

Deteriorating climate conditions for Australian wheat production

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Keywords: climate extremes, agricultural impacts, climate risk, crop yields, machine learning

Abstract

Wheat yields are highly sensitive to climate extremes, but previous studies risk underestimating their influence due to a reliance on highly aggregated agricultural data. Here we combine nationwide farm-level agricultural data with machine learning to identify the key drivers of Australian wheat yield and assess how climate conditions for wheat production have changed over recent decades. We find that extreme events dominate climate impacts on wheat yield and explain 53-74% of yield variability across Australia's wheat-growing states, with drought and late-season heatwaves having the largest impacts. This influence of extremes is more than double the estimates reported in previous studies that use spatially aggregated yield data. Between 1970 and 2020, 72% of the Australian wheat belt experienced a significant increase in growing season drought days, and over 90% experienced a significant increase in late-season heatwave intensity. These trends have driven a deterioration in Australia's wheat-growing climate conditions. Advances in agronomic technology and management practices have so far offset this deterioration, masking emerging climate risks to production in one of the world's major wheat-exporting nations. Because Australia is a key supplier to global wheat markets, these risks extend beyond domestic production and threaten global food security. Our findings highlight the need to strengthen the resilience of Australian wheat production to protect both local and global wheat supplies.

1. Introduction

Global agriculture is reliant on stable and predictable climate conditions to ensure sufficient food supply across the world. However, the increase in extreme weather events associated with anthropogenic climate change has increased weather-related risks to many of the world's key breadbasket regions [1]. Given global cereal production must double by 2050 to feed the global population [2], it is essential that we understand and mitigate climate risks for the agricultural sector. Wheat is of particular importance as it supplies around a fifth of the world's calories and protein [3]. Meeting the rising caloric demand will depend on the ability of major wheat-producing countries to sustain and grow yields under increasingly volatile climate conditions [4].

Wheat yields have been increasing in many regions due to improved agronomic management and technological advancements [5], but the rate has been too slow to match the rising global demand [6]. Slowing wheat yield trends have been linked to changes in climate [7], with growing-season climate conditions explaining up to two thirds of wheat yield variability in some regions [2,8,9]. Understanding which climate factors most strongly influence wheat yield and how they are changing in a warming world is critical for assessing whether future wheat production can continue to meet increasing global demand, and for identifying effective adaptation strategies.

Large gaps remain in our understanding of the impact of climate on wheat yields. Previous studies investigating climate impacts on crop yields have largely relied on national or highly aggregated subnational-scale yield data [2,9,10] or crop models [8]. While regionally dependent, these usually find heat and water stress as the drivers of wheat yield loss. However, past studies may overestimate the impact of spatially homogeneous variables (e.g. temperature) on crop yields while underestimating or even missing highly localised impacts of climate extremes [11]. Higher resolution agriculture data can be utilised to better quantify the influence of climate conditions on wheat yield but these datasets are often restricted in their availability [11,12].

The small number of available regional studies utilising higher resolution data over an extensive time period have largely focused on Northern Hemisphere wheat-growing regions [13–15]. No such studies exist for Australia, which is one of the world's major wheat suppliers, commonly ranking among the top five countries for wheat exports and contributing around 10–15% of the global export market [16]. Australia's wheat yield losses can therefore impact world markets, reducing wheat supply and increasing food prices globally [17]. Australian wheat production is almost entirely rainfed, making it particularly vulnerable to climate variability and extremes [2,9,18].

We use a newly available dataset - the Farm-level Longitudinal Agricultural Dataset (FLAD) [19] - to undertake the first nationwide farm-level assessment of the impact of climate on wheat yields across Australia. Combining 20 years of farm-level yield observations with high-resolution climate data, we build machine learning models for each major wheat-growing state in Australia to identify dominant climate drivers of wheat yields. We then use these models to understand how the timing of extreme events, including drought, heatwaves and frost, influence their impacts on wheat yields. Finally, we assess how wheat yield-relevant climate conditions have changed over recent decades, and how these manifest into impacts on wheat yield trends. By identifying the climate conditions that pose the greatest risks to Australian wheat production and untangling how these variables are changing, our findings provide actionable insights for adaptation planning.

2. Methods

2.1. Data

2.1.1. Agricultural data

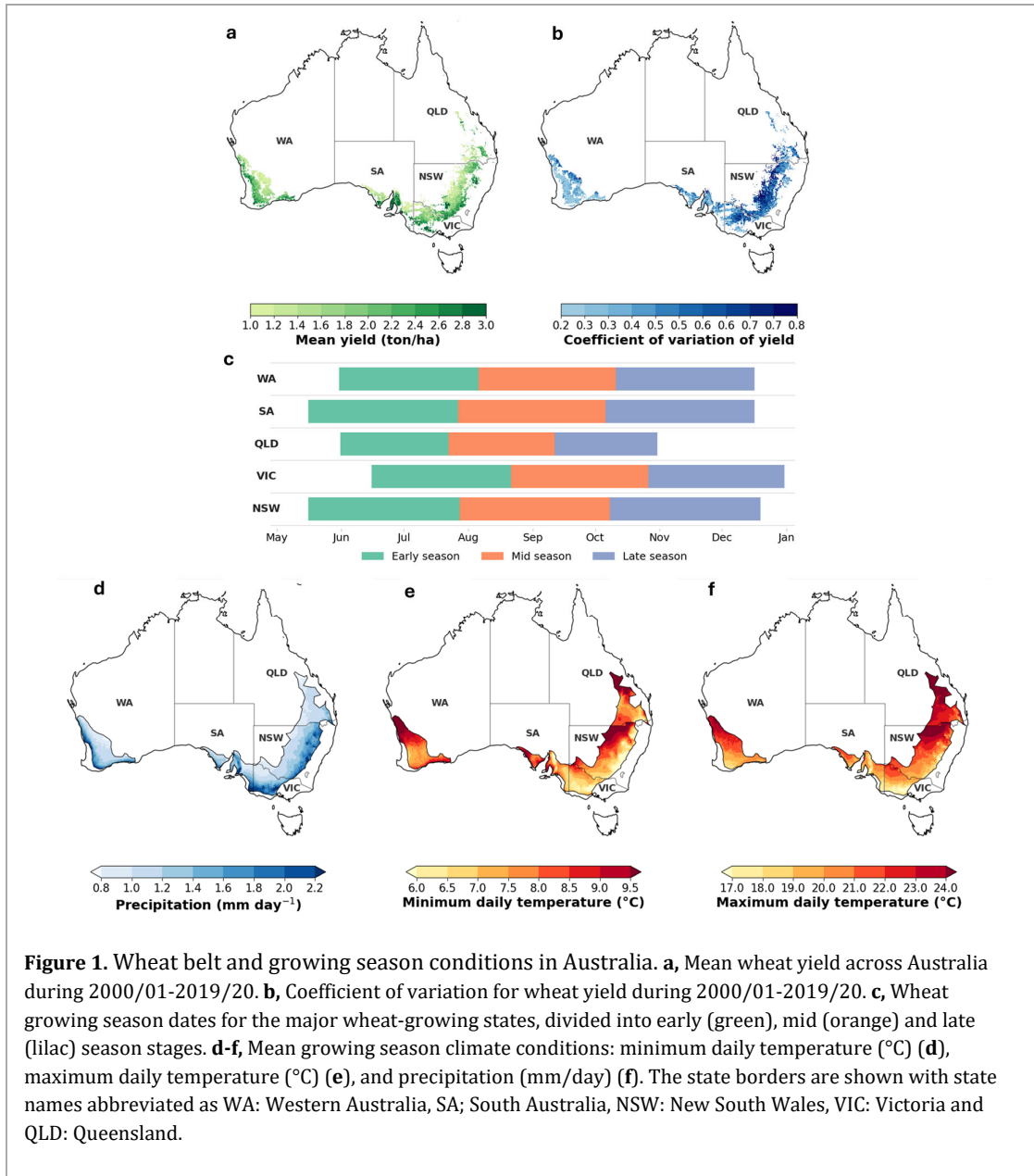
The primary yield data used for the analyses is from FLAD. This dataset is jointly curated by the Australian Bureau of Statistics (ABS) and the Australian Bureau of Agricultural and Resource Economics and Sciences (ABARES) as part of the Agricultural Data Integration Project (AgDIP) [20]. It combines all ABS agricultural surveys and censuses undertaken between 2000/01 to 2019/20 financial years forming the largest continuous multi-year farm-level agricultural dataset available across Australia [20]. Twentieth Century Crop Statistics dataset [21] was used to extend the yield dataset back to 1969/70. This data comes from the same source as FLAD but is only provided at state-level.

