Adapting Agriculture to Climate Change through Growing Season Adjustments: Evidence from Corn in China

Xiaomeng Cui and Wei Xie

Recent studies have shown that climate change will impose severe challenges on agriculture with profound implications. Although some hypothetical simulations have suggested that an optimal rearrangement of the growing season can substantially mitigate yield losses under future climate, no causal estimate has been provided on quantifying the extent to which farmers are adapting through growing-season adjustments. Using a novel microlevel data with detailed crop progress information in China over 1993–2013, we show that both planting dates and growing season lengths significantly respond to contemporaneous temperature and precipitation. Our estimates suggest that, for a median site in our sample, the adaptive behavior in growing season adjustments can lead to a two to six days earlier planting date and another three to six days shorter growing season by the end of this century. These induced adjustments can avoid up to 9% of the crop damages caused by climate change. However, our empirical analysis does not find clear evidence of long-run response or accompanied input adjustments, suggesting potential for developing policies and tools to further aid the adaptive process.

Key words: Adaptation, agriculture, behavioral response, climate change, growing season, inputs.

Climate change threatens global food security (Lobell et al. 2008; IPCC 2014). Recent studies have shown that crop yields are substantially decreased under high temperatures, and the projected losses in crop production are huge under future climate even with long-run adaptation considered (e.g, Schlenker and Roberts 2009; Burke and Emerick 2016; Chen, Chen, and Xu 2016; Gammans, Mérel, and Ortiz-Bobea 2017; Chen and Gong 2021). This climatic impact on agriculture can lead to profound implications on societies, because it brings further impacts and responses related to health, human capital accumulation, migration, and labor markets, among others, especially in developing countries (e.g., Cattaneo and Peri 2016; Springmann et al. 2016; Garg, Jagnani, and Taraz 2020; Huang et al. 2020).

Farmers may adapt to a changing climate through adjusting the time they plant and harvest crops. Numerous hypothetical simulations have suggested that optimal adjustments in growing seasons would lead to substantial mitigation in yield losses under future climate (e.g., Ortiz-Bobea and Just 2013; Kawasaki and Uchida 2016; Baum et al. 2020; Shew et al. 2020). However, these optimal rearrangements may not necessarily occur in reality due to various constraints farmers may face in achieving adaptation. Therefore, it is crucial to quantify to what extent farmers have actually been adapting through adjusting the growing seasons of their crops according to realized climatic conditions. The understanding of this behavioral response helps contextualize the potential yield benefits of growing season adjustments and informs policy designs that can aid farmers' adjustment process toward better adapting to climate change.

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In this article, we measure farmers' adaptive behavior in growing season adjustments by providing the first causal estimate on how changes in temperature and precipitation affect actual growing seasons, based on a novel panel dataset of nearly 800 agro-climatic monitoring sites in China from 1993 to 2013. The dataset contains detailed information on crop-specific planting and maturity dates recorded at each site in each year, providing a unique opportunity for exploring the induced growing-season adjustments with observational data.

Focusing on corn, we separately consider two margins of the growing-season adjustments: the planting date and the length of a growing season. On planting dates, we explore how temperature and precipitation realized before the normal planting time of each site affect the actual planting date in a year. On growing-season lengths, we measure how temperature and precipitation realized after the actual planting date factor into the duration of growing season in that year. In both cases, we exploit exogenous year-to-year variation in weather in the relevant time period to causally identify the effects of contemporaneous weather. Although our empirical strategy is still under a standard panel fixed effects framework, the effective within-variation in weather is measured over the relevant time period that is location specific, in accordance with the fact that the normal planting time of corn varies across space.

Tracing out the weather effects as a flexible function of time, we show that higher temperature and precipitation realized in roughly one month before the normal planting time have the largest effect on advancing planting dates. We find that, during the eight-week period before normal planting time, a 1°C higher weekly average temperature will result in a 1.21 days earlier planting date. This estimated effect reflects that higher pre-planting temperatures loosen the constraint of heat deficit for early planting. Additional results on regional heterogeneity show that the temperature effect is more substantive in the cooler northern region, lending further support on this mechanism. On precipitation, we find that a 1 cm increase in weekly cumulative precipitation during the eight-week pre-planting period is associated with a 1.68 days earlier planting, but this effect is statistically weaker than the temperature effect.

Our estimates on growing-season lengths suggest that, both temperature and precipitation realized after the planting date significantly affect the length of a growing season. Higher temperature and more precipitation during the early course of the growing season shorten the duration for crop growth. During the first twelve weeks of the growing season, increasing average temperature by 1°C would shorten the growing season by about three days, and rising weekly precipitation by 1 cm would lead to a roughly one-and-half days shorter growing season. These effects tend to reverse in the later course of the growing season as heat and water stress interfere with the normal pace of late-stage crop development.

We interpret our empirical estimates as contemporaneous short-run responses because they are essentially identified through year-to-year variation in weather. However, even without further long-run adjustments, the adaptive behavior reflected by these short-run responses will still lead to meaningful actions under future climate that partially mitigate the detrimental impacts of climate change. We combine our empirical estimates with a set of climate projection models to contextualize the implications of the induced growing season adjustments. We show that, all else equal, climate change will advance the planting dates and shorten the growing seasons for most of the sites in our sample. Depending on the climate model, the median site will shift forward its planting date by two to six days and have a threee to six days shorter growing season under RCP 8.5 by the end of this century. We also show that the induced earlier planting would not be prevented by freezing threats, whereas the shorter growing season avoids high temperatures detrimental to yields.

We further evaluate the economic consequences of these induced growing-season adjustments through their implications on corn yields. Specifically, we pair our empirical results on planting dates and growing season lengths with empirically identified yield-response parameters to recover yield benefits of the adjustments under future climate. The results indicate that the induced adjustments in planting dates and growing season lengths on average mitigate potential yield losses by 3.3%–9.0% under RCP 8.5.

In addition, we estimate potential long-run responses in growing-season adjustments using a moving-average specification. We also match our site-level data with a county-level panel to explore if changes in fertilizer and pesticide usage correlate with growing-season adjustments. However, we do not find significant long-run response in addition to the short-run response. There is also no indication that input adjustments are simultaneously involved with the induced adjustments in planting dates and growing season lengths. These results may suggest the existence of important obstacles impeding farmers from better utilizing their resources to further adapt to climatic conditions through growing-season adjustments.

This article makes important contributions to the understanding of climatic impacts on agricultural production by providing the first causal estimate of temperature and precipitation effects on growing-season adjustments. In the literature, some studies have shown large yield benefits of rearranging growing seasons through hypothetical simulations under projected future climate (e.g., Ortiz-Bobea and Just 2013; Kawasaki and Uchida 2016; Baum et al. 2020; Shew et al. 2020).[1] But these estimates correspond to a theoretically best scenario that does not necessarily occur in reality due to potential constraints. Previous phenological studies have also shown correlations between warmer spring temperature and earlier planting time by relating observed trends in historical data (e.g., Chen, Hu, and Yu 2005; Menzel et al. 2006; Butler, Mueller, and Huybers 2018; Zhu et al. 2018). However, these findings are only suggestive and do not represent a causal relationship, because the trends are subject to potential spurious correlation related to factors like technological progress over time. By exploiting rich within-variation based on a novel microlevel panel, we overcome the difficulty in causal identification and make important progress on quantifying the adaptive behavior in growing season adjustments.

The induced yield benefits reflected in our analysis help gauge the potential bias in the projected crop losses under future climate in the literature.[2] The contrast between our results and the simulated results under an optimal rearrangement also illustrates the difficulty in flexibly adjusting growing seasons in reality. The lack of evidence on long-run response and accompanied input adjustments further emphasizes this concern. Besides, with a country focus on China, this article extends the knowledge on how climate change would affect agriculture in this vast and populous country (Chen, Chen, and Xu 2016; Zhang, Zhang, and Chen 2017; Chen and Gong 2021).

