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Earlier planting fails to replicate historical production conditions for US spring wheat under future climates

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Global warming and heat stress can adversely affect crop yields and quality. Earlier planting that shifts the growing season to cooler periods is a widely considered adaptation strategy in climate change literature. We ask: How effective is earlier planting in reducing high-temperature-exposure across growth stages? What are the associated temperature-exposure tradeoffs, and can historical conditions be matched? With US spring wheat as a case study, growth-stage-specific temperature exposure signatures are developed to estimate tradeoffs from earlier planting. While earlier planting does reduce exposure to critical and lethal high temperatures during reproductive stages, it fails to replicate historical production conditions. The Pacific Northwest is an exception, although tail-end growth stages may require management. Historically-equivalent planting windows narrow presenting logistical challenges. Therefore, while many climate-change assessments list earlier planting as an effective adaptation strategy, it may not be as effective when tradeoffs are considered, and consideration of other strategies will be important.

With projected increases in food demands to meet the dietary requirements of a growing population[1], increases in current levels of crop yields and production are necessary[2–4]. Besides population increase, the impacts of increasing heat stress[3,5,6], water scarcity[7], and urbanization[8] pose additional challenges to global food security, and economic and social stability[9–11]. With respect to a changing climate, projected changes in temperature and precipitation impact both dryland and irrigated crop growth, yield and production, necessitating exploration of adaptation strategies that mitigate negative production impacts[5,6,12–14].

While selecting a suitable adaptation strategy remains challenging and necessitates the inclusion of region-specific nuances, several strategies, including earlier planting, crop selection, cultivar selection, and changes to management practices, have been pointed out[15]. Of the adaptation alternatives, one that is ubiquitously considered successful in modeling efforts is a shift in "when" crops are grown—often termed earlier planting[16–18]. Earlier planting of crops aids in reducing exposure to high temperatures that cause heat stress during critical crop growth stages and alleviates yield loss[19–23]. However, the effectiveness of earlier planting as an adaptation strategy to climate change is implicitly assumed, and the implications for detrimental temperature exposures have not been explored in a detailed manner, and key knowledge gaps exist.

Crop development can be broadly classified into vegetative and reproductive stages. With earlier planting in a warmer climate, emphasis has been on reducing heat stress exposure during the plant's reproductive stages[24]. However, overall crop productivity does not solely depend on the exposure to heat stress in some reproductive stages; it also hinges on the relative exposures to detrimental—lethal, critical (causing irreversible or complete damage), and sub-optimal (causing reduced growth rates)—and optimal temperatures[25–28]. Additionally, temperature thresholds corresponding to detrimental impacts and optimal growth vary by growth stage[27–29], an aspect that is ignored in the majority of climate change impact studies, given the paucity of relevant growth-stage-specific data.

The combined exposure across multiple temperature categories and growth stages can be referred to as the crop's temperature exposure signature. Evaluating the effectiveness of earlier planting requires quantifying the changes to a crop's relative exposure time to all parts of the temperature exposure signature. While earlier planting reduces the exposure time to heat stress in some growth stages, there has to be a corresponding increase in

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exposure time to other parts of the temperature exposure signature. The key question is: do these increases correspond to beneficial or detrimental parts of the exposure signature, and what are the resulting tradeoffs in exposure? It is unclear whether earlier planting in the future can result in an overall temperature exposure signature across all growth stages that is equivalent to or better than historical conditions. If not, and if the signature is worse than historical conditions, while earlier planting can minimize some negative effects of warming, future production might not match historical production levels with this adaptation strategy alone. Our goal is to characterize the potential effectiveness of earlier planting as an adaptation strategy by answering two questions:

1. How effective is earlier planting in reducing exposure to detrimentally high temperatures across growth stages?
2. What are the associated tradeoffs in the temperature exposure signature, and can we at least match historical conditions with this adaptation strategy?

We consider spring wheat production in the United States (US) as a case study with a focus on the top production regions. Wheat is a staple food worldwide but faces potential challenges from both biotic and abiotic stresses in a changing climate[30,31]. It is a cool-season crop that thrives under moderate temperatures and requires careful choosing of planting windows to optimize production[32]. Moreover, detailed information on growth-stage-specific temperature thresholds—essential for determining the temperature exposure signature across growth stages and critical for our analysis—is available for spring wheat[27,33–36], although with some uncertainties around thresholds. Historical simulations and future climate projections[37,38] were used to develop the temperature exposure signatures for a range of traditional and earlier planting scenarios, and associated tradeoffs were quantified.

Understanding these effects is important because overestimating the potential of earlier planting as an adaptation strategy to climate change could result in under-preparedness in managing associated risks. The findings from this study will provide a more realistic characterization of the effectiveness of earlier planting in aligning future temperature conditions during crop production with historical conditions. Additionally, we identify geographic regions where this strategy has the potential to be effective and highlight critical growth stages where potential detrimental effects must be mitigated. While quantifying specific yield impacts is beyond the scope of this work, the results can be used to hypothesize potential impacts that can be addressed via management or breeding strategies.

Results

The results are provided in five sections. The first section quantifies the change in future high-temperature exposure due to earlier planting. The second quantifies whether earlier planting results in temperature exposures that match or are better than historical levels. The third provides regional summaries. The fourth quantifies uncertainty in the regional summaries of the effectiveness of earlier planting. The fifth quantifies changes to the length of historically equivalent planting windows in the future. In each section, for space and visual clarity, we sometimes restrict plots to specific future time frames or representative concentration pathways (RCPs) while providing context for consistency or inconsistency of results for the other cases. All information can be accessed in the Supplementary Figs. which are saved on GitHub (link provided in the data and code availability section). In the results, we will look at four baseline historical planting dates (PD, i.e., traditional planting dates) PD1, PD2, PD3, and PD4. Earlier planting dates (EP) were determined by advancing the planting in 5-day increments relative to each traditional planting date (more details can be found in the methodology section "Baseline planting dates and future advancements" and Supplementary Table 2 in the Supplementary Information).

Change in future high-temperature exposure with earlier planting

If traditional planting dates are maintained in the future, there is increased exposure to damaging high-temperature categories (critical and lethal high) in the reproductive growth stages from heading to maturity (the right-most box plot in each panel of Fig. 1). This trend holds for the near term (2040s) and far out (2080s) future time frames, with a greater increase for the 2080s. Earlier planting reduces these damaging temperature exposures, although the degree of advancement required to align exposures to historical levels varies by time frame and growth stage (Fig. 1a). Nevertheless, even with the maximum planting advancement considered in the analysis, the maturity growth stage continues to be exposed to higher than historical levels of damaging high temperatures. Therefore, finding a single earlier planting date that effectively reduces high-temperature exposure across all growth stages presents challenges, and trade-offs are inevitable. Moreover, advancing planting to reduce exposure to high temperatures in later growth stages can inadvertently lead to increased exposure to damaging cold temperatures (critical and lethal low) in earlier growth stages (Fig. 1b), exemplifying another potential tradeoff. Although results are specifically shown for RCP 8.5 and 2040s and 2080s in this section, the overall storyline is consistent for RCP 4.5 as well.

Tradeoff analysis and effectiveness of earlier planting

Results in this section are restricted to the PD1 window, the earliest phase of the traditional planting timeline (late March), and the 2040s and RCP 8.5. When traditional planting dates are retained in the future, the earlier growth stages benefit from temperature exposures becoming equivalent to or better than historical conditions across the study region (blue shading in panel PD1 in Fig. 2). Some growth stages, like grain fill, also have this positive effect, but only for some parts of the study region. All other growth stages experience negative effects.

With earlier planting, although some regions show improvements while considering specific growth stages (as indicated by a switch from reds to blues in Fig. 2 when looking at one column at a time), there is no consistent earlier planting date that mitigates negative effects across all growth stages (looking across all columns for one row) for most of the region. Thus, using earlier planting as an adaptation strategy does not consistently provide an equivalent or better than historical conditions across all growth stages. This is true across all traditional planting dates, future time frames, and emission scenarios. An exception is observed in some parts of Washington and Oregon, where advancing the planting date by 3 weeks (with respect to early traditional planting, i.e., PD1) results in positive effects across most growth stages (blues in panel EP4 in Fig. 2).

