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RECEIVED
23 June 2022

REVISED
15 March 2023

ACCEPTED FOR PUBLICATION
29 March 2023

PUBLISHED
11 April 2023

LETTER

Increasing interannual climate variability during crop flowering in Europe

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Keywords: crop yield stability, interannual climate variability, climate change, agriculture, climate adaptation

Supplementary material for this article is available online

Abstract

Climate change has increasingly adverse effects on global crop yields through the occurrence of heat waves, water stress, and other weather-related extremes. Besides losses of average yields, a decrease in yield stability—i.e. an increase in variability of yields from year to year—poses economic risks and threatens food security. Here we investigate a number of climate indices related to adverse weather events during the flowering of wheat, maize and rapeseed, in the current cultivation areas as well as the main European producer countries. In 52 projections from regional climate models, we identify robust increases in the interannual variability of temperature, precipitation and soil moisture by $\sim$+20% in standard deviation in the model median. We find that winter wheat is most exposed to variability increases, whereas rapeseed flowering escapes the largest increases due to the early flowering time and the northern locations of cultivation areas, while the opposite (escape due to southern locations and late flowering) is true for maize to some extent. Considering the timing of crop development stages, we also find a robust increase in the variability of the temporal occurrence of flowering, which suggests a decreased reliability in the timing of crop stages, hampering management steps like fertilization, irrigation or harvesting. Our study raises concerns for European crop yield stability in a warmer climate and highlights the need for risk diversification strategies in agricultural adaptation.

1. Introduction

Agriculture is among the sectors that are most vulnerable to extreme weather. The increasing frequency of heat and water stress related to anthropogenic climate change already has a negative effect on the yields of crops like wheat, maize and barley (Lobell *et al* 2011, Moore and Lobell 2015) which is expected to amplify as climate change progresses.

The agricultural sector hence needs to adapt to climate change. This adaptation must not only maximize average yields, but also maintain a high level of yield stability. Due to the nonlinear response of plant physiology to environmental conditions, crop yields and crop yield stability are sensitive to changes in both the mean climate and climate variability (Urban *et al* 2012; figure 1). Previous studies identified empirical relationships between observed crop yields and weather, usually by applying regression models (tables S1 and S2). Ray *et al* (2015) found that climate variability explains 31%–51% of the wheat yield variability in parts of Western Europe, and 23%–66% in Eastern Europe. Frieler *et al* (2017) concluded that 'observed weather variations can explain more than 50% of the variability in wheat yields in Australia, Canada, Spain, Hungary, and Romania'.

Porter and Semenov (2005) estimate that a doubling in the standard deviation of temperature will lead to a doubling of wheat yield variability and cause the same decrease in wheat yields as an average warming of 4 °C.

Most studies identify near-surface air temperature as the most important climatic factor (Ceglar *et al* 2016, Zampieri *et al* 2018, Vogel *et al* 2019); others also find impacts of dry or excessively wet conditions (van der Velde *et al* 2012, Frieler *et al* 2017, Zampieri *et al* 2017), diurnal temperature range (DTR) (Lobell 2007), and downwelling solar radiation (Ceglar *et al* 2016). Interestingly, it is not only extreme events that affect yield variability, but also fluctuations in seasonal averages from year to year (Porter and Semenov 2005, Ray *et al* 2015, Vogel *et al* 2019). Physiological studies identified the reproductive stage (in particular flowering and grain filling) as the time period when crops are particularly vulnerable to heat stress (Porter and Gawith 1999, Asseng *et al* 2011, Farooq *et al* 2011, Barlow *et al* 2015, Rezaei *et al* 2015, Konduri *et al* 2020) and water stress (Powell *et al* 2012, Hatfield and Prueger 2015). While most studies focus on wheat and some on maize, rapeseed is also known to show particular vulnerability to heat and drought during flowering (Morrison and Stewart 2002, Gan *et al* 2004, Koscielny *et al* 2018), pollination (Hatfield and Prueger 2015), and pod production (Gan *et al* 2004).

In light of these findings, it is concerning that climate variability is already affecting yield stability (Iizumi and Ramankutty 2016, Liu *et al* 2021b). For the future, climate models project increasing temperature variability over large parts of the global land areas, and in Europe in particular, during the summer season on daily (Fischer and Schär 2009, Fischer *et al* 2012), monthly (Holmes *et al* 2016, Bathiany *et al* 2018, Suarez-Gutierrez *et al* 2018) and interannual time scales (Seneviratne *et al* 2006, Vidale *et al* 2007, Fischer and Schär 2009). Climate models also project an increase in interannual precipitation variability over large parts of the global land area (Boer 2009, Heinrich and Gobiet 2012, Pendergrass *et al* 2017).

These projections are however only recently being discussed in the context of crop yield stability. Previous modelling studies were not tailored to critical crop stages but meteorological seasons (Fischer *et al* 2012), or involved only a small number of variables from global climate models (Liu *et al* 2021a). In this study, we analyze an ensemble of 52 regional climate model simulations for Europe, investigating specific climate indices that have been identified as critical for yield stability during the flowering period. This spatiotemporal focus and the large model ensemble allow us to assess the robustness of different changes, and discuss their implications for the adaptation of agriculture to climate change.

2. Data and methods

2.1. Climate model simulations and climate indices

We analyze 52 simulations with a resolution of 0.11° (approx. 12.5 km) from the European regional climate modelling initiative EURO-CORDEX (Jacob *et al* 2014, 2020) of the World Climate Research Programme's Coordinated Regional Downscaling Experiment (CORDEX) project (table S3), selecting one realization for each model combination (driving global climate model and regional climate model). We only analyze the emission scenario with the largest greenhouse gas emissions until 2100, RCP8.5 (Meinshausen *et al* 2011), and always compare the years 2070–2099 with the reference period 1971–2000. The motivation for this 'worst-case scenario' is to obtain a high signal-to-noise ratio in our statistical assessments. Our approach can be understood as a sensitivity study, highlighting potential challenges to agricultural adaptation to climate change.

