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The impact of weather patterns on inter-annual crop yield variability

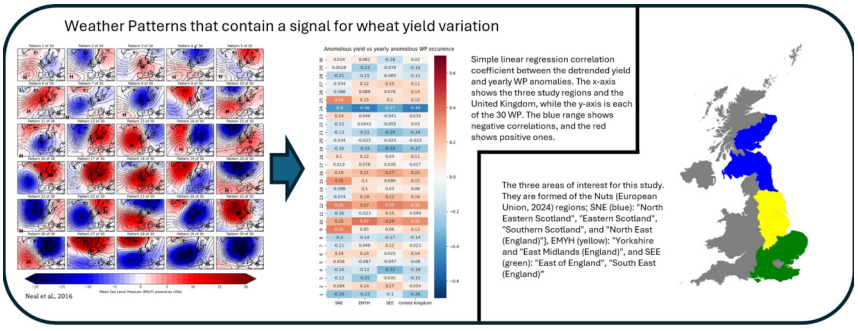
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HIGHLIGHTS

- Weather patterns exhibit a complex relationship with interannual variations in UK Winter Wheat yields.
- Northern UK shows differing relationship between weather patterns and yield compared to East and Southeast England.
- Future predicted weather pattern changes suggest that soils will need to store moisture to prevent yield reduction.

GRAPHICAL ABSTRACT



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ABSTRACT

Inter-annual variations in crop production have significant implications for global food security, economic stability, and environmental sustainability. Existing crop yield prediction models primarily using meteorological variables may not adequately encapsulate the full breadth of weather influences on crop development processes, such as compound or extreme events. Incorporating weather patterns into crop models could provide a more comprehensive understanding of the environmental conditions affecting growth, enabling more accurate and earlier yield predictions.

Our study examines 30 distinct UK Met Office weather patterns (MO30) based on mean sea level pressure. We investigate their association with weather conditions that limit winter wheat yield in the UK (1990–2020). Blocked, negative North Atlantic Oscillation (NAO) patterns create the highest risk of temperatures that are below optimal for crop yield. However, the connection between weather patterns and yield is complex, with differing effects at a regional scale and even at which point in the growth cycle they appear. It was found that anticyclonic weather patterns during sowing, emergence, vernalisation, anthesis, and grain filling exhibit a relationship with good crop yields with a Spearman correlation coefficient of up to 0.55 for a single weather pattern (WP3 during vernalisation in South East England), whilst cyclonic patterns can help during the terminal spikelet phenological phase. The strongest positive correlations were during sowing, emergence, and vernalisation, whilst the largest negatives were observed in anthesis and grain filling.

The potential of combining weather patterns with existing crop simulation models to produce earlier and more accurate yield predictions is shown. This would enable effective crop management and climate mitigation strategies, critical to strengthening food security. Projected changes in weather pattern occurrences in the late 21st century will likely reduce crop yields. This is due to increased cyclonic weather patterns, which bring

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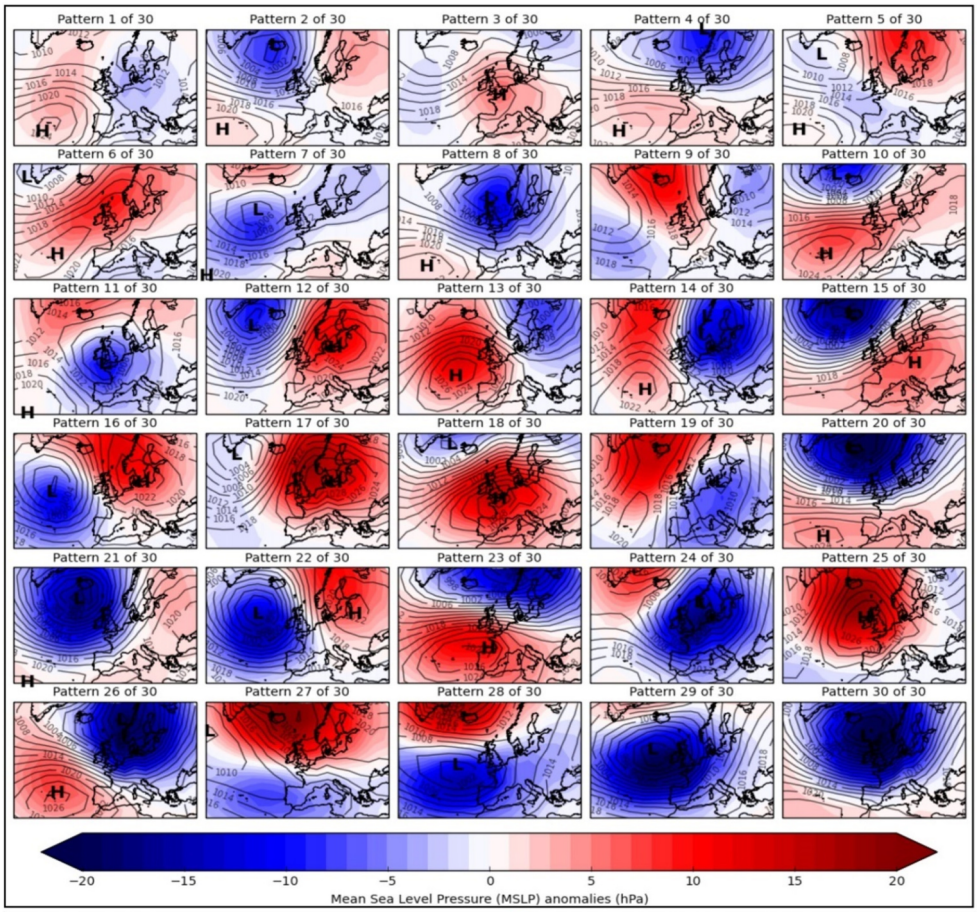
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warmer, wetter conditions during the wheat's vernalisation stage, followed by warmer, drier conditions during the anthesis and grain-filling phases.

1. Introduction

The world's agricultural landscape is dynamic and complex, with interactions between various meteorological, geographical, and agronomic factors that collectively influence crop yields (Lesk et al., 2016; Lobell et al., 2011). Inter-annual variations in crop production have significant implications for global food security, economic stability, and environmental sustainability (Kang et al., 2009). Understanding the underlying drivers of these fluctuations is a critical endeavour, particularly in an era marked by an accelerated change in climate patterns and a growing global population (Alexandratos and Bruinsma, 2012). Among these drivers are atmospheric circulation patterns, which play a crucial role in shaping weather conditions that affect agricultural productivity.

Circulation types represent specific configurations of atmospheric patterns, often associated with recurring weather conditions. In this



1 NW, Unbiased	16 S-SE, Anticyclonic, high east of Denmark
2 SW, Cyclonic, returning polar maritime airmass	17 E-SE, Anticyclonic, high over Denmark
3 SW, Anticyclonic, high over northern France	18 SW, Anticyclonic, high over northern France
4 Westerly, Unbiased	19 Northerly, Unbiased, low east of Denmark
5 Southerly, Unbiased, high over Scandinavia	20 Westerly, Cyclonic, intense low near Iceland
6 Azores high extension towards the UK, Anticyclonic	21 SW, Cyclonic, deep low south of Iceland
7 SW, Cyclonic, low W-NW of Ireland	22 Southerly, Cyclonic, low west of Ireland
8 Westerly, Cyclonic, low near Shetland	23 Westerly, Unbiased, windy in the north
9 N-NE, Anticyclonic, high near Iceland	24 Northerly, Cyclonic, low in the North Sea
10 W-SW, Anticyclonic, slight Azores high ridge	25 Northerly, Anticyclonic, high centred in the Irish Sea
11 Low centred over southern UK, Cyclonic	26 NW, Cyclonic, low near Norway, very windy
12 Southerly, Anticyclonic, high over Poland	27 Easterly, Anticyclonic, high in Norwegian Sea
13 NW, Anticyclonic, high SW of Ireland	28 SE, Cyclonic, low southwest of UK
14 N-NW, Cyclonic, low near southern Sweden	29 S-SW, Cyclonic, deep low west of Ireland
15 SW, Unbiased, windy in northwest Britain	30 W-SW, Cyclonic, deep low SE of Iceland

Fig. 1. Definitions for the set of 30 weather patterns (MO30, Mean Sea Level Pressure anomalies, hPa, Neal et al. (2016)). The numbers correspond to each weather pattern's flow over the UK. Numbers in blue represent cyclonic patterns, red indicates anticyclonic patterns, and black signifies unbiased patterns. Abbreviations: NW = northwesterly, S-SE = south-southeasterly, SW = southwesterly, W-SW = west-southwesterly, N-NE = north-northeasterly, E-SE = east-southeasterly.

paper, circulation types encompass Weather Patterns (WP) and Weather Regimes. A WP is characterised by the persistence of a specific atmospheric circulation system over a defined geographic area, typically for a duration of approximately one to a few days, as noted by various research (James, 2007; Lamb, 1972; Neal et al., 2016). In contrast, WRs are distinguished by a smaller set of patterns with longer duration, often extending up to a week (Fereday et al., 2008; Ferranti et al., 2015; Vautard, 1990). While alternative terminology and definitions exist, this paper adopts these terms and their associated meanings for clarity.