The findings in this article also build on the emerging literature on measuring agricultural adaptation to climate change. Specifically, finding induced adjustments in growing seasons complements previous studies that explicitly measure other behavioral adaptations, including crop choice, planting and harvesting decisions, double cropping, and input adjustments (e.g., Seo and Mendelsohn 2008; Kawasaki 2018; Cui 2020a, b; Aragón, Oteiza, and Rud 2021; Jagnani et al. 2021). The evidence of a warming-induced shift in growing season is also useful in explaining those documented acreage expansion and increased double cropping that would not have occurred without warming. In addition, the yield benefits associated with growing season adjustments provide a potential illustration of yield adaptation manifested through the implicit estimates under a unifying estimation framework (Mérel and Gammans 2021).

The article is organized as follows. The next section introduces data used and some facts on agricultural production and climate in China. The section of estimation and results elaborates the empirical strategy for identifying how weather affects planting dates and growing-season lengths, and discusses the empirical estimates. Building on these estimates, the section on yield implications evaluates the yield benefits of induced growing-season adjustments through a set of simulations under future climate. Following that, two more sections further explore potential long-run responses and input adjustments, respectively. The section on regional heterogeneity examines heterogeneous responses in the induced adjustments of planting dates and growing season lengths. The last section concludes.

Data

We merge site-level crop progress data with station-based weather data all over China for

[1]For instance, based on US data, Ortiz-Bobea and Just (2013) show that a two-week earlier planting of corn could result in a significant reduction in warming-induced yield damages up to 70% under a 5°F uniform warming.

[2]When measuring climatic impacts on agricultural production, the growing season of a crop is typically assumed fixed over time in the empirical literature using an econometric approach. In this literature, researchers normally pick a fixed time window that encompasses the typical growing season to fully capture weather fluctuations. For example, Schlenker and Roberts (2009) and Burke and Emerick (2016) use March–August and April–September for U.S. corn, respectively. Chen, Chen, and Xu (2016) consider differentiated growing seasons for different types of corn in China, but the growing season is unchanged over time for each specific corn type.

conducting the main analysis. The spatial distribution of crop sites and weather stations are presented in appendix figure A1, and we discuss more details of these data and other supplementary data as follows.

Crop Progress Data

We utilize data collected at agro-climatic monitoring sites to recover detailed information on actual growing seasons specific to different locations and crops in China. The government started to extend a network of these sites countrywide since early 1990s. The purpose of establishing this network is to monitor crop progress, evaluate yield risks, and forecast production in major agricultural areas over the country. Following a protocol, site locations are determined so that a site is representative of its regional climate niche. Specific parcels of land to be monitored are chosen in a way such that crops growing on these parcels represent regional cropping activities. The experts and staffs in this network are only involved in monitoring crop conditions, and the parcels being monitored are still managed by ordinary farmers. For each crop monitored, the site keeps tracks of all critical stages of its growth. Experts at the site determine the starting date of each stage for each crop based on on-site observations of crop conditions, following criteria in a technical manual made by agronomists (CMA 1993).

The data we use contain detailed site-level records of all the 778 sites over 1993–2013, stored in the data archive of the National Meteorological Information Center of China. We focus on corn in this study, considering that corn is one of the most important crops in China, and it is shown to be sensitive to changes in climatic factors (Schlenker and Roberts 2009; Chen, Chen, and Xu 2016). Among the 778 sites, 259 sites have planted corn for at least three years in the sample period. In our corn data, all sites only plant corn once in a year. We acknowledge that some places in southern China (e.g., Hainan province) are able to plant corn twice a year. However, this double-corn phenomenon is relatively rare because the heat accumulation is typically insufficient for feeding two consecutive corn growing seasons in a single year in most places in China, and our analysis does not cover this special case.

The planting time of corn varies across space. This time can be in as early as February and as late as June. We show cross-sectional variation in the normal planting time observed in our data in appendix figure A2. The last crop stage recorded in the corn data is *crop maturity*. Because our data do not include double corn, we use the number of days in between planting and crop maturity in a year to define the length of growing season at each site. The typical length of corn growing season also features cross-sectional variation in our data, as shown in appendix figure A3.

Additional Agricultural Data

In addition to crop progress information, we supplement data on the division of agricultural regions for exploring regional heterogeneity. A panel led by experts from multiple governmental agencies, including the ministries of agriculture, land and resources, environmental protection, and water resources, has enacted a zonal classification for agricultural development in China.[3] As shown in appendix figure A1, the entire mainland China is categorized into seven different zones based on agriculture-related environmental endowments (climate condition, soil type, water balance, etc.). The vast majority of the corn-planted sites in our sample is located in the following five zones: Northeast, Northwest, Huang-huai-hai, Southwest, and Yangtze River Delta.[4] Among the five zones, most of the corn is planted in the Northeast and the Northwest, followed by the Huang-huai-hai and the Southwest. The Yangtze River Delta, as a major rice-planting region, maintains a relatively modest share in corn planting.

We also assemble a county-level panel of input usage and cropland acreage over 2001–2015 based on county-level agricultural statistics obtained from the Ministry of Agriculture and Rural Affairs of China and Chinese Academy of Agricultural Sciences. The input data contain information on the total quantities of fertilizer and pesticide application (compound equivalent) at county-by-year level. We pair these data with the total amount of harvested acreage to obtain annual per-hectare usage of fertilizer and pesticide at the county level.

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[3]The official document is titled *Sustainable Development Plan for China's Agriculture (2015–2030)*, released in May 2015. The document can be retrieved from: http://www.gov.cn/xinwen/2015-05/28/content_2869902.htm.

[4]Only one site is located in the South, and another one is located in the Tibetan. In our empirical analysis on regional heterogeneity, these two sites are categorized in their nearest neighboring zones: the Yangtze River Delta, and the Southwest, respectively.

Weather and Climate Data

We obtain historical daily weather information from the China Meteorological Data Service Center. The data contain daily records of maximum and minimum temperatures and precipitation at 699 nationally certified weather stations since 1981. We spatially interpolate weather data to agro-climatic monitoring sites using inverse-distance weighting with a radius of 200 km. This strategy has proven to be effective and robust in various studies based on the same source of weather data (e.g., Zhang, Zhang, and Chen 2017; Chen and Gong 2021).[5]

Recent climatological studies document that these regions have experienced considerable warming over the past few decades (Lobell, Schlenker, and Costa-Roberts 2011). The trends observed in our weather data are consistent with these findings. Based on available information on site-specific weather over the thirty years before the end of our sample period, we obtain simple trend estimates in annual temperature using the following regression:

$$\mathrm{Temp}_{it} = \alpha_i + \beta_i \times t + \varepsilon_{it},$$

where i and t represent site and year, respectively; and Temp_{it} indicates yearly average temperature. In figure 1, we plot site-specific trend coefficients β_i for the five corn-planting agricultural zones. The distributions are mostly located on the right side of the zero-lines, suggesting systematic warming trends in all these regions.[6] The median trend coefficient is about 0.04, which can be translated into a 1°C warming in annual temperature over twenty five years.

For future climate, we obtain projected end-of-the-century temperature and precipitation conditions from five different global climate models (GCMs) derived from the Coupled Model Intercomparison Project Phase 5 (CMIP5): GFDL-ESM2M, HadGEM2-ES, IPSL-CM5A-LR, MIROC-ESM-CHEM, and NorESM1-M. As we show in a later section, climate model projections suggest that the observed warming trends will persist, which implies that crops will experience much more extreme heat detrimental to yields under a fixed growing season. These facts further highlight the importance and relevance of understanding how growing-season adjustments can mitigate the harmful impacts of climate change.

Estimation and Results

Growing-season adjustments involve two margins: the time for planting and the duration of crop growth. Relying on a site-level panel fixed effects estimation, we separately identify how temperature and precipitation induce adjustments on these two margins.

Planting Date

A successful planting of corn requires necessary conditions on temperature and soil moisture to be met for initiating crop emergence and development. If warmer temperature and sufficient rainfall arrive earlier than usual, the triggering conditions for planting corn may be satisfied earlier, possibly resulting in an earlier planting date.