Relying on observation-based literature, we select a number of common climate indices (tables 1 and S1), whose importance for yields is qualitatively similar for different crops, although absolute threshold values can vary. Apart from climate averages of fundamental variables (temperature, precipitation, DTR, soil moisture and radiation), we also select threshold-based criteria, e.g. number of dry days, days with relatively dry or wet soils, and the occurrence of hot days with dry soils.

For each index and each simulation, we compute results for a specific time period in each year (see section 2.2), for instance average temperature, number of dry days, etc. From these time series with annual resolution, we then select the two time periods 2070–2099 and 1971–2000, subtract a linear trend in each of the two 30 year periods, and then compute the interannual standard deviation and its difference between the two 30 year periods (also see Fischer and Schaer 2009).

2.2. Selection of crops, countries and seasons

In this study, we consider winter wheat and maize, the most important crops produced in the European Union with 120 Mt and 68 Mt produced each year (Eurostat 2021), as well as winter rapeseed, of which the EU27 is the largest producer with approx. 17 Mt per year (Eurostat 2021). We focus on the flowering period because physiological studies reveal a distinctive vulnerability to adverse weather effects during that time (see Introduction). To capture the spatiotemporal heterogeneity in crop cultivation and development, we apply three complementary methods:

2.2.1. Default approach: uniform flowering dates with focus on country level

Here, we assume that all regions we analyze share the same flowering period. We put particular focus

Table 1. Definition of indices in our study with the model variables they are derived from.

Main variable	Index
Daily average surface air temperature (Tmean)	Average Tmean
Daily minimum surface air temperature (Tmin)	Average Tmin
Daily maximum surface air temperature (Tmax)	Average Tmax
	Days with Tmax > 25 °C (summer days)
	Days with Tmax > 28 °C
	Days with Tmax > 30 °C (hot days)
	Days with Tmax > 35 °C
Amplitude of diurnal cycle of surface air temperature (DTR)	Average DTR
Precipitation (PR)	Average PR
	Longest duration of dry periods in a year (consecutive days with PR < 1 mm)
	Longest duration of wet periods in a year (PR > 1 mm)
	Longest duration of wet periods in a year (PR > 5 mm)
	Number of days with PR > 5 mm
	Number of days with PR > 10 mm
	Number of days with PR > 20 mm
	Number of days with PR > 40 mm
	Number of days with PR < 1 mm (dry days)
Soil moisture (SM)	Average SM
	Number of days with SM > 80th percentile of reference period 1971–2000 (wet-soil days)
	Number of days with SM < 20th percentile of reference period 1971–2000 (dry-soil days)
Downwelling solar radiation (SRAD)	Average SRAD
Combined heat and drought	Number of days with Tmax > 30 °C and SM < 20th percentile of reference period 1971–2000 (hot dry-soil days)
	Number of days with Tmax > 35 °C and SM < 20th percentile of reference period 1971–2000
Growing degree days (GDD)	Growing degree days above 0 °C (sum of daily Tmean for those days where Tmean > 0 °C)
	Growing degree days above 10 °C (sum of daily Tmean for those days where Tmean > 10 °C)

on France, Germany, Poland, Ukraine, and Romania because these countries produce the majority of the three crops on the European continent. To define the flowering stage, we consult a number of crop calendars for Europe (Sacks *et al* 2010, Becker-Reshef *et al* 2019). The calendar dates for the crop stages in the five countries and the sources of information are shown in table S4. While the timing of plant stages differs substantially between the three crops, the time windows in the different countries for one and the same crop and development stage differ much less, often by only 2 weeks. We find that climate and its projected change are not sensitive to such small differences in the selection of time periods. We therefore define identical seasons in each country. To assess the timing of the flowering stage via growing degree days, measured from the sowing time to the flowering time, we pick sowing dates from the same crop calendars. We also refer to the period 15 April–31 October as the growing season for all crops and countries, following Roetzer and Chmielewski (2001) (figures 1 and 2 therein). Table 2 shows our final choice for the dates of the crop stages.

2.2.2. Summary statistics for all European cultivation areas of wheat and maize with site-specific flowering dates

To avoid the assumptions above and to focus on current cultivation areas only, we also tailor all simulation data to the current regions of cultivation, as well as the location-specific flowering times of the year. To do so, we derive spatiotemporal masks from the C3S crop productivity indicators dataset (Wit *et al* 2022) considering all days that fall within crop development stage 0.8 and 1.3 (where 1.0 is defined as the start of flowering) at each site, after computing an average over the available period 2000–2018 (figure S1). The dataset combines satellite observations of fraction of absorbed photosynthetic active radiation, meteorological European Reanalysis data, and a simple crop simulation model. The resulting periods overall are similar to the 2 month period defined with approach

