Warmer growing seasons improve cereal yields in Northern Europe only with increasing precipitation

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Abstract. Crop yields depend on climatic conditions such as precipitation and temperature and their timing before and during the growing season. At high latitudes, climate change could lengthen the growing season and lead to temperatures more suitable for crops but also expose crops to more frequent damaging conditions. We quantified the response of regionally averaged winter and spring cereal yields in Sweden for 1965-2020 to a wide set of ecophysiologically-meaningful climatic descriptors. With statistical models, we explored the role of both short-term and average conditions over different crop developmental stages, as well as of a proxy of water availability during the period prior to the main growing season. Temperature and precipitation or dry spell lengths for the entire growing season explained 75-85% of yield variability, performing better than shorter-term potentially damaging conditions such as number of days with precipitation above 20 mm or temperatures above 25 °C. Low precipitation or extended dry spells combined with high temperatures and, conversely, high precipitation sums with cool temperatures were associated with reduced yields for all crops. Our findings suggest that under climate change crop yields will be reduced in Sweden, unless warming is accompanied by increase in precipitation during the main growing season. With unaltered or reduced growing season precipitation, benefiting from warmer temperatures caused by climate change will require adaptation measures.

Keywords. Climate change, precipitation and temperature, climatic indicators, crop yield, cereals, high latitudes

1 Introduction

Crop yields depend on climatic conditions such as precipitation, temperature, and their interactions (Porter and Semenov, 2005; Ray et al., 2015; Riha et al., 1996). These climatic conditions define the water and energy available for crop establishment, growth, and yield formation (Barron-Gafford et al., 2012; Song et al., 2016). Crop responses to climatic conditions are complex and nonlinear. Both excessive and insufficient precipitation, as well as excessively high or low temperatures, can damage the crop and reduce marketable yields (Hatfield and Prueger, 2015; Luan et al., 2021; Miedema, 1982; Mittra and Stickler, 1961). Excessively dry and warm conditions can cause water and heat stress, hasten development, reduce net photosynthesis, kernel numbers and size, and ultimately decrease yields (Hatfield and Prueger, 2015; Praba et al., 2009; Siebert et al., 2017). At the other extreme, excessive precipitation is often associated with reduced solar radiation (Díaz-Torres et al., 2017), causes nutrient losses and oxygen deficiency (Becker, 2014; Schreiber, 1999), and enhances fungal growth (Barnes et al., 2018). Intense precipitation can also damage crops mechanically. To assess expected climate change effects on crop yields and improve crop yield modeling, we need to identify the most damaging conditions and determine the extent of their impacts.

At high latitudes, such as in Northern Europe, current temperatures result in limited periods suitable for soil cultivation and crop growth. Global warming might create new opportunities by lengthening the growing season and improving growing conditions (Bindi and Olesen, 2011; Juhola et al., 2017; Olesen et al., 2011; Wiréhn et al., 2017), expanding the range of cultivable crops (Heikonen et al., 2025; Wiréhn, 2018), and enhancing photosynthesis and water-use efficiency due to rising CO_2 concentrations (Rezaei et al., 2023). At the same time, warmer conditions enhance evapotranspiration thus reducing soil water availability and increasing the risk of plant water stress unless precipitation increases. Moreover, frequency and magnitude of extreme conditions such as dry, hot or wet spells, are expected to increase globally, also in northern Europe (Song et al., 2016; Toreti et al., 2019; Wiréhn et al., 2017). Indeed, reduced yields due to excessively dry periods during the growing season or soil saturation that limits access to machinery, have already been observed in Northern Europe (De Toro et al., 2015; Trnka et al., 2011). Nonetheless, the net effect of positive and negative changes in climatic conditions in Northern Europe is still unclear.

Different aspects of climatic conditions and their co-occurrence affect crop yields. Even detrimental conditions of short duration can have large adverse effects (Hakala et al., 2020; Zhu and Troy, 2018). Averaging the climatic conditions over the growing season can mask the role of these short-term, but potentially severely damaging conditions (Lesk et al., 2022; Luan et al., 2021; Troy et al., 2015; Vogel et al., 2019). Considering short-term conditions is particularly important in the face of climate change because of the projected changes in timing and magnitude of short-term extreme events (Thiery et al., 2021; Tootoonchi et al., 2023; Wiréhn et al., 2017). Furthermore, combinations of damaging climatic conditions can have disproportionally large impacts compared with the sum of their individual effects (Alizadeh et al., 2020; Luan et al., 2021; Suzuki et al., 2014; Teutschbein et al., 2023a). To effectively evaluate the effects of climatic conditions on crop yields, we need to consider both seasonal averages and shorter-term conditions, as well as their combinations. Yet we lack quantification of the role of short-term conditions and combination of conditions on crop yields at high latitudes.

Crops response to growing conditions depend on their developmental stage, via often complex mechanisms and non-linear effects (Lüttger and Feike, 2018; Mäkinen et al., 2018; Suliman et al., 2024; Trnka et al., 2014).

For example, spring cereals tend to be more sensitive to water stress around flowering (Martyniak, 2008) compared with other developmental stages, and more so when co-occurring with heat stress (Barnabás et al., 2008; Dolferus et al., 2011; Senapati et al., 2021). Late-season precipitation can reduce crop yield and quality by enhancing fungal growth or delaying harvests due to wet soils (Olesen et al., 2011). Moreover, the conditions before the beginning of the growing season can have legacy impacts (Trnka et al., 2016). Accumulated soil water before the beginning of the growing season helps buffering the negative effects of limited precipitation after sowing of spring crops or after the end of winter dormancy for winter crops (Li et al., 2019). However, excessive soil water delays sowing of spring crops (Trnka et al., 2011). Despite the importance of the timing of conditions in relation to crop physiological development, the response to climatic conditions at different developmental stages, and the legacy effects of conditions before the main growing season remain largely uncharacterized, in particular at high latitudes.

Climatic conditions during a period can be summarized via a variety of climatic indicators (McMillan, 2021; Schmidt and Felsche, 2024; Wiréhn, 2021; Zhu and Troy, 2018). These are 'simple diagnostic quantities that are used to characterize an aspect of a geophysical system' (Schneider et al., 2013), such as states, variability, or frequencies of climatic conditions (Wiréhn, 2021). Selecting the most suitable indicators is challenging and depends on the purpose, regional climate, and most critical climatic conditions (Adger, 2006; Wiréhn, 2021). A systematic exploration of a wide range of relevant climatic indicators is essential to identify the most relevant indicators to explain crop yields.

Using county-level yield data of staple cereals and meteorological data for 1965-2020 across Sweden, we systematically explore the role of various climatic indicators on crop yields under Northern European conditions. Specifically, we ask:

1. Which climatic conditions and relative to which period (i.e., pre- (main) growing season, pre- or post-flowering, or whole growing season) explain crop yields best?
2. Which climatic conditions, and their combinations, are the most beneficial for yields? Which are the most detrimental?

The results can help predict crop yield through statistical models. They also provide insight into the climate change impacts on agriculture for Northern Europe and whether specific cereals are better adapted to the conditions likely to become more frequent in the future.

2 Data and Methods

We aimed to identify which climatic conditions, their combinations and timing during the year were most important in defining each crop yield in Sweden (Section 2.1, Fig. 1). The climatic indicators (section 2.2) were chosen based on our ecophysiological understanding of plant response to climatic conditions (as detailed in Section 2.2.1). We considered four periods of physiological relevance, defined for each crop and year based on a minimalist phenological model (Section 2.2.2). We then compared the performance of several statistical models, with yield of each crop as dependent variable and different climatic indicators and their interactions as explanatory variables (Section 2.3).

