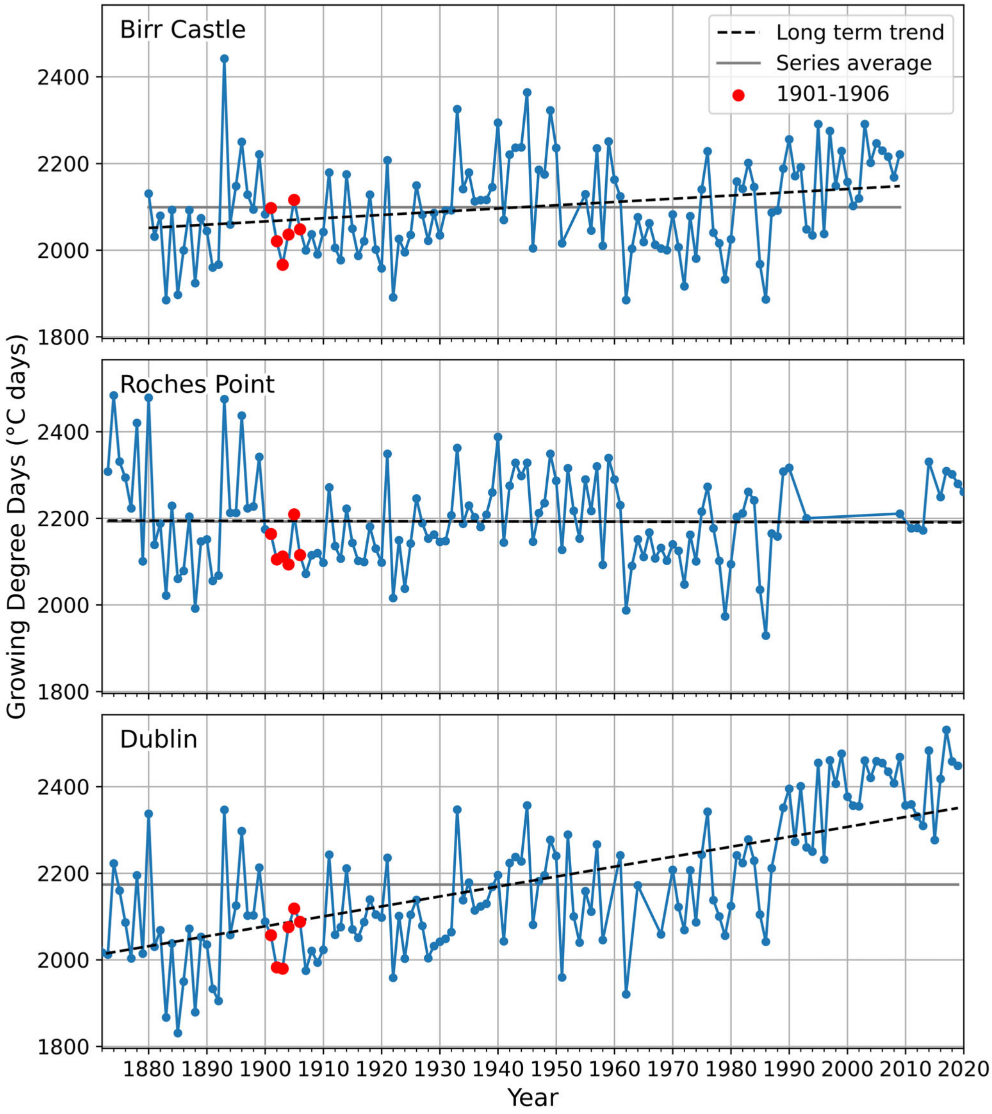

FIGURE 6 Growing season growing degree days (°C) for Birr Castle, Roches Point and Dublin stations for 1874–2020. Growing degree days is the sum of the mean temperature on days when mean temperature is above 0°C from March to August. Roches Point is missing data for 1998–2008.

average in Ireland (Figure 11). 1901 and 1904 show the largest positive PAR anomalies over the growing season. Breaking this down into months, the 4 years 1901, 1902, 1904 and 1905 all have positive PAR anomalies in July in sync with the grain fill period.

1905 was the only growing season in the period when Ireland had a positive temperature anomaly, of approximately 0.3°C. Higher than average temperatures were also experienced across the UK and most of central, eastern and northern Europe (Figure 12). 1903 was the coldest growing season in Ireland, about 1°C below the 1901–1930 average.