In this paper, we use a classification of WP developed by the UK Met Office known as MO30 (Neal et al., 2016). Fig. 1 provides a visual representation of the MO30 and offers a detailed description of each WP. The patterns were derived by applying a clustering algorithm to the European and North Atlantic Daily to Multi-Decadal Climate Variability (EMULATE, Ansell et al. (2006)) dataset. EMULATE provides a gridded daily historical Mean Sea Level Pressure (MSLP) anomaly dataset for a North Atlantic–European domain (30°W–20°E, 35°–70°N) at a 5° vertical and horizontal resolution spanning from 1850 to 2003. The MO30 classification has been applied in various contexts, including medium to long-range weather forecasting (Neal et al., 2024), fluvial and coastal flooding (Hendry et al., 2019; Neal et al., 2018; Schillereff et al., 2019), drought analysis and prediction (Richardson et al., 2018, 2020a, 2020b), characterisation of precipitation (Fereday et al., 2018; Richardson et al., 2020a, 2020b), temperature analysis (Kendon et al., 2020), forecasting lightning activity (Souto et al., 2023, Hayward et al., 2022; Wilkinson and Neal, 2021), marine operations and forecasts (Steele et al., 2017, 2018, 2022), future climate change impacts (Cotterill et al., 2023; Perks et al., 2023; Pope et al., 2022), volcanic ash disrupting UK air space (Harrison et al., 2022), weather-induced power outages in the national grid (Souto et al., 2024), business performance (Brown et al., 2019), and temperature-related excess mortality (Huang et al., 2020).

Crop yields are highly sensitive to temperatures outside the optimal range. Excessive high and low temperatures can reduce the production of dry matter and, in extreme cases, even halt growth entirely (Grace, 1988). Plants react more to absolute temperature changes than relative ones, showing distinct threshold responses to temperature. This differs from their response to water deficiency, where water uptake and dry matter production have a continuous and resilient connection across a broad spectrum of water availability (Tanner and Sinclair, 1983). Excessive rainfall can significantly reduce crop yields, similar to the effects of extreme drought. This is due to waterlogging, poor soil drainage, and increased soil water storage, which negatively affect plant growth and yield (Li et al., 2019; Slater et al., 2021).

Most of the commonly used crop simulation models, such as AquaCrop (Steduto et al., 2009), APSIM (Keating et al., 2003), SIRIUS (Jamieson et al., 1998), Yield-SAFE (Van Der Werf et al., 2006), CERESWheat (Bannayan et al., 2003) and WheatGrow-PROSAIL (L. Zhang et al., 2016), use precipitation, air temperature, and/or solar radiance to represent environmental conditions. While these models have been very successful in simulating and forecasting yield, they have limitations due to data availability (Corcoran et al., 2023). Weather can account for 80 % of crop yield variability (Hoogenboom, 2000), but these models do not consider how weather also affects interconnected processes such as pollinator activity and yield (Aldercotte et al., 2022; Kammerer et al., 2021; Reilly et al., 2020). Using WPs can help generalise the environment rather than focusing on specific meteorological variables such as temperature, humidity, and precipitation. Given the increased accuracy of models forecasting WPs at the medium to long range (beyond five days) (Büeler et al., 2021; Ferranti et al., 2015; Matsueda and Palmer, 2018; Neal et al., 2016, 2024), integrating them into crop growth simulation models could produce earlier predictions and improve accuracy.

There is a significant research gap in understanding the influence of WPs on crop yields, particularly regarding inter-annual variations in UK winter wheat. The present study aims to investigate the relationship between WPs and interannual crop yield variability, ultimately informing agricultural decision-making, resource management, and policy development by providing earlier and more accurate yield forecasts. The specific objectives are to 1) identify which WPs are associated with yield-limiting weather conditions, 2) investigate the direct relationship between WPs and crop yield across various winter wheat growth stages and regions, and 3) evaluate the implications of climate change on crop yields through future changes in WP occurrence.

2. Data and methods

2.1. UK wheat yield data

National and regional Winter Wheat (WW) yield data were obtained from the UK Department for Environment, Food and Rural Affairs (Defra, 2023) for the three main EU Nomenclature of Territorial Units for Statistics (NUTS) (European Union, 2024) growing regions in the UK (now referred to as International Territorial Levels (ITLs) in the UK). The geographic focus was on these central wheat production regions, which are (i) Northeastern Scotland, Eastern Scotland, and the Northeast England region (Northern, SNE); (ii) East Midlands, Yorkshire, and the Humber regions (Midlands, EMYH); and (iii) Southeast and Eastern region (Southern, SEE) (Fig. 2). All are level one NUTS/ITL regions except Northeastern Scotland and Eastern Scotland, which are level two. Combined, these areas account for over 80 % of wheat production in the UK (Defra, 2023). This Defra dataset is part of an annual survey of the UK agricultural industry. It is taken from the England Cereals and Oilseeds Production Survey and Scotland Cereal Production and Disposal Survey. National data starts in 1885, while regional data begins in 1990.

Measuring and contrasting the impact of WPs on annual WW yields over decades and across regions is a complex task due to the multitude of factors influencing both short (each season) and long-term (5–10 years) crop yield. The long-term factors encompass advancements in science and technology, such as plant genetics, fertilisers, pesticides, and irrigation systems, and short-term effects, such as meteorological conditions (highlighted in Supplementary Fig. 1). As a result, long-term WW yield data is non-stationary, characterised by varying means and standard deviations over long periods. To effectively model and visually represent the impact of WPs on agriculture, it is crucial to remove the long-term trends. Lu et al. (2017) reviewed several methods for detrending yield data, identifying the locally weighted smoothing curve (LOWESS) as one of the most effective approaches. LOWESS fits a smooth, locally weighted regression line through the data points, effectively capturing the underlying trend while minimising the impact of short-term fluctuations and outliers. By fitting this smooth curve to the yield data, LOWESS estimated the trend component. The yield values are divided by this estimated trend line to remove the long-term variations. This detrended data reveals the underlying seasonal and residual variations (yield anomalies).

We report the Spearmen correlation coefficient to determine whether there is a connection between anomalous WP occurrences and anomalous WW yields. Using the Northern, Midlands, and Southern regions, we compare the results of national and regional datasets.

2.2. Meteorological data

Daily minimum (T_{min}) and maximum (T_{max}) temperature data, as well as daily total precipitation data, were obtained from the HadUK-Grid 1 km observational dataset provided by the UK Met Office through the Centre for Environmental Data Analysis (Hollis et al., 2019). This gridded dataset was used to calculate regional averages of the meteorological variables for our areas of interest, Northern, Midlands, and Southern.