2.1 Crop yield and climatic data

Crop yield data for the period 1965-2020 over the 21 Swedish counties (län in Swedish) was obtained from Statistics Sweden (Statistikdatabasen), for the most commonly grown cereals in the country, i.e. winter wheat, spring wheat, spring barley and oats (Fig. 1). The percentage of unavailable data was 18%, 33%, 1% and 13%, respectively, and can be ascribed to either uncertainty in yearly yield cultivation (i.e., yield not meeting reporting criteria) or confidentiality reasons (i.e., crop sown only in few fields, Statistikdatabasen). The fraction of cultivated area per county was higher in the south where conditions are more favorable, permitting cultivation of all four crops, whereas only oats and spring barley were reported for the north (Fig. 1).

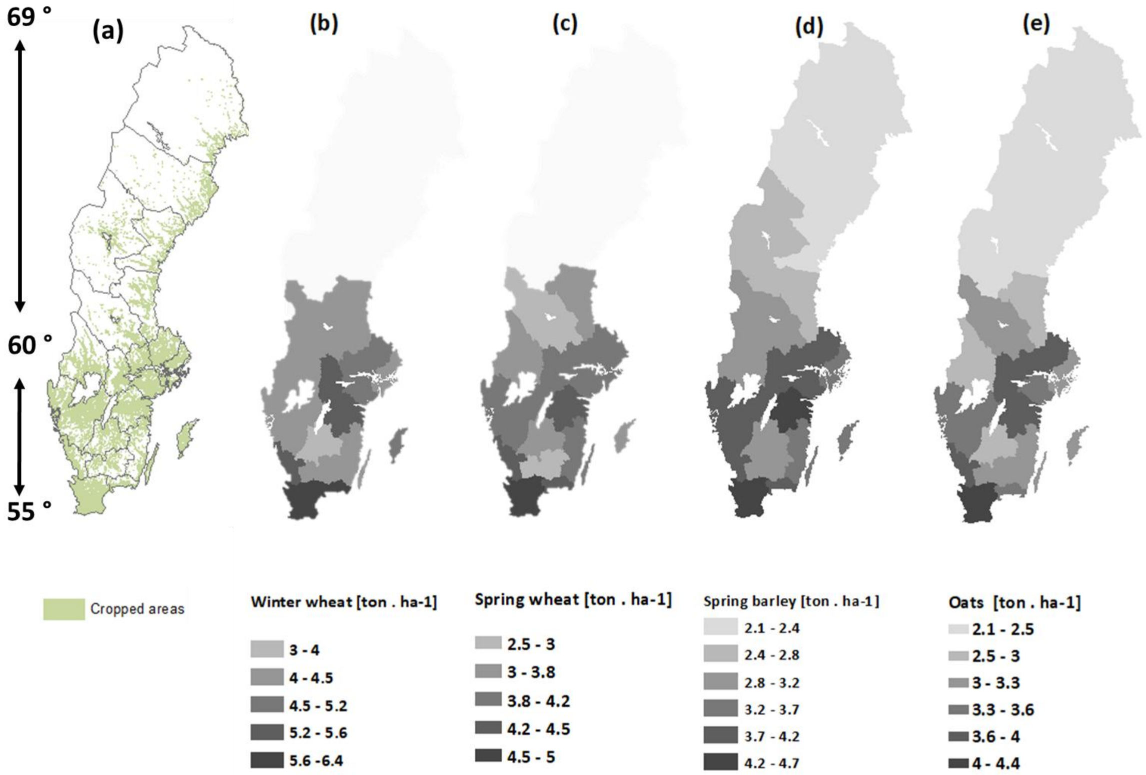

Figure 1: Overview of the study area including (a) the location of cropped areas in green and (b-e) the average yields of each of the four crops for each county in Sweden during the period 1965-2020. Only the counties corresponding to the regions where these crops are cultivated are reported, i.e., only to -latitudes of approximately 61 °N for winter and spring wheat.

For meteorological data, we used gridded observed daily precipitation as well as average, minimum and maximum daily temperature values from E-Obs gridded data (Cornes et al., 2018) version 26.0e at 0.1 resolution. Counties extend over 2.9-98.2 km^2 and include large areas that are not cropped due to unsuitable climatic and soil conditions. Hence, we considered as representative of each county the gridded meteorological data averaged over cropped areas of the county. The cropped area was assumed to match the Non-irrigated arable fields in the CORINE land cover map (European Environment Agency, 2020). The 2006 map (CLC2006) was used as representative of the entire period.

2.2 Climatic indicators

2.2.1 Selection procedure of climatic indicators

We selected candidate climatic indicators based on previous local and global analyses, to include those that had shown promise to explain crop yield variability across a wide geographic ranges (Kaseva et al., 2023; Luan et al., 2021; Mäkinen et al., 2018; Wiréhn et al., 2017; Zhu and Troy, 2018). We also considered some complementary indicators that had not been previously used to explain yield variability, but we deemed relevant in particular under Northern European conditions, based on the climatic conditions under which most commonly grown crops thrive or are damaged.

The selection process resulted in 20 candidate indicators (Table 1). These either reflected separate attributes of precipitation and temperature (averages over specific periods or frequency of exceedance of specific thresholds of either precipitation or temperature), or were composite in nature (i.e., included the role of both temperature and precipitation). Examples of composite indicators are the dryness index (DI) and total precipitation occurring in days with freezing temperature (P_T0).

Selected indicators captured complementary attributes of the climatic conditions, such as variability (e.g., standard deviation of precipitation and temperature, Pvar and Tvar), duration of specific conditions (e.g., maximum number of consecutive dry days, CDD), occurrence of peaks over thresholds (e.g., number of days with precipitation above 10 mm, NDP10) and magnitude (intensity) of a variable (e.g., maximum precipitation amount in a single day, MaxP_1D, or total precipitation over the period, Psum). The candidate indicators also reflected conditions over different time spans, such as averages over longer periods, up to the whole main growing season (e.g., mean temperature, Tmean; see Section 2.2.2 for the definition of the growing season), or short-term but potentially severely detrimental conditions lasting only one or few days (e.g., CDD). While even shorter-term extremes, such as intense rainfall over 15 minutes can impact crops, we cannot explore their effects as such data are not available at the spatiotemporal scale of this study.

We checked the candidate indicators for similarity, based on Spearman correlation coefficients (Spearman, 1904, Fig. 2). To focus on complementary indicators and reduce redundancy and collinearity, we eliminated one climatic indicator within each pair of highly correlated (>|0.5|) indicators (as in e.g. Addor et al., 2018 or Sjulgård et al., 2023). The pairwise correlations between precipitation and temperature indicators were generally lower (between -0.3 and 0.3) compared with correlation between indicators based on precipitation or temperature only. A general positive correlation prevailed among precipitation indicators, except for indicators of dryness (Ndry5 and CDD), which were negatively correlated with the rest of the precipitation indicators. Temperature indicators were negatively correlated for those representing low temperatures Frost and Icing days, as well as for daily temperature variance, but were positively correlated for the rest of the indicators.