Weekly average specification. To uncover the relationship empirically, we use the following panel fixed effects estimation to causally identify how weather realization prior to normal planting time affects the actual decision of planting date:

$$(1) \quad PD_{it} = \sum_{j=0}^{J} \beta_j T_{it,M_i-j} + \sum_{j=0}^{J} \gamma_j P_{it,M_i-j} + h_r(t) + \alpha_i + \varepsilon_{it},$$

where PD_{it} represents the planting date in year t recorded at site i. Specifically, the variable is coded as the number of days since the first day of year t, and therefore a smaller value represents an earlier planting date. T_{it,M_i-j} is a set of weekly average temperature variables at the site-by-year level, measuring temperature at the jth week prior to site i's normal planting time.[7] In practice, we define a site's normal planting time by referring to the median date of its planting dates during 1993–2013. The term P_{it,M_i-j} represents a set of weekly cumulative precipitation variables defined in a fashion similar to T_{it,M_i-j}. Specifically, we include

[5]Among all the stations, a non-negligible portion of the stations co-locate with agro-climatic monitoring sites. Weather at these sites almost solely rely on information collected by the co-located weather stations, because the inverse-distance weighting strategy assigns a weight approaching to one to the co-located station.

[6]We also conduct a similar analysis on precipitation, but we do not find systematic trends, as shown in appendix figure A4.

[7]In the subscript of the variable, $M_i - j$ denotes the jth week preceding M_i, the normal planting time of site i.

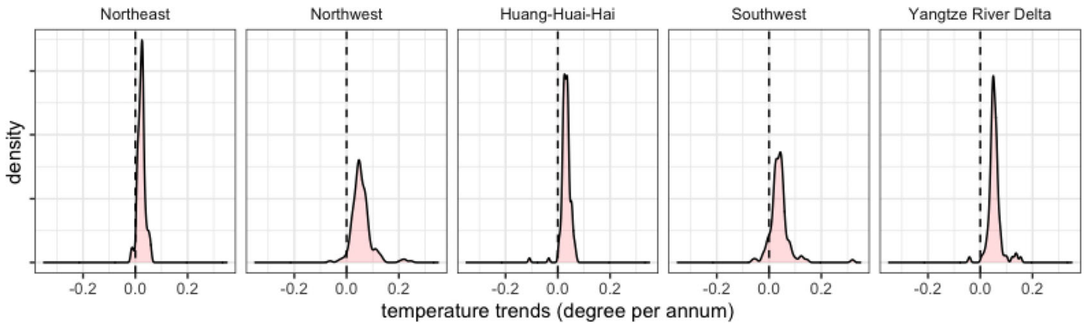

Figure 1. Regional trends in annual temperature: 1984–2013.

Note: Each panel plots the distribution of site-specific trend coefficients of annual temperature from 1984–2013 in a specific region. The trend coefficients are obtained by regressing annual temperature on site-specific time trends with site fixed effects.

weekly temperature and precipitation variables up to twelve weeks prior to each site's normal planting date to flexibly trace out potentially heterogeneous effects over time. The term $h_r(t)$ represents smooth regional time trends, specified as province-level quadratic trends of year. The term α_i is the site fixed effect, and ε_{it} represents the error term.

Under a standard panel fixed effects framework, the identifying assumption is that, controlling for differential time trends over regions, two sites would have changed their planting dates similarly had they experienced the same change in weather before their normal planting time. The identification is achieved through leveraging rich within-site variation observed in our sample, as illustrated in appendix figure A5. Because the error structure in this type of analysis typically features both spatial and temporal heteroskedascity and autocorrelation (Auffhammer et al. 2013), our statistical inference is based on a two-way clustering strategy developed in Cameron, Gelbach, and Miller (2011). Specifically, the two-way clusters are sites and province-by-year pairs, which allow for arbitrary correlations in the errors within the site over years and across nearby sites in the same year.

Figure 2 plots the estimates of temperature and precipitation variables in equation (1).[8] The pattern of the estimates suggests that higher temperature and precipitation around one month before normal planting dates have the most significant effect on advancing actual planting dates. For example, a 1°C higher average temperature in the fourth week before the normal planting date is associated with an earlier planting of 0.24 days, and a 1 cm more precipitation in the same week is associated with an early planting of 0.44 days. These estimates are not negligible considering that they only represent temperature and precipitation effects of one particular week. Weather, especially temperature, usually features high correlation between neighboring weeks. If a specific week becomes warmer in a year, it is very likely the neighboring weeks also become warmer than usual, and the joint effect will become much larger. For example, suppose the third and the fifth weeks also become 1°C warmer along with a 1°C warming in the fourth week, the 1°C warming effect of this three-week period would amount to a 0.66 days earlier planting date.

Alternative temperature measures. Different measures of temperature may reflect different aspects of the temperature effects, and solely relying on mean temperatures may potentially neglect other dimensions of the temperature effects. For instance, the planting decision could be more sensitive to cold temperatures as their occurrence likely precludes early planting. Therefore, we evaluate the sensitivity of our results to alternative measures of weekly temperature. Specifically, we consider weekly averages of daily minimum and maximum temperatures, as well as degree days and the number of non-freezing days.

Panel A in appendix figure A7 plots the estimates based on minimum and maximum temperatures along with baseline estimates

[8]In our data, a small fraction of observations only report planting dates but do not disclose maturity dates. We conduct a robustness check for the planting date regression by excluding these observations. In appendix figure A6, we show that the results are almost identical to those in figure 2.

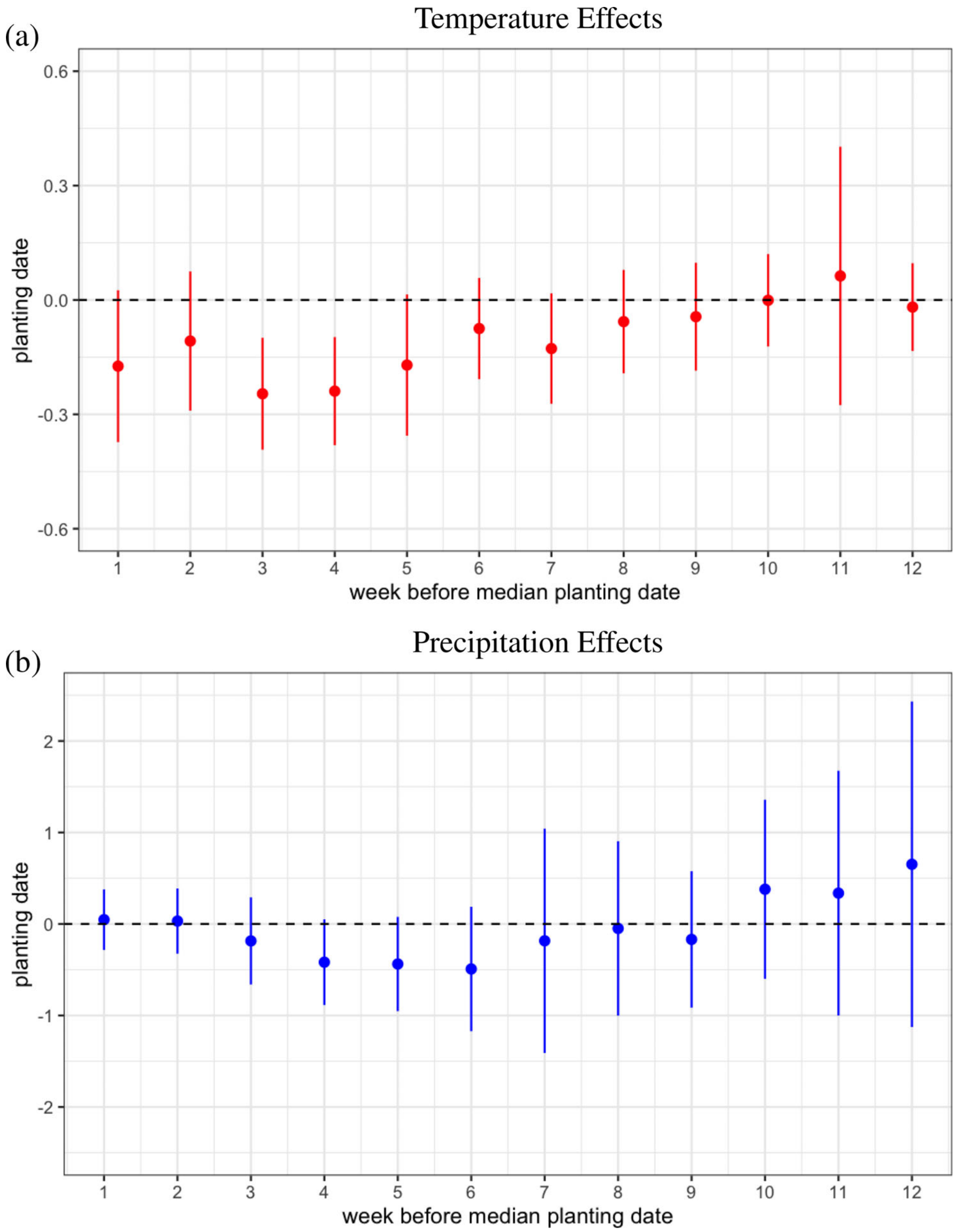

Figure 2. Effects of pre-planting weather on planting dates: Weekly averages.