Regional summaries and overall implications

Based on state-wise summaries on tradeoff analysis, earlier planting is not effective in allowing future temperature exposures that match or are better than historical temperature exposures for any traditional planting phase, future timeline, or emission scenario for three of the spring wheat production states: Minnesota, South Dakota, and Wyoming (Fig. 3a, b). For the two top production states, North Dakota and Montana, which make up more than 67% of the national production (Supplementary Table 1), the strategy is effective only for the late phase of the traditional planting time (late May) and for the near term (2040s). Washington and Oregon in the Pacific Northwest US are the only states with consistent effectiveness across the full traditional planting timeline, future time frames, and emissions scenarios. Even in these states, some of the earliest and/or latest growth stages will experience conditions worse than historical levels.

Uncertainty analysis of the effectiveness of earlier planting

First, we consider uncertainty in results arising from sensitivity to the temperature threshold assumptions for optimal, suboptimal, critical, and lethal temperatures via sensitivity analysis results from relaxing the temperature thresholds. Overall, the outcomes related to the effectiveness of earlier planting are consistent in the majority of cases across the full range of temperature thresholds considered (predominant gray and green color in Supplementary Fig. 7). Within the minority divergent outcomes, the predominant case is one where earlier planting is less effective in the future

under some relaxed thresholds (blue color in Supplementary Fig. 7). This is primarily in the Pacific Northwest states. Divergent outcomes where earlier planting is more effective under relaxed thresholds are the least frequent outcome—indicating that our baseline results reported in earlier sections are generally conservative and the story will be generally worse if the temperature thresholds are relaxed.

Next, we consider uncertainty in the storyline arising from each general circulation model (GCM) having a different storyline. By storyline, we mean the effectiveness of earlier planting in resulting in temperature exposures equivalent to or better than historical. First, we compare the storyline obtained as the majority vote across all GCMs versus the storyline calculated from mean temperature exposure values across GCMs reported in the prior

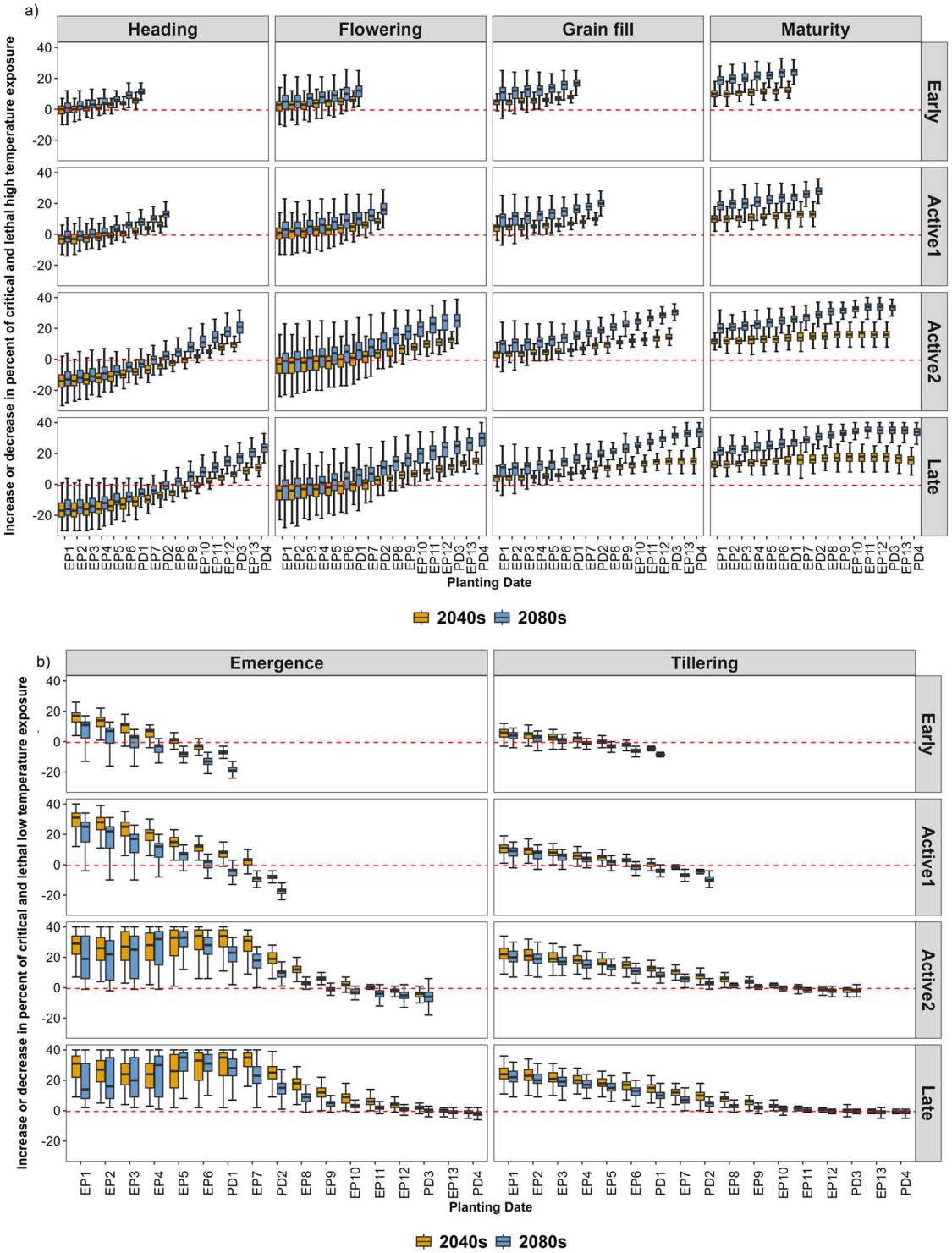


Fig. 1 | Increase or decrease in the percentage of future exposure to critical and lethal temperatures across multiple planting dates as compared to historical exposure. a Shifts in future high-temperature exposure. Only the four negatively affected growth states are displayed. **b** Shifts in future low-temperature exposure. Only the two negatively affected growth states are displayed. Zero value (red dotted line) indicates that the historical and future exposure to high or low temperatures is similar. Any value above zero indicates a future increase in high/low-temperature exposure, and a value below zero indicates a future decrease. Two time frames, the 2040s (near future) and 2080s (end of the century), are plotted for RCP 8.5.