Among pairs of highly correlated indicators linked to precipitation, we chose CDD over NDDry_5d because the former represents dry periods of various lengths. Between CWD and NDP1, we chose NDP1 as it may indirectly capture also the reduction in solar radiation (Díaz-Torres et al., 2017). We also kept the number of days with precipitation exceeding 20 mm (NDP20), instead of the indicator relative to 10 mm (NDP10), due to the damaging and extreme nature of the former. We also eliminated the maximum amount of precipitation over 1 and 5 days (MaxP_1D and MaxP_5D) because both were highly correlated with NDP20. For highly correlated temperature indicators, we selected the number of days above 25 °C (NDT25) instead of 30 °C (NDT30) because temperatures higher than 25 °C likely are at the high end of optimal temperatures of typical local varieties; moreover, the historically low frequency of days above 30 °C could reduce the robustness of the constructed statistical models. Between number of frost and icing days we retained frost days, because freezing nights can be sufficient to cause permanent damage in non-acclimated crops (François and Vrac, 2023). Regarding average temperatures, we focused on Tmean, i.e., the average mean daily temperature, because it was well correlated with both minimum and maximum daily temperatures, averaged over the same period. Moreover, Tmean is readily available in climatic data.

The two composite indicators, DI (Dryness Index, a proxy for water availability) and P_T0 (a proxy for snow amount), were highly correlated when calculated before the beginning of the main growing season (see Section 2.2.2), likely because of the low temperatures during that period. Between the two, we selected DI because of its direct influence on crops (Jackson et al., 2023). While sufficient snow cover is important for insulating winter crops (Zhu et al., 2022), directly assessing snow effects requires multiple additional indicators and reliable snow data, which are limited and uncertain at a high spatial resolution over 1965–2020 (Wood et al., 2025).

After the selection, we retained five precipitation indicators (Psum, Pvar, NDP1, NDP20 and CDD), four temperature indicators (Tmean, Tvar, frost and NDT25), and one composite indicator (DI; in bold in Table 1).

Table 1: List of 20 indicators that were identified from the literature or were deemed relevant to assess the impact of climatic conditions on crop yields at high latitudes. Indicators were categorized into 3 categories, representing (a) precipitation (b) temperature and (c) combined influence of precipitation and temperature. The indicators in bold are

those selected after a second round of screening, eliminating those showing high Spearman correlation with the selected ones, and after selecting those with complementary nature.

Variable	climatic indicators [Unit]	Description	Examples of application in crop response
(a)Precipitation	**Psum [cm]**	Total of daily precipitation	(Luan et al., 2022; Lüttger and Feike, 2018; Vogel et al., 2019)
	NDP1[days]	Number of days, also non-consecutive, with daily precipitation above 1 mm	(Copernicus Climate Change Service, 2019)
	NDP10 [days]	Number of days, also non-consecutive, with daily precipitation above 10 mm	(Copernicus Climate Change Service, 2019)
	NDP20 [days]	Number of days, also non-consecutive, with daily precipitation above 20 mm	(Copernicus Climate Change Service, 2019)
	MaxP_1D [$mm \cdot day^{-1}$]	Maximum precipitation amount in one day	(Lesk et al., 2020)
	MaxP_5D [$mm \cdot day^{-1}$]	Maximum precipitation amount in five consecutive days	(Vogel et al., 2019; Zhu and Troy, 2018)
	NDDry_5d [-]	Number of dry spells longer than 5 consecutive days	(Manning et al., 2023; Masupha et al., 2016)
	Pvar [$mm^2 \cdot day^{-2}$]	Variance of daily precipitation	(Tootoonchi et al., 2022; Zhu and Troy, 2018)
	CDD [days]	Maximum number of *consecutive* dry (< 1mm/day) days	(Luan et al., 2022)
	CWD [days]	Maximum number of consecutive wet (> 1mm/day) days	(Copernicus Climate Change Service, 2019)
(b)Temperature	**Tmean [°C]**	Mean of daily mean temperature	(Carter et al., 2018; Luan et al., 2022; Vogel et al., 2019)
	Tmin [°C]	Mean of daily minimum temperature	(Copernicus Climate Change Service, 2019)
	Tmax [°C]	Mean of daily maximum temperature	(Copernicus Climate Change Service, 2019)
	NDT25[days]	Number of days, also non-consecutive, with maximum temperature above 25°C	(Lüttger and Feike, 2018; Zhu and Troy, 2018)
	NDT30 [days]	Number of days, also non-consecutive, with maximum temperature above 30°C	(Lüttger and Feike, 2018; Zhu and Troy, 2018)
	Frost [days]	Number of days, also non-consecutive, with daily minimum temperature below 0°C	(Copernicus Climate Change Service,2019)
	Icing [days]	Number of days, also non-consecutive, with daily maximum temperature below 0°C	(Zhu and Troy, 2018)
	Tvar [$°C^2 \cdot day^{-2}$]	Variance of daily mean temperature	(Tootoonchi et al., 2022; Zhu and Troy, 2018)
(c) Combined P and T	**DI**[$mm \cdot mm^{-1}$]	Dryness index, i.e., the ratio of total potential evapotranspiration (PET) calculated via Hamon (Hamon, 1961) to total precipitation. DI >1 indicate water-limited conditions, whereas DI < 1 indicate water availability exceeding crop demand.	(Luan et al., 2022; Todorovic et al., 2022)
	P_T0 [$mm \cdot day^{-1}$]	Sum of precipitation occurring when mean daily temperature is below 0°C	(Climate indicator - Snow | SMHI, 2023; Fontrodona-Bach et al., 2023)

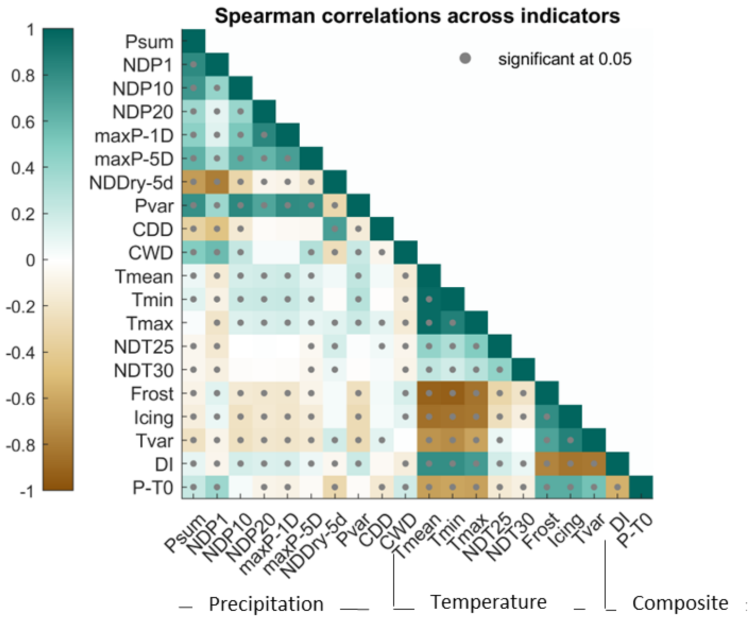

Figure 2: Spearman correlation between pairwise indicators representing magnitude, variation and duration of precipitation and temperature, as well as two composite indicators over the entire growing season (see Table 1 for indicator definitions and section 2.2.2 for the definition of periods). The significant correlations ($p < 0.05$) are marked with a grey circle. The figure refers to the main growing season of winter wheat for all indicators except the composite indicators DI and P-T0, which refer to the pre-growing period. Similar patterns were observed when considering spring crops and sub-periods.

2.2.2 Periods of interest

For each crop and cropped land in each county, we defined the (main) growing season, pre-flowering and post-flowering based on estimated sowing, flowering and maturity dates, averaged over the 56 years spanned by yield data. Lacking phenological observations, we estimated these dates via a phenological model based on growing degree days (GDD) and day length, with crop-specific thresholds previously employed across Europe (Marini et al., 2020; Olesen et al., 2012). This approach complements the crop growing calendar (Caparros-Santiago et al., 2021; Minoli et al., 2022) by accounting for year-to-year variations in flowering and maturity due to temperature variability. We also tested the effects of different GDD thresholds and of using year-to-year variations instead of averages and found that neither affected the results.