Note: The dots represent the point estimates of temperature or precipitation effects in the corresponding weeks. The error bars represent 95% confidence intervals based on two-way clustered standard errors. Temperature and precipitation are measured in degrees Celsius and centimeter, respectively. See numerical results in appendix table A2.

based on mean temperature. The three sets of temperature estimates are highly consistent and almost indistinguishable statistically. We interpret this consistency as evidence that weekly averages of daily mean temperatures are sufficient for characterizing farmers' behavioral response in planting date decision regarding pre-planting temperature realizations.

Referring to agronomic knowledge on crop planting, we use degree days above 10°C as an alternative measure of temperature to evaluate the effects of temperature prior to normal planting time. This measure of degree days characterizes cumulative heat by summing degrees by days above the threshold of 10°C for the corresponding time period.[9] The threshold of 10°C comes directly from technical documents of corn seed-breeding in China, in which 10°C is regarded as a triggering threshold for initiating corn growth (Cui 2007). Taking diurnal variation in daily temperature into account, we conduct a sinusoidal interpolation between daily maximum and minimum temperatures for each day when constructing the degree days. Besides, we also consider the number of days with daily minimum temperature above 0°C as another measure that emphasizes the role of coldness in affecting planting dates.

Panels B and C in appendix figure A7 plot temperature effects measured through degree days and non-freezing days, respectively. Although the magnitude of these estimates is not directly comparable with that of the baseline, the general patterns of the estimates are consistent. Higher degree days and more non-freezing days, correlated with higher weekly average temperature, induce relatively earlier planting, especially when it is close to the normal planting time.

Some studies in the recent literature have adopted an out-of-sample prediction approach to make variable selection (e.g., Schlenker and Roberts 2009), but this approach may not be perfectly suitable in our analysis. Conceptually, our purpose in this research is more about identifying the causal effects than obtaining a model that delivers the highest predictability. Besides, our limited sample size keeps us from utilizing a highly data-driven approach as the results are likely very sensitive. Nevertheless, we examine commonly used in-sample model selection criteria and do not find any of the alternative temperature measures showing a significantly better model fit over the baseline using mean temperature, as shown in Panel A in appendix table A1.

Additional robustness checks. We provide additional robustness checks to address potential concerns on omitted variables. Previous analysis has shown that weather variables other than temperature and precipitation may confound the identification of temperature and precipitation effects in the context of estimating yield response (Zhang, Zhang, and Chen 2017). To check if this issue also occurs in our context, we perform a regression of the baseline estimation controlling for weekly averages of air pressure, humidity, wind speed, and sunlight duration. In appendix figure A8, we show that the identified temperature and precipitation effects on planting dates are not significantly affected by the inclusion of other weather variables.

Another omitted variable concern is related to socio-economic factors. Although we are unable to control additional socio-economic variables directly because our agricultural data do not provide these information, we address this issue by conducting an estimation with the inclusion of province-by-year fixed effects. This rich set of interactive fixed effects effectively absorb any arbitrary socio-economic shock that is specific to a region in a specific year. As we show in appendix figure A8, the results are still robust upon controlling for province-by-year fixed effects.[10] In the case that certain unobserved site characteristics would lead to response heterogeneity, our baseline estimates should be viewed as an average effect of the potentially heterogeneous responses.[11]

Four-week combined estimates. It should be noted that the flexibility of estimating each week's impact comes with a cost of inefficiency when coefficients of the neighboring weeks are not substantially different. Therefore, we use a specification that combines every four weeks to more precisely estimate the temperature and precipitation effects, and we discuss the magnitudes of the results in more details based on this specification:

$$(2) \quad PD_{it} = \beta_1 T_{it,[M_i-1,M_i-4]} + \beta_2 T_{it,[M_i-5,M_i-8]} + \beta_3 T_{it,[M_i-9,M_i-12]} + \gamma_1 P_{it,[M_i-1,M_i-4]} + \gamma_2 P_{it,[M_i-5,M_i-8]} + \gamma_3 P_{it,[M_i-9,M_i-12]} + h_r(t) + \alpha_i + \varepsilon_{it},$$

[9]For example, if the temperature is 11°C in each day of a week, the degree days above 10°C for that week is 7°C.

[10]As noted in Fisher et al. (2012), the inclusion of region-by-year fixed effects could absorb too much useful variation and potentially amplify the impact of measurement errors.

[11]For instance, weather impacts may be different across irrigated versus non-irrigated sites. Unfortunately, we do not have any information on irrigation at the site level to verify this hypothesis.

where $T_{it,[M_i-\tau_1,M_i-\tau_2]}$ and $P_{it,[M_i-\tau_1,M_i-\tau_2]}$ are site i in year t's weekly average temperature and weekly cumulative precipitation averaged over the τ_1-τ_2 weeks before the site-specific normal planting date, respectively. Other terms follow the definition in equation (1), and standard errors are two-way clustered by sites and province-by-year pairs.

Column (1) in table 1 presents the estimated effects of average temperature and precipitation over every four weeks prior to median planting dates. A 1°C higher average temperature in the first and second four-weeks before median planting dates significantly brings forward the actual planting dates by about 0.75 and 0.46 days, respectively. Combining these effects suggests that if the average temperature during the eight weeks before median planting dates increases by 1°C, corn will be planted about 1.21 days earlier in that year. This prompting temperature effect disappears when warming occurs too early before planting. As shown in column (1), rising temperature during more than nine weeks before the normal planting time does not significantly affect actual planting time. The precipitation estimates in column (1) suggest that rainfall fluctuations only affect planting dates when they occur during the 5th–8th weeks before the normal planting time. Over this four-week period, a 1 cm increase in weekly cumulative rainfall is associated with about a 1.23 days earlier planting time.

Column (2) in table 1 shows the results using degree days above 10°C as temperature variables. The identified temperature effects are in general qualitatively similar to those based on average temperature measures, except that the magnitude of the effects does not differ much across the first and second four weeks. During both the first–fourth and fifth–eighth weeks prior to the median planting date, an additional degree day is associated with an advanced planting time of roughly 0.03 days. In column (3), we show that the pattern of temperature effects based on non-freezing days is more similar to that based on average temperatures. One more non-freezing day during the first–fourth pre-planting weeks induces a 0.47 days earlier planting, and the corresponding effect during the fifth–eighth weeks shrinks to roughly 0.18 days. These results suggest that the warming-induced reduction in freezing days is important for inducing earlier planting, and using average temperature in the estimation has successfully captured this response channel. The precipitation effects presented in columns (2) and (3) are generally similar to those in column (1), despite that the statistical significance is compromised.

Length of Growing Season

After planting, necessary heat accumulation and water supply are essential for crop growth, and crops become mature when they have received and materialized sufficient heat and water. An early reception of sufficient heat and water supply may reduce the necessary duration for crop growth, whereas water and heat stress during crop development may also affect the pace of crop growth.