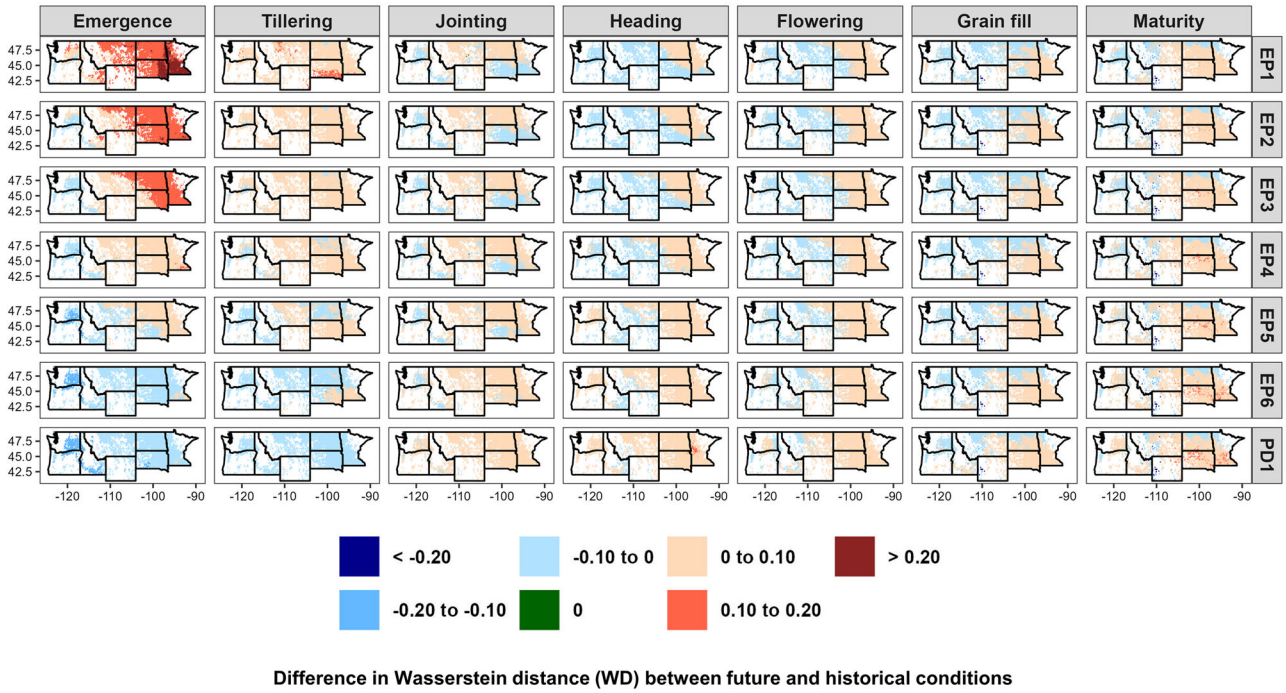


Fig. 2 | Difference in Wasserstein distance for future conditions (RCP 8.5 and 2040 s) as compared to historical levels for all growth stages and multiple future planting dates. The bottom row is the future baseline traditional planting (earliest planting; PD1; mid-March). Each row above that is an incremental 5-day planting advancement, with the top row, EP1, corresponding to a 30-day advancement. For each growth stage (column) and future planting date (row), the colors correspond to the Wasserstein distance of temperature exposures with that future planting date and optimal conditions minus the Wasserstein distance of historical temperature exposures with the traditional planting date and optimal conditions. From the "Methods section" on tradeoff analysis, this would correspond to [WD(F_t, Opt) - WD (H_t, Opt)] for the bottom row and [WD(F_a, Opt) - WD (H_t, Opt)] for other rows. Shades of blue and green indicate that future exposures are as close or closer to optimal conditions as historical levels. In contrast, reds indicate that future temperature exposures are further from optimal conditions than historical levels.

results section. For RCP 4.5 (Supplementary Fig. 3a, b), while there are some differences, the storyline that earlier planting does not result in temperature exposures equivalent or better than historical for most regions and time frames, except the Pacific Northwest US, is largely consistent across both approaches, except for PD1, the early traditional planting window. Additionally, the majority vote story line in Supplementary Fig. 3b comes from agreement across more than 70% models in most cases (Supplementary Fig. 4). There are only three out of the 672 possible outcomes where the GCM uncertainty is high with the majority vote resulting from agreement across less than 50% of the GCMs (Supplementary Fig. 4). These correspond to (a) emergence in the 2060s for the PD2 traditional planting window (the first active planting window) for Washington and Oregon states and (b) tillering in the 2080s for the PD2 traditional planting window for Oregon. For RCP8.5, the results are similar except that by the majority vote, earlier planting is not as effective in the Pacific Northwest for both PD1 and PD2 traditional planting windows (Supplementary Figs. 5 and 6). In summary, the results presented earlier in the paper from mean exposures across GCMs indicate a better outcome for the Pacific Northwest for PD1 and PD2 than many individual GCMs. For other regions, the outcomes are largely similar across most GCMs.

Shrinkage of historical-equivalent planting windows

Historical planting windows for spring wheat have spanned ~11 weeks between late March and late May as per USDA statistics. This time frame is typically necessary to accommodate market timing requirements and logistical constraints to the amount of planting that can be accomplished in a given time. We identified the weeks during which temperature exposures were equivalent or better than historical conditions for the early (late March), start of active (early April), end of active (early May), and late (late May) planting time frames within the 11-week window. Depending on the state, time frame, and emissions scenario, the historically equivalent future planting window shrinks to as low as 1–7 weeks (Fig. 4).

Discussion

We found that while earlier planting can alleviate heat stress during certain critical reproductive growth stages, this strategy is generally ineffective in reducing overall future temperature exposures across all growth stages to levels similar to or better than historical patterns. This finding holds true across all projected time frames and emission scenarios for the primary spring wheat growing regions in the US. The exception to this is seen in Washington and Oregon states in the Pacific Northwest, and to a limited extent, in neighboring Idaho. Even in these states, temperatures during the early growth stages (emergence and tillering) and/or during later maturity stages are projected to be worse than historical levels, depending on the specific time frame, emission scenario, and the traditional planting window used as the baseline. These adverse effects will need to be carefully managed. Furthermore, even in these regions, the window for planting with historically equivalent temperature conditions shrinks significantly, from 11 weeks to 1–7 weeks. This poses either logistical challenges in accomplishing planting within a much shorter time frame or requires adopting planting dates that expose crops to temperatures worse than historical conditions. While the Pacific Northwest may be somewhat better positioned for climate change adaptation through earlier planting, it only accounts for less than 15% of national spring wheat production. Therefore, it may not be able to offset potential losses in the other major production regions.

Consequently, relying on earlier planting as a primary adaptation strategy to maintain historical US spring wheat production levels appears unlikely, and other strategies to enhance spring wheat production will need to be explored. Additionally, spring wheat is one among multiple cereal crops. From a national cereal production perspective, adaptation strategies broader than within-crop strategies will need to be considered. For example, for Sub-Saharan Africa, van Ittersum et al.[39] recently highlighted that changes in crop mix—expansion of higher-yielding maize to regions where millet or sorghum were traditionally grown—have played a much larger role in historical yield gains than within-crop adaptation strategies alone. A