We defined the growing season as the period between sowing and maturity dates for spring cereals, and between beginning of the main growing season and maturity for winter wheat, which in the region is sown in the autumn and harvested the following summer. Similarly, the pre-flowering period ran between sowing (for spring crops) and beginning of the main growing season (for winter wheat) and flowering, whereas the post-flowering period extends between flowering and maturity. We focused on the main growing season, i.e., when most of the plant activity occurs, for winter wheat as this is the most important period for yield formation, although damages to the plant can occur also during the winter. The beginning of the main growing season, i.e. the timing of the release of winter dormancy, was estimated as the first yearly occurrence of an increase in GDD corresponding steeper than ≥ 4 °C·d^{-1} (Costa et al., 2024). The date did not considerably change when other thresholds beyond 4 °C·d^{-1} were considered.

We calculated the retained indicators (Table 1, in **bold**) for each year and cropped land in each county, relative to the three crop-specific periods: entire growing season, pre- and post-flowering. Dryness index was calculated in the above-mentioned periods and also during pre-growing season periods as this variable is most likely to capture effects extending beyond the main growing season for winter crops and the actual growing season for spring crops, while simultaneously reflecting the combined influence of temperature and precipitation. Lacking clear evidence on the duration of any legacy effects prior to sowing or beginning of the growing season, we examined the dryness index averaged over or 30, 60, 90 day-long periods before the sowing date for spring crops, or the beginning of the main growing period for winter wheat and selected the period resulting in highest model performance for each crop.

2.3 Statistical analyses

We used linear mixed effect models (Bürger et al., 2012; Smith et al., 2005) to explore crop yield responses to climatic indicators during the identified periods. We fitted separate models for each crop, with yield Y as the dependent variable, and a set of explanatory climatic indicators as fixed effects. Neither yields nor climatic indicators were de-trended, and log-transformation of yields was unnecessary because the yields were not skewed. This also had the advantage that fitted parameters could be directly interpreted as changes in yield per unit change in the climatic conditions. We included time elapsed from year 1965 (t) as a continuous variable in all models, thus accounting for the combined impacts of climate change and increasing CO_2 emissions, as well as technological improvements, including variety and management changes. Furthermore, year and county were included as categorical random effects in all models to consider spatiotemporal heterogeneity and variations over the study area.

We considered three types of models for each crop. The first type had the composite precipitation-temperature indicator, dryness index, as explanatory variable to capture the role of precipitation and temperatures at the same time. Dryness index can summarize key aspects of soil water availability essential for crop growth through interplay between precipitation and temperature, thus being used as an indicator to capture balance between water supply and energy-driven demand. As such, dryness index provides a more process-oriented view at the relationship between precipitation, temperature, and their interactions. We included also quadratic dependence of yield on dryness index to account for excessive dryness (Luan et al., 2022). The fixed part of the model was

$$Y = \beta_0 + \beta_t t + \beta_{DI}(DI) + \beta_{DI2}(DI)^2 \quad \text{eq. 1}$$

Where Y is the yield of the crop of interest, β_0 is the global intercept, β_t, β_{DI} and β_{DI2} represent dependences of yield on t, DI and DI^2, respectively.

The second type of model aimed at quantifying the role of conditions that either extend over the whole period considered (e.g., averages), or for a potentially substantial part of that (e.g., dry spells). We focused on pairs of interacting indicators representing precipitation (x_P) and temperature (x_T) characteristics, separately. We considered three pairs of x_P and x_T indicators, each reflecting different aspects: i) Precipitation sums (Psum) and temperature averages (Tmean), characterizing average conditions, ii) precipitation and temperature variance (Pvar and Tvar), characterizing the variability of the conditions, or iii) maximum length of the dry spells (CDD) and temperature averages (Tmean), characterizing the occurrence of dry spells, the effect of which is expected to be more marked at higher temperature. As fixed effects, in its most complex form, the model included a quadratic dependence on x_P and x_T as well as all the possible two-way interactions, because the damaging effects of low precipitations are stronger with high temperatures and vice versa. The fixed part of the model was

$$Y = \beta_0 + \beta_t t + \beta_P(x\_P) + \beta_T(x\_T) + \beta_{P2}(x\_P)^2 + \beta_{T2}(x\_T)^2 + \beta_{PT}(x\_P)(x\_T) + \beta_{P2T}(x\_P)^2(x\_T) + \beta_{PT2}(x\_P)(x\_T)^2 + \beta_{P2T2}(x\_P)^2(x\_T)^2 \qquad \text{eq. 2}$$

where β_0 is the global intercept, β_{t}, β_P and β_T are the slopes of the linear dependencies of crop yield on time, precipitation and temperature indicators, respectively, and β_{P2} and β_{T2} are quadratic dependencies of crops to the same indicators. Including a quadratic dependence on x_P and X_T allows for intermediate yield-maximizing conditions. The interactions between precipitation and temperature indicators are represented by β_{PT}, β_{P2T} and β_{PT2}. We compared the performance of the most complex model (eq. 2) with nine model variants of decreasing complexity, for a total of 10 model variants for each of pair of x_P and X_T indicator, period of the year, and crop. For each period of the year, crop and pair of climatic indicators, among the variants of eq. 2, we first selected the model with lowest Akaike Information criterion (AIC). AIC is a statistical performance measure that accounts for the model complexity, thus allowing a fair comparison of models differing in number of coefficients. For each crop and for each set of explanatory indicators, among the models with lowest AIC relative to the different periods, we picked the one with highest complexity as the final model. With this strategy, we had models of comparable complexity for separate crops and separate indicators.

The third type of model focused on short-duration, but potentially damaging, conditions. We considered four short-term indicators as explanatory variables. These indicators were selected from the pool of reviewed indicators (2.2.1), due to their damaging nature and reflected complementary behaviors, two reflecting precipitation characteristics (NDP1, NDP20), and two temperature characteristics (NDT25 and Frost). The fixed part of the model was

$$Yield = \beta_0 + \beta_t t + \beta_{NDP1}(NDP1) + \beta_{NDT25}(NDT25) + \beta_{NDP20}(NDP20) + \beta_{Frost}(Frost) + \beta_{NDP1-2}(NDP1)^2 + \beta_{NDT25-2}(NDT25)^2 + \beta_{NDP20-2}(NDP20)^2 + \beta_{Frost-2}(Frost)^2 \qquad \text{eq. 3}$$

where β_{NDP1} and β_{NDP20} represent the linear dependencies of yield to two precipitation indicators NDP1 and NDP20 and β_{NDT25} and β_{Frost} to two temperature indicators NDT25 and Frost, respectively. β_{NDP1-2}, $\beta_{NDP20-2}$, β_{NDT25} and β_{Frost} represent the quadratic dependencies of the crops to the same indicators. We introduced quadratic dependences to allow for yield-maximizing intermediate conditions and high levels of damaging conditions. We did not include any interaction terms, because these conditions do not likely compound. We did not perform any model selection and simplification for this model.

We applied the first type of model, that based on DI, to all four periods, including pre- growing season, while the second and third types of models were applied on three periods, i.e., the entire growing season, pre-flowering and after flowering.