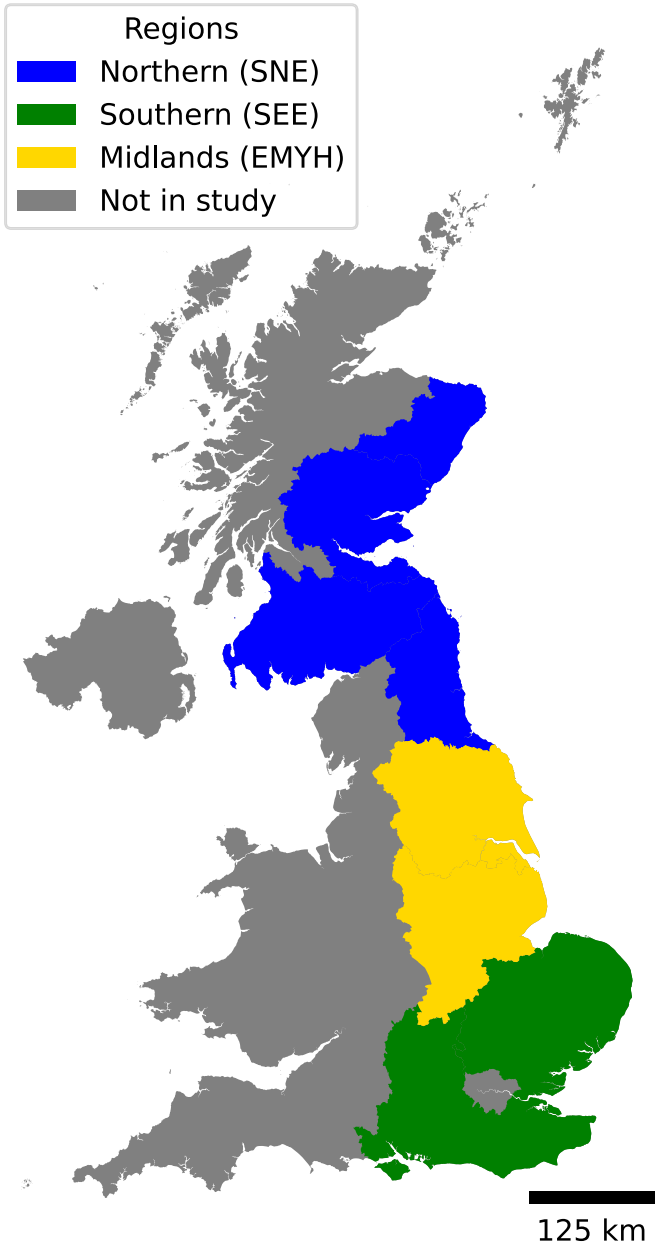


Fig. 2. The three areas of interest for this study. They are formed of the Nuts (European Union, 2024) regions: Northern, SNE (blue): "North Eastern Scotland", "Eastern Scotland", "Southern Scotland", and "North East (England)", Midlands, EMYH (yellow): "Yorkshire" and "East Midlands (England)", and Southern SEE (green): "East of England", "South East (England)".

2.3. Weather pattern occurrence data

A daily historical MO30 WP classification dataset (Neal, 2022) was used. This dataset is based on daily MSLP from the ERA5 reanalysis (Hersbach, 2020). The process involves converting 1200 UTC ERA5 MSLP fields to anomalies, using a smoothed ERA5 daily climatology for the same period. The anomalies are then assigned to the closest matching WP definition from MO30 (Fig. 1), also defined by its MSLP anomalies. The assignment method is determined by pairing with the smallest grid point average sum of squared differences (Harrison et al., 2022; Neal et al., 2016).

2.4. Connecting WP to crop-limiting weather conditions and yield

While many studies linking weather patterns to extreme weather events focus on meteorological definitions (e.g., emphasising the magnitude and rarity of events like annual maxima or events exceeding thresholds) (Neal et al., 2018; Richardson et al., 2018, 2020a, 2020b), this study adopts an agricultural perspective. We define extreme temperatures based on their direct impact on crops rather than solely on their statistical frequency. Crop sensitivity to weather conditions varies across phenological stages (Porter and Gawith, 1999). Therefore, we divide the crop calendar year into four key phases: sowing to emergence (Planting), which is hereafter termed the planting stage for simplicity (the initial growth phase when seeds germinate and seedlings emerge); Vernalization (Growth), referred to as the establishing stage (a cold period crucial for the plant's development and flowering); Terminal Spikelet (Heading), termed the heading stage (when the plant develops its grain-bearing structures); and Anthesis and Grain-filling (Filling), referred to as the filling Stage (the final phase when the plant flowers and produces grains). These stages' dates and associated optimal minimum and maximum temperatures are summarised in Table 1. To identify weather patterns associated with exceeding crop-specific extreme temperature thresholds, we analysed T_{min}, T_{max}, and WP anomalies for key phenological stages over the period from 1990 to 2020. We identified dates when T_{min} and T_{max} exceeded extreme temperature thresholds for WW and recorded the corresponding weather patterns. Finally, we calculated the percentage of each WP's total occurrence during each phenological stage that coincided with extreme temperature events.

Access to water significantly impacts wheat yields (Clarke et al., 2021; Kuresova et al., 2022; Lu et al., 2017), as it is a rainfall-dependent crop susceptible to water availability throughout its growth cycle. Building upon the work by Richardson et al. (2018), which highlighted the utility of MO30 patterns for regional precipitation and drought analysis; we identified the WP that can affect access to water in our defined growing regions and key phenological stages. Our analysis examines daily precipitation distributions for the three study regions during specific MO30 patterns. We employ the Standardised Precipitation Index (SPI, Mckee et al. (1993)) to classify wet months (SPI3 value above one) and dry months (SPI3 value below minus one). We then calculate each MO30 pattern's anomalous occurrences across the study period (1990–2020). This allows us to identify specific MO30 patterns that consistently coincide with wet periods in all three regions of interest and during which key phenological phase they have the strongest connection.

We use WP occurrence anomalies, calculated by taking the climatology of daily WP occurrences over each growth stage from 1990 to 2020. The climatology is then subtracted from the observed occurrences for each growth stage over the study period. We also calculate WP anomaly occurrences over the entire WW growing season, which spans from September to August of the following year.

Table 1
Summary of UK lethal minimum and maximum temperatures (°C) of winter wheat (WW) along with base (Tmin), optimum (Topt), and maximum (Tmax) for the key phenological phases and the corresponding meteorological season (e.g. SON:Sep, Oct, Nov), (Porter and Gawith, 1999; AHDB, 2023).

Phenological phase	Meteorological seasons	T_{min}	T_{opt}	T_{max}
Lethal limits	All year	−17.2	N/A	47.5
Sowing to emergence (Planting)	Autumn, SON	3.5	22.0	32.7
Vernalisation (Growth)	Winter, DJF	−1.3	4.9	15.7
Terminal spikelet (Heading)	Spring, MAM	1.5	10.6	20.0
Anthesis and grain-filling (Filling)	Summer, JJA	9.5	20.85	31.0

2.5. Using WP to determine the impact of climate change on WW yield at a regional scale

By utilising future projections of MO30 occurrences in the late 21st century (Pope, 2024), based on the UK Climate Projections (UKCP) 2018, we discuss these projections to our study's findings on their potential impact on winter wheat yields in the UK. We examine how changes in occurrence at each phenological stage could influence overall yield.

2.6. Interpreting the links between WP and WW yields through Defra reports

Here, we look at 2012 and 2019 yields to demonstrate how the research findings can be applied to analyse end-of-year yields. According to Defra's annual report, 2012 was an exceptionally poor year (Defra, 2013), whereas 2019 was notably favourable (Defra, 2021). These reports provide official UK Government statistics on farming output, along with excerpts from the UK Met Office meteorological data. The data from these reports, combined with the published MO30 classifications for the relevant growing seasons, are used to compare with this study's findings.

3. Results and discussion

3.1. WP frequency distribution over the growing season

Higher-numbered WPs (12 and above), which Neal et al. (2016) associated with winter conditions, show a marked prevalence in the growth stage. This contrasts the Filling stage, where lower-numbered WPs (11 and below) are much more common, suggesting a clear distinction in weather patterns between phenological phases. The Planting and Heading stages correspond to transitional autumn and spring meteorological periods, displaying significant variability in WP occurrences. This variability indicates a broad transition in WPs as seasons change from the cold to the warm phases of the year and vice versa. The climatological distribution of MO30 WP (WP1 to 30) across different phenological stages of WW (i.e. Planting, Growth, Heading, and Filling) over the 30-year study period from 1990 to 2020 can be seen in Supplementary Fig. 2.