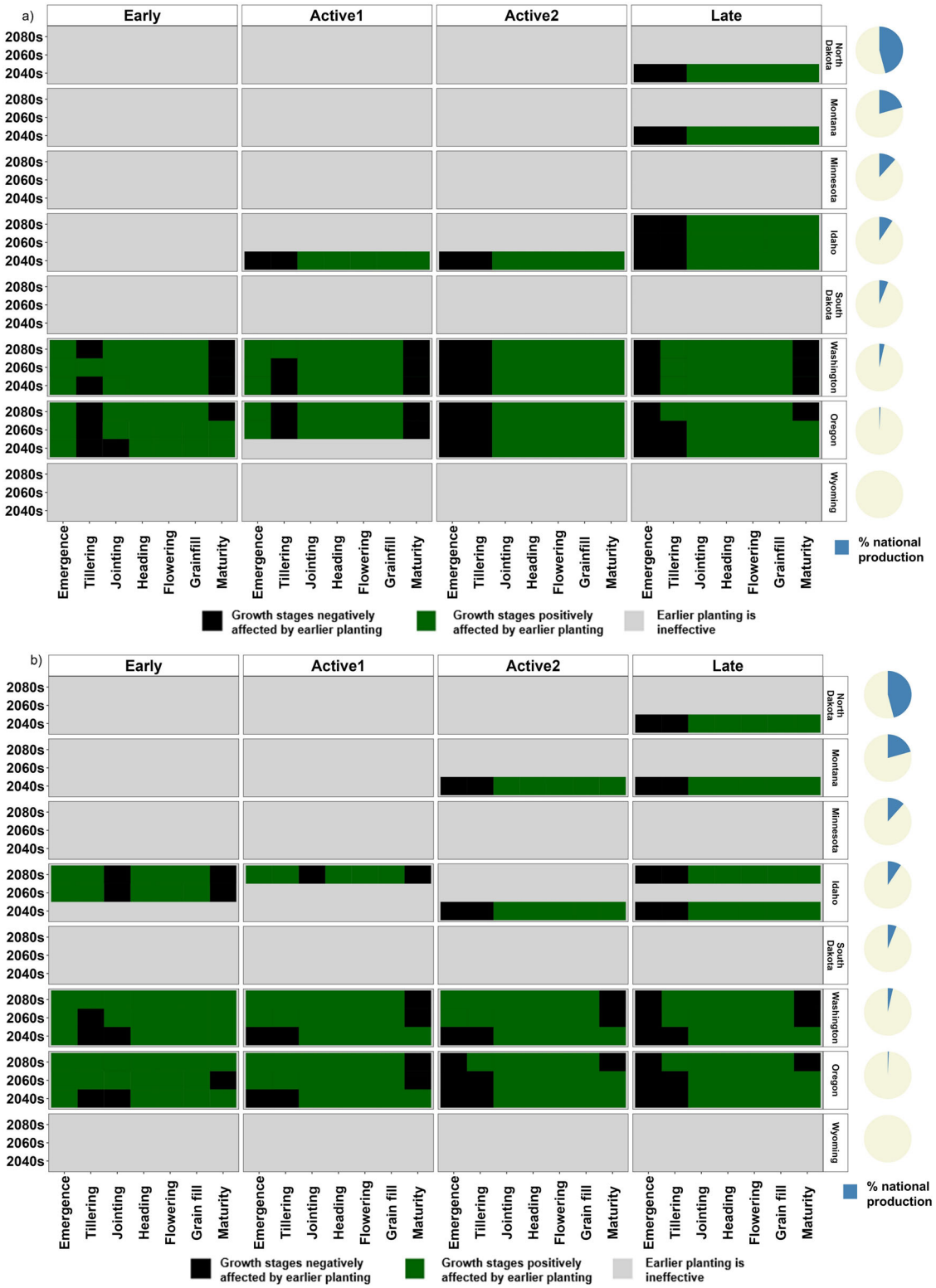


Fig. 3 | Heat map of the effectiveness of earlier planting across regions, scenarios and time frames. Heat map of the effectiveness of earlier planting for each of the seven states, three future time frames, and four baseline traditional planting dates for **a** RCP 4.5 and **b** RCP 8.5. Effectiveness can have three values: gray is ineffective for the specified criteria (at 75% grids and five growth stages need at least one planting date where future temperature exposures are at least as good as historical). The non-gray color implies that earlier planting is effective as per the criteria. Green and black refer to growth stages that are positively and negatively affected, respectively. This is relevant only for cases where earlier planting is determined to be effective overall as per our criteria. The states are sorted from top to bottom based on the share of national production coming from each state (pie chart), with percentages coming from Supplementary Table 1.

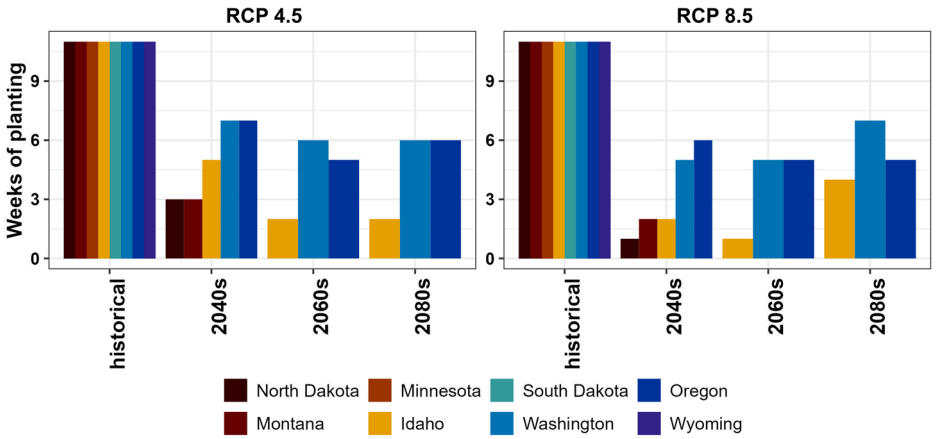


Fig. 4 | The number of weeks of planting available with historically equivalent temperature exposures as per the effectiveness criteria in the statewise summary. For each time frame, only states that have non-zero historical weeks are displayed. For example, for states like Minnesota and Wyoming, earlier planting is ineffective in the future time frames, and the historical planting window of 11 weeks shrinks completely in all future scenarios and time frames to a zero value. Washington, Oregon, and Idaho are the only states that appear across all time frames and scenarios.

combination of strategies, such as an increase in crop extent, intensification, and crop mix changes, were also demonstrated to contribute to future cereal self-sufficiency. However, in a place like the US, the fact that crop extent has been fairly stagnant[40], and with a focus on sustainable intensification[41], challenges to maintaining production can be high.

This work is focused only on temperature exposures and does not quantify yield impacts from exposure to the detailed growth-stage-specific temperature thresholds considered. It is an important diagnostic tool and foundation for identifying the tradeoffs associated with earlier planting. However, developing an empirical association between growth-stage-specific temperature exposure and historical yield observations is an important next step in assessing production impacts. While growth-stage-specific empirical relationships are lacking, observational evidence of general negative impacts on yields from exposure to higher than optimal temperatures for spring wheat specifically[42] and wheat in general[43,44] exists, and they point to potential negative impacts from our simulated changes in temperature exposure. Other supporting evidence also points in this direction. Exposure to non-optimal temperatures during vegetative and reproductive stages can impact grain yield[45,46]. The reproductive growth stage is particularly sensitive to temperature changes[27,46–48], with vegetative stages showing more plasticity and robustness to high-temperature exposure with multiple avoidance, escape, and stress tolerance strategies at its disposal[46]. High temperatures during early to late reproductive stages can reduce dry mass and cause pollen and floret sterility, further impacting grain yield[27,49,50]. Additionally, declines in the duration of reproductive growth associated with high-temperature exposures[34] can lead to a shortening of the duration of seed filling and reduce both yield and seed size[48]. Process-based crop models have known limitations in fully accounting for these impacts of high-temperature exposure across growth stages on yields[18,25,28,51]. Therefore, tradeoffs associated with earlier planting and negative impacts on yields are likely underestimated in current crop-model climate change assessments that list earlier planting as an effective adaptation strategy.

In our simulations, the top spring wheat-producing states of North Dakota, Montana, and Minnesota experience conditions worse than historical patterns across both vegetative and reproductive stages under all planting advancements considered. Specifically, the reproductive stages show prolonged exposure to critically high temperatures, potentially resulting in production losses compared to historical levels, even with earlier planting. Therefore, it is crucial to explore additional adaptation strategies such as developing wheat variants for warmer climates[52,53], modifying agricultural and irrigation systems[54], shifting production regions[52], or adopting short-season crop varieties[55], either individually or in conjunction with earlier planting. While perhaps less critical, this is also relevant for the Pacific Northwest, where ways to manage early and late season impacts will be necessary with earlier planting.

Specifically with respect to breeding as an adaptation strategy, the results of this study can provide some pointers. First, breeding strategies will likely be region-specific. Where earlier planting is not effective, breeding goals may focus on overall productivity enhancements. However, average winter wheat yield increases for newer varieties in the Great Plains region have come at the cost of lower tolerance to high temperatures[44], and newer spring wheat varieties in North America seem less resilient to warming[56], highlighting the challenges of breeding as an adaptation strategy. For the Pacific Northwest, there could be an additional focus on the impacts of earlier planting. With large shifts in planting dates to as early as February, the photoperiod exposure will reduce, and therefore, photoperiod sensitivity can pose challenges[49,57]. Breeding programs might need to prioritize varieties that better handle these challenges, as well as cold stress early on, including emergence in cold soils. Varieties that can better handle heat stress during the later reproductive stages, leading into maturity, will also be necessary.