3.4 | Modelling Irish spring barley and climate

3.4.1 | Variable selection methods

We found the best subset selection, forwards and backwards selection and the elastic net methods did not significantly reduce the climate model (3) and still contained at least 13 variables each. This was too many whence to include the selected climate covariates in the mixed model with year, variety and site (2) (Table S2). A combination of using too many highly correlated variables (Figure S1) and too few farm growing seasons likely contributed to this. The worst performing was backwards stepwise selection which did not drop any variables. The two lasso methods reduced the model complexity from 19 to less than 7 climate variables, but these models had very low adjusted R^2 values of close to 0, indicating a poor model fit (Table S3). Using the mixed-model backwards elimination approach, we found that all the climate variables were dropped. In all methods except this, July maximum temperature was kept in the model

3.4.2 | Pearson's correlation and PCA

In yield-climate correlation analysis we found July rainfall and July maximum temperature have the largest absolute correlation with yield: −0.49 and 0.45, respectively (Figure S2). These variables have a strong negative correlation. To test the importance of weather in the

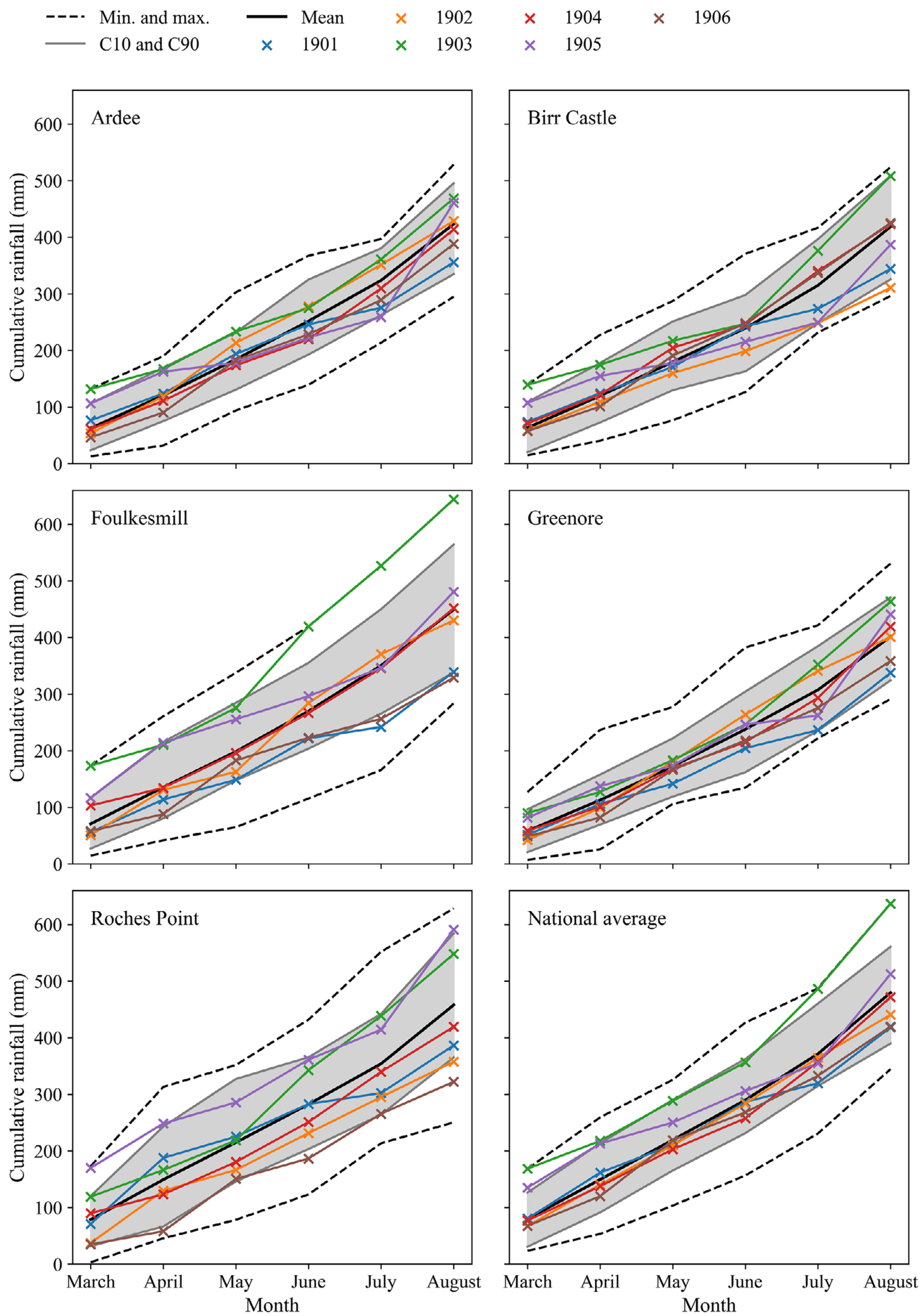

FIGURE 7 Cumulative monthly rainfall (mm) for Ardee, Birr Castle, Foulkesmill, Greenore, Roches Point stations and the national average across 25 stations for 1901, 1902, 1903, 1904, 1905 and 1906. The 1891–1920 average is shown (solid black line) along with the period 10th and 90th percentile values (grey lines) and the period minimum and maximum values (dashed black line). Ardee station only has data for 1891–1913 therefore the averages are for this period instead. Data from Ryan et al. (2020).

months leading up to drilling, we also tested the correlation between temperature and rainfall from January and February and yield (Table S4). This indicated that high rainfall in these months can have yield penalties, which could be linked to delays in drilling date.