Across the 30-year study period from 1990 to 2020, higher-numbered WPs (12 and above), which Neal et al. (2016) associate with winter conditions, show a marked prevalence during the Establishing growth stage. In contrast, the Planting stage is dominated by lower-numbered WPs (11 and below), suggesting a clear distinction in WP between phenological phases. The Planting and Heading stages correspond to transitional autumn and spring meteorological periods, exhibiting significant variability in WP occurrences. This variability reflects the broad transition in weather patterns as the seasons shift between cold and warm phases of the year. The climatological distribution of MO30 WPs (WP1 to 30) across these phenological stages is presented in Supplementary Fig. 2.

3.2. WP anomalies during wet periods

Changes in rainfall patterns and increased evapotranspiration resulting from elevated temperatures lead to decreased wheat production, even in regions historically less prone to drought (Kuresova et al., 2022). Research on wheat grain yield under varying access to water conditions revealed that grain output fluctuated based on rainfall levels, with spike numbers showing a positive relationship with yield (Zhang et al., 2023). Notably, rainfall variability, especially during Growth, significantly influences wheat yields (Tafoughalti et al., 2018).

Here we used SPI3 to identify which WPs can be linked with particularly wet and dry phases to understand how they affect crops' water access in our three WW growth regions (only results for the Northern and Southern regions are plotted, as the Midlands show patterns similar to the Southern region). Fig. 3 shows that cyclonic WPs (in blue) are strongly linked with precipitation and wet periods in all regions and all phenological phases, especially during the crop establishment stage in the two left columns (Fig. 3). This corroborates with other studies that found cyclonic WPs, especially the higher numbered, more impactful patterns (WP12 and above) (Neal et al., 2016), are more prevalent during winter. This increases the chances of spells of heavy rainfall during the WW Growth phase. Persistent anticyclonic WP (in red) increases the risk of heatwaves and droughts during the Filling phase in the two right-hand columns (Fig. 3). The Planting stage is a transitional period for WP as the Northern Hemisphere shifts from warm to cold seasons (Autumn); it is often characterised by a mixture of WP, reflected in Fig. 3 by no WP standing out. During the Growth stage, all regions have strong WP20, 21, 22, 24, 29, and 30 occurrences during wet periods (at the top right of Northern and Southern regions Fig. 3). All these WP are cyclonic, with 8, 26, and 30 categorised as Positive North Atlantic Oscillation (NAO+), linked to stormy and wet weather over the UK. Unbiased (in grey) refers to WP that is not dominated by a clear cyclonic or anticyclonic pattern (Fig. 3) and does not correlate to wet or dry periods in any phase.

The four columns on the right of Fig. 3 show that most dry periods occur during the Filling phenological phase. This makes sense, given that these are mostly summer months. WP6, 10 and 12 are the most prevalent during dry periods, while WP4 and WP5 also occur frequently in the Northern and Midlands regions. WP6 is described as 'Anticyclonic Azores high extension towards the UK' (Richardson et al., 2018) and is a blocking negative NAO pattern. Other studies have linked Anticyclonic weather types with drought (Fleig et al., 2010; Richardson et al., 2018).

3.3. WP and excess temperatures

Increasing temperatures have been demonstrated to impact wheat production negatively, especially during the Filling stages of crop growth (Kuriachen et al., 2022; Sayilğan, 2016; Ullah et al., 2020). The heightened temperatures during flowering can decrease the grain count per spike, consequently impacting productivity (Hlaváčová et al., 2017). Here, we examine whether WP can be used to identify periods when extreme temperatures may affect crop yield.

Table 1 forms the basis of this study's definition of UK extreme temperature. T_{min} and T_{max} should not be interpreted as threshold values beyond which crops immediately begin losing yield or die. Even the 'lethal limit' value only defines the point when critical failures can begin to occur as Porter and Gawith (1999) defines temperatures below −17.2 ± 1.2 °C and above 47.5 °C as being terminal (Table 1). The UK has never recorded a temperature above this. During the study period, the maximum temperature was 38.7 °C on 25th July 2019 and the minimum was −16.2 °C on the 14th of January 1982. Throughout the study period, which spanned 10,958 days, temperatures exceeded T_{min} on 1418 days, accounting for 13 % of the study duration. Conversely, T_{max} was exceeded on only 241 days, representing 2.2 % of the total period. This pattern highlights the more significant impact of colder conditions on wheat cultivation in the UK.

WP19 (Unbiased northerly with a low east of Denmark) is the standout pattern for exceeding T_{min} in all regions and phases, as shown in Fig. 4. WP14 also regularly exceeds T_{min} in all regions and in all phases, while WP18 is the strongest for all regions during the Filling phase. Analysis of Fig. 4 shows that overall the 'Blocked, negative NAO' patterns (WP6, WP9, WP11, WP19, WP25, WP27, and WP28) are the most likely to drive temperatures below T_{min}, while the 'Zonal, positive NAO patterns' (WP4, WP8, WP20, WP23, WP26, and WP30) are less likely to do so. During the Filling phase, the negative NAO patterns often have high occurrence; however, the 'Anticyclonic west-south-westerly with a centre of high pressure over northern France' (WP3 and WP18) has the highest occurrence of exceeding T_{min}. This corroborates with other research that has found a high NAO index during Growth is