The choice of planting time is an important agricultural management decision influenced by several factors such as field workability, market pressures, mechanical issues and soil temperature. The choice of the planting date not only has a direct impact on crop growth and potential yields, especially for cool-season crops like spring wheat[32], but has several other implications not considered in this study. It can impact the alignment of crop growth stages with specific climatic conditions, altering the susceptibility to pests and diseases[49,58]. Crop establishment failure can necessitate replanting with increased seed and other input costs, which can financially strain a grower. Planting time can also affect soil moisture availability or irrigation needs through the season, impacting productivity. Additionally, high soil moisture early in the season can impede soil workability and field operations that avoid soil compaction[16,59–61], although advanced planters can overcome this challenge. Planting methodologies may have to adapt to seeding in cold wet conditions. Earlier planting can also affect radiation exposure, an important consideration for yields. A shift in production to an earlier part of the season with lower radiation exposure could reduce yields and necessitate exploring late-maturing crop varieties. This of course brings in potential higher heat stress exposure. Also, cooler temperatures and slower growth early in the season may lead to overall season length not decreasing with earlier planting (Supplementary Fig. 8). While these aspects have not been considered here, they can be viewed as additional challenges to adopting earlier planting as an adaptation strategy that can result in negative consequences beyond what is already highlighted in this study.

Additionally, CO_2 fertilization benefits, not considered here, can enhance yields[62] and counter the negative effects of a lack of effectiveness of earlier planting. However, our understanding of these enhancements are typically for benign conditions and CO_2 fertilization benefits can be reduced under suboptimal conditions[62] and heat stress[63], which, as per our simulations, are likely to persist even with earlier planting. Furthermore, CO_2

increase in seed mass is associated with a reduction in seed nutritional value and seed vigor[64].

The weighting system used in this study is discrete across lethal, critical, suboptimal, and optimal temperature range categories. The methodology can be improved by formulating a continuous weighing mechanism or additional discrete categories. Another limitation of this study is its lack of specificity regarding wheat varieties, as it considers a representative spring wheat crop, whereas different varieties may have varying temperature thresholds. While variety-specific data are currently unavailable, the approach used in this study can be adapted for variety-specific research or applied to broader contexts, including other crops, when data become available. Our temperature threshold sensitivity analysis does show that the results described in this paper are robust across a range of thresholds.

While newer CMIP6 data are available, we utilized the CMIP5 projections due to the availability of bias-corrected and downscaled data at the commencement of our research effort. For our study region, the average temperature bias between the CMIP6 Shared Socioeconomic Pathway (SSP) 5-8.5 and CMIP5 RCP8.5 for the end of the century timeframe ranges between −0.5 °C and 2 °C with most grids having values at the low end of this range (Fig. 1a in Martel et al.[65]). There is more agreement across GCMs in CMIP6 SSP5-8.5 with a lower standard deviation (Fig. 1b in Martel et al.[65]). CMIP6 projections have been shown to better capture climate extremes than CMIP5 projections. However, there is a known general warming bias in CMIP6 projections as compared to observations, indicative of the climate sensitivity being too high[66], although the level of bias has been shown to be dependent on the reference data considered[67]. Our framework is generalizable and can be easily applied on CMIP6 projections. The likely implications of this application are (a) temperature exposures skewed a bit to the warmer side as compared to our CMIP5 projections and likely higher heat stress estimates, and (b) higher agreement across GCMs. However, we would need to be cognizant of the warm bias in CMIP6 projections in making interpretations.

Conclusions

Earlier planting does help reduce the time spring wheat crop spends in critical and lethal high-temperature categories during some reproductive stages. However, this strategy is ineffective in aligning temperature exposures during crop growth with historically equivalent or improved conditions across all growth stages in much of the US spring wheat production regions. This trend persists across multiple future time frames and emission scenarios. Exceptions to this trend were observed in the Pacific Northwest, which contributes to less than 15% of US production. Additionally, some early and late growth stages may face worse-than-historical conditions in this region that will require management. Moreover, the planting window with historically equivalent temperature exposures is shrinking, posing an additional logistical challenge for planting. Therefore, on a national scale, current levels of spring wheat production may not be sustained by primarily relying on earlier planting as an adaptation strategy. An integrated effort focusing on breeding for adaptation to temperature change, sowing technology, and cropping system changes will be needed, along with consideration of other broader strategies such as crop mix changes. This is an important consideration, especially in the context where process-model-based climate change assessments commonly list earlier planting as an effective adaptation strategy, often without fully considering the range of trade-offs and potential impacts on yields. The work here provides the foundation for a diagnostic tool that can help better evaluate the tradeoffs associated with earlier planting.

Methodology

Study area

We consider eight US states that account for 98% of the national spring wheat production (Supplementary Table 1). These include Idaho, Minnesota, Montana, North Dakota, Oregon, South Dakota, Washington, and Wyoming. Within these states, we restrict our analysis to only cropland areas (Fig. 5). These areas were identified using the US Department of Agriculture (USDA), National Agricultural Statistics Service (NASS), Cropland Data Layer[68], an annual georeferenced dataset of cropland use. This satellite-imagery based dataset is available at a 30 m grid resolution. We filtered out areas with pasture and non-agricultural land use categorizations to focus solely on cropland. The data were then upscaled to the resolution of the meteorological input data (1/16th degree) (see "Tradeoff analysis and effectiveness of earlier planting") by coding a climate data grid as having significant cropland if at least 1/8th of the grid area is comprised of cropland pixels. This resulted in 10,446 cropland grids across the selected US states for analysis. We included all cropland grids rather than limiting to wheat-growing regions to account for the potential expansion of wheat cultivation in these areas in the future. We did overlay this study extent with grids that had wheat production sometime in the last 15 years (based on USDA's crop frequency data layer), and the extents more or less matched with the cropland extent, being slightly larger.

Meteorological input data

The historical simulation (1950–2005) and future climate projections (2006–2099) were based on GCMs that were part of the Coupled Model Intercomparison Project 5 (CMIP5)[38]. This data was bias-corrected and downscaled based on a Modified Multivariate Adaptive Constructed Analog method[37] to a 1/24th degree (~4 km) spatial resolution, which was further re-gridded by linear interpolation to 1/16th degree (~6 km) for computational efficiency. The future projection data was segmented into three time frames for summary statistics: near future (2025–2055, 2040s), mid-century (2045–2075, 2060s), and end of the century (2065–2095, 2080s). Seventeen GCMs under two concentration scenarios, RCP 4.5 and RCP 8.5, were utilized to capture a range of outcomes. RCP 8.5 represents a fossil-fuel-intensive future with high projected temperature increases, while RCP 4.5 represents some emission reduction and stabilization resulting in lower projected warming. The 17 GCMs considered include bcc-csm1-1, BNU-ESM, CanESM2, CNRM-CM5, CSIRO-Mk3-6-0, GFDL-ESM2G, GFDL-ESM2M, HadGEM2-CC365, HadGEM2-ES365, inmcm4, IPSL-CM5A-LR, IPSL-CM5A-MR, IPSL-CM5B-LR, MIROC-ESM, MIROC-ESM-CHEM, MIROC5, MRI-CGCM. Rather than utilizing the historical observation directly, we use the historical simulations from each of the GCMs as the baseline, so that projected changes between future and historical data will be less affected by model bias. We use a mean temperature exposure (explained in section "Temperature thresholds") across the GCMs but undertake additional GCM level uncertainty analysis described in section "Uncertainty in estimates of effectiveness of earlier planting".

Baseline planting dates and future advancements

The baseline historical planting dates (referred hereafter as traditional planting dates), were obtained from USDA's planting and harvesting date manual[69] which provides four sets of dates representing the beginning, most active, and end of planting season for different crops. For spring wheat, across our study region, these dates showed little variation (less than ±10 days), and we averaged values across the states considered. The four traditional planting dates are referred to as PD1, PD2, PD3, and PD4 (Fig. 6).