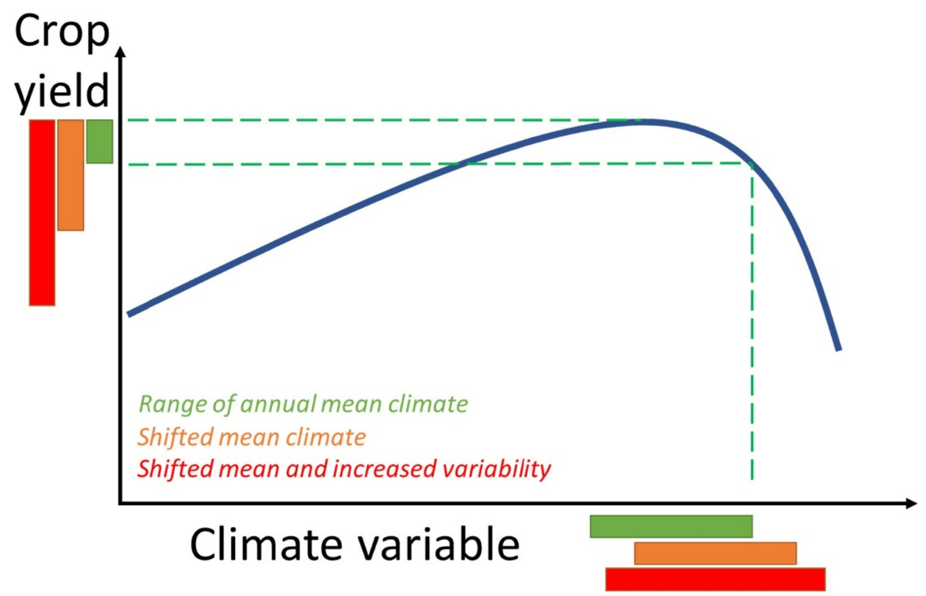

Figure 1. Idealized relationship between a climate variable (for example temperature) and crop yield. The blue curve shows the impact of climate on yield in a particular year. The full interannual distributions for many years are shown as colored ranges near the axes. Shifted mean climate and increased interannual variability both nonlinearly increase yield variability. The figure is a modified version of figure 1 in Urban *et al* (2012). Adapted from Urban *et al* (2012), with permissions from Springer Nature.

1 but include spatial differences in the flowering stage. This method by definition does not involve any regions other than current cultivation areas and hence does not provide spatially explicit maps. As the dataset is not available for winter rapeseed, we restrict this analysis to winter wheat and maize. We do not use simulations with HadGEM3 as the global model because of its 360 day calendar (see table S3).

2.2.3. Considering climate-induced shifts of flowering period

In approach 1, we neglect that the timing of plant stages in a warmer climate can shift by several days per decade (Fatima *et al* 2020). Extrapolating current estimates, flowering might hence occur up to 1 month earlier than today in the end of the century (Anwar *et al* 2015). However, management practices like irrigation or adjusting the sowing date, as well as advances in plant breeding will to some extent counteract this change in order to avoid crop damage from frost or from ecological mismatch (desynchronization from pollinators). In section 4, we therefore shift our time window to earlier calendar dates as predicted by a 'thermal time' approach (table 2) to test the robustness of our results.

3. Results

3.1. Temperature variability

Monthly temperature averages over Europe show an increase in interannual variability during the growing season, and a decrease during winter months (figure 2); daily minimum and maximum temperature variability shows similar results (not shown). These changes are in agreement with previous studies addressing daily to interannual time scales (Seneviratne *et al* 2006, Fischer and Schär 2009). The increased summer temperature variability is associated with the limitation of evapotranspiration by soil moisture (Seneviratne *et al* 2006, Bathiany *et al* 2018), while decreased winter temperature variability results from reduced advection related to the weaker meridional temperature gradient (Holmes *et al* 2016).

Consequently, we find a robust and significant increase in temperature variability during the flowering of the three crops in most countries (figure 3, table S5), as well as in current cultivation areas overall (figure 4, table S5). The transition from decreasing variability in spring to increasing variability in summer occurs later in northern and eastern Europe than in south-eastern Europe (figure 3), suggesting that rapeseed flowering is less affected by increasing temperature variability than wheat or maize because it flowers earlier and because cultivation areas are largest in more Northern areas. During the flowering of wheat and maize (between June and August) models show a tendency of increased temperature variability by approx. 0.1 °C–0.2 °C (10%–20% compared to the reference period) in the model median (figures 2 and 4).

A few models show much higher changes: in the current cultivation areas, the maximum of the model ensemble shows an increase of 50% (figure 4). The increases are not restricted to cultivation areas; in large areas of the producer countries, even the 80th