Weekly average specification. We use the following panel fixed effects estimation that relates growing season lengths with weekly weather realized after the exact planting dates:

Table 1. Effects of Pre-Planting Weather on Planting Dates

	Average temp (1)	Degree days (2)	Non-freezing days (3)
Temperature before normal planting date:			
First–fourth weeks	−0.750*** [0.180]	−0.032*** [0.006]	−0.471*** [0.065]
Fifth–eighth weeks	−0.457** [0.170]	−0.034** [0.011]	−0.176* [0.075]
Ninth–twelfth weeks	0.009 [0.091]	−0.007 [0.016]	0.008 [0.092]
Precipitation before normal planting date:			
First–fourth weeks	−0.446 [0.542]	−0.465 [0.572]	−0.033 [0.451]
Fifth–eighth weeks	−1.229* [0.530]	−1.342 [0.719]	−0.641 [0.428]
Ninth–twelfth weeks	0.983 [1.669]	1.184 [1.543]	1.239 [1.089]
Observations	3,225	3,225	3,225

Note: Temperature variables are weekly average temperatures in column (1), degree days above 10°C in column (2), and the number of days with minimum temperature above 0°C in column (3). All precipitation variables are weekly cumulative precipitations measured in centimeter. All regressions control for site fixed effects and provincial quadratic time trends. Standard errors in brackets are two-way clustered at sites and province-by-year pairs.
Significance: *<0.05, **<0.01, ***<0.001.

$$(3) \quad GS_{it} = \sum_{k=1}^{K} \beta_k T_{it,D_{it}+k} + \sum_{k=1}^{K} \gamma_k P_{it,D_{it}+k} + h_r(t) + \alpha_i + \varepsilon_{it},$$

where GS_{it} is the length of the growing season at site i in year t. Because the last stage in a crop cycle recorded by the site is *crop maturity*, we define the length of a growing season by counting the number of days in between the exact planting date and the maturity date for each site in each year. $T_{it,D_{it}+k}$ and $P_{it,D_{it}+k}$ represent temperature and precipitation in the k-th week after the site- and year-specific actual planting date D_{it}, and the parameters of β_k and γ_k trace out the effects of weekly temperature and precipitation over time starting from the actual planting of the crop. Referring to the observed lengths of growing seasons in our sample, we estimate temperature and precipitation effects up to twenty four weeks after the actual planting date. The definition of other terms follows those in equation (1), and the standard errors are two-way clustered by sites and by province-by-year pairs.[12]

We plot the weekly estimates of equation (3) in figure 3. Panel A of figure 3 clearly shows that a higher temperature in the first half of the growing season strongly reduces the length of growing season. In the first twelve weeks, a 1°C increase in the average temperature of any week is associated with a length reduction in the range of 0.1–0.5 days. This temperature effect becomes close to zero during the next six weeks and then inclines to reverse in the last few weeks. In the last six weeks of the twenty four-week time window, a 1°C increase in the average temperature of any week is associated with a lengthening of the growing season in the range of 0.1–0.3 days. We interpret this lengthening effect as suggestive evidence that high temperature causes delay in crop growth in the later course of the growing season, consistent with some agronomic findings that high temperatures slow down corn growth during grain filling through reducing certain enzyme rate (Keeling et al. 1994).[13]

Panel B of figure 3 shows a similar pattern that the precipitation effect on shortening the growing season is more pronounced in the earlier course of the growing season and then diminishes and even reverses in the later course. The largest shortening effect occurs in the first four weeks, during which a 1 cm increase in weekly precipitation is associated with a 0.2–0.3 days reduction in growing season. The precipitation coefficients become modestly positive starting from the thirteenth week after planting. We interpret these positive estimates as evidence that stress associated with water deficits accelerates crop growth, consistent with agronomic knowledge.

Similar to the sensitivity checks we have conducted on the planting date regression, we also estimate the weekly average regression on growing season lengths using alternative temperature measures. In addition to minimum temperature, maximum temperature, and degree days, we also construct a measure of hot days based on the number of days with daily maximum temperature above 30°C in order to capture the effects of very high temperatures. As we show in appendix figure A10, the estimated patterns of temperature effects are consistent across specifications using different temperature measures.[14] Besides, we also address potential omitted variable concerns by conducting estimations with additional weather variables and including province-by-year fixed effects. The results are still robust as shown in appendix figure A11.

Four-week combined estimates. For higher efficiency and easier interpretation of the estimation results, we also estimate the relationship by grouping weekly temperature and precipitation measures into every four weeks:

$$(4) \quad GS_{it} = \beta_1 T_{it,[D_{it}+1,D_{it}+4]} + \beta_2 T_{it,[D_{it}+5,D_{it}+8]} + \beta_3 T_{it,[D_{it}+9,D_{it}+12]} + \gamma_1 P_{it,[D_{it}+1,D_{it}+4]} + \gamma_2 P_{it,[D_{it}+5,D_{it}+8]} + \gamma_3 P_{it,[D_{it}+9,D_{it}+12]} + h_r(t) + \alpha_i + \varepsilon_{it},$$

[12]We show rich within-site variation in growing-season lengths and post-planting weather in appendix figure A9.

[13]We note that some agronomic studies have also discussed the potential of heat and water stress accelerating crop growth. Our empirical finding is slightly different from this understanding, and we only find the accelerating effect to be associated with water stress in our case.

[14]Panel B in appendix table A1 suggests that the alternative temperature measures have no significant advantage over the mean temperature in terms of in-sample model fit.

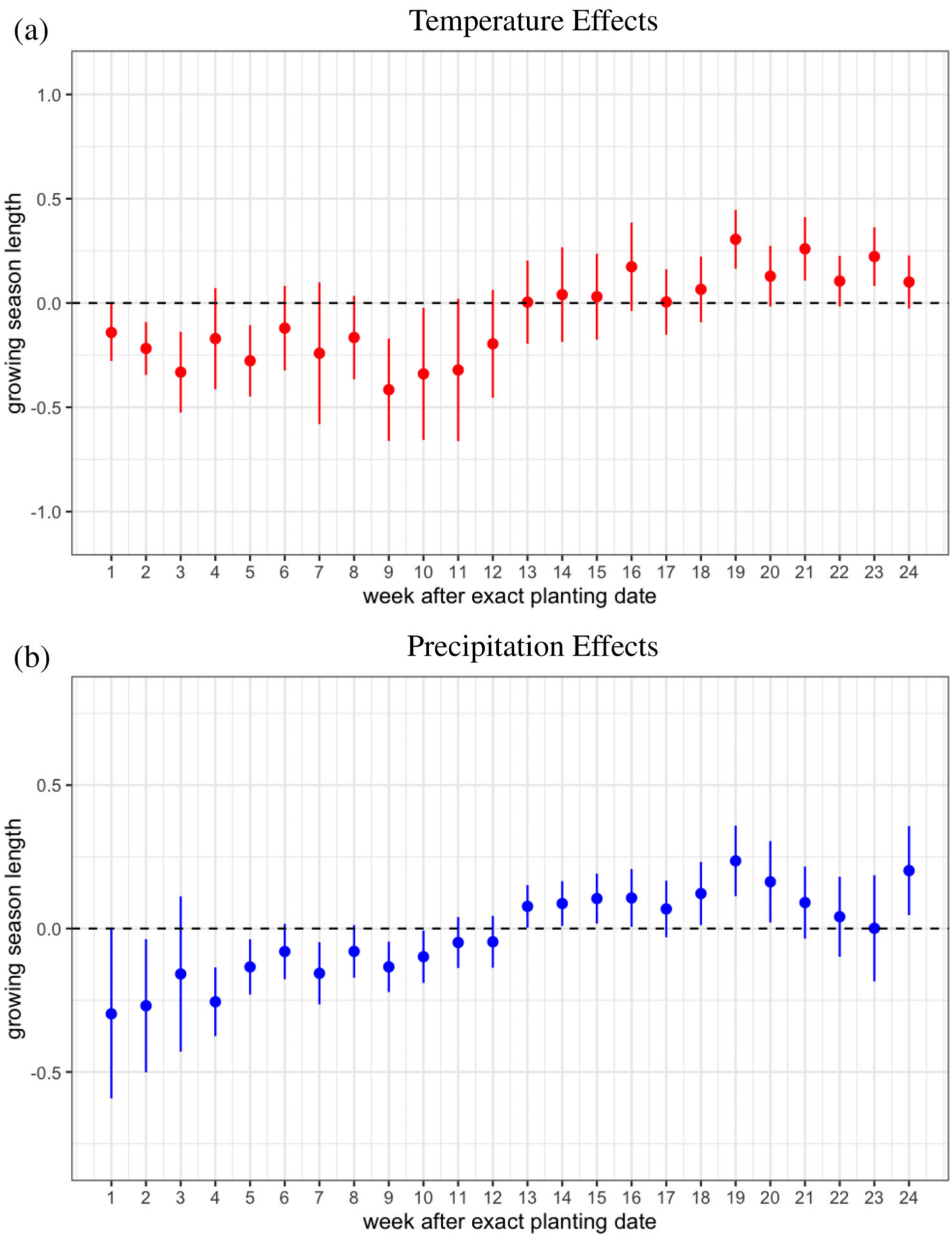

Figure 3. Effects of post-planting weather on the length of growing season: Weekly averages.