We selected indicator combinations and models to balance data availability, simplicity, and interpretability, guided by our ecophysiological understanding (Luan et al., 2022; Ortiz-Bobea et al., 2021; Ray et al., 2015). This approach allowed us to avoid physiologically unsupported or overly complex combinations. We fitted each model via the restricted maximum likelihood method using fitlme function in MatLab R2023a. Based on AIC, we determined which climatic indicators, model structures and periods had the highest performance (Fig. 3). The same approach was used to compare the different lengths of the pre- (main) growing periods (30, 60, 90 days). Beyond AIC, we considered the fraction of explained variance by fixed effects only (r2marg) or by both fixed effects and random effects (r2cond) as additional metric of model performance (Nakagawa & Schielzeth 2013). We considered effects significant when $p < 0.05$. We then plotted crop yield as a function of best performing set of climatic indicators and pre- (main) growing dryness index, relative to the intermediate year 1992 (Fig. 4-5). The MatLab statement for each of the three types of models can be found in Supplementary Information (SI), showing yield dependence to both random and fixed effects.

3 Results

The best performing model had precipitation sum and temperature averages as explanatory variables for winter wheat (Fig. 3a) and spring barley (Fig. 3b), and maximum length of the dry spell (CDD) and temperature average for spring wheat (Fig. 3c) and oats (Fig. 3d). The fraction of explained variance by fixed effects ranged from 0.15 to 0.50 (Fig. 3), and from 0.76 to 0.85 when considering also the random effects (Table 2; SI Table S1-S4). The fraction of explained variance was lowest for oats and highest for winter wheat.

Conditions relative to the entire (main) growing season had the highest performance for all crops according to the AIC. Models based on post-flowering conditions for winter wheat (Fig. 3a) and oats (Fig. 3d), pre-flowering conditions for spring barley (Fig. 3b), and pre-growing dryness index for spring wheat (Fig. 3c) had the second best performance. However, despite a higher AIC, these models explained a fraction of the variance comparable with the models of the entire growing season, for a given set of indicators. The difference in marginal r2 was 2 to10% depending on the crop (Fig. 3).

Models based on the dryness index had intermediate performance (Fig. 3) for all periods and crops except spring wheat. The effects of dryness index, as a proxy of the legacy effects of the period before the beginning of the (main) growing season, were best captured when considering the 60 days prior to the sowing for spring wheat, and 90 days for the other crops (not shown).

Models based on either short-term indicators or the variability of precipitation and temperature had the lower performances (Fig. 3).

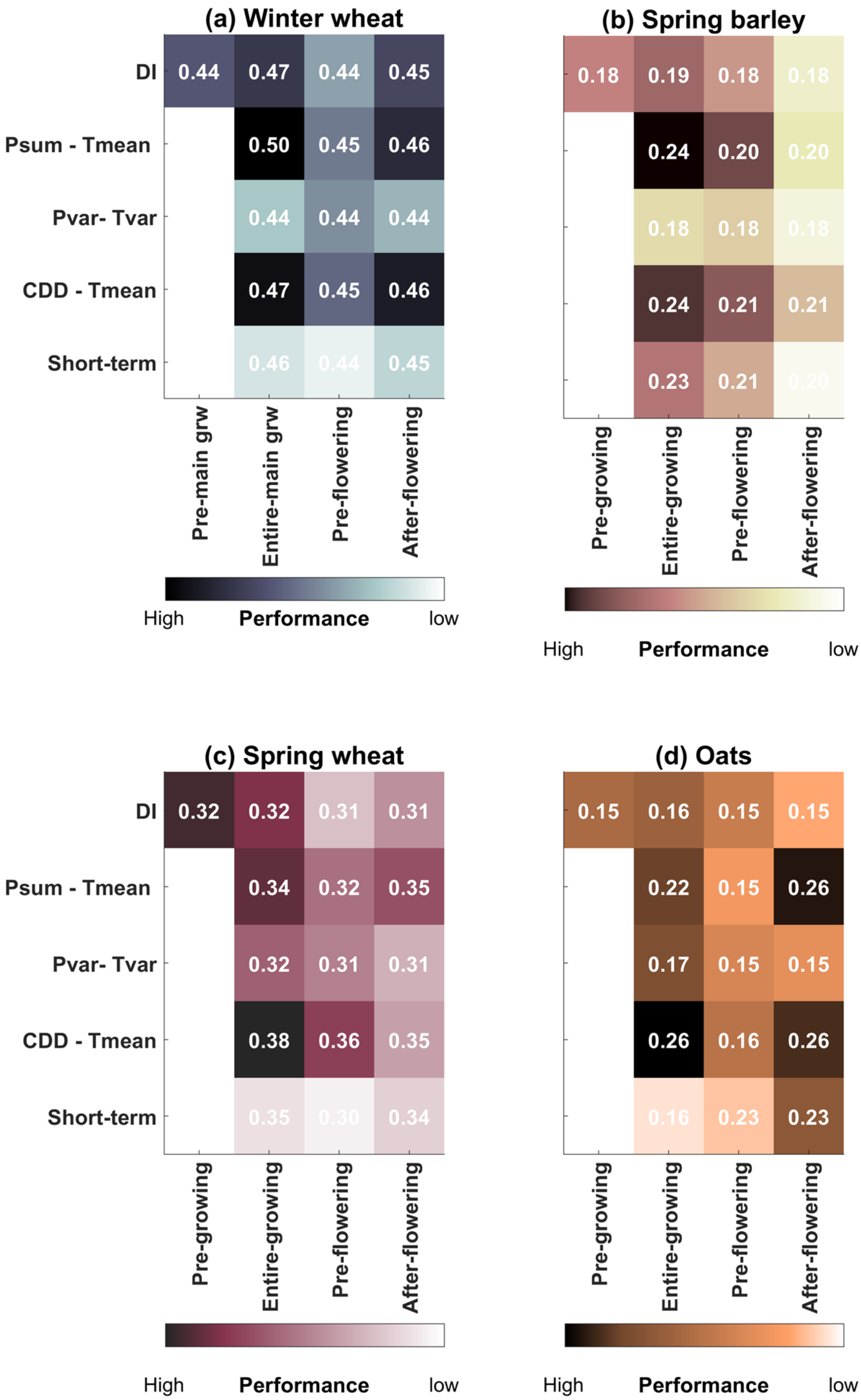

Figure 3: Performance of statistical models for yields differing in explanatory variables and period, for four crops (a) winter wheat (b) spring barley (c) spring wheat and (d) oats. Performance is assessed based on the AIC. The darker the color the lower the AIC and hence the higher the performance. Values in each cell indicate the corresponding

r2marg for each model, representing the fraction of variance explained by climatic conditions and time. Duration of the pre- (main) growing season is 2 months for spring wheat and 3 months for other crops. Short-term conditions refer to the model combining addictively two precipitation indicators (NDP1, NDP20) and two temperature indicators (NDT25, Frost). For a full list of abbreviations, see Table 1.

Table 2 Best performing combination of model, climatic indicators and period for each crop (a-d) and associated estimated coefficients, standard error (SE) and p. For each model we report also the fraction of explained variance when using only the fixed effects (r2marg) and when using both fixed effects and random effects (r2rand). Cases for p<0.05 are highlighted in bold.