PCA was explored to reduce multi-collinearity in the climate data set and as input to the linear mixed model (Table S5). However, using the PCs as predictors proved to be inadequate because each PC was not defined by a small number of climate variables,

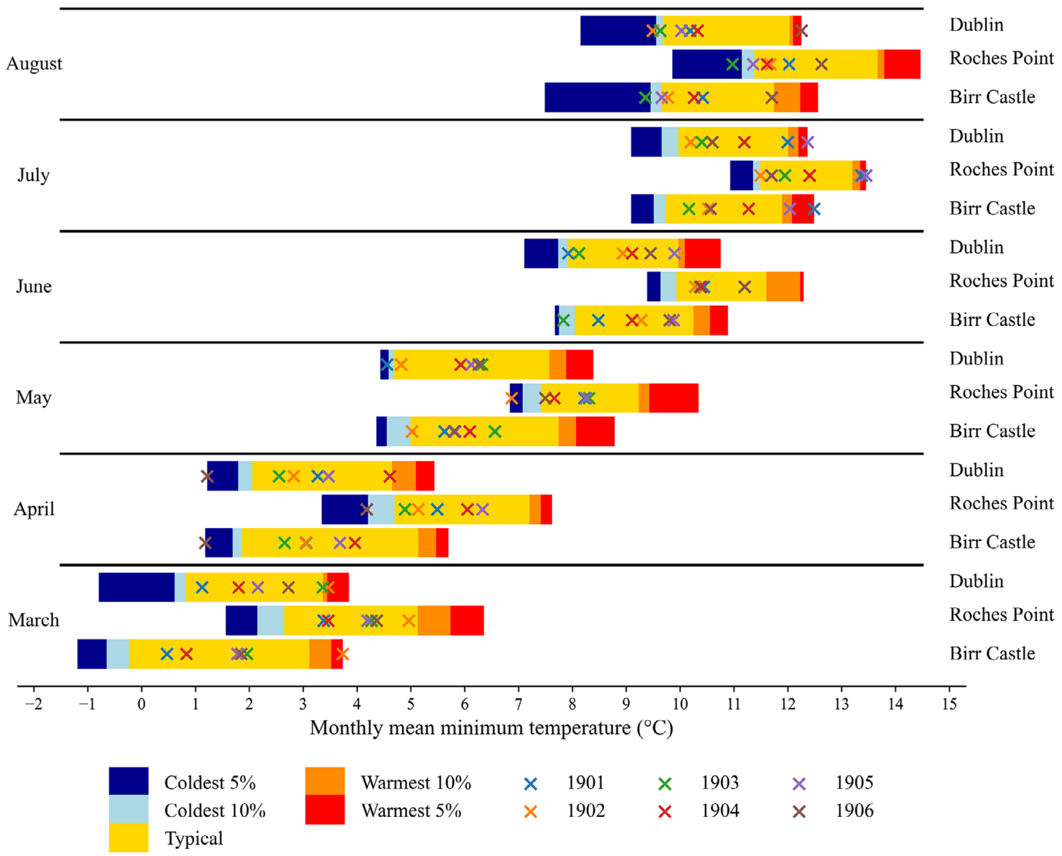

FIGURE 8 1891–1920 monthly mean minimum temperatures (°C) for Birr Castle, Roches Point and Dublin stations for the growing season. The range in temperatures for the coldest 5%, coldest 10%, warmest 10% and warmest 5% mean minimum temperatures are shown. Monthly mean minimum temperatures for 1901, 1902, 1903, 1904, 1905 and 1906 are also presented. Data from Mateus et al. (2020).

and so an easily interpretable and simple model was not forthcoming.

3.4.3 | Akaike information criterion

To understand if adding temperature or rainfall climate variables to the mixed model (2) improves the fit, the AIC of the mixed model of (2) without any climate covariates was first calculated (Table 2). We then added each climate variable and its interaction with variety to the model one at a time. None of the interactions with variety were significant, the variety × climate interaction term was dropped from the model and the models with each climate variable were looped through again.

Only three variables—July maximum temperature, August maximum temperature and July total rainfall—were significant ($p < .05$, *F*-test) when included in the model. The models which included either July maximum temperature or August maximum temperature improved the AIC and model fit, with the July maximum temperature model selected as the best model based on its AIC value. Notably all the models that contained temperature had a lower AIC and better fit than any of the rainfall models, including the significant July rainfall model (Table 2).

Both July mean maximum temperature and August mean maximum temperature had a positive relationship with yield (Table 2), such that yield increased by approximately 1/4 t/ha per 1°C increase in July mean maximum temperature and by approximately 1/5 t/ha per 1°C increase in August maximum temperature. Increased July rainfall decreased yield by −0.7 t/ha/100 mm.