Note: The dots represent the point estimates of temperature or precipitation effects in the corresponding weeks. The error bars represent 95% confidence intervals based on two-way clustered standard errors. Temperature and precipitation are measured in degrees Celsius and centimeter, respectively. See numerical results in appendix table A3.

where $T_{it,[D_{it}+\tau_1,D_{it}+\tau_2]}$ and $P_{it,[D_{it}+\tau_1,D_{it}+\tau_2]}$ are weekly average temperatures and weekly cumulative precipitations averaged over the τ_1-τ_2 weeks after the exact planting date at site i in year t, respectively. Other terms are defined in the same way as in equation (3), and standard errors are also two-way clustered.

Table 2 presents the estimation results. Along with baseline estimates in column (1), we also provide estimates based on degree days and hot days in columns (2) and (3). Higher temperatures during the first twelve weeks are shown to significantly reduce the length of growing season. A 1°C higher average temperature in the first–fourth, fifth–eighth and ninth–twelfth weeks after planting significantly shortens the growing seasons by about 0.89, 0.82, and 1.31 days, respectively.

Table 2. Effects of Post-Planting Weather on Growing-Season Lengths

	Average temp (1)	Degree days (2)	Hot days (3)
Temperature after planting date:			
First–fourth weeks	−0.885*** [0.110]	−0.036*** [0.005]	−1.625*** [0.311]
Fifth–eighth weeks	−0.816*** [0.199]	−0.029*** [0.006]	−0.933*** [0.143]
Ninth–twelfth weeks	−1.310*** [0.169]	−0.043** [0.014]	−0.756* [0.292]
Thirteenth–sixteenth weeks	0.228 [0.149]	0.014 [0.012]	0.621 [0.360]
Seventeenth–twentieth weeks	0.586*** [0.138]	0.024** [0.008]	0.983* [0.421]
Twenty-first–twenty-fourth weeks	0.695*** [0.104]	0.035*** [0.008]	1.472** [0.509]
Precipitation after planting date:			
First–fourth weeks	−0.936*** [0.230]	−0.961*** [0.266]	−1.225* [0.504]
Fifth–eighth weeks	−0.460*** [0.126]	−0.425 [0.340]	−0.723** [0.249]
Ninth–twelfth weeks	−0.330 [0.177]	−0.270 [0.223]	−0.342 [0.359]
Thirteenth–sixteenth weeks	0.368* [0.158]	0.428* [0.174]	0.620*** [0.178]
Seventeenth–twentieth weeks	0.551*** [0.139]	0.570 [0.301]	0.960*** [0.265]
Twenty-first–twenty-fourth weeks	0.364* [0.169]	0.422 [0.311]	0.453 [0.361]
Observations	2,759	2,759	2,759

Note: Temperature variables are weekly average temperatures in column (1) and degree days above 10°C in column (2), and the number of days with maximum temperature above 30°C in column (3). All precipitation variables are weekly cumulative precipitations measured in centimeter. All regressions control for site fixed effects and provincial quadratic time trends. Standard errors in brackets are two-way clustered at sites and province-by-year pairs.
Significance: * <0.05, ** <0.01, *** <0.001.

These estimates can be translated into a more than three-day reduction in the length of growing season if the average temperature over the entire twelve weeks is 1°C higher. Temperature effects become insignificant during the thirteenth–sixteenth weeks, and then become positive in the later course of the growing season. A 1°C higher average temperature in the seventeenth–twentieth and twenty-first–twenty-fourth weeks prolongs the growing season by about 0.59 and 0.70 days, respectively. In general, the shortening effect in the first half of the season still dominates.

The temperature estimates in columns (2) and (3) support those in column (1). An additional degree day reduces the season length by about 0.03–0.04 days in the first half of the growing season, whereas this effect turns to positive in a comparable magnitude over the last eight weeks. The early-season length-reduction effects associated with hot days shown in column (3) mainly captures the beneficial warming impacts as hot days are rare in the early season and their occurrence highly correlates with higher average temperatures. In contrast, the large positive coefficient of hot days in the later course of the season more likely reflects the role of high temperatures in slowing down crop growth as hot days occurs much more frequently during this period.

Through columns (1) to (3), precipitation increases in the first eight post-planting weeks are shown to substantially shorten the growing season in general. A 1 cm increase in weekly precipitation over this period significantly reduces the length of growing season by 0.42–1.23 days. The estimates also suggest that rainfall deficits significantly accelerate the crop cycle since the thirteenth post-planting week. During these weeks, the effect of a 1 cm increase in weekly precipitation ranges from 0.36–0.96 days, depending on the specification and weeks evaluated. We note that the precipitation estimates are noisier than the temperature estimates as they are shown to be slightly sensitive to different regression specifications.

Yield Implications

As warming persists, the induced shift in growing seasons can bring more flexibility in corn planting. An earlier planting date, together with a shortened growth duration, could justify corn planting in places used to be too cold and avoid damages caused by extreme heat in places used to be too hot. Based on our empirical estimates, we conduct a set of calculations to illustrate that, even without long-run responses, the short-run adjustments in growing seasons can amount to substantial adaptation to climate change in corn production.

We first combine our weekly estimates shown in figures 2 and 3 with projected future climate to contextualize how growing seasons would shift under future climate. We consider two emission scenarios (RCP 4.5 and RCP 8.5) under five different global climate models (GCMs) derived from the Coupled Model Intercomparison Project Phase 5 (CMIP5): GFDL-ESM2M, HadGEM2-ES, IPSL-CM5A-LR, MIROC-ESM-CHEM, and NorESM1-M. These models have recently been thoroughly evaluated and applied on climate projection practices in the scientific community (e.g., Warszawski et al. 2014; Yin, Tang, and Liu 2015; Xie et al. 2018).[15]

For each model-scenario combination, we use average monthly temperature and precipitation over 2070–2099 to represent future climate, preserving intra-annual variation in weather at the monthly level. Based on historical weather observations, we define current climate by averaging monthly temperature and precipitation over the last thirty years of our sample (i.e., 1984–2013). At each site, we calculate the projected change in temperature and precipitation from 1984–2013 to 2070–2099 at the monthly frequency. Appendix Figure A12 shows the distributions of these projected changes. Relying on these calculated monthly differences, we recover future climate at the daily frequency by adding the monthly differences back to daily temperature and precipitation averaged over 1984–2013.[16] We eventually construct ten site-level, daily-frequency datasets that represent projected changes in climate of the five climate models based on the two different emission scenarios.

Relying on the weekly average estimates in figures 2 and 3, we calculate the induced adjustments in growing seasons under different model-scenario pairs by multiplying all the estimated coefficients with projected changes in climate of the corresponding weeks. In this calculation, we use site-specific median planting dates as the reference dates for calculating weekly temperature and precipitation in both planting date and growing-season length equations. This practice preserves cross-sectional variation in normal planting time at the site level.

Figure 4 plots the empirical distribution of the induced shifts in planting dates and growing season lengths under RCP 4.5 and RCP 8.5 based on the five different climate projection models. The predicted growing-season adjustments display a consistent pattern across climate models and emission scenarios. In all projections, the median site is predicted to have an earlier planting date and a shorter growing-season length. Appendix Figure A13 further illustrates that the induced shifts are almost exclusively caused by temperature, not precipitation.