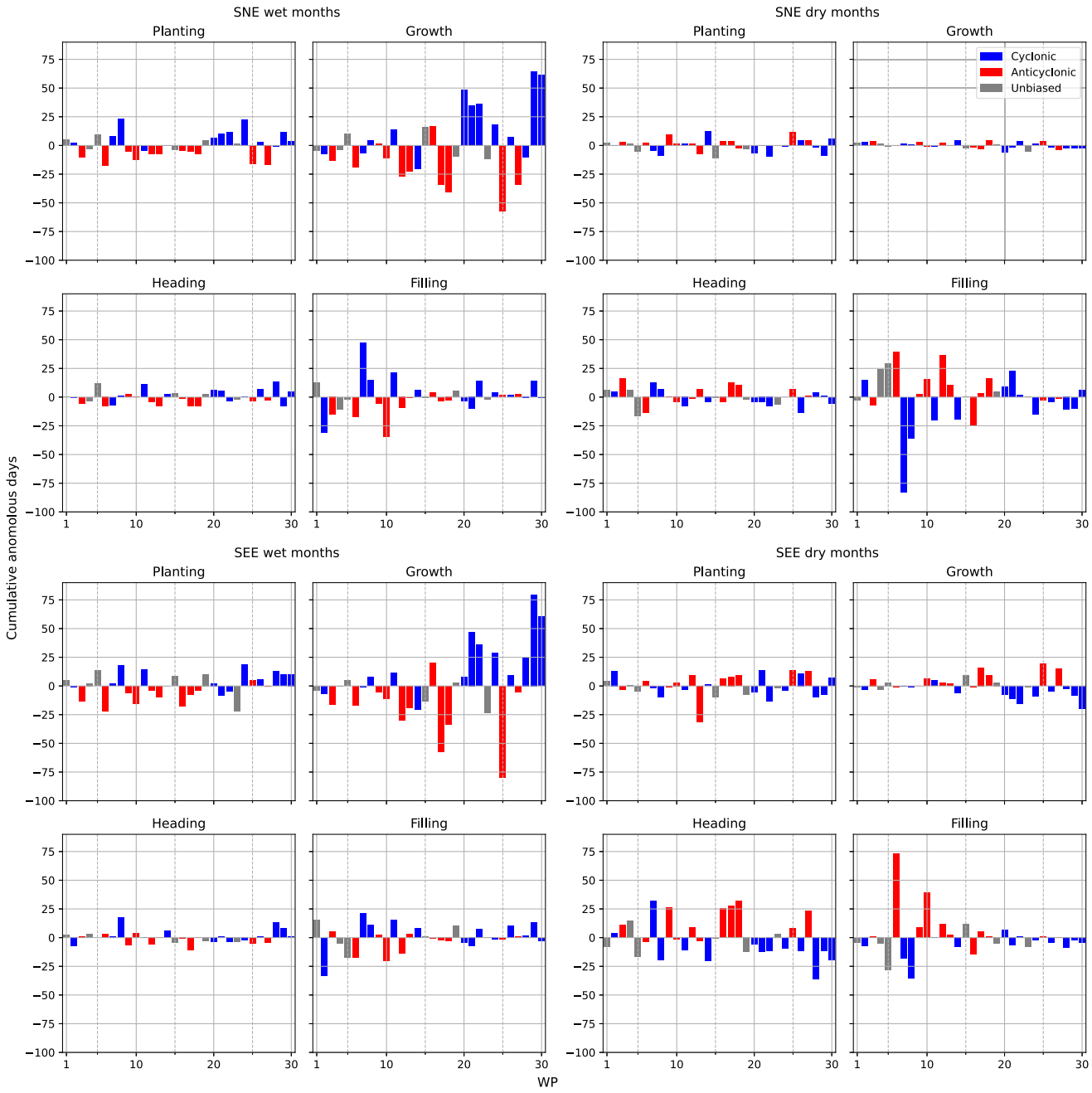


Fig. 3. The accumulated anomalous days when each WP (1−30) was observed during wet (SPI3 $\geq$ 1) and dry (SPI3 $<$ −1) months between 1990 and 2020. Blue bars highlight cyclonic WP, red bars are anticyclonic, and grey are unbiased. The top two rows show the Northern region, and the bottom two are for the Southern (Midlands and Southern are very similar, so Midlands was not included). The left four columns show wet periods, and the right four columns show dry periods. For both wet and dry periods, the data is further broken down into the four key phenological phases, top left of each region's rows and in a clockwise order: Planting, Growth, Heading, and Filling.

associated with better postharvest quality of the UK wheat crop (Atkinson et al., 2005) and can account for up to 6 % of globally aggregated wheat production variability (Anderson et al., 2019).

3.4. Direct association between WP and wheat yield variations

The previous sections investigated the links between WP and indirect yield contributors such as T_{min}, T_{max}, and precipitation. Fig. 5 shows the direct Spearmen coefficient correlation between WW yield anomalies and WP occurrence anomalies broken down into regions and growth stages. We can see that the strongest relationship between occurrence and positive anomalous yield during Planting is WP6 (anticyclonic), while the strongest with bad yield is WP24 for all regions apart from the North, which is WP26, both are cyclonic. While the strongest positive correlations are during the Planting and Growth phases, the strongest negative relationships are in the Filling phase, possibly hinting that early growth stages are important for good yield, whilst significant yield-limiting events can happen late in growth.

While good yield years typically have higher Anticyclonic WP occurrences in the Planting, Growth, and Filling phases, Cyclonic WP occurrences during the Heading phase can also help end-of-year yields. The Northern region is slightly different, as good yields are observed in years with higher Anticyclonic WP occurrences in all growth stages. This may result from the crop having better access to water due to higher

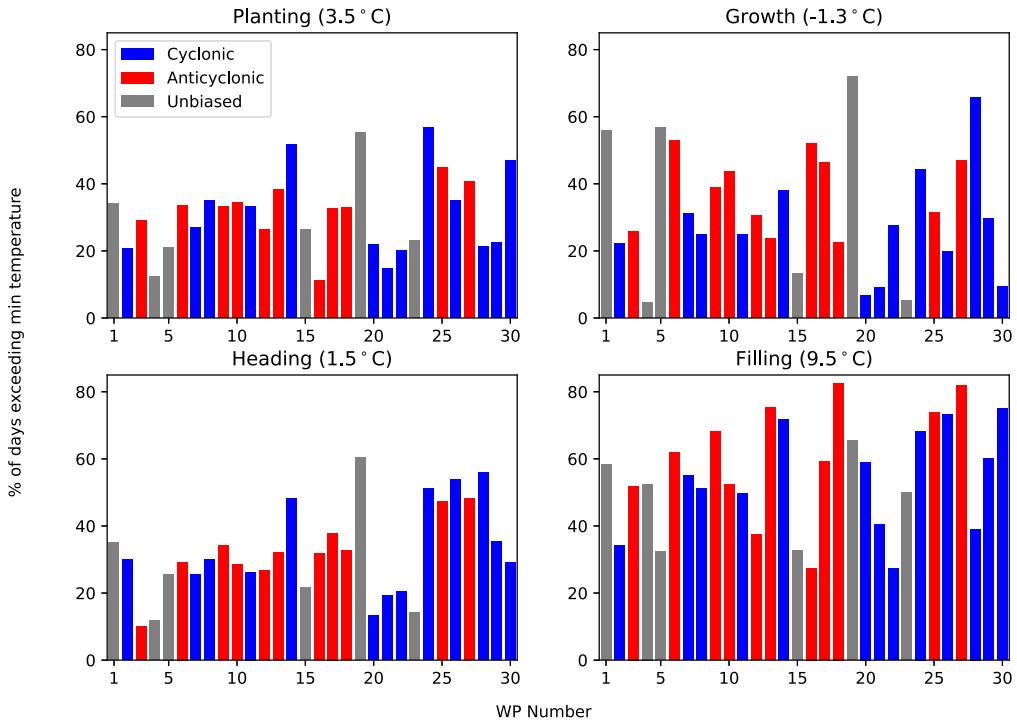


Fig. 4. The percentage of days that each WP occurred where temperatures were below the T_{min} threshold for WW in the Northern region (1990–2020), as defined by Table 1. Blue bars highlight cyclonic WP, red bars are anticyclonic, and grey are unbiased.

rainfall in the region, which means it doesn't rely on further rain during Heading. Cyclonic weather patterns have been connected to heavy rainfall and flooding, particularly during winter. This is evident from the record rainfall in 2013/2014 and 2019/2020 winters, driven by strong cyclonic atmospheric circulation and a positive NAO (Burt et al., 2015; Davies et al., 2021; Knight et al., 2017). The strongest positive correlations between detrended yield and WP anomalies are WP6 (Anticyclonic Azores high extension towards the UK) during the Planting phase, WP3 (Anticyclonic south-westerly with a high-pressure ridge over northern France) in the Growth phase, and WP25 (Anticyclonic northerly with a high centred in the Irish Sea) in the Filling phase, taken from Fig. 5. WP24 (Cyclonic northerly with a low in the North Sea) in the Planting phase, WP28 (Cyclonic southeasterly with a low southwest of the UK) during Growth, WP25 (Anticyclonic northerly with a high centred in the Irish Sea) in Heading, and WP29 (Cyclonic south-southwesterly with a deep low west of Ireland) in Filling were more strongly linked to bad yields. Examples of some complications are WP16 (Anticyclonic south-southeasterly with a high east of Denmark) and WP11 (Cyclonic with a low centred over southern UK). Despite being anticyclonic, WP16 has a negative correlation during the Growth stage and a positive one in the Heading phase, contrary to the overall findings. WP11 has a positive correlation during Planting and a negative in Growth, Heading, and Filling phases for the Northern region, while the Midlands and Southern regions have the opposite correlation, except for Growth in the Midlands, which has a minor agreement with the Northern.

Breaking WPs into their phenological phase occurrence anomalies shows improved correlations over using yearly data (Supplementary Fig. 3 is as Fig. 5 but shows yearly WP anomalies). Crops have differing thresholds and requirements at different stages of their growth (Table 1) and are susceptible to different stresses as they grow. Using yearly anomalies does not consider these differences and assumes that WPs have the same impact on crop growth and weather all year round.

3.5. Historical and future changes in WP and their impacts on crop yield

Fig. 6 shows the 10-year rolling average occurrence for each MO30 WP at an annual and seasonal scale. If we look at 1960 for WP1 (top-left panel of Fig. 6, leftmost point on the line), we can see that the 10-year rolling average yearly occurrence for this pattern is 15 days, as indicated by the blue line. The Planting, Growth, Heading, and Filling occurrences are represented by the purple, yellow, red, and green lines (respectively). Their sum is equal to the blue yearly line.