Due to data privacy reasons, FLAD is provided to users by mapping data onto meshblocks, the smallest geographic areas defined by the ABS. These are based on land-use, road, and area constraints and are at far finer resolution than any previously available agricultural data (the median area of meshblocks used in this study was 82km²).

During the processing of the wheat yield data, a high-resolution land-use dataset - Catchment Scale Land Use of Australia v2 (CLUM) - was used to improve the reliability of farm locations. This provides land use information across Australia at a 50m resolution [22]. This was used to remove meshblocks in areas with no cropping land and reduce the area of other meshblocks to cropping land only. Additionally, farms reporting yields greater than 10 tons/ha were excluded to remove erroneously high values, as this threshold approximates the maximum yield achievable in Australia even under optimised conditions in simulated wheat yields [23]. The farm-level data was aggregated from its native meshblock form to a 0.05° x 0.05° grid to match the climate and soil moisture data (see Supplementary Information (SI) Section S1.1). Figures 1a and 1b show the mean and standard deviation of yield on this grid. Subsequently, the gridded yield data were standardised per grid cell by subtracting the mean and dividing by the standard deviation. This removes spatial differences in yield while retaining temporal variability. Without this step, the model can pick up spatial patterns in yield and link them to spatially coincident patterns in climate variables, without any physical basis. We did not detrend the yields, as the yield trend over the 20-year span is small compared to the overall interannual variability and detrending the yield data risked removing important information of the climate impacts on yield without providing major benefit to the analysis.

2.1.2. Agroclimatic data

Precipitation, maximum daily temperature and minimum daily temperature were obtained from the Australian Gridded Climate Data v1 (AGCD) [24] and are available on a 0.05° x 0.05° grid across Australia (see Figure 1d-f for average values of these over the growing season). Continental-scale gridded root zone soil moisture data was obtained from the Bureau of Meteorology's hydrological model AWRA-L version 6 [25]. While this is a modelling product, it is widely used in similar applications across Australia [26] and to provide historical gridded soil moisture estimates in the absence of observational datasets of root zone soil moisture [27]. From these four variables, 14 agroclimatic indices were defined which capture growing season climate conditions, temperature extremes and drought (Table 1). These were split into categories of "extreme" or "non-extreme" variables, with the "extremes" being further split into "drought" or "temperature extreme". We chose variables to only be classed as an extreme if it was truly an anomalous condition, e.g. consecutive dry days are classed as a non-extreme variable since a dry day is not an abnormal occurrence.



The extreme variables used in this study were precipitation drought, soil moisture drought, heatwave and frost. These were selected as they have previously been shown to have the largest impacts on wheat yield in Australia [28] and in other regions [10,29]. Other extremes, such as heavy rainfall, hail and fire can also affect wheat yield but were excluded due to their likely smaller impact (heavy rainfall), infrequent occurrence (hail), or because their effects are already captured through the other extremes (e.g., drought and heat preceding fire).

The agroclimatic variables were aggregated over the whole wheat growing season and three growing season sub-stages. The start and end dates of the growing season were taken from crop calendars of the Center for Sustainability and Global Environment [30]. These provide state level data on average wheat planting and harvest dates. The growing season substages are defined by splitting the full growing season into three equal parts (early, mid and late season).

These stages broadly correspond to the early plant growth, stem growth and flowering, and grain filling stage. The dates for the growing season and its stages are shown in Figure 1c.

2.2. Random forest models

Random forest (RF) models were developed for each major wheat growing state in Australia: Queensland (QLD), New South Wales (NSW), Victoria (VIC), South Australia (SA), and Western Australia (WA) (see Figure 1 for state locations). Wheat is also grown in Tasmania, however it accounts <1% of Australia's wheat production and there was not enough available data to gain sufficient model skill, so the state was excluded from the analysis. Alternative methods of clustering areas by climate conditions were tested but resulted in similar skill so the state-based regionalisation was used for simplicity and ease of communication.

To assess the relative importance of the different types of agroclimatic variables, we developed and compared five RF models: 1) a model trained with all agroclimatic variables, 2) a model using solely the non-extreme variables, 3) a model using only the extreme variables, 4) a model using drought variables only, and 5) a model using temperature extremes only. All predictors were aggregated over the full growing season for this analysis.

To understand the influence of timing of climate extremes on wheat yields, we trained RF models using the extreme predictors at sub-seasonal scales (see Section 2.1.2). Four models were created using the extreme variables aggregated over the early, mid and late season, respectively, plus one model using sub-seasonal predictors at all three stages.

We identified which subset of predictors has the greatest influence over wheat yield in Australia using temporally withheld out-of-sample R^2 values calculated from predicted against observed yield data, aggregated per state (see SI Section S1.3.1 for details on the cross-validation and calculation of R^2 values). Feature importances, using a permutation-based method (see SI Section S1.3.2), were calculated to assess the relative importance of model predictors. A randomly generated variable was added as a predictor to serve as a baseline, and predictors ranking below the random variable were deemed to have no significant influence on wheat yield.

2.3. Climate and yield trends

Trends in climate extremes and yields were calculated using the Yue-Wang variation of the Mann-Kendall trend test and Theil-Sen slope estimator [31], a common non-parametric method for detecting trends and estimating their slope. Trends were calculated for the extremes identified as most influential within each season stage (see Section 2.2 and 3). For drought trends, we used a 30 day aggregation period instead of 180 days, as drought trends show a strong seasonal pattern which is largely positive over winter and spring, but flat or negative over summer and autumn [27]. Over the longer 180-day window, these opposing seasonal trends can cancel out, while the 30-day aggregation period also had substantial influence on yield and better captures sub-seasonal changes. Yield trends were calculated from observed and modelled yield timeseries, from 1969/70 to 2019/20. Climate-driven yield was modelled using the RF model based on all growing-season agroclimatic predictors (see Section 2.2).

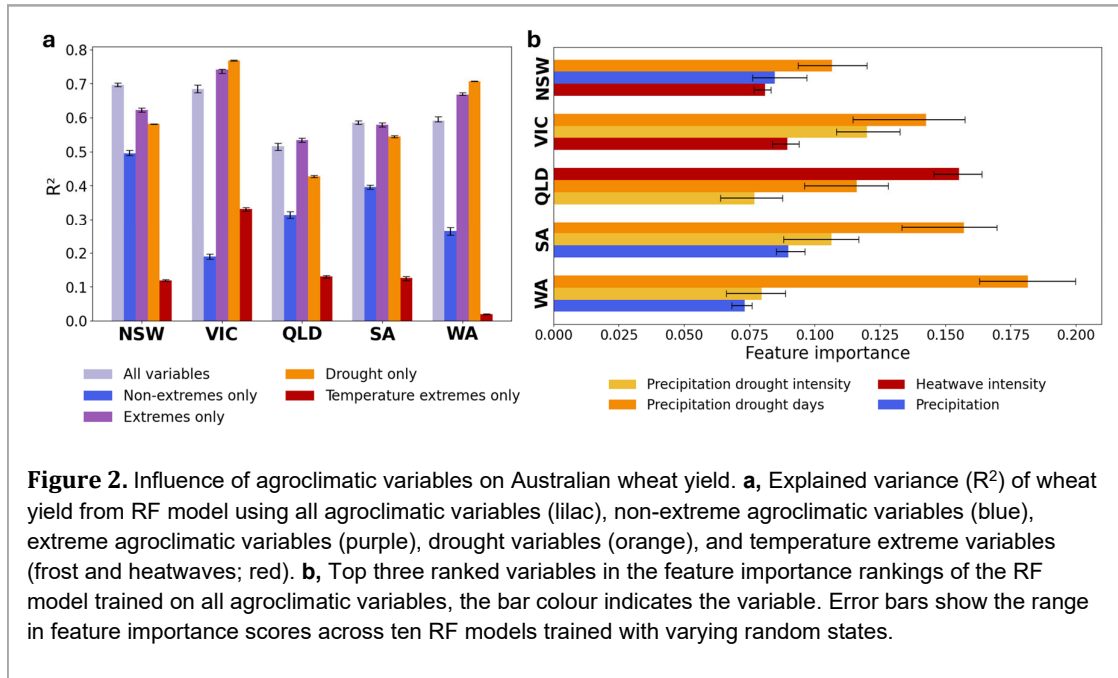
Table 1. Agroclimatic variables used in the Random Forest (RF) yield models. Identifies the variable and whether it was defined to be an extreme or non-extreme variable, specifying the category of extreme variable it is, and a brief description of the variable (see SI Section S1.2 for detailed descriptions).