Earlier planting dates (Supplementary Table 2 in the Supplementary Information, Type = Earlier) were determined by advancing the planting in 5-day increments relative to each traditional planting date (Supplementary Table 2 in the Supplementary Information, Type = Traditional). We restricted earlier planting to post mid-February as the soil may be frozen or have higher moisture content prior to this period, even with warming, impeding soil workability and creating unfavorable conditions for crop development. The time windows starting from mid-February are named sequentially with an EP (for earlier planting) or PD (for traditional planting) prefix (Fig. 6). The four PDs correspond to four anchor points that cover the full traditional planting timeframe. Any time window to the left of a traditional planting date with a PD prefix is considered a candidate earlier planting option for that traditional planting date. Therefore, the earlier planting options vary across PD1, PD2, PD3, and PD4 and some windows

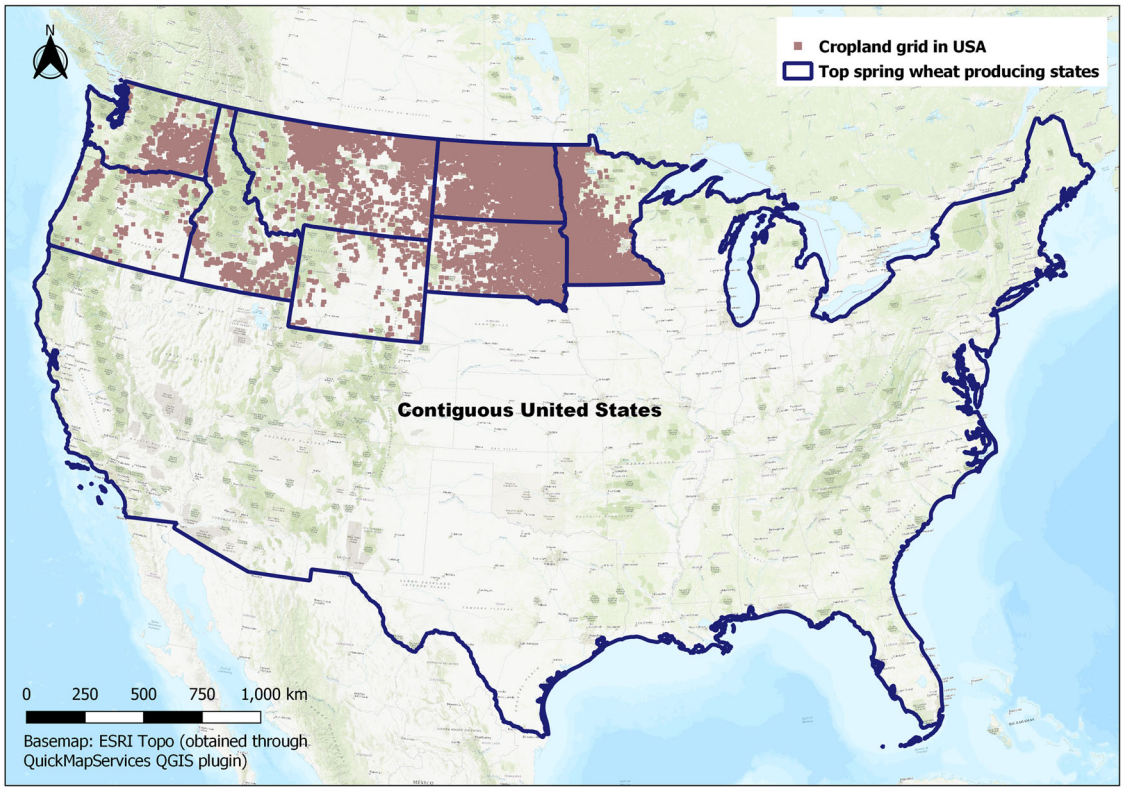


Fig. 5 | Cropland grids in major spring wheat-producing states of the USA.

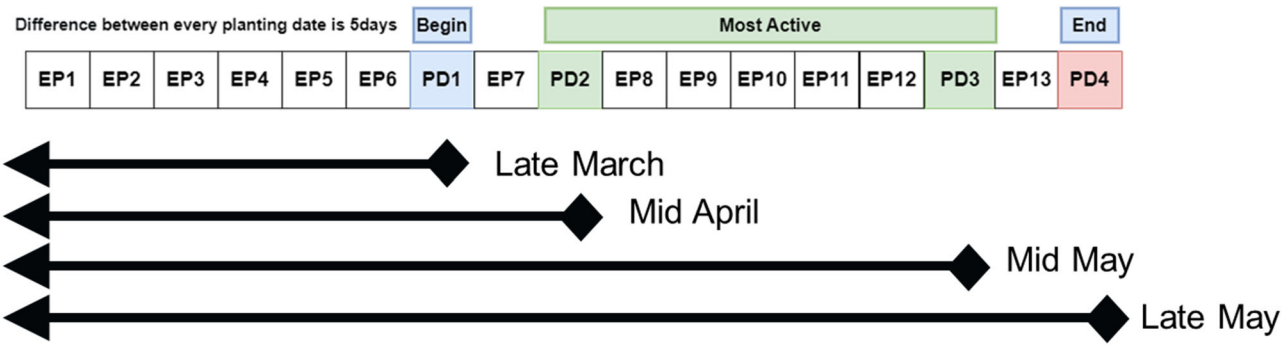


Fig. 6 | Planting dates considered. These are in 5-day increments starting mid-February and named sequentially with the prefix EP (for earlier planting) or PD (for traditional planting). PD1, PD2, PD3, and PD4 correspond to the four traditional planting windows: early start of planting, start of active planting, end of active planting, and end of planting. All time windows to the left of PD1, PD2, PD3, and PD4 would be considered earlier planting windows with respect to each of them (see lines at the bottom of the figure). For example, EP1 through EP6, PD1, and EP7 would be earlier planting windows with respect to PD2.

with a PD prefix can be an earlier planting option for other windows with a PD prefix to its right (e.g., PD3 is a 10-day earlier planting window for PD4; Fig.6).

Crop phenological stage and growing degree day requirements

The phenological stages of spring wheat can be grouped into vegetative and reproductive stages. Vegetative growth comprises three initial stages: emergence (root growth), tillering (shoot growth), and jointing (leaf initiation), while reproductive growth consists of the four later stages: heading (terminal spikelet), flowering (anthesis), grain fill (milk, dough) and maturity[27,70]. Each growth stage has specific temperature, photoperiod and moisture requirements[5,71–73].

Crop phenology and development were determined based on thermal accumulation measured in growing degree-days (GDD, °C day)[74,75] and GDD requirements for each growth stage can vary across varieties and we consider a representative variety. Daily GDD accumulation can be approximated using a linear method following the conditions described below, where T_{avg} is $\frac{T_{max}+T_{min}}{2}$, with T_{max} and T_{min} representing the daily maximum and minimum temperatures. T_b and T_c denote the base and cutoff temperatures below and above which no growth occurs.

(a) If $T_b < T_{avg} < T_c$, GDD accumulation is $T_{avg} - T_b$,
(b) If $T_{avg} > T_c$, GDD accumulation is $T_c - T_b$, and
(c) If $T_{avg} < T_b$, GDD accumulation is $T_b - T_b = 0$.

We used a base temperature of 0 °C[76] and a cutoff temperature of 30 °C[77,78]. The GDD accumulation starts from the day the crop is planted and stops when the crop reaches maturity; transitions between growth stages occur when the cumulative GDD requirement to complete a growth stage (Table 1) has been achieved. We do not have variety-specific information on GDD thresholds; therefore, these thresholds from the literature can be considered as that for a representative wheat crop. We also confirmed them with crop breeders, agronomists and crop modelers.