3.5 | Comparison of standard error of difference between means

The mean difference in the variety values is £1.52/ha (12 shillings/acre) with a standard deviation of £2.95/ha (23.9 shillings/acre) and corresponding standard error of the mean difference £0.41/ha (3.3 shillings/acre), in accordance with Student (1923). This corresponds to a *t*-statistic of 3.680, which was statistically significant ($p = .0006$) at the 95% level ($df = 50$). This provided strong evidence that there was a difference in varietal performance.

Calculating the standard error of difference between variety values in the three mixed models containing significant climate effects (Table 2) gives identical values (to 2 s.f.) of £0.41/ha (3.3 shillings/acre). This indicates that this model does not reduce the standard error, which is expected given no variety x climate interactions were

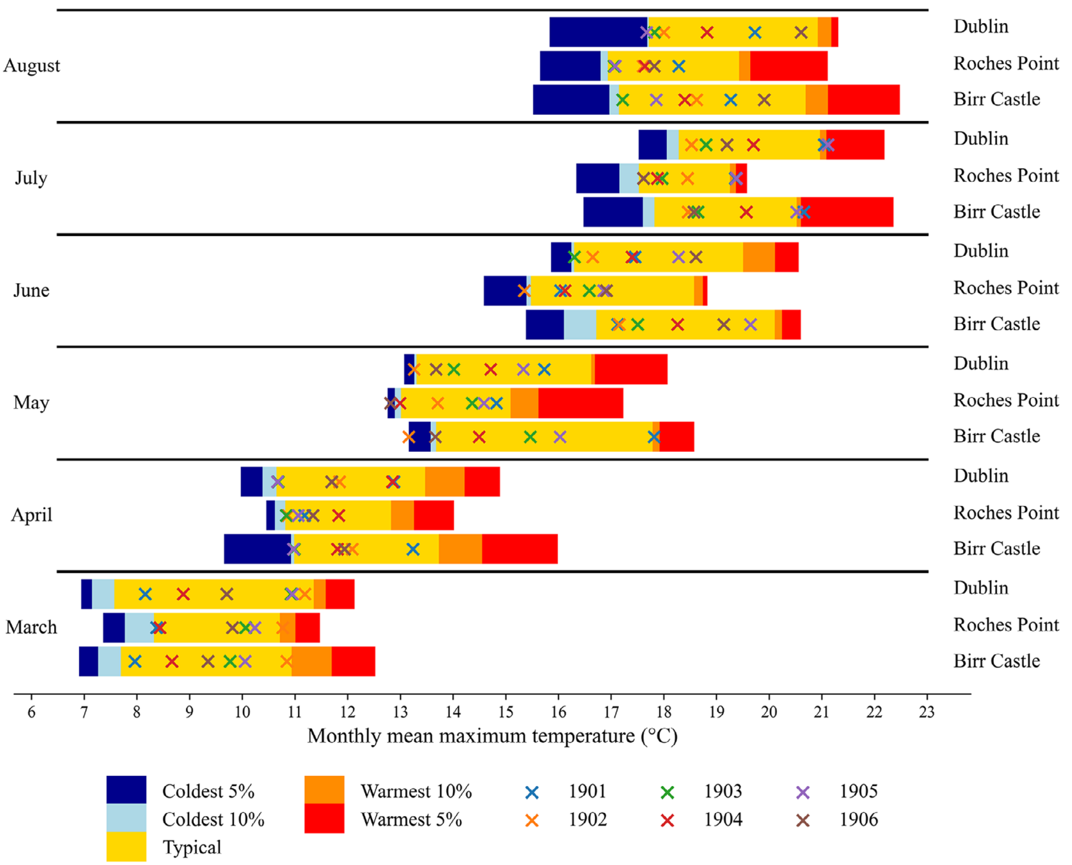

FIGURE 9 1891–1920 monthly mean maximum temperatures (°C) for Birr Castle, Roches Point, and Dublin stations for the growing season. The range in temperatures for the coldest 5%, coldest 10%, warmest 10% and warmest 5% mean maximum temperatures are shown. Monthly mean maximum temperatures for 1901, 1902, 1903, 1904, 1905, and 1906 are also presented. Data from (Mateus et al., 2020).

included in the final models. The climate variables simply partitioned the effects of Farm and Year and did not affect the Variety effect.

4 | DISCUSSION

4.1 | Climatic causes of yield variability

Use of recently digitised weather data for the early 20th century has allowed us to show that contrasting climatic conditions in 1903 and 1905 coincided with variation in spring barley varietal performance. In 1903 a wet March (Figure 7) likely made it challenging to drill the crop, resulting in delayed planting shortening the growing season and potential difficulties in crop establishment. Furthermore, a significant storm event was recorded across Ireland and the UK on 26–27th February 1903, which will have contributed further to high levels of soil moisture at the time of planting, increasing the possibility of delayed drilling and potentially contributing to the negative correlation between February rainfall and yield (Table S4) (Craig & Hawkins, 2020; Shaw, 1903). Nationally, the 1903 growing season received over 20% more rainfall than average (Figure 5), contributing to greater cloud coverage and lower than average growing season PAR (Figure 11), notably during April, May, June and July. Reduced solar radiation interception during the grain fill period in June and July constrains photosynthesis, reducing the contribution to final ear weight amassed in this period (TEAGASC, 2017). The 1903 growing season was also cooler than average (Figure 12) with low GDDs (Figure 6). This coincides with the year of lowest mean yields and greatest yield variability for *Archer*, but much lower variability for *Goldthorpe* ($SD = 0.22$ t/ha) (Figure 2).