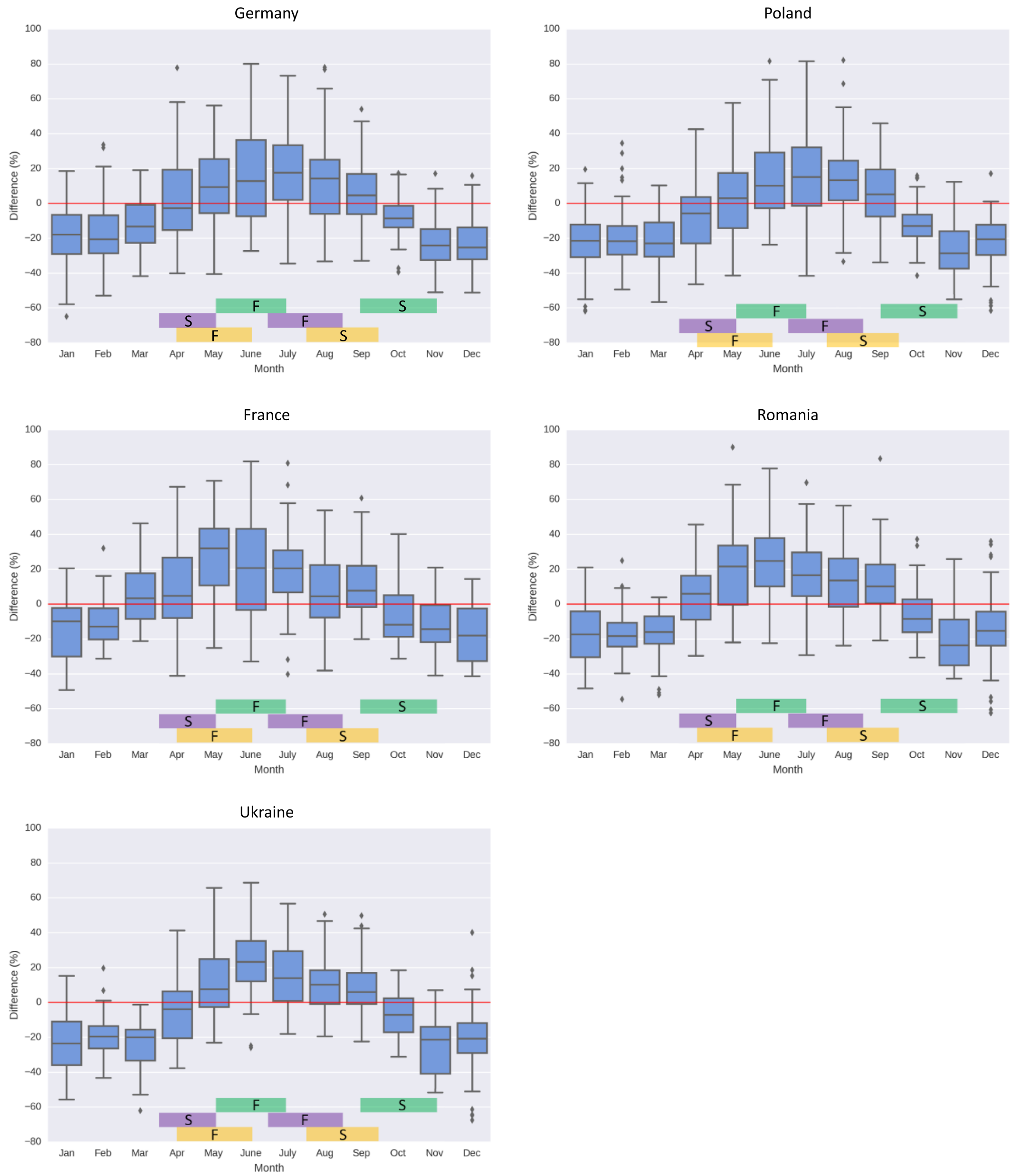

Figure 2. Projected relative changes in standard deviation of monthly average temperature in five countries. Blue boxes cover the range from the first quartile (Q1) to the third quartile (Q3) of the model ensemble, the black horizontal mark is the multi model median. Outliers (black dots) are below Q1 − 1.5(Q3 − Q1) or above Q3 + 1.5(Q3 − Q1). Whiskers extend to the last data point that is not an outlier. The zero line is marked in red. Colored bars at the bottom of each figure show the time periods defined in tables 2 and table S4 for the sowing (S) and flowering (F) of winter wheat (green), maize (purple) and rapeseed (yellow). All changes are based on years 2070–2099 versus 1971–2000 in RCP8.5.

percentile of the ensemble reaches 50% (not shown). This implies that shifting cultivation areas might be a very limited adaptation option (also see Trnka *et al* 2015).

Variability changes in threshold-based indices (days with Tmax or PR above a fixed value) usually increase where the occurrence of these events switches from essentially no occurrence to intermediate values (see supplementary text). There is also a tendency for increased variability of the DTR and downwelling solar radiation during the flowering of wheat and rapeseed (supplementary text, figures 4 and S2, table S5), with most models projecting an increase around 10%–20%. In contrast, maize flowering occurs later in the year when DTR changes are small, and when large areas are so dry that SRAD variability tends to decrease rather than increase. In this regard, maize will face more extreme but constant conditions in a future climate, whereas the other two crops will face substantial changes in mean and interannual variability of DTR and SRAD.

Table 2. Choice of calendar dates for the different stages in the crops' development.

		Winter rapeseed	Winter wheat	Maize
Flowering period	Default	15/04–15/06	15/05–15/07	01/07–31/08
	Advanced by 2 weeks	15/04–15/06 in 1971–2000 versus 01/04–31/05 in 2070–2099	15/05–15/07 in 1971–2000 versus 01/05–30/06 in 2070–2099	01/07–31/08 in 1971–2000 versus 15/06–15/08 in 2070–2099
	Advanced by 4 weeks	15/04–15/06 in 1971–2000 versus 15/03–15/05 in 2070–2099	15/05–15/07 in 1971–2000 versus 15/04–15/06 in 2070–2099	01/07–31/08 in 1971–2000 versus 01/06–31/07 in 2070–2099
Period from sowing to flowering	Default	30/08–15/05	15/10–15/06	22/04–30/07
	GDD conserving	30/08–15/05 in 1971–2000 versus 23/09–22/04 in 2070–2099	15/10–15/06 in 1971–2000 versus 8/11–23/05 in 2070–2099	22/04–30/07 in 1971–2000 versus 01/05–21/07 in 2070–2099
Growing period	Default	15/04–31/10	15/04–31/10	15/04–31/10