Warmer temperature during the pre-planting period encourages earlier planting. Under RCP 4.5, a median site will advance its planting date by about one to three days depending on the climate model used, and this advancement becomes about two–six days under RCP 8.5. One potential concern is that the simulated advancements could shift the planting time into freezing periods that damage yields or physically prevent earlier planting (Dalhaus et al. 2020; Zohner et al. 2020). In appendix table A5, we show that this is not a concern as the minimum temperatures during the simulated planting weeks are comparable or even higher than those during the observed normal planting weeks.

Under future climate, the reduction in growing season is comparable in magnitude with the advancement in planting dates. A median site will have a roughly one–three and three–six days shorter growing season under RCP 4.5 and RCP 8.5, respectively. These estimates suggest that the shortening effects in the early course of the growing season outweighs against the lengthening effects in the later course.

The induced changes in planting dates and growing season lengths can have profound implications on corn yields under future climate. Conceptually, comparing with a counterfactual that no adjustments occur on the growing season, the shorter growing season could avoid high temperatures detrimental to yields, but the earlier planting time could also reduce moderate heat beneficial to crop growth. To evaluate the net effect of induced growing-season adjustments on corn yields, we pair our growing-season simulations with empirically identified yield-response function of corn in China. Because our site-level data do not record yield information, we adopt the

[15]RCP is short for Representative Concentration Pathway, a greenhouse gas concentration trajectory adopted by the IPCC. RCP 4.5 represents an intermediate scenario and RCP 8.5 represents a business-as-usual scenario, both are commonly used as benchmarks in impact evaluations.

[16]This practice has been widely adopted in previous work since Schlenker and Roberts (2009). It is a necessary procedure when the projected outcome is coarser in frequency. The assumption imposed here is that the changes in monthly temperature and precipitation are uniformly distributed on all days in the same month.

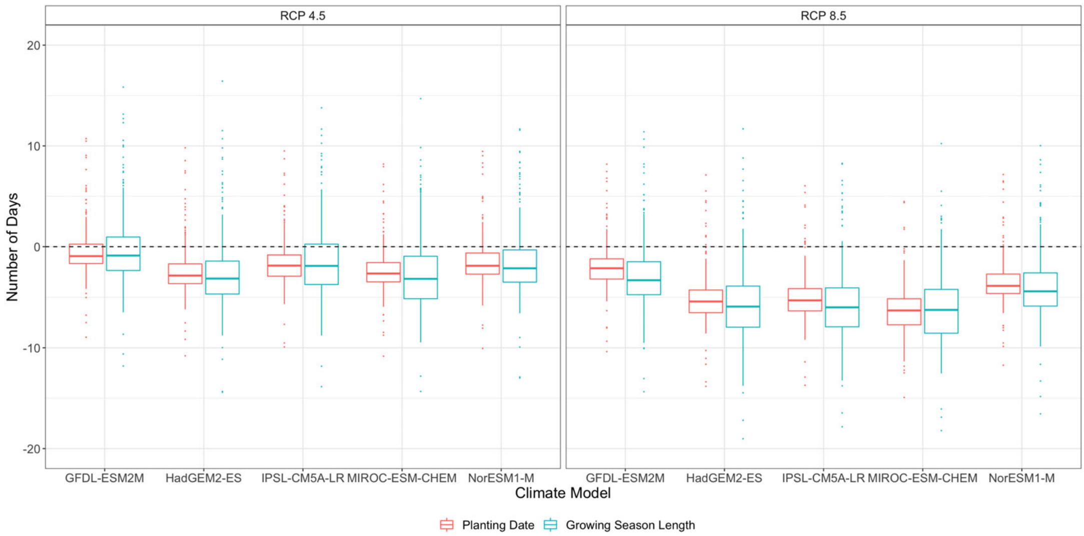

Figure 4. Empirical distribution of growing-season adjustments induced by future climate.

Note: Boxplots report induced adjustments in planting dates and growing-season lengths of the corn-planted agro-climatic monitoring sites under five climate models and two emission scenarios, by the end of this century (2070–2099). For each climate model, planting date result is on the left and growing season length result is on the right. Each box consists of the three quartiles, the whiskers extend from hinges to 1.5 times of the inter-quartile range, and outliers are plotted in dots. See numerical results in appendix table A4.

empirical estimates in Chen, Chen, and Xu (2016) that measure the weather-yield relationship for China's corn using a county-level panel over 2001–2009.

For each pair of climate model and emission scenario, we add the projected changes in monthly temperature to daily maximum and minimum temperatures of the current climate. For each site, we define two time windows for measuring growing seasons: the fixed and the adjusted. The fixed window is governed by the site-specific median planting and maturity dates, whereas the adjusted window factors in the predicted changes in planting dates and growing-season lengths on top of the fixed window. Using projected climate, we recover the weather variables used in the yield-response function in Chen, Chen, and Xu (2016) over the fixed and the adjusted growing-season windows, respectively. We multiply the empirical estimates identified in Chen, Chen, and Xu (2016) with the two sets of constructed weather variables and calculate the differences in log yields between the adjusted and the fixed growing seasons for each site under each pair of climate model and emission scenario.[17]

Table 3 shows the log changes in corn yields associated with induced growing-season adjustments and their distributions under different climate models and emission scenarios. On average, the induced growing-season adjustments mitigate potential yield losses by about 1.1%–3.7% and 3.3%–9.0% under RCP 4.5 and RCP 8.5, respectively. Extrapolated to total outputs in the entire country, these yield benefits translate into 2.9–9.7 and 8.6–23.5 million metric tons of corn outputs based on the current production level.[18] Although distributional effects exist, corn yields at most of the sites will benefit from these growing-season adjustments, especially under the higher emission scenario.

It is worth noting that these numbers are obtained by comparing projected yields under the adjusted with the fixed growing seasons by the end of this century, holding all else equal. In this regard, the role of time trends does not factor into this comparison directly because both the adjusted and the fixed growing seasons are evaluated at the same time period in the future. Still, we believe these yield benefits are likely lower bound estimates for the long run. Because the empirical

[17]Chen, Chen, and Xu (2016) use the degree days over 8–32°C, its squared term, and the squared root of degree days above 34°C as temperature variables, and they use cumulative precipitation and its squared term as precipitation variables. For predicting log yields, we rely on their baseline estimates shown in column (1) in table 4 in Chen, Chen, and Xu (2016).

[18]We use mainland China's domestic corn production in 2019 for this calculation.

Table 3. Predicted Log Changes in Yields Associated with Induced Growing-Season Adjustments

	Climate projection model				
	GFDL-ESM2M (1)	HadGEM2-ES (2)	IPSL-CM5A-LR (3)	MIROC-ESM-CHEM (4)	NorESM1-M (5)
Under RCP 4.5:					
Mean	0.011	0.036	0.024	0.037	0.017
SD	(0.101)	(0.111)	(0.093)	(0.115)	(0.100)
Percentiles:					
1%	−0.170	−0.118	−0.134	−0.118	−0.195
5%	−0.035	−0.017	−0.020	−0.022	−0.029
10%	−0.014	−0.006	−0.007	−0.006	−0.008
25%	−0.005	0.001	−0.001	0.000	−0.001
50%	0.001	0.015	0.006	0.011	0.006
75%	0.012	0.041	0.028	0.039	0.023
90%	0.081	0.114	0.101	0.124	0.070
95%	0.128	0.193	0.145	0.196	0.131
99%	0.348	0.384	0.307	0.488	0.256
Under RCP 8.5:					
Mean	0.033	0.075	0.079	0.090	0.052
SD	(0.091)	(0.136)	(0.124)	(0.162)	(0.110)
Percentiles:					
1%	−0.114	−0.049	−0.018	−0.039	−0.079
5%	−0.007	−0.006	−0.004	−0.006	−0.006
10%	−0.003	0.000	0.000	0.000	−0.001
25%	0.001	0.013	0.014	0.013	0.008
50%	0.015	0.036	0.039	0.040	0.023
75%	0.038	0.081	0.077	0.075	0.049
90%	0.130	0.189	0.239	0.275	0.177
95%	0.169	0.298	0.321	0.341	0.248
99%	0.448	0.810	0.678	0.874	0.488

Note: The predicted log changes in yields are obtained by differencing the predicted log yields under adjusted and fixed growing seasons evaluated at the period of 2070–2099. The adjusted growing seasons are obtained by multiplying weekly average estimates with the predicted changes in temperature and precipitation under different climate models and emission scenarios. The yield response function is based on the baseline estimates in Chen, Chen, and Xu (2016).

parameters we used for projecting growing-season adjustments and yield implications only rely on short-run estimates, the projected changes do not capture potential long-run adjustments that could occur in reality.