	Winter wheat and spring barley						
	Period	**Entire growing season**					
	Indicators	Psum (denoted as x_P) and Tmean (denoted as x_T)					
	Model structure	$\beta_0 + \beta_t t + \beta_P x\_P + \beta_T x\_T + \beta_{P2} x\_P^2 + \beta_{PT}(x\_P)(x\_T)$					
		a) Winter wheat			b) Spring barley		
Predictor	Coefficient	Estimate	SE	p	Estimate	SE	p
-	β_0 [ton·ha^{-1}]	10.432	1.253	**<0.05**	9.138	0.765	**<0.05**
Time t	β_t [ton·ha^{-1}·yr^{-1}]	0.054	0.004	**<0.05**	0.028	0.002	**<0.05**
Precipitation indicator P	β_P [ton·ha^{-1}·cm^{-1}]	-0.330	0.074	**<0.05**	-0.259	0.034	**<0.05**
Temperature indicator T	β_T [ton·ha^{-1}·°C^{-1}]	-0.568	0.088	**<0.05**	-0.530	0.050	**<0.05**
P x T	β_{PT} [ton·ha^{-1}·cm^{-1}·°C^{-1}]	0.032	0.005	**<0.05**	0.022	0.002	**<0.05**
P^2	β_{P2} [ton·ha^{-1}· cm^{-2}]	-0.003	0.001	**<0.05**	-0.001	0.000	**<0.05**
	r2marg		0.50			0.24	
	r2cond		0.87			0.82	
	Spring wheat and oats						
	Period	**Entire growing season**					
	Indicators	CDD (denoted as x_P) and Tmean (denoted as x_T)					
	Model structure	$\beta_0 + \beta_t t + \beta_P x\_P + \beta_t x\_T + \beta_{T2} x\_T^2 + \beta_{PT}(x\_P)(x\_T)$					
		c) Spring wheat			d) Oats		
	Name	Estimate	SE	p	Estimate	SE	p
-	β_0 [ton·ha^{-1}]	-12.394	4.354	**<0.05**	-9.544	2.905	**<0.05**

Time t	β_t [ton·ha^{-1}·yr^{-1}]	0.033	0.003	**<0.05**	0.023	0.002	**<0.05**
Precipitation indicator P	β_P [ton·ha^{-1}·day^{-1}]	0.130	0.054	**<0.05**	0.134	0.036	**<0.05**
Temperature indicator T	β_T [ton·ha^{-1}·°C^{-1}]	2.116	0.612	**<0.05**	1.741	0.419	**<0.05**
P x T	β_{PT} [ton·ha^{-1}·day^{-1}·°C^{-1}]	-0.009	0.003	**<0.05**	-0.011	0.002	**<0.05**
T^2	β_{T2} [ton·ha^{-1}·°C^{-2}]	-0.071	0.021	**<0.05**	-0.060	0.015	**<0.05**
	r2marg		0.38			0.26	
	r2cond		0.85			0.77	

In all crops, precipitation and temperature indicators interacted in defining yields (Table 2). Yields increased between 0.2 ton·ha^{-1} per decade for spring crops and 0.5 ton·ha^{-1} per decade for winter wheat (Table 2), i.e., 7% to 10% of the long-term average. Winter wheat and spring barley yields were maximum or near maximum for combinations of jointly increasing precipitation sums and average temperatures during the (main) growing season (Fig. 4a-b). Yields of spring wheat and oats were maximum at approximately average temperature 14 °C and 7 day CDD (Fig. 4c-d). The yield maximizing temperatures decreased with increasing CDD.

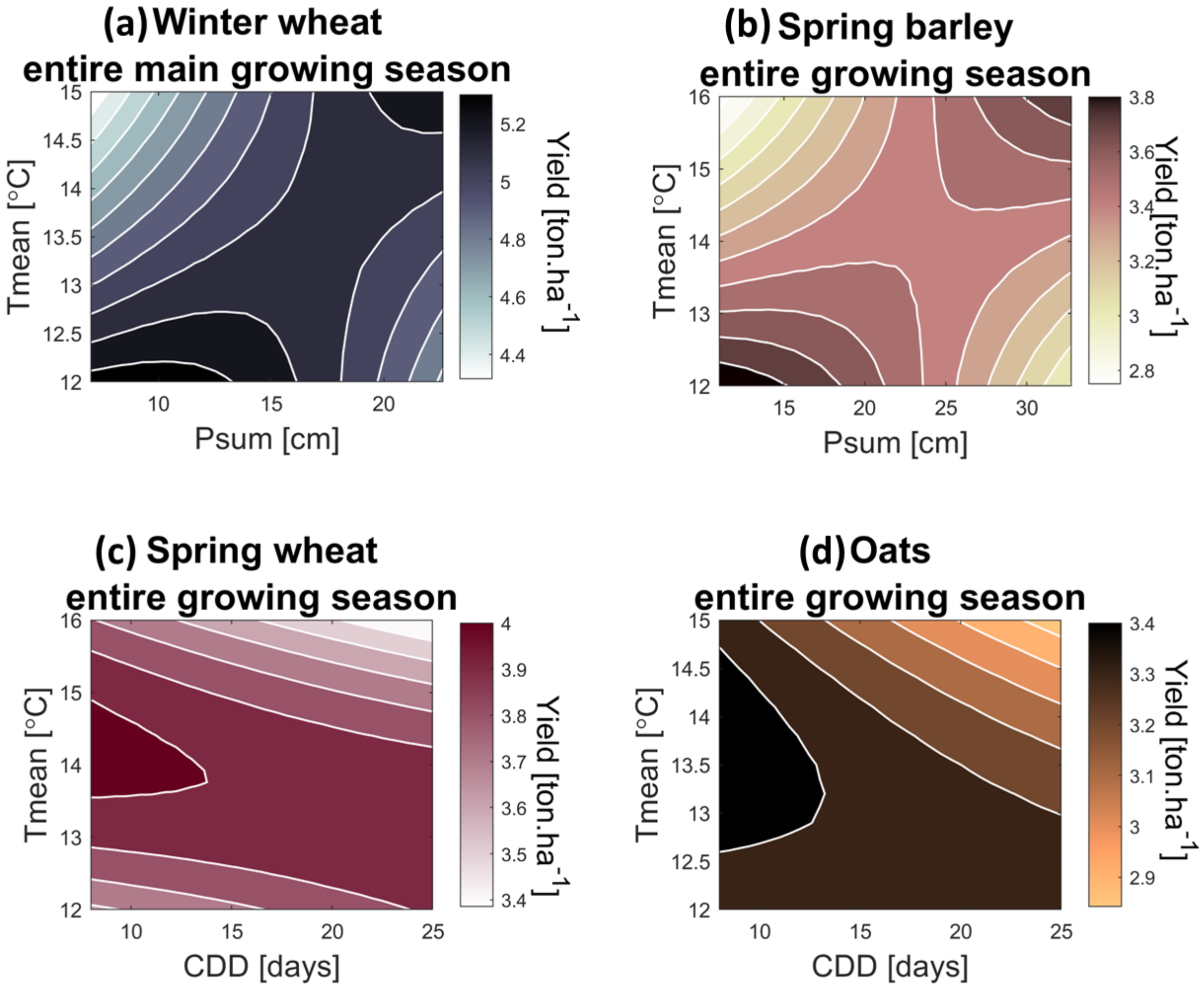

Figure 4: Crop yield as a function of best performing set of climatic indicators. (a) winter wheat, (b) spring barley, (c) spring wheat, (d) oats. Winter wheat and spring barley were best explained through precipitation sum (Psum) and temperature averages (Tmean) of the entire growing season, while spring wheat and pats were best explained through CDD and Tmean of the entire growing season. The contour plots are based on the fixed parts of the statistical models estimated for each crops separately. Time is set to the year 1992 which is an intermediate year within the study period (1965-2020). The ranges of the climatic indicators correspond to the 5th and 95th percentiles of each indicator.

Yields of all crops except oats depended non-linearly on the pre-(main) growing dryness index (DI, Table 3). The yield maximizing DI was 1.2 mm·mm^{-1} for winter wheat and 2.7 mm·mm^{-1} for spring wheat (Fig. 5a,c) – corresponding to the 60th and 90th percentiles of the observed range respectively. Spring barley yield also depended non-linearly on DI, but the yield maximizing DI was above the 95th percentile of the observed range (Fig. 5b). For oats pre-growing proxy of water availability did not affect yield (Table 3d).