Agroclimatic Variable	Variable Type	Description
Mean daily maximum temperature	Non-extreme	N/A
Mean daily minimum temperature	Non-extreme	N/A
Mean daily precipitation	Non-extreme	N/A
Mean daily soil moisture	Non-extreme	N/A
Maximum consecutive dry days	Non-extreme	Maximum number of consecutive days with <1mm of precipitation
Growing degree days	Non-extreme	An estimation of the phenological development of the crop measured using accumulated optimum temperatures
Mean daily temperature range	Non-extreme	Mean difference in daily maximum and minimum temperature
Number of precipitation drought days	Extreme (drought)	Number of days when precipitation was below the 15 th percentile
Mean intensity of precipitation droughts	Extreme (drought)	Average deviation from the mean precipitation on days defined as drought days
Number of soil moisture drought days	Extreme (drought)	Number of days when soil moisture was below the 15 th percentile
Mean intensity of soil moisture droughts	Extreme (drought)	Mean deviation from the mean soil moisture on days defined as drought days
Number of heatwave days	Extreme (temperature extreme)	Number of days when maximum daily temperature was above 32°C
Mean intensity of heatwaves	Extreme (temperature extreme)	Mean deviation from mean maximum daily temperature
Number of frost days	Extreme (temperature extreme)	Number of days when minimum daily temperature was below 0°C

3. Results

3.1. Droughts dominate yield variability across Australia

The influences of “non-extreme” and “extreme” agroclimatic variables on wheat yield were assessed using the relevant RF models (see Section 2.2). When using all agroclimatic variables as predictors, the RF models can explain over two thirds of inter-annual yield variability across Australia (out of sample R^2 : 0.69) and over half of the variability in each individual state, with R^2 values ranging from 0.52 to 0.70 (Figure 2a). This suggests that up to 70% of the year-to-year variability in Australian wheat yields are driven by hydro-climate conditions during the growing season. RF models that only use climate extreme predictors explain 53% to 74% of the variability, a comparable performance to the model that contains all agroclimatic variables. On the other hand, RF models that only use non-extreme climate variables exhibit substantially lower performance with explained variances ranging between 19% and 49%, suggesting that climate extremes dominate yield variability. Previous work using aggregated yield data has estimated that extremes add 7 percentage points to the climate's influence on wheat yield variability in Oceania [9]. Our farm-level analysis reveals a contribution over double that, with extremes increasing explained variance by 17 percentage points nationally and up to 49 percentage points in key regions, suggesting their influence has previously been underestimated due to the spatial aggregation.



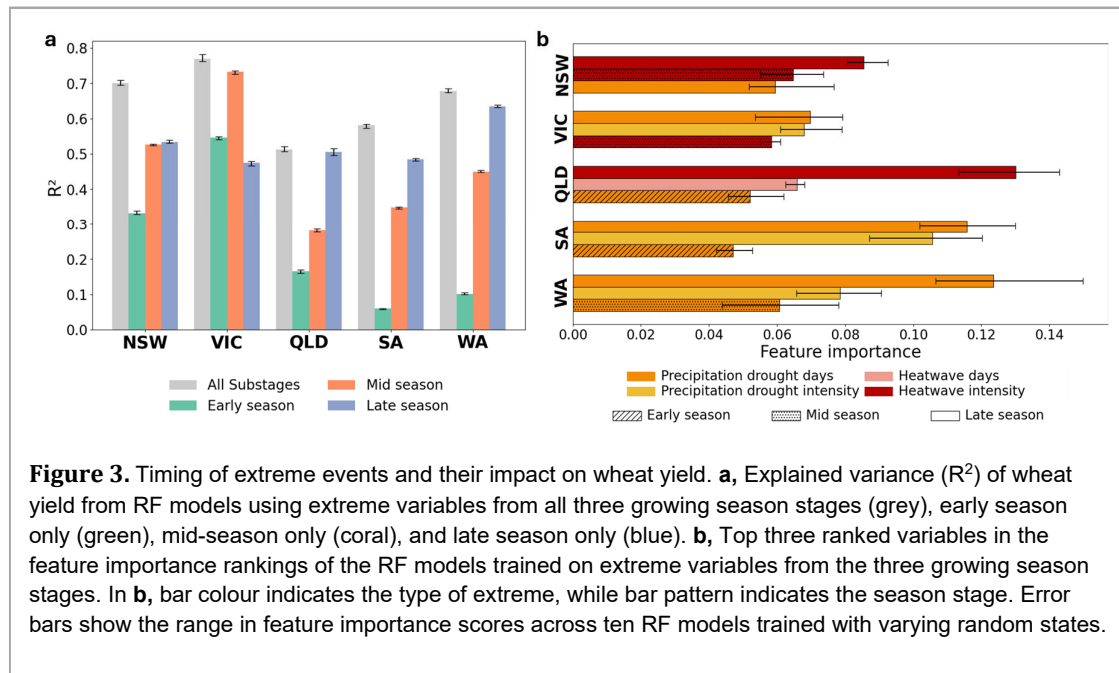
We further separated the influence of drought and temperature extremes on wheat yields. RF models using only temperature extremes as predictors fail to capture much of the yield variability, with R^2 values ranging from 0.02 to 0.33 (Figure 2a). However, RF models using only drought predictors explain 43% to 77% of yield variability, which is comparable to the explained variance using all agroclimatic variables. Our findings demonstrate that droughts are the key driver of Australian wheat yield, with the number of drought days and the intensity of those droughts explaining over three quarters of wheat yield variability in some regions.

Precipitation drought days during the growing season ranks as the most important variable in four of the five states, and second most important in the remaining state (Figure 2b). The time

spent in drought is more important than the intensity, however precipitation drought intensity still ranks among the top three most important variables in four states. Somewhat surprisingly, soil moisture droughts were not among the top three predictors. This may reflect uncertainties in the modelled soil moisture product, which could carry larger biases than the observed precipitation data, or simply that precipitation drought captures similar information, leading the model to favour it over soil moisture drought. While precipitation drought predictors tend to dominate, heatwaves also play a significant role in eastern and south-eastern Australia (NSW, VIC, QLD). However, temperature extremes alone fail to explain much of the variability (Figure 2a), suggesting their high feature importance may be due to interactions with droughts and the tendency for drought conditions to exacerbate heat extremes [32]. All variables showed a feature importance score greater than that of the random variable, indicating a meaningful contribution to wheat yield prediction (see Section 2 and SI Figure S1).

3.2. Mid and late season extremes have the greatest impact on wheat yield

Next the influence of extreme events during the three growing season stages were compared. Climate extremes during the early season provide less predictive skill than extremes during the mid or late season and only explain 38% of Australia's yield variability (Figure 3a). The models for the mid and late seasons have comparable skill across most states and capture a similar fraction of the interannual yield variability (29%-73%). In the south-east (VIC), the late season model has the lowest R^2 , suggesting that climate extremes during the last part of the growing season are least impactful here.



Late-season precipitation drought is generally the most impactful extreme. The number of late-season drought days rank within the top three most important variables in four of the five states (Figure 3b). In three of those states, the number of drought days is the highest ranked predictor, while drought intensity is the second highest. Partial dependence plots show that an increasing number of late-season drought days lead to severe reductions in wheat yield (SI Figure S2a-e). While droughts have the greatest influence overall, late-season heatwave intensity also has a large impact and is the most important predictor across eastern Australia (NSW and QLD). An increase in late-season heatwave intensity leads to substantial decreases in wheat yield (SI Figure S2f-j).