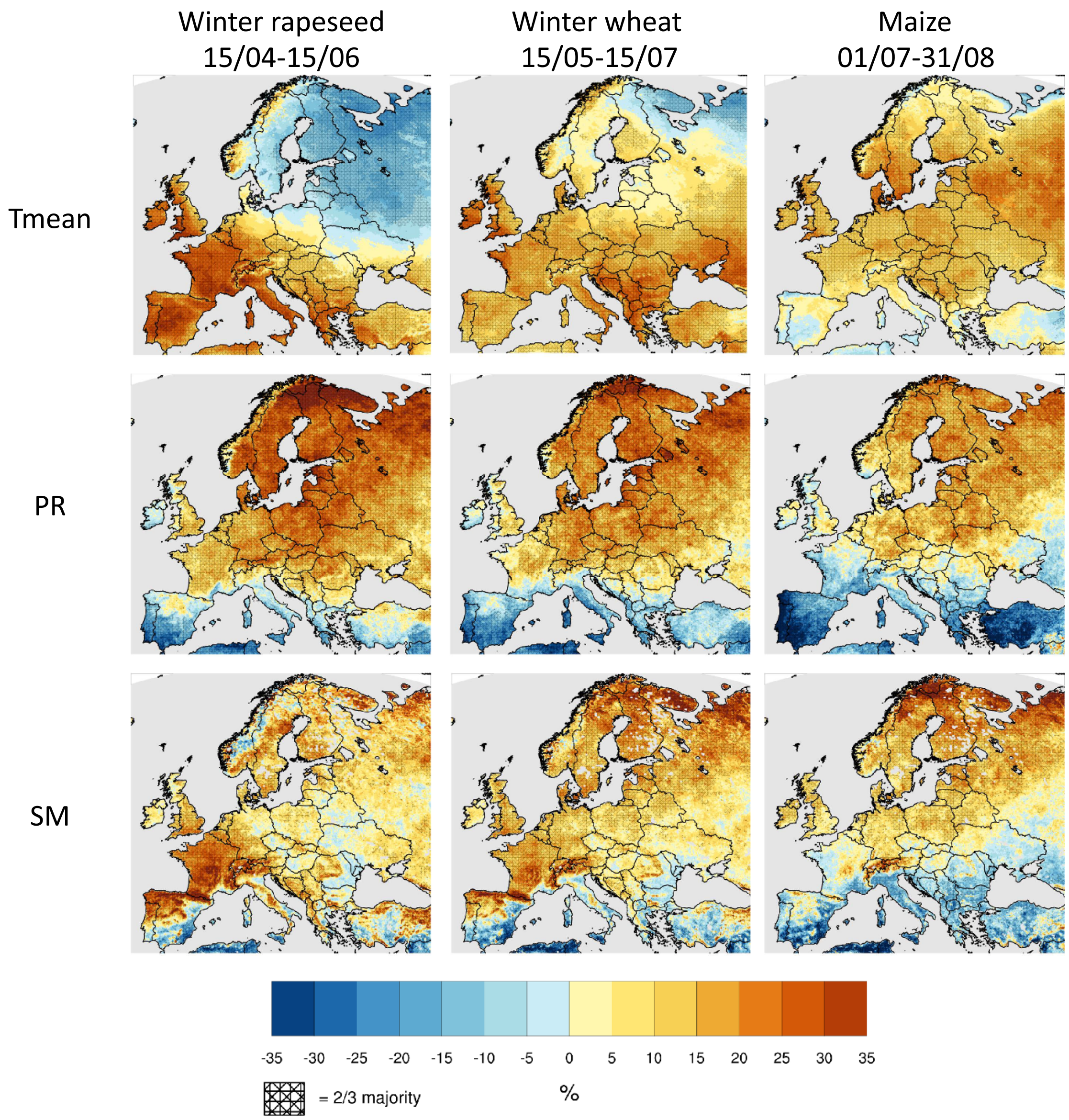

Figure 3. Projected relative changes in standard deviation of daily mean temperature (Tmean), precipitation (PR) and soil moisture (SM) of the model median, averaged over the flowering stages of each crop. In areas overlayed with black grid pattern, 2/3 of the models agree on the sign of the change. All changes are based on years 2070–2099 versus 1971–2000 in RCP8.5.

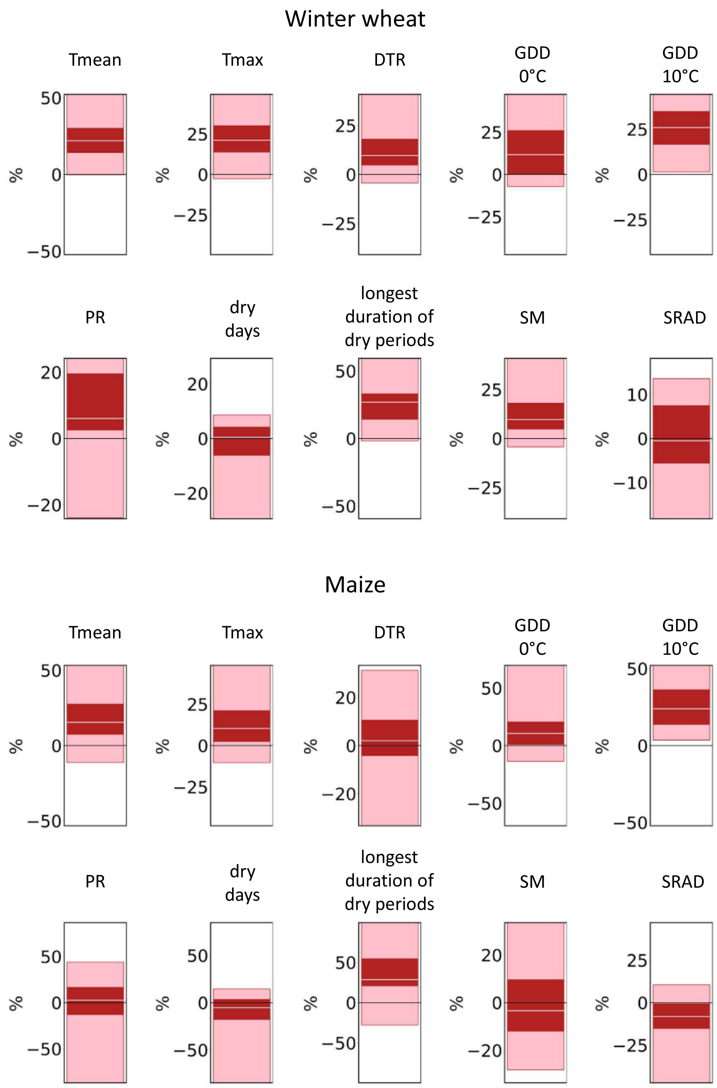

Figure 4. Projected relative changes in standard deviation during the location-specific flowering stage of wheat and maize, averaged over all current European cultivation areas. Each box plot shows the distribution of the model ensemble (default ensemble without HadGEM simulations) with the 20th to 80th percentile of changes in dark red, and lower and upper 20% of the ensemble in light red. The white vertical line in each box plot marks the multi-model median, the black line is at zero change.