Table 3 Model representing the legacy effects of water availability during pre-main growing period for winter wheat and pre-growing period for spring cereal. The table has the identified length of the period prior to (main) growing, model structure, estimated parameters and their units. Each model also included the fraction of explained variance when using only the field effects (r2marg) and when using both fixed effects and random effects (r2rand).

Crop	a) Winer wheat	b) Spring barley	c) Spring wheat	d) Oats

Identified length of the period prior to (main) growing	90 days			90 days			60 days			90 days		
Model Structure	$\beta_0 + \beta_t t + \beta_{DI} DI_1 + \beta_{DI2} DI^2$											
Name	Estimate	SE	p	Estimate	SE	p	Estimate	SE	p	Estimate	SE	p
β_0 [ton·ha^{-1}]	3.147	0.285	**<0.05**	2.149	0.214	**<0.05**	2.747	0.228	**<0.05**	2.764	0.184	**<0.05**
β_t [ton·ha^{-1}·yr^{-1}]	0.050	0.005	**<0.05**	0.025	0.003	**<0.05**	0.028	0.004	**<0.05**	0.021	0.004	**<0.05**
β_{DI}[ton·ha^{-1}]	0.884	0.298	**<0.05**	0.195	0.055	**<0.05**	0.414	0.145	**<0.05**	-0.053	0.065	0.41
β_{DI2} [ton·ha^{-1}]	-0.351	0.109	**<0.05**	-.014	0.004	**<0.05**	-0.075	0.032	**<0.05**	0.001	0.005	0.77
r2marg	0.44			0.18			0.32			0.15		
r2cond	0.85			0.80			0.80			0.75		

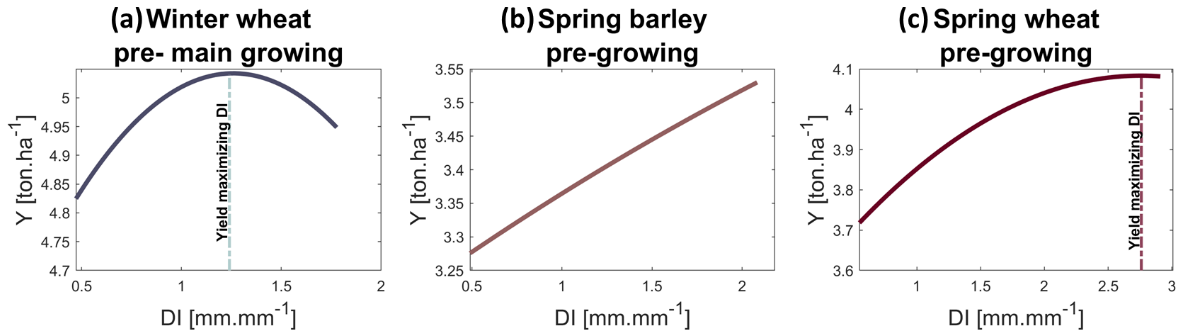

Figure 5: Crop yield as a function of pre-growing dryness index (DI) based on the estimated length of legacy impacts for (a) winter wheat (3 months), (b) spring barley (3 months) and (c) spring wheat (2 months). The estimated yield is based on the fixed parts of the statistical models estimated for each crops separately. Time is set to 1992, the intermediate year in the study period 1965-2020. The ranges of the DIs correspond to the 5th and 95th percentiles of each indicator.

4 Discussion

4.1 Average conditions explained crop yields better than short-term conditions

Our models explained up to 85% of yield variability, in line with results of previous analyses relative to other climates (e.g., Luan et al., 2021; Ray et al., 2015; Zampieri et al., 2017). The models including average conditions performed better than those based on short-term potentially damaging conditions (Fig. 3). Although negative effects of heatwaves (i.e., temperatures exceeding 28 or 30 °C) at flowering have been observed in spring barley in Finland and winter barley in Minnesota (Hakala et al., 2020; Sadok et al., 2022), models based on such short-term damaging conditions performed less well in our analysis. We surmise that the lower performance of models based on short-term damaging conditions is in part due to their infrequent occurrence in our records. Moreover, the effects of these short-term conditions might be averaged out across the cropped land in each county, either because crops in different fields are not simultaneously at the most sensitive stage or because of extreme-cancelling averaging of climatic conditions.

Crop yields were better explained by growing season conditions compared with those during a specific developmental stage, in line with results from analyses of data from long-term experiments in Sweden and Poland

(Marini et al., 2020). This could be due to crops compensating any unfavorable conditions during one period with growth during other periods (Foulkes et al., 2011). In contrast to our results, conditions around and after flowering explained yields better than those of the entire growing season over larger climatic gradients (Hamed et al., 2022; Hoffman et al., 2020; Suliman et al., 2024). However, these large scale analyses extended over warmer conditions compared to our study area, with temperatures at flowering likely exceeding the crop optimum. We also acknowledge the uncertainties inherent in estimating the developmental stages through models, as done here, instead of observations, and in assuming that the model-estimated maturity date coincides with the harvest date. Despite performing worse according to the AIC, conditions relative to sub-periods of the (main) growing season, as well as pre- (main) growing dryness index explained a fraction of yield variance comparable to that of the conditions during the entire (main) growing season for all crops. As such, conditions during sub-periods add complementary information to what can be deduced from the entire (main) growing season.

The explanatory power of climatic conditions were lower for oats and spring barley yields compared with spring and winter wheat (Fig. 4). A possible explanation is that wheat yield data refer to southern Sweden only, whereas spring barley and oats are grown under a wider range of latitudes and hence conditions, including soil characteristics and day length. Moreover, the need to adapt to such a wide variety of conditions likely resulted in cultivation of different varieties, e.g. six- vs. two-row barley (Skoglund, 2022), which was not explicitly considered in our analyses.

4.2 Coordinated temperature and precipitation conditions maximized crop yields

The temperature at which yields approached their maxima increased with precipitation sums and decreased with dry spell length (Fig. 4), highlighting the strong interacting effects of temperature and precipitation. These patterns are consistent with survey analyses across a wider climatic gradients (e.g., Carter et al., 2018; Luan et al., 2021; Matiu et al., 2017) and ecophysiological evidence that crop response to temperature depends on water availability (e.g., Suzuki et al., 2014). High temperatures combined with prolonged dry periods reduce yields through water and heat stress, lowering net photosynthesis and shortening the grain filling period (Fischer, 1985; Porter and Semenov, 2005; Slafer et al., 2023), ultimately producing smaller kernels and lower yields (Hatfield & Prueger, 2015). Yield losses from high temperatures can be partly offset by higher precipitation, which enhances evaporative cooling via transpiration, particularly in oats and wheat (Martin et al., 2012; Peltonen-Sainio et al., 2018; Schauberger et al., 2017; Tack et al., 2015). At the opposite extreme, wet and cool conditions could reduce yields (Sjulgård et al., 2023), via waterlogging, which limits root functioning and growth (Tian et al., 2021) and/or reduced solar radiation (Díaz-Torres et al., 2017; Ewel, 1999).

The dryness index (DI) explained a fraction of yield variability that was lower than that of the best-performing model including precipitation and temperature indicators, but of comparable magnitude, consistent with findings from studies conducted across broader climatic gradients and under warmer conditions. (Luan et al., 2022). Its relatively high performance is the result of DI inherently capturing the interactive effects of temperature and precipitation, by combining precipitation with the potential evapotranspiration, which increases with temperature.