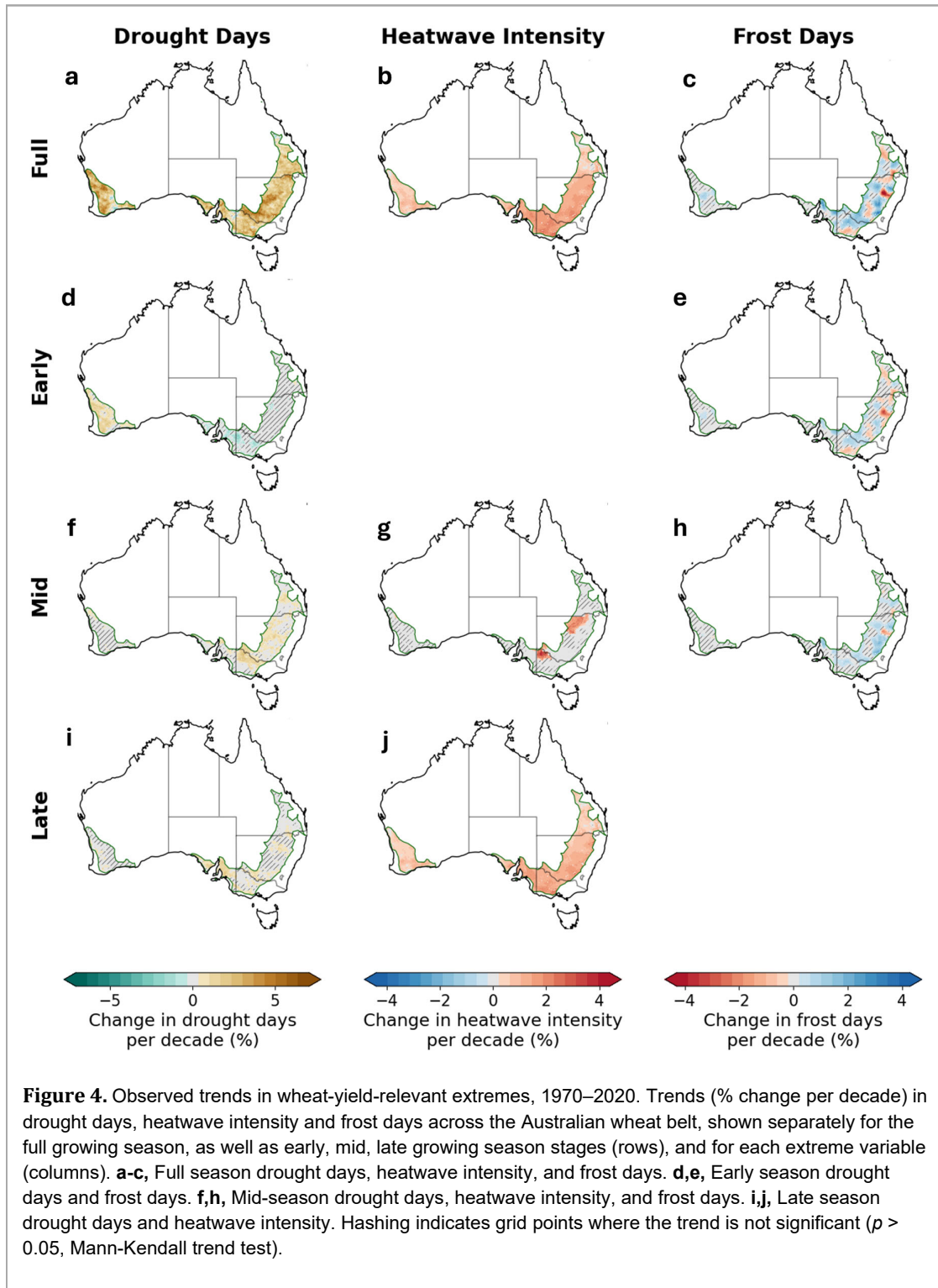
While late-season drought and heatwaves are the most influential extremes, extremes at all stages of the growing season have an impact on yield. The exceptions are early-season heatwaves and late-season frosts, due to the rarity of their occurrences. The importance of all season stages is reflected in the models' explained variability, as models nearly always have the highest R^2 when using predictors aggregated across all three season stages, compared with using predictors aggregated across any single growth stage (Figure 3a). In addition to the late-season extremes, early-season drought days and mid-season heatwave days rank in the top three most important predictors in some states (Figure 3b). Mid-season drought additionally features in the top three predictors in WA. Droughts can therefore impact yields at any stage of the growing season, while heatwaves are important across the latter two thirds of the season. Early- and mid-season frost days also show a significant influence on yields in all states (SI Figure S3). These results provide a detailed picture of how the timing of extremes shapes their impact on wheat yield, informing more targeted climate adaptation strategies for the sector.

3.3. Increasing extremes have worsened growing conditions for Australian wheat

Climate extremes with the largest impact on wheat yield have changed in many parts of the Australian wheat belt over recent decades (Figure 4). When considering the full growing season, nearly three quarters of the wheat belt faces a significant increase in the number of drought days, reaching as much as 7 extra days per decade (Figure 4a). Some regions therefore now experience 35 more days of drought during the growing season than they did in 1970. This is a substantive change as the growing season experiences an average of 31 days of drought per year (1970-2020). SI Figure S4a shows the spatial variation in average drought days over the growing season.

There are also substantial areas of increasing drought days at each season stage. In the early season, over half of the WA wheat belt has experienced a significant increase in drought days, while the eastern wheat belt shows a reduction in drought in the south and no significant changes in the north (Figure 4d). In the mid and late season, the increase in drought is concentrated in the eastern wheat belt, with 78% and 57% of its area experiencing statistically significant increases in the number of drought days, respectively (Figure 4f,i). Only small areas of WA see significant change for these season stages. Increasing drought days have a clear negative impact on wheat yield, with wheat yield dropping substantially as drought days increase in each season stage (SI Figures S2a-e, S5a-e, and S6a-e).

Heatwave intensity has been significantly increasing in over 90% of the wheat belt during both the full growing season and the late season, when heatwaves are most influential (Figure 4b,j). The strongest trends in the late season are seen in eastern regions, where heatwave intensity increases by 4 percentage points per decade in some areas. The average heatwave intensity over the growing season is 25%, indicating substantial changes over the past five decades (SI Figure 4b). Significant heatwave intensity trends are more limited in the mid-season (Figure 4g), with around half the wheatbelt experiences significant trends. The insignificant trends in the remaining areas are due to a lack of heatwave occurrences during this time of year. The relationship between late-season heatwaves and yield is generally negative, particularly in NSW and QLD where it has the greatest influence (SI Figure 2f,h), suggesting an increasing risk of yield declines from late-season heatwaves.



Frost days are increasing in parts of the wheat belt during the times for which they are influential (early and mid-season) with up to 1.7 and 2.4 extra frost days per decade in each stage, respectively (Figure 4e,g). These stages experience an average of 5 and 3 frost days a year; indicating large changes from the mean growing season conditions (SI Figure 4e,h). The

increasing frost days mainly occur in the eastern wheat belt in both the early and mid-season (27% and 34% of the area, respectively), with smaller areas of increase in WA (17% and 10%, respectively). The trend is inconsistent across the domain, with substantial areas of decreasing frost days also present in the early season, particularly in the northern parts of the eastern wheat belt (Figure 4e). However, these decreasing areas are seen far less in the mid-season (Figure 4g). Increasing frost days in the early season have a negative impact on wheat yield (SI Figure S5f-j), while their influence in the mid-season is more uncertain (SI Figure S6k-o).

The increasing frequency and intensity of impactful extremes has led to a deterioration in climate conditions for wheat production across the country. Observed wheat yields increased in all major wheat-growing regions from 1969/70 to 2019/20 (Figure 5, blue lines). In contrast, climate-driven yields (Figure 5, red lines) declined across the country, significantly so in four of the five states and nationally. This pattern holds when extended to 2024/25, with the same four states and the national trend remaining significantly negative despite recent years of more favourable growing conditions (SI Figure S7). This indicates a steady worsening of climate conditions for wheat productivity over the last 50 years. The positive observed trend is likely associated with technological advancement in agricultural processes, which has so far offset the deteriorating climate conditions.