Fig. 6 highlights several key aspects of WP variability across different timescales. Specific WPs, such as WP8, WP14, and WP29, display variability, fluctuating over extended periods at the decadal to multidecadal scale. This indicates the presence of pronounced cycles in these patterns. Seasonal variability is also evident, with some WPs, like WP12 and WP21, showing minimal differences in occurrence across seasons, suggesting an even distribution throughout the year. In contrast, WPs like WP1 to WP5 exhibit more significant seasonal variability, with certain patterns more dominant during specific periods. Notably, higher variability is often associated with cyclonic patterns, reflecting these weather systems' more dynamic and fluctuating nature. The variability observed in some patterns may be linked to changes in large-scale atmospheric circulation over time, potentially driven by climate variability.

These occurrences are typically driven by changes in each WP typical season rather than becoming more prevalent during their offseason. As previously discussed, WP1-WP11 are more common during summer, with WP12-WP30 often appearing during winter. The decadal changes do not change that observation. If WP1-WP11 occur during the transitional phase of Autumn, it can be said this extends Summer, creating more dry and warm days over the year; if WP11–30 occur more often, it extends the Growth phase, meaning the year has more wintery, cold and wet periods. The same can be said for the other transition season, Spring.

Analysis of future WPs over the UK conducted by Pope et al. (2022), reveals a shift towards increased cyclonic and westerly wind conditions in winter, leading to warmer, wetter weather during Growth. At the same time, summers show a trend towards drier settled WP. Historically,

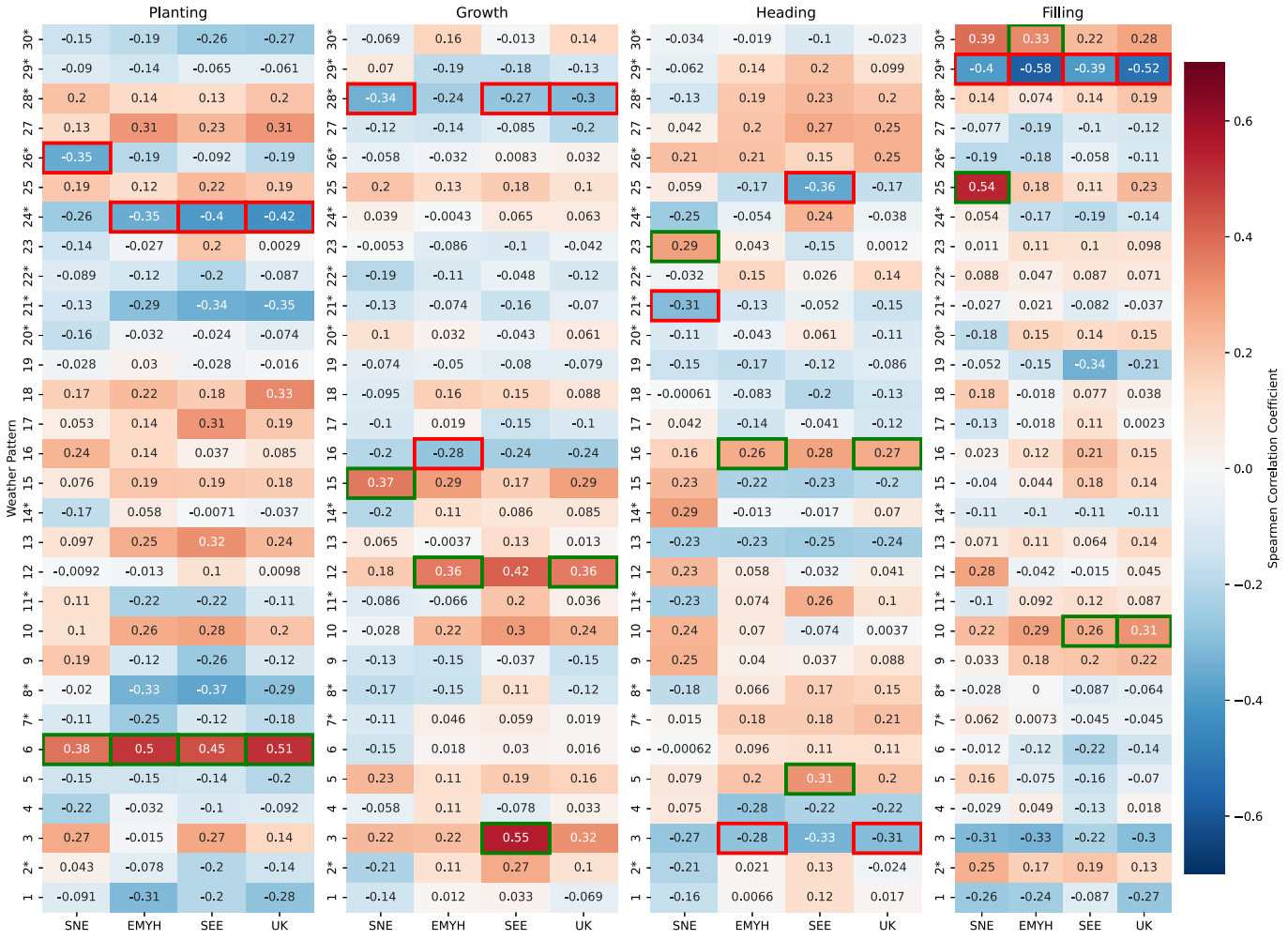


Fig. 5. Spearman correlation between the detrended yield and WP anomalies (1990–2020). Each of the four columns represents the phenological phases (Planting, Growth, Heading, and Filling); in each column, the x-axis shows the three study regions and the entire United Kingdom, while the y-axis indicates each of the 30 WPs. The blue range shows negative correlations, and the red shows positive ones. WPs with an asterisk on the y-axis denote that they are cyclonic. Correlation scores with a green outline indicate the column's (region) maximum value, while red outlines show the minimum. We can see that the cyclonic patterns during Planting correlate to good yield years yet bad yield years during Heading. WP6 during Planting shows a stronger correlation to good yield and WP29 in Filling for bad yield years.

we have seen those changes in the transitional seasons, Autumn and Spring, which can either shorten or lengthen Filling and Growth (from a meteorological perspective). It has been found that between 2071 and 2099, climate changes are expected to extend the summer period, with Planting becoming 4–14 % drier, which, combined with a warmer and also drier Filling, increases the likelihood of droughts (Cotterill et al., 2023). Table 2 summarises the change in WP occurrence expected by the end of the 21st century during each phenological phase.

In Section 3.4, we found a connection between cyclonic/anti-cyclonic WP anomalous occurrences at different key phenological phases and end-of-year yield. Using those results and combining them with the results from Cotterill et al. (2023) and Pope et al. (2022) we can deduce how climate change may impact each region at the end of the 21st Century. Given that the expectation is that Growth will become warmer and wetter and Filling will become drier, yield may become more dependent on how well soils hold their moisture. These changes could pose significant challenges to wheat production in the UK, particularly due to increased temperatures and altered rainfall patterns (Tataw et al., 2016). Hamble soils (silt loam) have the highest and sustained crop production compared to Fyfield (sandy) or Denchworth (clay) soils in the UK under water-limited production in these future scenarios (Ghaffari et al., 2002; Ludwig and Asseng, 2010; Nouri et al., 2016; Young, 1995). Warmer conditions have a complex impact on wheat yields, with positive effects observed in cooler climates, such as the UK, and negative effects in warmer regions (Grant et al., 2011; He et al., 2019; Hou et al., 2012; Ye et al., 2021; Zheng et al., 2017). WW generally benefits from moderate warming, while spring wheat suffers yield reductions. Genetic improvements and targeted breeding for heat tolerance, along with effective management practices, will become essential strategies to adapt to and mitigate the impacts of climate change on wheat production (Gourdji et al., 2013).

3.6. *Analysis of WW yield variations in relation to WP using Defra reports*

Here, we compare WP anomalies during a low-yield year (2012, see Section 3.6.1) and a high-yield year (2020, see Section 3.6.2), as identified by Defra's annual agricultural reports. The analysis uses compiled data to deepen our understanding of the climatic influences on yield variations, focusing specifically on the impact of WP anomalies in these contrasting years.