Dryness index prior to the (main) growing season explained yields of all crops except oats, showing the importance of legacy effect and supporting its use as an early indicator of the final yield (Anand et al., 2024), possibly to guide management decision and planning, for example by informing the timing and location of sowing or the choice of crops. The period with the highest performance was 60-day period before the growing season for spring wheat yields, and 90 days for the other crops. The shorter period emerging for spring wheat might be due to this crop being grown exclusively in southern Sweden (Fig. 1), where snowpack is shallower than in the north, and hence the memory in the form of accumulated snow more limited. An increase in DI, i.e. an increase in temperature or a decrease in precipitation, was beneficial for winter wheat up to DI=1.2 mm·mm-1 and over most of the observed range for spring crops, although absolute changes in yields were small. High DI generally reduces soil saturation, which can advance sowing and benefit yields by improving field access (Trnka et al., 2011). Excessive soil moisture can increase nitrogen losses through denitrification and leaching (Guo et al., 2014). Further, a higher temperature can contribute to earlier snowmelt (Pan et al., 2022), reduced soil water and quicker warming in spring, that can hamper crop establishment due to rapid drying of superficial soil layers.

During pre-flowering, the range of required precipitation for winter wheat was lower than for spring wheat (SI, Fig. S1-S2). This is likely a consequence of winter wheat being already established prior to the start of the main growing season, i.e. with deeper roots that can access larger water stores (He et al., 2020; Thorup-Kristensen et al., 2020; Wang et al., 2017).

4.3 Implications under climate change

Our models, explaining a large fraction of yield variability, can provide insights into the effects of specific climatic conditions on cereals in Northern Europe, including future climates.

Under conditions like those of the Northern Europe, warming is often presumed to be beneficial for crops thanks to lengthened growing season (Slafer et al., 2023; Wiréhn, 2018). Rising CO_2 concentrations could further support crop production by increasing photosynthesis and improving water-use efficiency (Rezaei et al., 2023). In Sweden, the average annual temperature is expected to increase by 2-6 °C by the end of the century, depending on greenhouse gas emission scenarios (IPCC, 2021). At the same time, annual precipitation is projected to increase (Grusson et al., 2021; Teutschbein et al., 2023b), but with increases concentrated in the winter and no change or even a slight decrease during summer (Breinl et al., 2020). Furthermore, climate change is expected to intensify hot and dry damaging periods, making the prolonged 2018 warm drought common (Toreti et al., 2019) and shift precipitation toward more frequent short, intense events while reducing growing-season water availability (Westra et al., 2014).

Our models clearly show that warming benefited yields only when precipitation increased or dry spells shortened, otherwise warming reduced yields (Fig. 4). As such, the combined effects of projected changes in temperature and precipitation in Sweden is negative (Grusson et al., 2021), particularly in southern Sweden where precipitation is already limited and crops correlated negatively with temperature (Sjulgård et al., 2023; Skoglund, 2022; Wallén, 1917). In line with our results, yields were reduced by 50% on average in 2018 in Sweden (Beillouin et al., 2020; Statistiska-Meddelanden, 2018), when summer temperature was on average 2.8 °C warmer than the 1981-2010 average temperatures and the maximum dry spell length was on average 37 days - more than three times the long-term mean of 11.5 days in May August 1950-2020 (Teutschbein et al., 2023a; Wilcke et al., 2020). Our results also point to abundant precipitation being associated with reduced yields, although they had low explanatory power (Fig. 3, SI, Tables S1-S4). As their frequency increases, the mechanical damage or increased frequency of excessive soil water (Iizumi et al., 2024) might become more common.

Crops had their highest yields at (main) growing season temperature averages of 12-14 °C. Cultivars bred and sown in Sweden have so far been selected to perform best under these cool temperatures, with short growing seasons compensated by long days (Hakala et al., 2012). If warmer conditions locally result in exceeding this range, warm-adapted varieties will be necessary. At the same time, increasing temperatures might push northward the optimal ranges of climatic conditions for crop growth beyond central Sweden, opening new possibilities for wheat where it has been historically difficult to cultivate it (Elsgaard et al., 2012). The timing of sowing of spring crops is and will remain critical under climate change, offering an important adaptation measure. High soil moisture in spring can delay sowing of spring crops, while warmer temperatures might allow an earlier start, enabling better use of winter-stored soil water**.** However, higher summer temperatures counteract this positive effect by e.g. shortening the grain filling period (Sofield et al., 1977; Zhou et al., 2024). There is therefore a relatively small time-window that allows for sowing of spring crops between these two contrasting contributions of water. Climate change could further reduce this window, as higher temperatures increase soil water evaporation, While early-season precipitation, already limited in Sweden, is expected to decline further, potentially compromising crop establishment without irrigation (Peltonen-Sainio et al., 2021).

Another promising adaptation to warmer and drier growing seasons is to replace spring cereals with winter wheat and other winter cereals. Winter cereals are already well established at the onset of the main growing season. They can thus handle precipitation deficits better than spring cereals, thanks to their more extensive root system that allow access to water deeper in the soil (Thorup-Kristensen et al., 2020). However, high precipitation in winter through climate change, combined with high temperatures will result in lower snow accumulation (Tootoonchi et al., 2023) that can negatively impact winter crops, due to the damaging effects of cold spells without the mitigating effects of snow (Vico et al., 2014). Milder winters can also facilitate damage from repeated freezing and thawing cycles or snow mold development (Andrews, 1996). As such, the net effects of altered winter and spring conditions on winter crops need further examination. An alternative adaptation measure to reduce failure risk from both insufficient and excessive water is mixing crops or varieties with different rooting depths and architectures allowing for the use of water at different depths (Manevska-Tasevska et al., 2024).

5 Conclusions

We systematically evaluated the role of various climatic indicators on explaining county-level cereal yields in Sweden for the period 1965-2020. Average growing season temperatures and precipitation totals, or maximum dry spell length explained yields best. Pre- and post- flowering, as well as pre- (main) growing season climatic conditions had a comparable range of explained variance, whereas short-term potentially damaging conditions, such as hot days and intense rainfall events, had the lowest explanatory power. High temperatures were associated with high yields, but only with adequate precipitation or sufficiently short dry spells. While we focused on crop yields in Sweden, our findings are likely applicable also to other high latitude regions.

Our results provide insights into the potential effects of climate change on crop yields at high latitudes. While warmer temperatures allow for wider areas to be cultivated by current crops, increasing temperature through climate change will not necessarily result in higher yields, if total precipitation during the main growing season does not increase. The potentially damaging short-term conditions were rare in the study period and did not explain yields, but they can become more frequent in the future. Adaptation to climate change will thus likely be necessary.

Code and data availability. All runs and analysis were performed with the Matlab coding language and are available upon request. Crop yield data is freely available from Statistics Sweden (Statistikdatabasen). Climatic data and land cover data are publicly available from E-Obs dataset (Cornes et al., 2018) and Corine land cover maps (European Environment Agency, 2020). Further information can be found in Section 2.

Author contributions. FT: Conceptualization, data curation, formal analysis, investigation, methodology, data curation, visualization, software, writing and editing. GB: review and editing. GV: Conceptualization, methodology, supervision, funding acquisition, review and editing.

Competing interests. Authors declare no competing interests.

Acknowledgments. We acknowledge the partial support of the Swedish Research Council for Sustainable Development (FORMAS) (grant number 2023-02530). We also acknowledge the E-OBS dataset from the Copernicus Climate Change Service (C3S, https://surfobs.climate.copernicus.eu) and the data providers in the ECA&D project (https://www.ecad.eu).

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