A more recent experiment detailed by Gothard et al. (1983) found that *Goldthorpe* outperformed *Archer* when spring and summer rainfall was high. Along with our results, this suggests *Goldthorpe* may be able to withstand much higher soil moisture and waterlogging. Hunter (1929) notes that *Goldthorpe* requires plenty of moisture to produce the best yields and quality, supporting this theory. Continual dampness can also increase disease pressures for diseases such as Barley Scald (*Rhynchosporium*) which prefer cool wet weather and which, if present early in the season, can reduce tiller survival and potential yields (TEAGASC, 2017). If Barley Scald was present in 1903, the results may indicate greater resistance of *Goldthorpe* to the disease at that time.

In contrast, the 1905 growing season was warmer than average (Figure 12) with high growing season GDDs (Figure 6). There was low growing season PAR (Figure 11), but high PAR in July, when high solar radiation is important for grain fill. The growing season was drier than

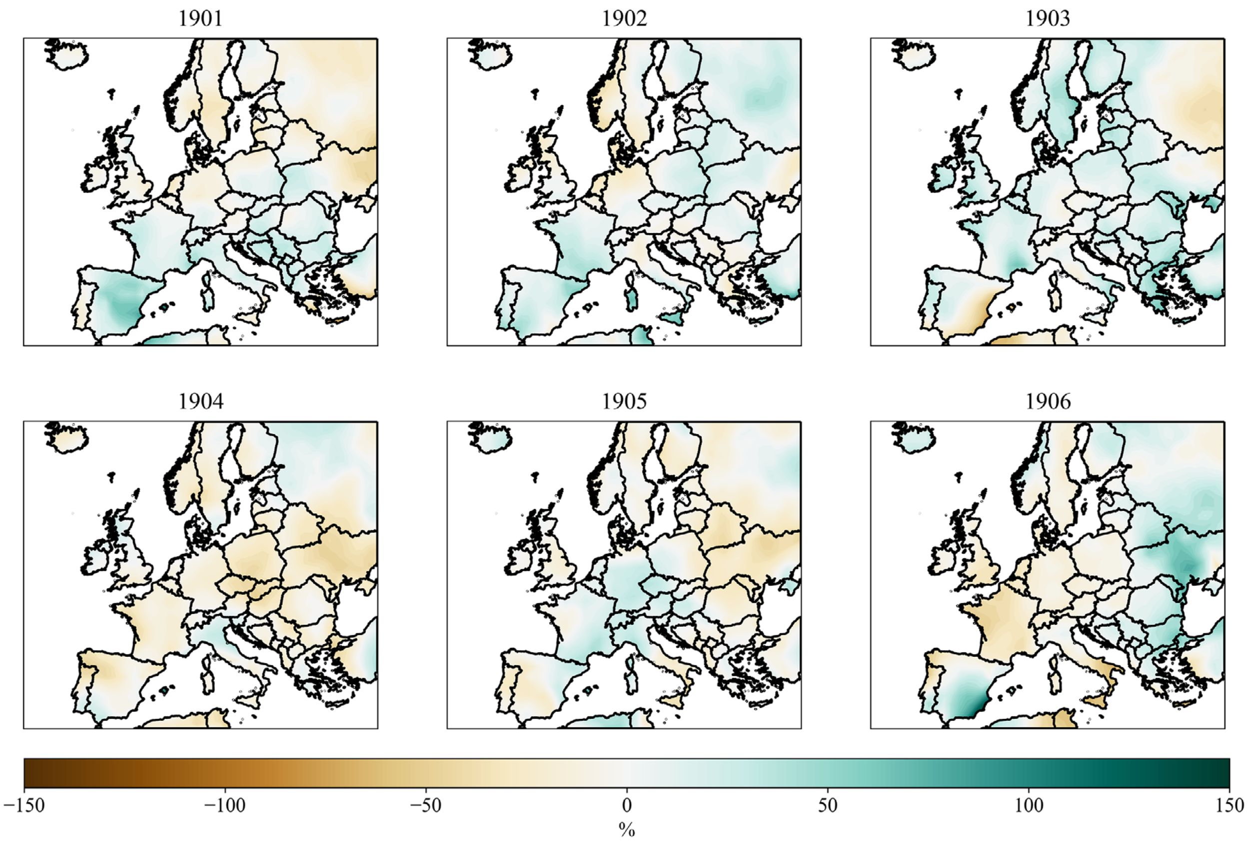

FIGURE 10 Growing season (March to August) rainfall anomalies (%) relative to the 1901–1930 average. Brown corresponds to drier than average and blue corresponds to wetter than average. Data from ERA-20C (Poli et al., 2016).

average, starting wet but drying in June and July (Figure 7). These favourable conditions likely contributed to the relatively high yields seen in 1905 for both varieties.