3.6.1. *2012 harvest, lower than the five-year average yield*

In 2012, the UK's wheat area increased by 1.1 %, while yields (6.66 t/ha) fell by 14 % compared to the previous year (7.7 t/ha), falling below the five-year average (7.66 t/ha). This was primarily due to disease pressure, limited sunlight during grain fill, and excessive rainfall

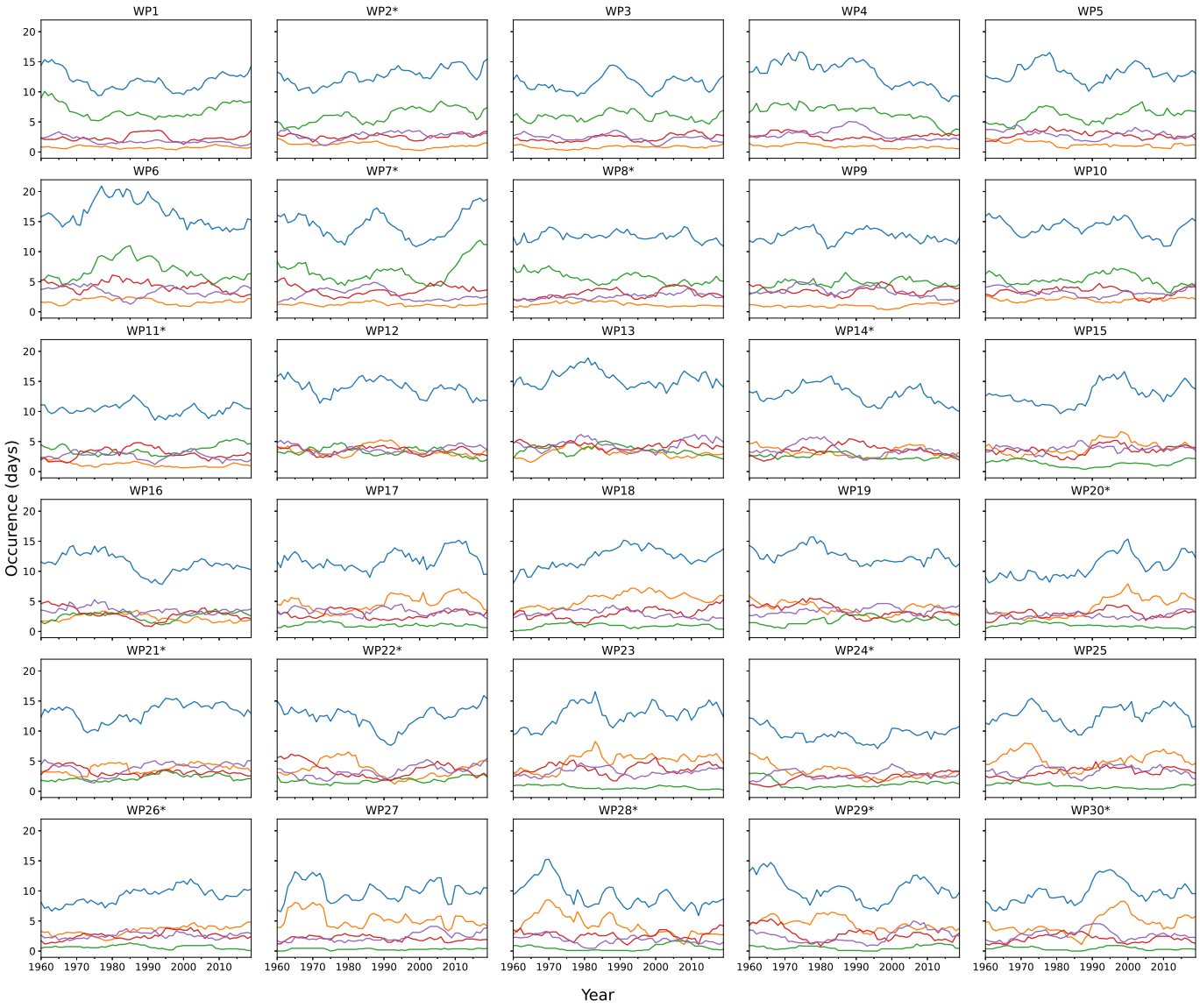


Fig. 6. Shows the number of days each WP occurred between 1960 and 2020 as a rolling average with a window size of 10 years. There is a pane for each MO30; the Y-axis is the number of days the relevant WP occurred, and individual lines represent the four key penological phases and full-year occurrences. The blue line is the full-year occurrence, purple Planting occurrences, yellow Growth occurrences, red Heading occurrences, and green Filling occurrences. WP with an asterisk are cyclonic patterns.

Table 2
Summary of which WP will increase and decrease in occurrence during the late 21st Century as found by Cotterill et al. (2023) and Pope et al. (2022). There was no data for the Heading phase at the time of writing. WP with asterisks are cyclonic.

	Increased occurrence	Decreased occurrence
Planting	1, 2*, 3, 4, 5, 6, 10, 12, 15, and 23	7*, 9, 11*, 16, 19, 20*, 21*, 22*, 24*, 27, 28*, and 29*
Growth	3, 4, 14*, 15, 18, 20*, 23*, 26*, and 30*	2*, 5, 11*, 16, 17, 19, 22, 27, 28*, and 29*
Filling	1, 2*, 5, 6, 10, 19, and 25	3, 4, 7*, 9, 12, 15, 16, 17, 18, 20*, 21*, 22*, 23, 24*, 26*, 28*, 29*, and 30*

affecting heavier soil crops, resulting in the poorest crop quality since 1977.

The UK experienced its second warmest Planting in over a century, with a mean temperature of 11.3 °C, marked by exceptionally warm spells and the lowest number of air frosts in 50 years. Rainfall (332 mm) was 96 % of the 1981–2010 average (346 mm), with significant regional variations. Growth had a mean temperature of 3.3 °C, slightly below the long-term average (3.7 °C), with February being the coldest month. This phase was marginally wetter (350 mm) than the long-term average (330 mm), marked by the wettest December since 1999 and significant snowfall in January, which led to widespread disruption followed by a rapid thaw. Summer was cooler than the long-term average (14.3 °C), with a mean temperature of 13.9 °C, making it the coolest since 1998, except for 2011. It was also an exceptionally wet season (379 mm, long-term average 241 mm), marked by the wettest June on record and the second-wettest summer overall since 1912.

Harvest 2012 Planting had over occurrences of cyclonic WP (7, 8, 11, 20, 21, and 24), which correlate with bad crop years in this phase, particularly WP24, which has the strongest negative correlation. The Growth stage was relatively unbiased towards cyclonic or anticyclonic; however, WP5, 11, 16, and 19 are particularly susceptible to extreme colds, with WP16 having one of the strongest negative correlations to yield. The Heading and Filling phases had a mix of positive and negative correlated WP (13, 27, 28, and 29 for Heading; 6, 10, 15, 16, 17, and 18 for Filling), suggesting that the yield was limited during the Planting and

Growth phases.

3.6.2. 2019 harvest, higher than the five-year average yield

The UK's total wheat production in 2019 reached 16.2 million tonnes, a 20 % increase from 2018. This increase was attributed to expanded cultivation area and higher yields, resulting in a 16 % increase in production value, primarily driven by elevated domestic production levels. Crop quality met end-user requirements, with wheat yields (9.0 t/ha) surpassing the previous year and exceeding the five-year average (8.32 t/ha), particularly benefiting crops grown on heavier soils.

The summer of 2018 was arid, and whilst not technically part of the 2019 harvest year, it should be considered to have affected 2018 Planting by potentially creating dry soils. The 2019 planting season (Autumn 2018) experienced fluctuating temperatures, starting warm and cooling significantly with growth, with some areas seeing early frosts. Rainfall was above average, particularly in October and November 2018. The Growth phase began cold and dry, but February brought record-high temperatures (1.4 °C above the long-term average), making it one of the warmest, sunniest, and driest winters on record. Heading saw warmer-than-average temperatures in March and record-breaking April temperatures, especially in the east, with East Anglia receiving only 25 % of its usual rainfall. Filling was marked by significant rainfall in June and the then hottest day on record in July, with Cambridge reaching 38.7 °C, making it the twelfth warmest and seventh wettest summer since 1910 up to the end of the study period (2020).