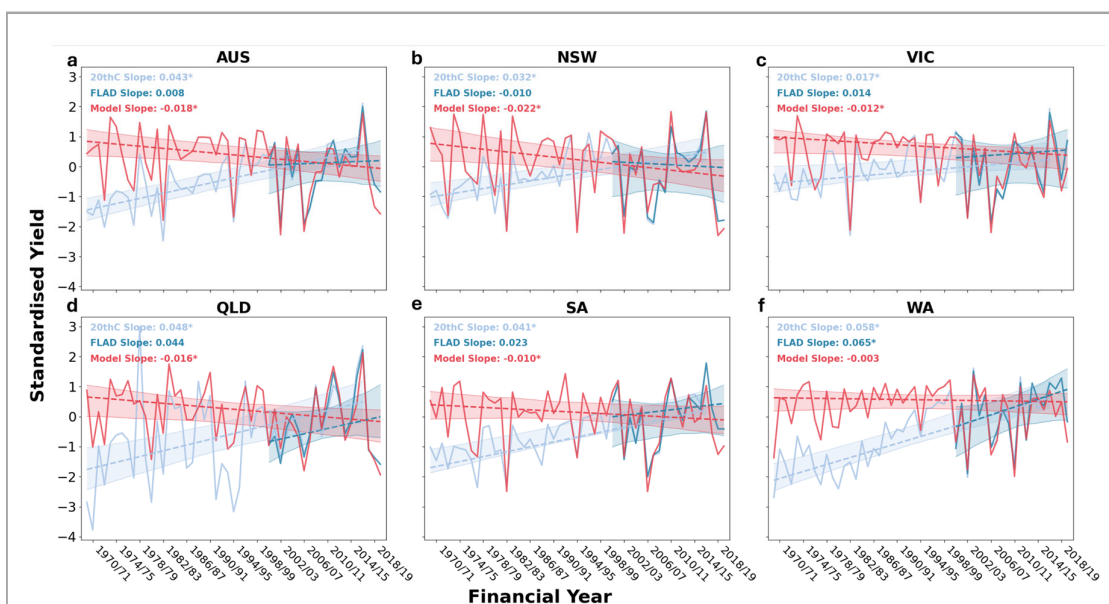


Figure 5. Changes in observed wheat yield against climate-driven yield. Changes are shown across regions from 1969/70-2019/20 for **a**, Australia; **b**, New South Wales; **c**, Victoria; **d**, Queensland; **e**, South Australia; and **f**, Western Australia. Blue lines indicate observed yield, with light blue showing timeseries from 20th Century Crop (20thC), for 1969/70-2016/17, and dark blue showing the timeseries of FLAD data (2000/01-2019/20); red lines show climate-driven yield (i.e., predicted yield from the RF model using all agroclimatic variables across the growing season). Solid lines are the standardised yield values (standardised around 2000/01 to 2016/17) for each region; dotted lines are the trends in those yields (Theil-Sen slope estimator), shading around the trend lines is the uncertainty in the trend. Uncertainty bands are the 95th confidence intervals of this slope from 1000 bootstrapped resamples of the data. The slope is labelled on each plot with an asterisk indicating significance of the trend (Mann-Kendall trend test, $p < 0.05$).

4. Discussion

Australia is a key breadbasket region, and its wheat production is essential for satisfying both local and global calorie needs. To keep up with the demand of rising global populations, agricultural efficiency must constantly improve. Across most wheat growing regions of Australia, wheat yields have increased over the past five decades influenced by crop variety, technological advancement, and improved fertilization methods, while climate conditions for wheat have been deteriorating [7,33]. Our study investigated, for the first time, the historical impact of climate extremes on Australian wheat yield using machine learning applied to high-resolution, farm-level agricultural data.

We show that climate variations dominate the interannual variation of Australian wheat yields, explaining over two thirds of year-to-year variability across the country, consistent with other studies [2,8,9]. In fact, Australian wheat production is among the most sensitive to growing season climate conditions of any major crop-producing region globally [8,9]. We show that this explained variance is largely driven by climate extremes, and their importance depends on their timing, linked with the growing stage. This result is masked in studies that focus on mean growing season conditions [2] or rely on large spatial aggregations of agricultural data [10,34,35]. Our results suggest that the influence of extremes could be more than double that estimated previously [9]. Heatwaves have often been cited as the driver of wheat yield loss, but this may be an indirect effect by which the heatwaves co-occur and are amplified by water stress [36], as well as the highly aggregated data in previous studies masking the effects of more localised extremes.

By modelling wheat yield using agroclimatic predictors, we show that climate-driven yield has been declining in all major wheat producing regions in Australia since 1970, with a significant decline across the whole country. This decline in conditions has so far been offset by strong technological gains [26]. These encompass a combination of genetic improvements and management practice changes, with an emphasis on practices that conserve and exploit summer and autumn soil moisture as an adaptation to reduced winter rainfall [37]. Modern practices combining no-till farming with strategic deep ripping have been shown to deliver large gains in yield and water use efficiency, particularly in Western Australia [38]. Another key farm-level change has been earlier planting supported by new slower developing wheat varieties [39]. At a national level, some of the gain in crop yields can also be explained by changes in the spatial distribution of wheat crops, with a general shift away from lower-rainfall zones on the margins of the traditional wheat belt, into cooler higher rainfall coastal zones, particularly in southern Victoria [37,40].

The climate extremes that drive the deteriorating growing conditions across the Australian wheat belt are projected to continue increasing with climate change. Heatwaves will almost certainly continue to intensify under a warming climate [1]. Similarly, projections show a likely increase in droughts across much of the wheat belt [41,42], with high confidence across climate models on more frequent and intense future droughts in the southern parts of the wheatbelt. Future increases in these extremes, and the resultant declining climate-driven yields, bring into question the extent to which the improved agricultural advancements would be able to prevent large declines in wheat yields. As a major global exporter, any climate risks to Australian wheat production threaten the food security of import-dependent nations [43,44]. Hence, improving our understanding of the changes in wheat yield and the climate extremes which impact wheat is essential to understanding the risks and adaptation needs to support local and global food supply.

Our findings demonstrate that high-resolution agriculture data can be utilised to better understand the climate risks imposed on Australian wheat production. We have shown the substantial influence that extreme events exert on wheat yield, and how increases in these

extremes translate to declining conditions for Australian agriculture. By identifying where the greatest risks are emerging across the country, this work contributes to a growing understanding of how climate extremes threaten global food systems in a warming climate and provides a critical step towards developing a resilient and robust agricultural sector. The findings of our study are relevant beyond Australia, as climate change is reshaping the structure and stability of global agriculture. As the impacts of climate change continue to escalate, high-resolution analyses will be needed across the world's breadbasket regions to untangle the complex impacts of climate extremes on agriculture.

Acknowledgements

This study was funded by the Australian Research Council (ARC) Centre of Excellence for Climate Extremes (grant no. CE170100023). A.U. was supported by an ARC Discovery Early Career Researcher Award (DE200100086). E.V. is supported by a University of Melbourne McKenzie Fellowship. This research was undertaken with the assistance of resources from the National Computational Infrastructure (NCI Australia), an NCRIS-enabled capability supported by the Australian Government.

Conflict of Interest

All authors confirm they have no conflict of interests.

Data Availability

The yield data from FLAD [19] used in this study is not publicly available due to their confidential nature and the requirements of the *Census and Statistics Act 1905*. These data can be accessed by approved researchers through the Australian Bureau of Statistics DataLab, subject to application and approval by the ABS. Details on eligibility and the application process are available at <https://www.abs.gov.au/statistics/microdata-tablebuilder/datalab>. The yield data from 20th Century Crop can be obtained at <https://doi.org/10.7927/tmsp-sg82> [21]. Land-use data from CLUM can be obtained at <https://doi.org/10.25814/2w2p-ph98> [22].

The AGCD observed precipitation and temperature data can be obtained at <https://doi.org/10.25914/6009600b58196> [45]. The soil moisture data from the AWRA-L hydrological model can be obtained at <https://doi.org/10.25914/6130680dc5a51> [46].

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Supplementary Information: Deteriorating climate conditions for Australian wheat production

S1. Supplementary methods

S1.1. Yield Data Processing

Due to data confidentiality, the Farm-level Longitudinal Agricultural Dataset (FLAD) data provided by the Australian Bureau of Statistics are available on mesh blocks instead of their actual point locations. We aggregated the agricultural data onto the same 0.05°x0.05° grid which the climate and soil moisture data are provided on. The steps to do this are outlined below.

1. When multiple farms were assigned to the same meshblock for any given year, the wheat area harvested and wheat production of these farms were summed together.
2. Using the Catchment Scale Land Use of Australia v2 (CLUM) data [1], the percentage of cropping land in each grid cell of the 0.05°x0.05° grid was calculated. Grid cells with less than 20% cropping land were removed.
3. The remaining cells of the 0.05°x0.05° grid were overlaid onto the meshblock shapefiles and the production and area harvested data were mapped from the meshblock to the grid. If multiple grid cells overlapped with a meshblock, the production and area harvested values were distributed between the grid cells, weighting the distribution by the area of overlap.
4. Wheat yield was calculated per grid cell and year by dividing the wheat production by the area harvested.
5. Wheat yield was then standardised for each grid cell with:

$$yield_{stand.} = (yield_t - yield_{mean}) / yield_{std} \quad (1)$$

where $yield_{stand.}$ is the standardised yield, $yield_t$ is the yield at a given year, $yield_{mean}$ is the mean yield and $yield_{std}$ is the standard deviation of yield, respectively. The mean and standard deviations were taken across the number of years for which that grid cell had data. To ensure robustness in mean and standard deviations, grid cells with under 5 years of data were removed from the analysis.