Of the farms with 6 years of trials data, Farmer Wolfe performed the best on average (Figure 3). This farm was located approximately 30 km south-west of Birr Castle and experienced higher summer temperatures and less summer rainfall than the other two farms. Other factors such as favourable agronomy, farm management and soil type may also have encouraged higher yields here.

4.2 | Statistical methods

Through trialling various variable selection methods, we have highlighted the importance of identifying collinearity early on in analysis involving multiple covariates. The use of these methods and PCA was limited by the high correlation between covariates within a small dataset, but it was still possible to extract information on the most important variables using simple mixed models. We were able to show that July maximum temperature and August maximum temperature had a positive relationship with yield and that July total rainfall had a negative relationship with yield (Table 2). July rainfall can also be used as a proxy for solar radiation, so a wet July would usually be associated with more cloud cover, reducing solar radiation interception during grain fill. Likewise wet weather during grain filling can encourage ear and grain diseases, such as fusarium ear blight and ergot, which can cause shrivelled grain and mycotoxins (AHDB Cereals & Oilseeds, 2018). Hence the plant benefits from more solar radiation and less rainfall in July. Higher July maximum temperature implies less daytime cloud cover intercepting solar radiation, hence the correlation between these two July variables and yield is of opposite polarity. In future analysis of more recent crop yield data, inclusion of solar radiation data in the models would be desirable to directly quantify the relationship between solar radiation and yield.

Our finding that July temperatures are positively correlated with spring barley yield contrasts with other published research which shows that warmer temperatures during anthesis and grain fill can have a detrimental effect (Addy et al., 2021; Hakala et al., 2020). This result is highly likely due to July maximum temperatures in Ireland in the early 20th century falling well short of those more regularly seen today in some major UK spring barley growing areas. Specifically, maximum temperature did not exceed 28°C during the 6-year trials period whereas those in South-East England now regularly exceed 30°C in summer months. This finding shows the importance of region-specific crop-climate research: despite the proximity of the UK to Ireland their climates differ and the same relationships between weather variables and yield cannot be assumed.

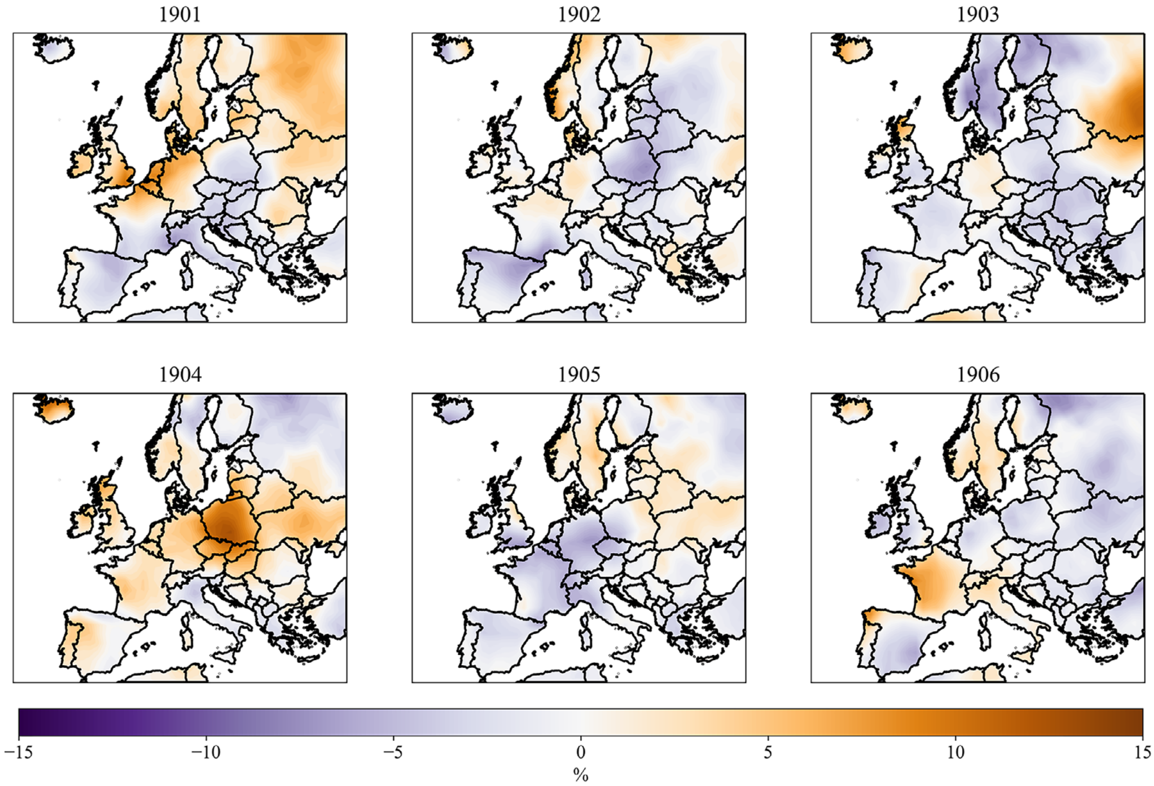

FIGURE 11 Growing season (March to August) total photosynthetically active radiation (PAR) anomalies (%) relative to 1901–1930 average. Purple corresponds to less PAR than average while orange corresponds to more PAR than average. Data from ERA-20C (Poli et al., 2016).