The Planting phase was balanced with an increased occurrence of cyclonic (WP2, 21, and 22) and anticyclonic (WP6, 10, 13, and 27), which caused fluctuations in weather conditions, with the former producing rain (Fig. 7). It should also be noted that WP6 has the strongest correlation to good yield for this phase. The Growth phase fluctuated between different WPs again, causing a contrasting period, but also had an occurrence of one of the most positively correlated WP at any phase, WP3. The Heading and Filling phases were again mixed; however, several consecutive days of WP7 (Cyclonic south-westerly with a low-centred wester-northwest of Ireland) caused the high July temperatures.

4. Conclusions and future research

This study has shown that Weather Patterns (WPs) can highlight phenological phases that experienced yield-limiting events caused by either sub-optimal crop temperatures or water access issues. The relationship is complex as anomalous occurrences (occurrences outside a climatic period's average) in anticyclonic WP, such as WP14 and 19, are connected to periods of excessive heat, which can decrease the grain count per spike, consequently impacting productivity. Similarly, WPs 4, 5, and 6 can highlight intervals of insufficient rainfall, potentially resulting in drought conditions that restrict water availability and impair crop development. Conversely, cyclonic WP such as WPs 8, 26, and 30 can identify excessively wet periods that may cause waterlogging, root diseases, or other detrimental effects on crop health.

We have shown that, while complex, there is an underlying direct relationship between WPs and Winter Wheat yield in the UK. It is challenging to attribute good or bad yields to specific individual WP occurrences. Each WP's positive or negative effect depends on which phenological phase it occurs, but they can also have different effects at a regional scale. For example, WP9 is connected to good yield years in the Scotland and North East England (Northern) regions whilst having a negative impact on the East Midlands, Yorkshire, and Humber (Midlands) and South East England (Southern) regions. Even within the Northern region, WP9 is only connected to good yield years when it occurs in the Sowing and Emergence (Planting) and Vernalisattion (Growth) phenological phases. However, it can have a negative association if it appears during the Terminal Spikelet (Heading) and Anthesis and grain-filling (Filling) phases. In general, it has been demonstrated that anticyclonic patterns correlate with good crop yields, although cyclonic patterns can benefit crops during the Heading phase in the Southern and Midlands regions. Future work could consider using the persistence of WP (Harrison et al., 2022; Richardson et al., 2019) rather than just occurrence or perhaps combining them to strengthen the correlation.

Using WPs as a framework to evaluate the impact of climate change on crop yields, this study, supported by recent research, suggests that changes in WP occurrences can indicate shifts in precipitation patterns,

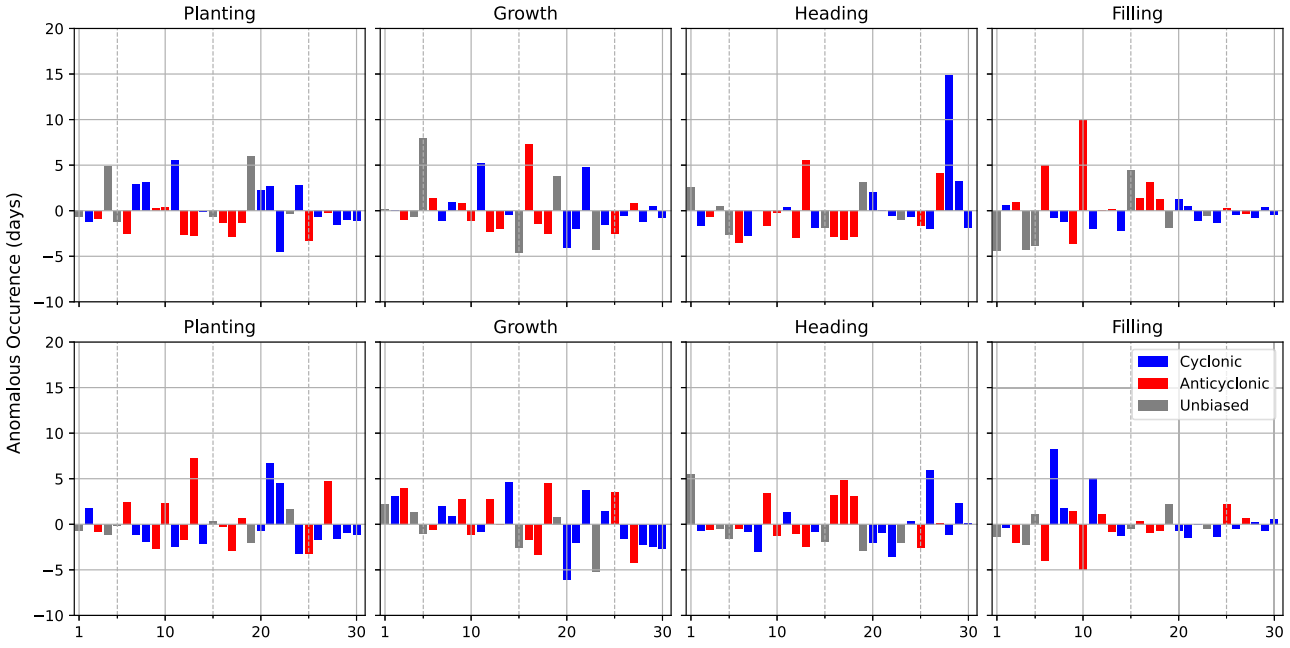


Fig. 7. The number of anomalous days for each WP (the number of days each WP was observed minus the average occurrence over the growing season between 1990 and 2020) for each key phenological phase during the 2012 harvest year (top row, lower than average yield) and 2020 harvest (bottom row, higher than average yield). Blue bars highlight cyclonic WP, red bars are anticyclonic, and grey are unbiased. The columns represent each phenological phase, from left to right: Planting, Growth, Heading, and Filling.

highlighting the importance of soil texture. A shift towards more frequent cyclonic patterns will bring wetter and warmer Growth conditions. Combined with warmer and drier Filling conditions, this can increase yields, but only if the soil has strong moisture retention capabilities (clayey). Lighter (sandy) soil will present more significant challenges; however, adaptive strategies—such as earlier sowing dates, increasing organic carbon content (Rawls et al., 2003), and developing wheat cultivars with traits like early vigour and deeper rooting (Ludwig and Asseng, 2010)—may help mitigate the adverse effects of climate change.

The findings offer insights into how WPs influence crop phenology, which is essential for creating tailored agricultural strategies for specific regions. This understanding enables earlier predictions of end-of-season harvest yields, giving farmers and the broader food supply chain more time to address potential yield fluctuations. A medium to long-range yield prediction model helps farmers determine the best crops to plant and guides management strategies throughout the growing season, reducing yield losses and boosting productivity (Mundhe et al., 2023; Sharma et al., 2023; van Klompenburg et al., 2020). Increased yield prediction accuracy can help improve resource management by optimising water, fertilisers, and pesticides, which can result in cost savings and lessen environmental impact (Mundhe et al., 2023; Nyéki and Neményi, 2022; Pradeep et al., 2023a). Additionally, yield predictions enable farmers to plan harvests more effectively, minimising losses and ensuring they secure the best prices for their produce (Pradeep et al., 2023b; Sellam and Poovammal, 2016).

This framework helps translate global climate models into regional agricultural effects, providing earlier warnings of potential future challenges and offering opportunities to adapt to changing conditions.

CRediT authorship contribution statement

Chris Knight: Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Abdou Khouakhi:** Writing – review & editing, Validation, Supervision, Conceptualization. **Toby W. Waine:** Writing – review & editing, Validation, Supervision, Conceptualization.

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Declaration of competing interest

The authors declare no conflict of interest. The funders had no role in the study's design, data collection, analysis, interpretation, manuscript writing, or decision to publish the results.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2024.177181.

Data availability

Data supporting this study are openly available. The MO30 UK weather patterns from the UK Met Office at https://doi.org/10.1594/PANGAEA.942896 and UK winter wheat yield data from Defra at https://www.gov.uk/government/statistics/cereal-and-oilseed-rape-production.

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