Temperature thresholds

Crops are exposed to a wide range of temperatures, and the exposures can be broadly categorized into lethal, critical, suboptimal, and optimal ranges. Lethal, critical, and suboptimal temperatures are further divided into lower and higher threshold bands that fall on either side of the optimal range. Exposure to critical temperatures causes irreversible damage, while suboptimal temperatures slow growth rates and exposure to optimal temperatures is ideal for crop growth and yields[28]. Obtaining growth-stage-specific temperature thresholds is challenging for most crops but has been documented for spring wheat[27,33–36,79] based on field trials (Table 2). Given the uncertainty in these thresholds, we also undertake a sensitivity analysis as described in section "Uncertainty in estimates of effectiveness of earlier planting".

Temperature exposure signatures

Once temperature thresholds across growth stages were established, we calculated the temperature exposure signatures for all cropland grids by quantifying the percentage of time a crop is exposed to specific temperature categories during each growth stage. The process involved the following steps.

(a) Identifying the growth stage for each day based on the GDD accumulation and requirements outlined in section "Crop phenological stage and growing degree day requirements" and Table 1.
(b) Using the growth-stage-specific temperature thresholds to categorize hourly temperature exposure into relevant temperature categories (see Table 2). To obtain hourly temperatures, the daily temperature data were disaggregated using a sine-logarithmic function[80].
(c) Repeating the above steps for each year (between planting and maturity), considering traditional planting dates for the historical time frame and both traditional and earlier planting dates for the future time frames. This is performed for all planting dates, time frames, GCMs, emission scenarios, and years.
(d) Calculating the percentage of time the crop spends in each temperature category for each growth stage, based on the hourly categorizations from step c.
(e) Determining the mean percentage exposure time across GCMs for each growth stage, time frame (historical or future (2040s, 2060s, 2080s)), emission scenario (RCP 4.5 and RCP 8.5), and planting date under consideration. These temperature exposure signatures are calculated for the historical time frame using traditional planting dates and for the future time frames with both traditional and earlier planting dates.
(f) Determining the future change in exposure for each growth stage, time frame (historical or future (2040s, 2060s, 2080s), emission scenario (RCP 4.5 and RCP 8.5), and planting date under consideration. This is the difference between the future and historical temperature exposure signature. For future scenarios, this difference is calculated for both traditional and earlier planting. Zero values in the change matrix are indicative of conditions similar to historical conditions. Positive (negative) values in detrimental growth stages indicate future conditions worse (better) than historical levels. Conversely, positive (negative) values in the optimal temperature categories indicate conditions better (worse) than historical levels.

An example walking through these calculations is provided in Supplementary Section 3 of the Supplementary Information.

Table 1 | Cumulative growing degree-day (GDD) requirements for all crop growth stages based on Ritchie[84] and Tomson et al.[85]

Phenological stage	Cumulative GDD (°C-day)
Emergence	(0, 110]
Tillering	(110, 440]
Jointing	(440, 670]
Heading	(670, 1100]
Flowering	(1100, 1300]
Grain fill	(1300, 1675]
Maturity	(1675, 1800]

If the cumulative GDD value in a day is within the specified range for a growth stage, that means the plant is in that corresponding growth stage on that day. Round and square brackets next to numbers are the typical math nomenclature to signify the exclusion and inclusion of the number in the corresponding range, respectively. For example, when the cumulative GDD hits 441 °C-day, the crop will transition from the tillering to the jointing growth stage and will remain in that stage until the cumulative GDD hits 670 °C-day and later transition to the heading stage.

Effectiveness of earlier planting: tradeoff analysis

A tradeoff analysis is performed to quantify the effectiveness of earlier planting in the future; i.e., does earlier planting result in a temperature exposure that is equivalent or better than historical exposure? We quantify the tradeoff in exposure using the Wasserstein distance (WD) metric, which is a distance function defined between probability distributions on a particular metric space[81,82]. This distance metric, also known as the earth mover's distance, is widely used in the optimal transport problem across various domains. Here, each distribution is viewed as a unit pile of earth on the metric space, and the distance between the distributions is calculated as the minimum amount of work done to transform one distribution into another by moving the earth. Here, work done is measured as the product of the distribution weight that has been moved and the distance it has been moved. To determine the distance, we use the function wasserstein_distance() from the scipy.stats sub-package of the SciPy Python library[83].

For each growth stage, we compare the temperature exposure signature, represented as a distribution, with an optimal distribution to calculate the WD. The temperature exposure distribution for a particular growth stage is a vector of size seven with values of percent time spent in LL, CL, SOL, OT, SOH, CH, and LH temperature categories. The WD for this distribution will quantify how far this distribution is from the optimal distribution of (0, 0, 0, 100, 0, 0, 0), where 100% of the time is spent in

Table 2 | Cardinal temperature thresholds for spring wheat across all phenological stages[27,33–36,79]

Phenological stage	Temperature categories[a] (°C)						
	LL	CL	SOL	OT	SOH	CH	LH
Emergence	<−17.2	−17.20 to 4.23	4.23 to 16.33	16.33 to 18.07	18.09 to 22.79	22.79 to 47.50	>47.5
Tillering	<−17.2	−17.20 to 5.26	5.26 to 17.00	17.00 to 20.80	20.80 to 20.90	20.90 to 47.50	>47.5
Jointing	<−17.2	−17.20 to 2.02	2.02 to 19.25	19.25 to 21.75	21.75 to 22.55	22.55 to 47.50	>47.5
Heading	<−17.2	−17.20 to 2.99	2.99 to 13.70	13.70 to 18.30	18.30 to 20.00	20.00 to 47.50	>47.5
Flowering	<−17.2	−17.20 to 11.12	11.12 to 21.25	21.25 to 24.75	24.75 to 27.00	27.00 to 47.50	>47.5
Grain fill	<−17.2	−17.20 to 14.45	14.45 to 24.47	24.47 to 27.53	27.53 to 30.00	30.00 to 47.50	>47.5
Maturity	<−17.2	−17.20 to 14.45	14.45 to 24.47	24.47 to 27.53	27.53 to 30.00	30.00 to 47.50	>47.5

[a]*LL* lethal low, *CL* critical low, *SOL* suboptimal low, *OT* Optimal, *SOH*- suboptimal high, *CH*- critical high, *LH* lethal high.

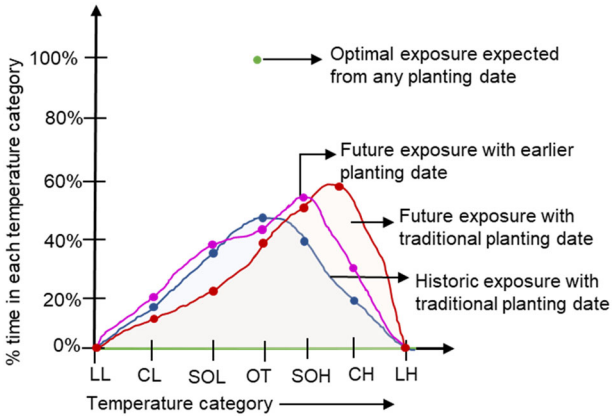


Fig. 7 | A hypothetical example demonstrating the distribution of temperature exposures across the seven temperature categories for any particular growth stage. Three cases are considered: historical exposures with traditional planting dates (blue), future exposure with traditional planting dates (red) and future exposure with advancements in planting (pink). Each condition will have a vector of length seven with values representing the % of time spent in each of the seven temperature categories. These are represented as points in the figure. The points are connected by lines for visual clarity. The Wasserstein distance of these distributions from an optimal distribution (green dot) where 100% of the time is spent in the optimal (OT) category is computed. The difference in distances is used to quantify tradeoffs. Here, LL is lethal low, CL is critical low, SOL is suboptimal low, OT is optimal, SOH is suboptimal high, CH is critical high, and LH is lethal high-temperature category.