S1.2. Agroclimatic Variables

Daily maximum temperature, daily minimum temperature, daily precipitation, and daily soil moisture values were averaged across the growing season to be used in the required yield models. Consecutive dry days were found by counting each run of consecutive days where precipitation was less than 1mm. Maximum consecutive dry days was defined as the longest run of consecutive dry days within the growing season. Growing degree days (GDD) were calculated as a measure of heat accumulation used to predict phenological development of wheat over the growing season. At each day, growing degree days were defined using the equation:

$$\frac{T_{max} + T_{min}}{2} - T_{base} \quad (2)$$

Where $T_{\max}$ is daily maximum temperature, $T_{\min}$ is daily minimum temperature, and T_{base} is the baseline temperature for crop growth, which is 0°C for wheat [2]. The daily growing degree day was capped at 0 at the lower end (i.e., it is assumed that wheat does not negatively develop in substandard conditions and daily GDD cannot be negative). Once calculated per day, the daily GDDs were then summed over the growing season. The daily temperature range was the difference between the daily minimum and maximum temperatures; it was then averaged over the growing season.

Heatwave days were defined as days when the daily maximum temperature was above 32°C , a known physiological threshold of when wheat plants begin to die [3]. Frost days were defined as days when the daily minimum temperature was below 0°C . Various metrics were used to define drought as there is no definitive drought definition for agricultural impact. Both precipitation and soil moisture droughts were used in the model. The precipitation and soil moisture time series were first converted to a 180-day rolling mean time series. We then defined 15th percentile as the drought threshold, calculated separately for each calendar day using the daily rolling mean time series between 1990-2021. Drought days were then defined as days when the rolling mean value (precipitation or soil moisture) fell below the 15th percentile threshold. The choice of threshold and the use of rolling means is analogous to other commonly used drought metrics including the Standardised Precipitation Index, with the 15th percentile threshold approximately equal to an SPI of -1. Other drought aggregations (30- 90-days) were tested in the model development and had similar explained variances as the results presented using the 180-day aggregations. For each extreme, the number of days was then summed over the growing season (or growing season stage).

For heatwaves, precipitation droughts, and soil moisture droughts, the mean intensity of the extreme was also included as a predictor in the yield models. Daily intensity was defined as the percentage deviation of the underlying variable (e.g., temperature, precipitation, soil moisture) from its 1990-2021 baseline average, calculated only for days flagged as experiencing that extreme. Mean intensity was then computed by averaging this daily deviation across all extreme days within the growing season (or growing season stage).

S1.3 Yield model

S1.3.1. Cross validation

We identified which subset of predictors has the greatest influence over wheat yield in Australia using out-of-sample R^2 values based on a temporally withheld cross validation method. First, one year of the data was withheld from the training dataset and used for testing. The Random Forest (RF) model was trained on the remaining years and used to predict the yield of the withheld year. This process was then repeated 20 times, each time withholding a different year of data. This provides a full dataset (from 2000/01 to 2019/20) of out-of-sample predicted yield data, which can be compared to the corresponding withheld observed yield data. The yield values were averaged across the state, providing an annual timeseries of mean observed and predicted yield values per state. The skill was then quantified by computing the R^2 value between predicted and observed state-level yields. This process was repeated 10 times, each time varying the random state of the RF model to ensure robustness and repeatability of the methodology.

R^2 values can also be computed directly for each grid cell from gridded predicted and observed yields (i.e. not aggregating across the state). The grid-cell based R^2 values tend to be lower than aggregated R^2 values, but the conclusions of the study remain unchanged. R^2 values aggregated to the state were used in the final analyses as they reflect the ability of the RF models in capturing the year-to-year variability of yield. These scores may be a fairer comparison to other

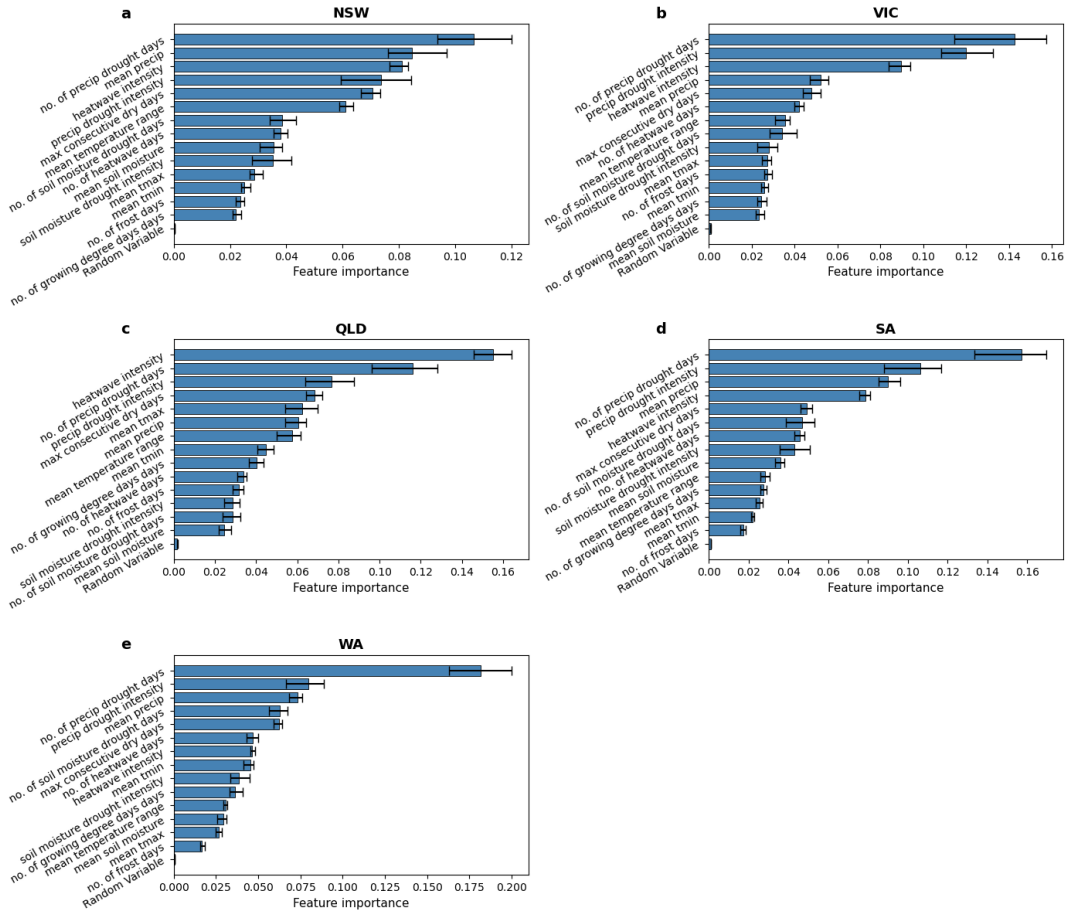
climate-yield studies as they often use yield data aggregated over large regions, which is easier for the models to capture due to the limited noise within the data [4].

S1.3.2. Feature importance

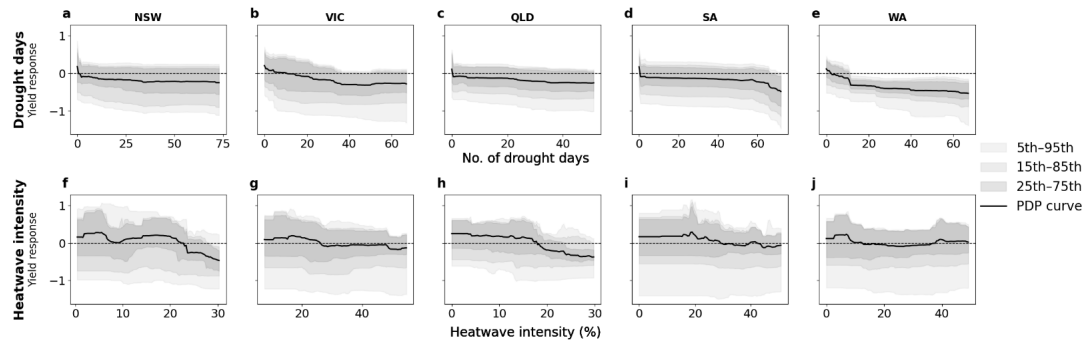
Feature importances were calculated to assess the relative influence of individual climate drivers on wheat yield, using the *permutation_importance* function in the Python package *scikit-learn* (sklearn.inspection). For each predictor, the importance was quantified as the increase in mean squared error (MSE) that resulted when that predictor's values were randomly permuted, breaking its relationship with yield while preserving the marginal distributions of all other variables. A larger increase in MSE indicates greater reliance of the model on that predictor, and therefore greater inferred influence on yield.