3.2. Precipitation and soil moisture variability

Precipitation is involved in several adverse effects on crop yields: first, insufficient or temporally inhomogeneous rainfall can exacerbate drought stress. In terms of crop water availability, soil moisture is the most essential variable; the combined occurrence of heat and drought is particularly stressful for crops (Trnka *et al* 2015).

The general pattern of precipitation changes during the growing period is an increase in mean precipitation in Northern Europe (including Germany, Poland and Northern Ukraine), and a decrease in Southern and Western Europe (in agreement with Heinrich and Gobiet 2012; not shown). The interannual variability of precipitation however increases in almost all times of the year, including the flowering period of wheat and rapeseed (figures 3 and S3, table S5), in line with earlier modelling studies (Heinrich and Gobiet 2012, Russo *et al* 2013). Maize is an exception (figure 4) because of its cultivation in more southern locations and at a later time in the year, when overall drying is so pronounced that precipitation variability is also reduced.

Regarding intra-seasonal extremes, models project longer dry periods, shorter wet periods, more days with heavy rainfall (especially for high threshold values), and more dry days (PR < 1 mm), the latter particularly in Western Europe where even the model median shows 10–20 more dry days in the growing season. However, we find only few variability changes in these extremes (table S5), apart from an increased variability in the duration of dry periods (figure 4, table S5).

Soil moisture related changes are typically more robust. Models project decreasing mean soil moisture, more days with dry soils, and more hot days with dry soils in the entire growing season (figure S4), including the flowering stages, in particular in Southern and Western Europe (table S6). Interannual variability in mean soil moisture is projected to increase in many places in France, Germany and Poland. This change is particularly pronounced during the flowering of wheat (figures 4 and 3) and rapeseed in France (figure 3), where soil moisture fluctuations show relative increases up to 40% in the multi-model median. The increase in interannual soil moisture variability is clearly detrimental for agricultural yield stability (Modanesi *et al* 2020) and also mechanistically consistent with the increased variability in temperature and DTR reported above, due to the soil-moisture-temperature feedback that also explains variability on shorter time scales (Seneviratne *et al* 2006).

Overall, variability changes in indices related to water supply during maize flowering are smaller than during wheat flowering, but mean changes are larger. In this regard, breeding maize types that are optimized to such conditions (with smaller focus on robustness against interannual variability) may be a viable strategy.

Apart from indices related to such drought-related events, we also analyze indices related to excessive water supply, which can limit the trafficability of fields, reduce oxygen supply in the root zone, and lead to nutrient depletion, soil erosion, and (in combination with wind) physical damage to plants (Li *et al* 2019). While precipitation-based variability indices show only few relevant changes (see Supplementary Text), days with high soil moisture content are projected to become less common (table S6) and also show lower variability in a future climate (table S5).

3.3. Timing of flowering inferred from growing degree days

As average temperature increases in all seasons, crops are expected to reach the flowering stage during earlier calendar dates, alleviating the risk of heat stress. A useful proxy for flowering dates is the 'thermal time' measured in growing degree days (Parent *et al* 2019), for example the integral of temperature on days with values above 0 °C (GDD0). While it is obvious that global warming increases mean GDD0 between fixed calendar dates (table S6, last two rows), we here focus on changes in the interannual variability. From a conceptual perspective, larger average temperature and larger daily temperature variability can both be expected to increase GDD0 variability (figure S5). In similarity to monthly temperature variability in global models (Holmes *et al* 2016, Bathiany *et al* 2018), and to the interannual variability in figure 2, the EURO-CORDEX ensemble projects reduced daily temperature variability during winter, i.e. the period from sowing to flowering for winter rapeseed and winter wheat. However, this decrease occurs in the coldest season where temperature contributes least to GDD0. It is therefore not obvious from conceptual considerations how interannual variability in GDD0 would change, and we therefore compute these changes for EURO-CORDEX models.

Interestingly, the model ensemble projects increasing interannual variability in GDD0 by ∼20–30 degree days from the seeding to flowering stage of winter wheat and winter rapeseed (figure 5 top; last two rows in table S5). Apparently, the fact that the temperature threshold is exceeded on more days of the year due to the mean trend overcompensates the effect of the reduced daily temperature variability in winter. This suggests that the timing in plant development stages is becoming less predictable, making it harder for farmers to find the optimal timing for management interventions.

In reality, the seasons of sowing and flowering will change with the climate. Assuming that actual flowering occurs at a fixed GDD0 value each year, the period from sowing to flowering will cover a shorter time span in a warmer climate. We hence repeat our analysis but reduce the time span between the calendar dates in a way that the model median GDD0 between sowing and flowering is conserved. This reflects the assumption that the thermal time approach holds for a different climate, neglecting adverse weather events (e.g. late frost), ecological mismatch (e.g. due to the lack of pollinators), or climate adaptation by farmers and crop breeders. We find only small changes in GDD0 variability in this case (figure 5 bottom). Apparently, variability and mean GDD0 tend to change in the same direction, though a tendency toward increased GDD0 variability still persists at many grid cells. Assuming that the most plausible future lies somewhere in between our two extreme assumptions (fixed calendar dates versus fixed GDD0), we conclude that the variability of the flowering dates will likely increase in a warmer climate.