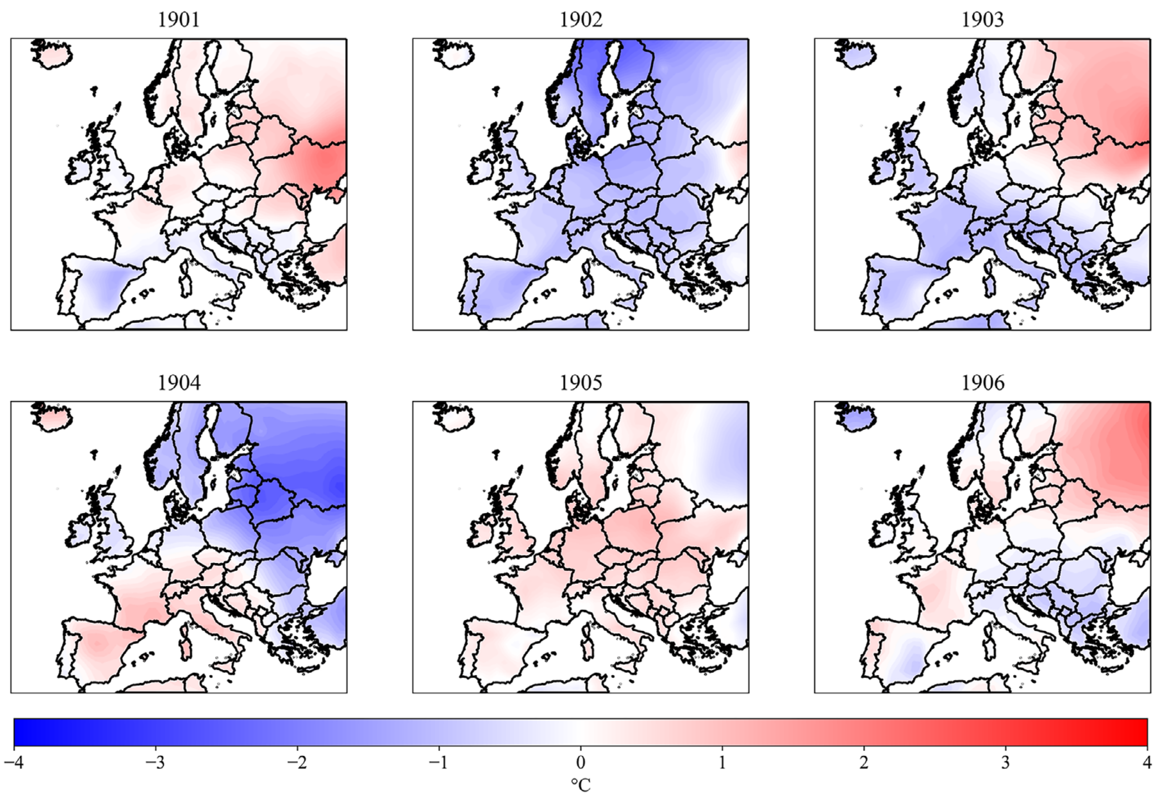

FIGURE 12 Growing season (March to August) mean temperature anomalies (°C) relative to 1901–1930 average. Blue corresponds to colder than average while red corresponds to warmer than average. Data from ERA-20C (Poli et al., 2016).

TABLE 2 Statistical significance (*F*-test) and corresponding coefficient of each climate variable in the mixed model (2) with year, variety and sites within years.