To establish a baseline against which predictor importance could be judged, a randomly generated variable was included as an additional predictor in the model. Any predictor that ranked below this random variable in importance was deemed to have no significant influence on wheat yield.

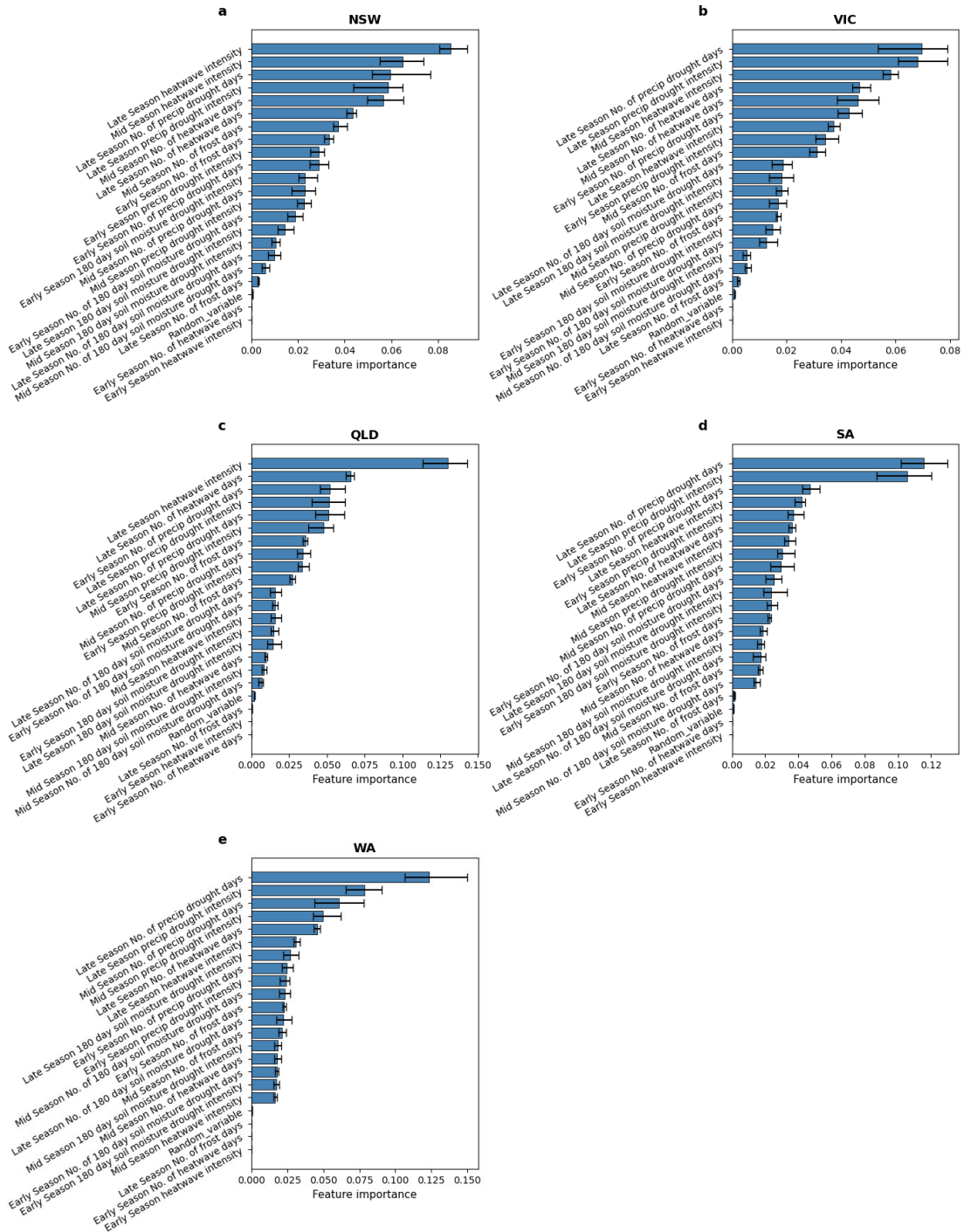
S2. Supplementary figures



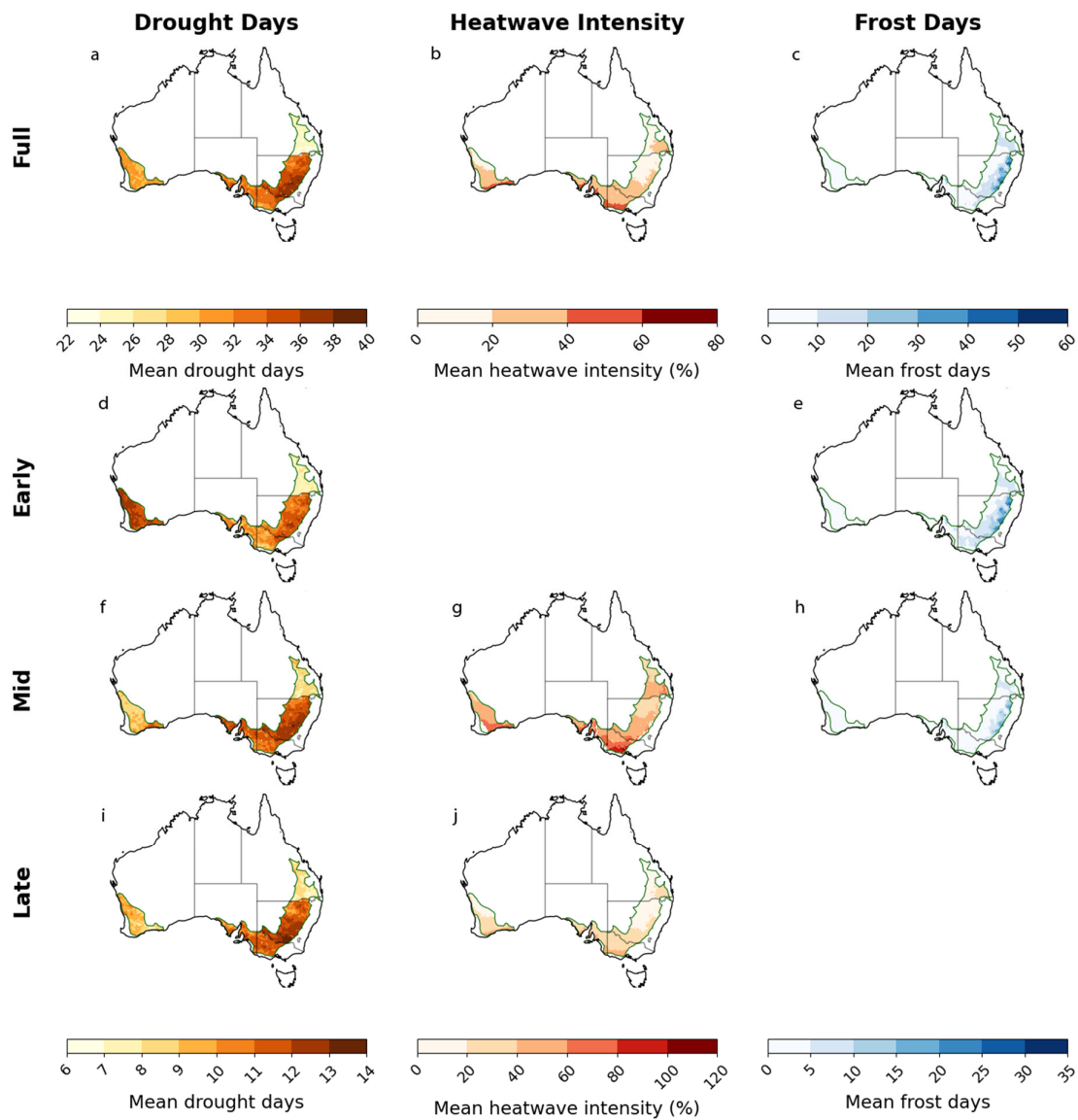
Supplementary Fig. S1: Feature importance rankings for the random forest yield model, using all agroclimatic variables over the growing season. Feature importance for the full set of agroclimatic predictors included in the RF model, shown separately for each major wheat-growing state: **a**, NSW; **b**, VIC; **c**, QLD; **d**, SA; **e**, WA. Error bars indicate the range of importance scores across 10 model runs with different random states. This figure shows the full predictor set underlying the summarized results in Fig. 2b.