4. Robustness of results

The changes in variability we find (table S5) are statistically less reliable than changes in mean conditions (table S6). Even where most models agree on the sign of change, the majority of models does not show a statistically significant change. However, when comparing the fraction of models showing significant increases versus decreases of variability in temperature, we find that in many regions of central and Eastern Europe, up to 20% of the models show statistically significant increases, whereas almost no model shows a significant decrease at any grid cell. When applying an F-test with alpha = 10% (following Donat and Alexander 2012), we find significant increases of up to 30%–50% in wide parts of France, Germany, Poland, Ukraine and Romania.

The fact that the changes of interannual temperature and precipitation variability (figure 3) agree with

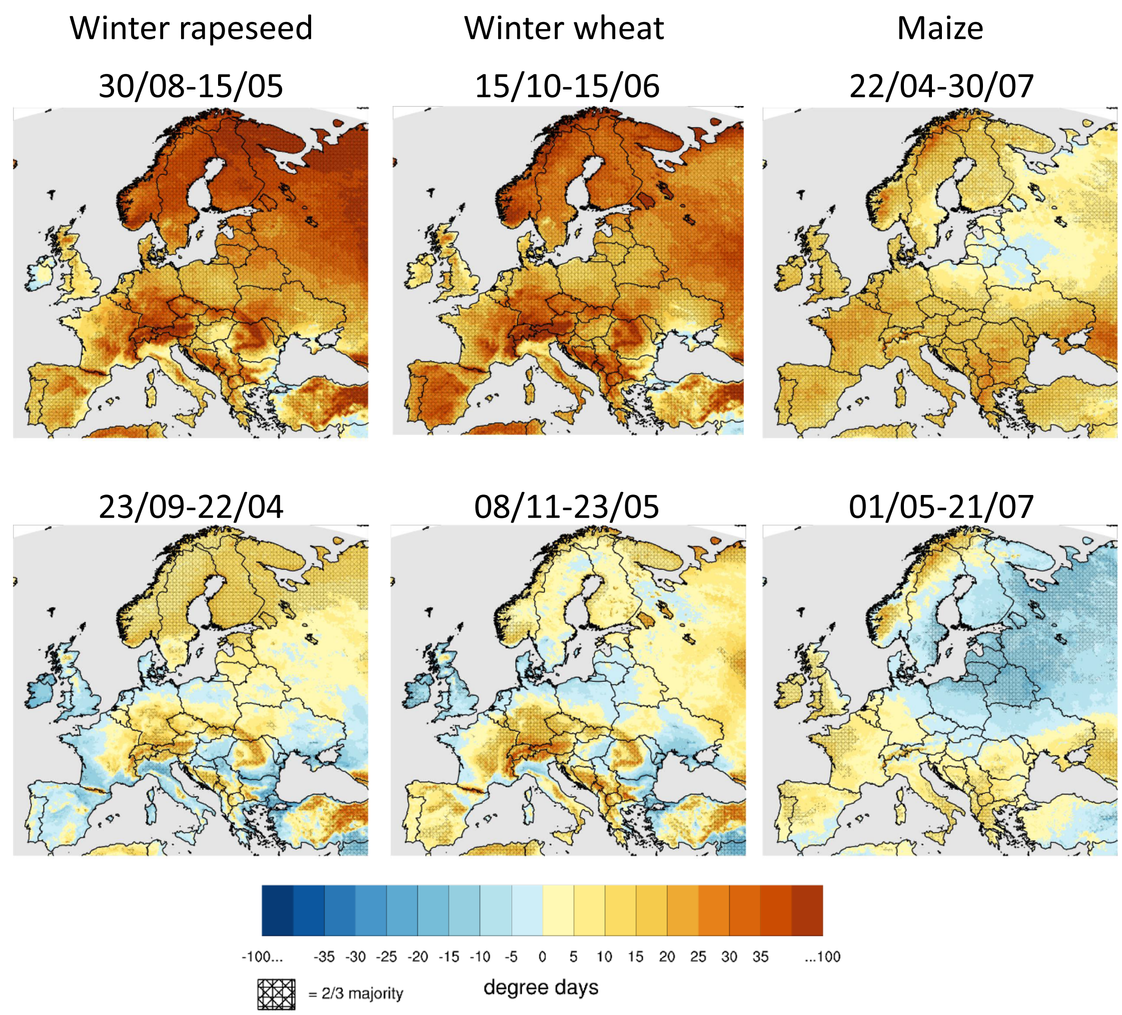

Figure 5. Projected relative changes in standard deviation of growing degree days above 0 °C of the model median, integrated over the time periods between seeding and flowering for each crop. Top row: plant stages occur on the same dates for 1971–2000 as well as 2070–2099. Bottom row: the time until flowering is assumed to be shorter in 2070–2099 (see dates in the title) in a way that the median (and in fact the mean) of growing degree days is conserved between 1971–2000 and 2070–2099. In areas overlayed with black grid pattern, 2/3 of the models agree on the sign of the change.

the patterns in seasonal analyses (e.g. Seneviratne *et al* 2006, Fischer and Schär 2009) adds further credibility to our results. To verify that our findings indeed reflect a meaningful model agreement on the response to greenhouse forcing, we also assess the effect of selecting two different ensembles of models: an extended ensemble, where we include all available realizations (not only one per model combination), and a reduced ensemble where we (i) first compute the bias in interannual temperature variability during the growing season compared to E-OBS observations (Cornes *et al* 2018), (ii) then select all grid cells from the five target countries in each model, (iii) compute the spatial root mean square error from these grid cells in each model, and (iv) rank the models, and pick the 26 models with the smallest bias (table S3). Although the median of the model ensemble can differ from observations by up to 0.3 °C or ∼40% in south-eastern Europe (figure S6(c)), the fact that the default ensemble (figure S6 (e)) and reduced ensemble (figure S6(f)) show very similar results despite the biases is an additional indication that the results are a robust feature of the model ensemble and not resulting from model biases.