Climate variable	Significance in model	Coefficient	AIC	Marginal R^2	Conditional R^2	RMSE
-	-	-	127.5	0.033	0.78	0.207
Jul_temp_max	**0.004**	0.27	123.6	0.22	0.79	0.209
Aug_temp_max	**0.024**	0.20	127.4	0.16	0.81	0.208
Jul_rain_tot	**0.028**	−0.0069	135.0	0.17	0.77	0.207
Apr_temp_min	0.06	−0.097	130.0	0.091	0.80	0.207
Jun_temp_min	0.09	−0.11	130.4	0.061	0.81	0.207
May_temp_min	0.1	−0.10	130.5	0.067	0.78	0.207
Mar_temp_min	0.1	−0.095	130.7	0.068	0.79	0.207
Jun_temp_max	0.1	0.11	130.6	0.084	0.78	0.206
Jun_rain_tot	0.1	−0.0037	137.4	0.068	0.77	0.206
Mar_rain_tot	0.2	−0.0035	137.7	0.080	0.79	0.207
May_temp_max	0.2	0.098	131.2	0.066	0.80	0.207
Jul_temp_min	0.3	−0.075	131.9	0.048	0.80	0.206
May_rain_tot	0.5	0.0034	137.8	0.047	0.81	0.206
Aug_temp_min	0.5	−0.044	132.5	0.039	0.79	0.206
Apr_rain_tot	0.6	0.058	132.0	0.036	0.80	0.206
Mar_temp_max	0.6	−0.0020	138.6	0.042	0.79	0.206
Aug_rain_tot	0.6	0.062	131.5	0.037	0.79	0.206
Apr_rain_dmax	0.7	−0.0013	139.0	0.033	0.79	0.206
Apr_temp_max	0.8	−0.026	131.7	0.033	0.79	0.206

Note: Significant variables are shown in **bold**. The Akaike Information Criterion (AIC) of the overall model is given, with lower values corresponding to a better model fit. Marginal R^2, conditional R^2 and root mean square error (RMSE) are also given. The conditional R^2 takes both the fixed and random effects into account while the marginal R^2 considers only the variance of fixed effects (Nakagawa et al., 2017).

We were unable to detect any G×E within the mixed models used. The lack of significance throughout of climate variety interactions may well be related to the relatively small trials dataset, approximation of site locations and sometimes large distances to weather stations. However, it is clear from the higher performance of *Goldthorpe* in 1903 relative to *Archer* coupled with wider evidence (Gothard et al., 1983; Reid et al., 1929) that G×E is a driver of performance here. This highlights the importance of considering the local climate in crop variety selection.

The last few years have seen a surge in the growing of heritage barley varieties from the early 20th century. *Goldthorpe*, its predecessor *Chevalier* and offspring *Irish Goldthorpe*, as well as hybrids of *Archer*, such as *Plumage Archer*, have been grown for breweries across the UK and Ireland and are currently being investigated by organisations such as New Heritage Barley. Some heritage varieties display highly desirable traits, such as Fusarium fungal disease resistance in *Chevalier* (UKRI, 2015). How these varieties perform in the current and future climate is of interest given the performance of these varieties in the 1901–1906 trials. It is hoped that *Archer* and *Goldthorpe* will be trialled on large scale field plots to allow for comparisons with the yields from 1901–1906, but also to enable application of our modelling using current climate data with larger datasets.

4.3 | Historical perspective of Student's, 1923 paper

Student's comments in 1923 on the requirement for large scale farm testing remains as relevant today. In recent years a greater emphasis is also placed on grower input through participatory breeding approaches (Ceccarelli et al., 2007; Weltzien & Christinck, 2017) and large-scale farm trials in strip tests (Lacoste et al., 2022; Marchant et al., 2019; Piepho et al., 2011).

Student states that the advantage for the farmer of large scale trials is that s/he '…always has a healthy contempt for gardening' and … 'some varieties which have come out well on the small scale have not done as well in the field, though this is not at all common'. That said, two-acre plots (0.8 ha) are very large, as Student recognises, even for large-scale plots, though the produce was also intended to provide seed for subsequent manufacturing tests, presumably including malting, though we have no record that they took place.

The importance of collaboration is also commented on: here between farmers in carrying out large scale experiments—'… it is only by co-operation [between farmers] that enough evidence can be obtained to be of any value', though he sees such co-operation as being most likely co-ordinated by government bodies. It is unfortunate that, as far as we are aware, any collaboration that has occurred has not incorporated evaluations of sets of varieties across farms and has not been published.

Another laudable feature of Student's paper is that he made the data available. Admittingly this was largely to illustrate the method of analysis, but full data release is still not the norm. Subsequently, the data was reanalysed by Patterson (1997), also for educational purposes. We do not know whether Student had soil and weather records available to him (he was analysing the yield data when it was already 20 years old) or whether he would have felt it advantageous to include them. In fact, we find near identical results to Student: *Archer* yields more than *Goldthorpe*. In the absence of any detectable variety × climate variable interactions (as here), this is expected. The climatic variables which are available to us have, however, been used to identify drivers of yield differences between sites and years in a dataset approximately 120 years old.

5 | CONCLUSION

Through combining recently published historical rainfall and temperature data with spring barley trials data, it has been possible to identify climatic influences on spring barley yield variability seen in early twentieth century trials data in Ireland, building on the earlier findings of Student (1923).

Despite being available for approximately 100 years, we have demonstrated that there is value in adding historical climate data to this small trials' dataset. Today's large-scale trial datasets provide a great opportunity for further insight on crop-climate interactions in a changing climate.

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CONFLICT OF INTEREST STATEMENT

The authors have no competing interests to declare.

ORCID

Joanna Raymond https://orcid.org/0000-0002-8815-528X

Ian Mackay https://orcid.org/0000-0002-1109-4730

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