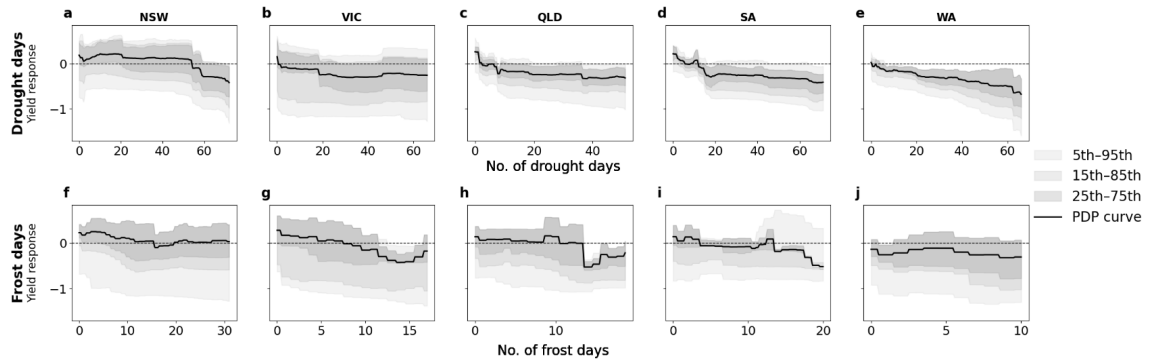
Supplementary Fig. S2: Late season partial dependence plot. Modelled relationship between wheat yield and the number of precipitation drought days (**a-e**) and heatwave intensity (**f-j**), generated using the RF model by stepping each predictor through 100 evenly spaced values across its observed range while holding all other predictors at their observed values. Each column shows a major wheat-growing state (NSW, VIC, QLD, SA, WA). The black line shows the mean predicted yield response; shaded bands show the 25th-75th, 15th-85th, and 5th-95th percentile range



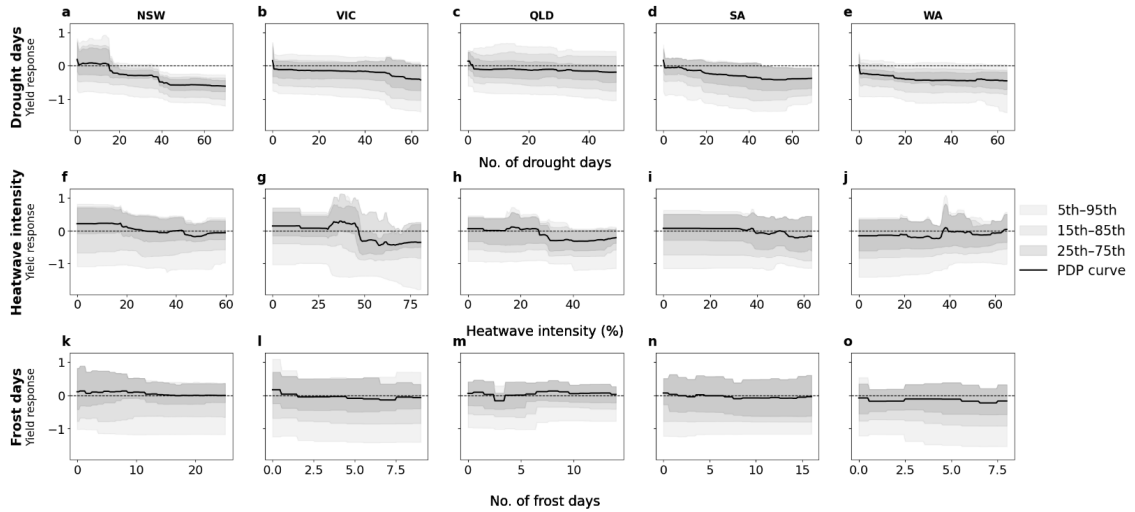
Supplementary Fig. S3: Feature importance rankings for the random forest yield model, using extremes at season stages. Feature importance for the full set of extreme predictors aggregated over growing season stages included in the RF model, shown separately for each major wheat-growing state: **a**, NSW; **b**, VIC; **c**, QLD; **d**, SA; **e**, WA. Error bars indicate the range of importance scores across 10 model runs with different random states. This figure shows the full predictor set underlying the summarized results in Fig. 3b.



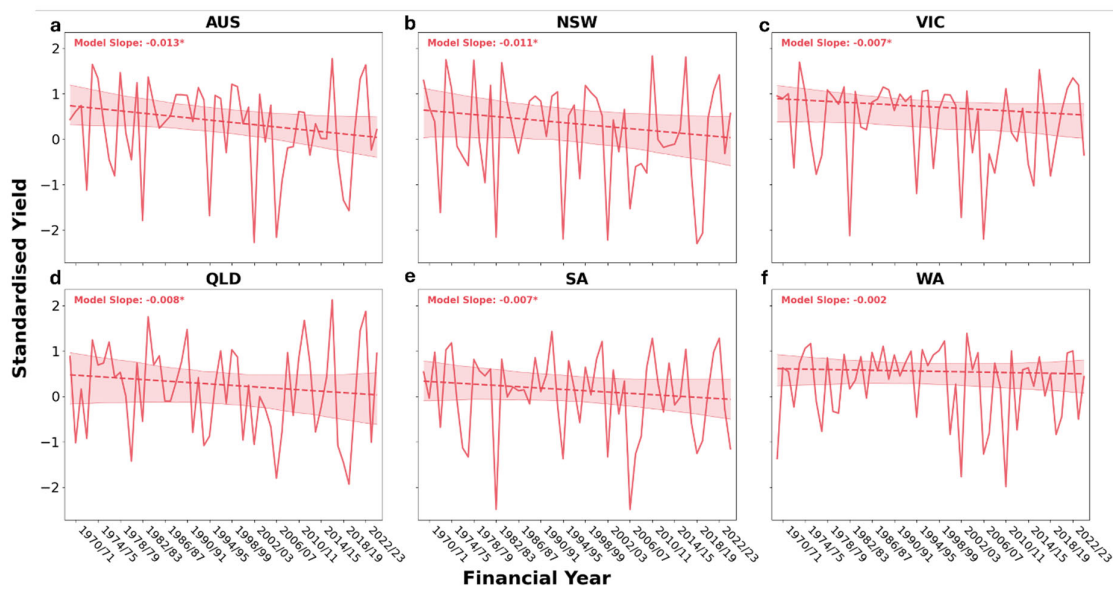
Supplementary Fig. S4: Mean values of key climate extremes across the growing season, 1970-2020. The mean values of drought days, heatwave intensity and frost days across the Australian wheat belt. Shown separately for the full growing season, as well as early, mid, late growing season stages (rows), and for each extreme variable (columns). **a,b**, Early season frost days and drought days. **c-e**, Mid season frost days, drought days and heatwave intensity. **f,g**, Late season drought days and heatwave intensity. **h-j**, Full season frost days, drought days and heatwave intensity.



Supplementary Fig. S5: Early season partial dependence plot. Modelled relationship between wheat yield and the number of precipitation drought days (a–e) and number of frost days (f–j), generated using the RF model by stepping each predictor through 100 evenly spaced values across its observed range while holding all other predictors at their observed values. Each column shows a major wheat-growing state (NSW, VIC, QLD, SA, WA). The black line shows the mean predicted yield response; shaded bands show the 25th–75th, 15th–85th, and 5th–95th percentile range.



Supplementary Fig. S6: Mid season partial dependence plot. Modelled relationship between wheat yield and the number of precipitation drought days (a–e), heatwave intensity (f–j), and number of frost days (k–o), generated using the RF model by stepping each predictor through 100 evenly spaced values across its observed range while holding all other predictors at their observed values. Each column shows a major wheat-growing state (NSW, VIC, QLD, SA, WA). The black line shows the mean predicted yield response; shaded bands show the 25th–75th, 15th–85th, and 5th–95th percentile range.



Supplementary Fig. S7: Climate-driven yield 1969/70-2024/25. Time series of climate driven wheat yield, predicted from the RF model using all agroclimatic variables across the growing season, for **a**, Australia; **b**, New South Wales; **c**, Victoria; **d**, Queensland; **e**, South Australia; and **f**, Western Australia. Solid lines are the standardised yield values (standardised around 2000/01 to 2016/17) for each region; dotted lines are the trends in those yields (Theil-Sen slope estimator), shading around the trend lines is the uncertainty in the trend. Uncertainty bands are the 95th confidence intervals of this slope from 1000 bootstrapped resamples of the data. The slope is labelled on each plot with an asterisk indicating significance of the trend (Mann-Kendall trend test, $p < 0.05$).

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