Finally, we also check whether our assumption of fixed time periods for the phenological stages affects our results. Assuming that flowering instead occurs earlier in the end of the 21st century compared to our default dates, we compute the according changes in the variability shown in figure 3 but advancing the flowering date by 2 weeks (figure S7) or 4 weeks (figure S8) in 2070–2099 (see table 2 for new calendar dates). Most changes are qualitatively similar, with the exception that soil moisture variability rather shows decreases instead of increases after the adjustment, at least in Germany, Poland, Northern France and Northern Ukraine.

5. Discussion and conclusions

We have shown that for many climate indices and seasons that are essential to yield stability, regional climate models show increased interannual variability in those parts of Europe that contribute large fractions of wheat, maize and rapeseed yields. In particular, this concerns fluctuations in temperature, radiation, precipitation and soil moisture (figures 3 and S2). We identify France as a particular hotspot of concern because it is projected to not only experience much dryer climate, but also the largest increases. Overall, we find that most models show either increases in extreme events per se (table S6) or their interannual variability (table S5) in most countries during flowering of the three crops. The few decreases in interannual variability that we identify occur only because conditions considered extreme in the reference period have become either so common or so rare that the variability decreases.

The transition from decreasing temperature variability in winter to increasing variability in summer occurs later in north-eastern Europe. Consequently, crops that flower early in the year like rapeseed, will not necessarily be exposed to increased temperature variability in Northern Germany, Poland and Ukraine (the countries where most rapeseed is cultivated). This statement is further supported by the fact that flowering will likely occur earlier in the year due to the overall warming and the reduced daily temperature variability (allowing to avoid late frost). However, increases in the variability of precipitation are specifically large in these regions and at that time of year. Hence, since most climate indices identified as critical to yields in previous literature show increasing variability, it seems very plausible that these changes (in combination with the changing background state) will act to increase the interannual variability of yields regardless of the crop considered.

We also find that a shift to earlier flowering dates can ameliorate these changes, but does not reverse the sign at most grid cells, except in the case of soil moisture variability. Advancing the flowering date of crops may therefore help improve yield stability at sites where soil moisture (as opposed to temperature) is an essential limitation, and where crops can be adapted to the changes in mean soil moisture that will also occur. The fact that we find increased variability in growing degree days also implies that the timing of plant stages and required management interventions may become less reliable. The increased standard deviation by 20–30 degree days in spring and early summer translates to a few days of additional uncertainty. This change may not appear dramatic, but can make farm management more difficult because the weather situation often offers only small windows of opportunity for management interventions.

While our results highlight the need to consider climate variability changes in agricultural adaptation planning, we point out that our findings rely on regional climate models whose representation of mechanisms has limitations. Most importantly, models are known to have biases. We have not adjusted these biases in our study because most changes we discuss are threshold-independent (Dosio 2016) and because the model median changes can be expected to show smaller biases than individual models. Consequently, as discussed in section 4, model biases do not appear to affect our conclusions. However, models should be further developed in order to constrain the range of projections, and to make their output more directly applicable to agricultural impact studies. The surface and soil hydrology of the models is of particular concern in this context (Schlemmer *et al* 2018). Although the model ensemble can qualitatively reproduce observed soil moisture variability and its annual cycle (Knist *et al* 2017), models differ substantially in the parameterizations, the maximum depth and field capacity.

Our study highlights the need to further assess the effects of changing climate variability on yields and on the timing of plant development. Field observations and crop model studies are required to better quantify the effects on yield stability, to study compound events like combined heat and drought (Matiu *et al* 2017), and to assess the potential of different adaptation options. The adaptation of agriculture to climate change however does not require scientific progress alone, but steps by all relevant actors in the sector. Regarding farmers, an adjusted timing of sowing dates, and a shift in cultivation areas might help evade the most damaging extreme events during vulnerable plant stages. Regarding plant breeders, new crop varieties with an adapted timing of development stages are required (Parent *et al* 2018), and increased heat- or drought resistance that goes beyond what is implied by mean climate change. Current breeding strategies are known to reduce genetic diversity and make crop yields even more vulnerable to climate variability (Kahiluoto *et al* 2019).

Adaptation options, however will only be of limited benefit. For instance, even crops in relocated cultivation areas will face adverse weather effects, as the large-scale patterns we found suggest (also see Trnka *et al* 2015). The increased climate variability we identify here, and the large climate model uncertainty and scenario uncertainty, hence call for climate mitigation as well as alternative breeding strategies that diversify risks, for example the cultivation of evolutionary populations (Ceccarelli and Grando 2020), and a diversification in crop species, which needs to be supported by consumer behavior. In this context, we see the need for more collaboration between practitioners like plant breeders and agricultural advisors with the crop modelling and climate modelling community. Only interdisciplinary or even transdisciplinary approaches can generate actionable knowledge and climate services that practically help society to cope with the negative impacts of climate change.

Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: https://esgf-data.dkrz.de/projects/esgf-dkrz/.

Acknowledgments

We acknowledge funding from the Impulse and Networking Fund of the Helmholtz Association for the project ADAPTER (Adapt Terrestrial Systems, WT-0104), www.adapter-projekt.de. We are also grateful to our anonymous reviewer for constructive criticism that helped us to improve the manuscript, and to Katharina Bülow for test reading and sharing her valuable comments. S B acknowledges the highly pleasant collaboration with all ADAPTER colleagues as well as noteworthy experiences at GERICS in the last years.

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