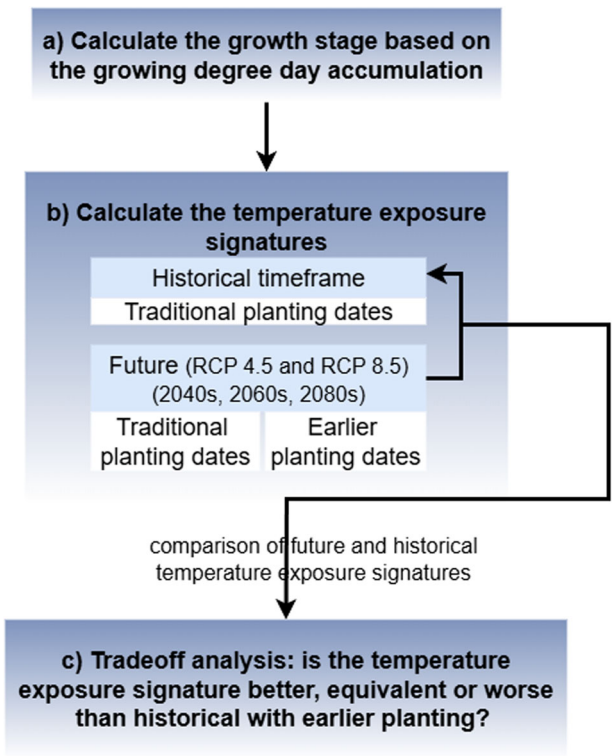


Fig. 8 | Simulation workflow summary.

optimal conditions. The distance values can range from 0 to finite or infinite value depending on the metric space (bounded or unbounded). A distance of 0 implies that 100% of the time is spent in optimal conditions, and smaller distance values are indicative of temperature exposure signatures closer to optimal conditions. Comparing distances between two scenarios will indicate which scenario is closer to optimal conditions. After computing the distance for historical and future conditions, if the future distance is equivalent to or less than the historical distance, it indicates future conditions are similar to or better than historical conditions.

Let WD(H_t, Opt) indicate the WD between historical temperature exposure with traditional planting date (H_t) and the optimal temperature exposure (Opt). Similarly, let WD(F_t, Opt) indicate the WD between future temperature exposure with traditional planting date (F_t) and the optimal temperature exposure (Opt). Let WD(F_a, Opt) indicate the WD between future temperature exposure with an advanced planting date (F_a) and the optimal temperature exposure (Opt). Once these distances are determined for each growth stage, the difference in distance between future conditions and historical conditions is indicative of whether the future temperature exposures are better (negative difference) or worse (positive difference) than historical exposures. When traditional planting dates are retained in the future, the difference in distance is given by [WD(F_t, Opt)-WD(H_t, Opt)]. When advancement in planting dates is considered in the future, the difference in distance is given by [WD(F_a, Opt)-WD(H_t, Opt)]. To explain this with an example, let us assume that the distance from the optimal for,

(a) Historical time frame with the traditional planting date (i.e., WD(H_t, Opt)) to be 1.20,
(b) Future time frame with the traditional planting date (i.e., WD(F_t, Opt)) to be 1.45, and
(c) Future time frame with an earlier planting date (i.e., WD(F_a, Opt)) to be 1.30.

Here, case b is farther from optimal than case *a* (difference in distance, $b - a = 0.25$). Case *c* is better than *b* (difference in distance, $c - a = 0.10$). But still not as good as historical conditions as the difference is not 0 or negative. That is, in this case, earlier planting in the future does not result in a temperature exposure that is equivalent to or better than historical exposure. This is exemplified in Fig. 7.

Note that this tradeoff analysis is performed on the mean temperature exposure across GCMs for computational efficiency. We complement this with an uncertainty analysis around GCMs based on a sample of grids, as described in the methods section "Uncertainty in estimates of effectiveness of earlier planting".

State-wise summaries based on the tradeoff analysis

To provide an overall picture of the effectiveness of earlier planting in at least matching historical temperature conditions across the full traditional planting spectrum, emission scenarios, and future time frames, we provide state-wise summaries. To develop state-wise summaries on the effectiveness of earlier planting, we make some assumptions that, although arbitrary, aim to capture overarching trends. We define early planting as effective for a state under the following conditions: we can identify at least one earlier planting date that results in temperature exposure signatures equivalent to or better than historical levels for at least 75% of the cropland grids in the state and for at least five out of seven growth stages. We impose an additional constraint that the three reproductive stages of heading, flowering, and grain fill cannot be among the compromised stages and must be equivalent to or better than historical conditions. In cases where earlier planting meets these criteria but is not effective across all seven growth stages, we identify the one or two affected growth stages to aid in assessing ways to address potential detrimental impacts.

Simulation pipeline

In summary, the workflow consists of three main steps (Fig. 8). First, we determine the growth stage based on growing degree day accumulation. Next, we characterize the temperature exposure signature for the historical time frame using traditional planting dates and for future time frames using earlier and traditional planting dates. The future time frame is divided into three sub-periods: near, mid, and end of the century under two emission scenarios (RCP4.5 and RCP8.5). Finally, we conduct a tradeoff analysis to assess the effectiveness of earlier planting by quantifying whether the temperature exposure signature in future time frames is better, equivalent to, or worse than historical levels when earlier planting is considered.

Uncertainty in estimates of the effectiveness of earlier planting

We account for uncertainty in the estimates of effectiveness of earlier planting from two sources: uncertainty related to different effectiveness outcomes from different GCMs and uncertainty in the cardinal temperature thresholds (listed in Table 2). Given this is computationally intensive, and prohibitively so, we perform the analysis on a sample of grids that is representative of the study area. We employ a stratified sampling approach across the eight states in our study region. We randomly sample (without replacement) 100 grids per state for the GCM analysis and a higher 200 grids per state for the temperature threshold analysis where the number of simulations are less than that for the GCM analysis.

To account for uncertainty arising from different GCMs, we perform the tradeoff analysis described in section "Effectiveness of earlier planting: tradeoff analysis" for each GCM individually. We run the tradeoff analysis and compute state-wise summaries of the effectiveness of earlier planting based on (a) the mean value of temperature exposure across GCMs and (b) individually for each GCM. From the individual results, we summarize an effectiveness outcome as a majority vote across outcomes from individual GCMs. We also quantify the level of agreement between the models as the fraction of models that have the same effectiveness outcome as the majority vote.

To account for uncertainty in the cardinal temperature thresholds (Table 2) because they are based on field trials outside the US and because there can be cultivar-specific differences, we undertake a sensitivity analysis of the effectiveness of earlier planting by relaxing the temperature thresholds in Table 2. To determine the level of relaxation, we used the standard error of thresholds across multiple studies as reported in Table 1 of the review by Porter and Gwaith[27]. We apply relaxations of ±0.5 °C up to ±2 °C in increments of 0.5 °C to the temperature thresholds that are specified in Table 2. These relaxations are applied to OT, SOL, SOH, CL, and CH temperature categories (Table 2). The thresholds were modified as a one-sided decrease of −0.5 °C to −2 °C for CL and an increase of 0.5 °C to 2 °C for CH; a two-sided decrease of −0.5 °C to −2 °C for SOL and an increase of 0.5 °C to 2 °C for SOH; for the OT temperature category, a decrement was applied to the end closer to SOL and an increment was applied to the end closer to SOH. In essence, this is equivalent to making the crops increasingly less susceptible to detrimental conditions as the relaxation level increases from 0.5 °C to 2 °C. We performed the tradeoff analysis and quantified the effectiveness of earlier planting for the different levels of relaxation and compared the effectiveness outcome to that from the baseline thresholds in Table 2 to quantify the sensitivity of effectiveness to the cardinal temperature threshold assumptions.

Data availability

The publicly available climate datasets used in the study are large files and can be downloaded from original sources whose downloading information can be found at https://www.climatologylab.org/maca.html. Additional figures not provided in the manuscript (for different time frames and planting dates) can be found in the folder Supplementary Figs. on GitHub whose link can be found in the code availability section.

Code availability

The codes used for the current study are available on GitHub at https://github.com/savalkar46/Earlier-planting-dates.git. Running the codes will generate the data analyzed in the study and figures provided in the manuscript.

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Competing interests

The authors declare no competing interests.

Additional information

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