Induced technological improvements likely aid the planting adjustments in the long run, as historical evidence has long been suggesting (Olmstead and Rhode 2011; Beddow and Pardey 2015). In the context of our discussion, genetic engineering and seed improvements can potentially facilitate lower triggering temperatures for planting crops and lower demand of heat for crop maturity, contributing to even earlier planting and shorter growing seasons without compromising yields.[19] However, in lack of data on seed breeding and adoption, we are unable to further explore the role of crop genetics in affecting growing-season adjustments to climate change.

Long-Run Response

Important distinctions exist between short-run and long-run adaptations, because economic agents are usually constrained in their ability to adjust in the short run, but they could be more adaptive in the long run. Building on our short-run estimates, we further explore potential long-run response in this section. In particular, we focus on long-run impacts on planting dates because planting adjustment mainly reflects induced behavioral responses, whereas changes in growing season lengths, conditional on planting dates, are mostly

[19] In a different context, Tack, Barkley, and Nalley (2015) and Ortiz-Bobea and Tack (2018) also highlight the role of genetic improvement in reducing climatic sensitivity and maintaining yields under future climate.

governed by bio-physical processes. We extend our four-week regression in equation (2) to allow for estimating long-run effects along with contemporaneous weather effects.

Using moving averages of past weather to approximate for local climate, we postulate that the long-run effects on planting time are realized as past experience shapes farmers' expectation on a changing local climate.[20] It is important to note that, in the context of long-run effects, farmers likely make decision on planting date incorporating potential long-term change that also matters for the length of growing season. In this regard, past weather experience in both the pre-planting and post-planting periods potentially factors into farmers' decision making on planting dates. Therefore, we specify moving averages of both pre-planting and post-planting weather realizations as follows:

$$(5) \quad \begin{aligned} PD_{it} = {} & \beta_1 T_{it,[M_i-1,M_i-4]} + \beta_2 T_{it,[M_i-5,M_i-8]} + \beta_3 T_{it,[M_i-9,M_i-12]} \\ & + \gamma_1 P_{it,[M_i-1,M_i-4]} + \gamma_2 P_{it,[M_i-5,M_i-8]} + \gamma_3 P_{it,[M_i-9,M_i-12]} \\ & + \theta_1 \tilde{T}^K_{it,[M_i-1,M_i-12]} + \theta_2 \tilde{T}^K_{it,[M_i+1,M_i+12]} + \theta_3 \tilde{T}^K_{it,[M_i+13,M_i+24]} \\ & + \delta_1 \tilde{P}^K_{it,[M_i-1,M_i-12]} + \delta_2 \tilde{P}^K_{it,[M_i+1,M_i+12]} + \delta_3 \tilde{P}^K_{it,[M_i+13,M_i+24]} \\ & + h_r(t) + \alpha_i + \varepsilon_{it}, \end{aligned}$$

In the equation above, $\tilde{T}^K_{it,[M_i-1,M_i-12]}$ represents the K-year moving average of the twelve-week pre-planting mean temperatures, $\tilde{T}^K_{it,[M_i+1,M_i+12]}$ represents the K-year moving average of the first twelve-week post-planting mean temperatures, and $\tilde{T}^K_{it,[M_i+13,M_i+24]}$ represents the K-year moving average of the second twelve-week post-planting mean temperature. Their precipitation counterparts $\tilde{P}^K_{it,[M_i-1,M_i-12]}$, $\tilde{P}^K_{it,[M_i+1,M_i+12]}$, and $\tilde{P}^K_{it,[M_i+13,M_i+24]}$ are defined in a similar fashion. We combine every twelve weeks in forming moving averages to alleviate the low-power concern as the temporal variation in moving averages is relatively small. The separation of the first and second twelve-week post-planting weeks accommodates the differential short-run impacts identified in estimating growing-season lengths. Other variables are defined in the same way as in equation (2). In this estimation, the parameters of β's and γ's identify contemporaneous short-run effects, whereas the parameters of θ's and δ's identify potential long-run effects. The estimation results based on $K = 5$ and $K = 10$ are presented in table 4, and additional results using other values are reported in appendix table A6.

In both columns in table 4, the first six estimates represent the effects of current-year weather, and the last six estimates of moving averages approximate for long-run impacts of climate. Not surprisingly, the contemporaneous temperature and precipitation effects in table 4 are highly similar to the baseline results in table 1. However, we do not find evidence of long-run adjustments because none of the moving-average coefficients are statistically significant. As we show in appendix table A6, this statistical insignificance remains when we estimate equation (5) using alternative values of K.

Theories imply that long-run adjustments to climate change typically involve a learning process with non-trivial costs (Kelly, Kolstad, and Mitchell 2005). It can take a long time to realize this process, because the change in local climate has to be manifested and perceived by economic agents, and costly actions have to be taken to achieve effective adaptation. Although the data variation in our sample is sufficient for identifying responses to contemporaneous weather fluctuations, the variation in moving average weather is still fairly limited. Therefore, the limited time span we can observe from the data may have prevented us from detecting long-run adjustments, even if they exist. The potentially slow learning

[20]This empirical strategy is similar to that in Cui (2020b) for identifying long-run climatic impacts on crop acreage.

Table 4. Effects of Weather and Climate on Planting Dates

	Five-year MA (1)	Ten-year MA (2)
Temperature before median planting date:		
First–fourth weeks	−0.770*** [0.114]	−0.766*** [0.138]
Fifth–eighth weeks	−0.470*** [0.121]	−0.492*** [0.097]
Ninth–twelfth weeks	−0.012 [0.093]	−0.004 [0.090]
Precipitation before median planting date:		
First–fourth weeks	−0.458 [0.383]	−0.501 [0.847]
Fifth–eighth weeks	−1.217* [0.551]	−1.277 [0.996]
Ninth–twelfth weeks	0.924 [0.938]	0.959 [1.598]
Moving averages of temperature:		
First–twelfth pre-planting weeks	−0.046 [0.641]	−0.978 [1.156]
First–twelfth post-planting weeks	1.012 [0.662]	−1.291 [2.201]
Thirteenth–twenty-fourth post-planting weeks	0.620 [0.649]	3.323 [2.292]
Moving averages of precipitation:		
First–twelfth pre-planting weeks	−0.582 [2.874]	−4.044 [6.104]
First–twelfth post-planting weeks	0.921 [0.985]	1.113 [1.612]
Thirteenth–twenty-fourth post-planting weeks	0.248 [0.831]	0.665 [2.688]
Observations	3,225	3,225

Note: Temperature variables are weekly average temperatures measured in degrees Celsius and precipitation variables are weekly cumulative precipitations measured in centimeter. The moving averages are constructed over the five and ten years preceded the current year for columns (1) and (2), respectively. All regressions control for site fixed effects and provincial quadratic time trends. Standard errors in brackets are two-way clustered at sites and province-by-year pairs. Significance: * <0.05, ** <0.01, *** <0.001.

process brings additional difficulties for discovering the existence of such adjustments.

Input Adjustments

Farmers adapt to different weather realizations through growing-season adjustments because climatic factors like temperature and precipitation, as inputs, directly affect crop production. These adjustments could be accompanied with adjustments in other inputs like fertilizer and pesticide, especially considering that fertilizer and pesticide applications may display substitutability and/or complementarity with heat and water supply. Therefore, it will be interesting to explore the relationship between growing-season and input adjustments. Unfortunately, our site-level data do not have information on input usage. To make progress, we supplement a county-level dataset that records fertilizer and pesticide applications over 2001–2015.

We restrict our analysis to counties in which we have site-level information on corn growing seasons.[21] We obtain within-county variation in input use by demeaning county-level data on per-hectare fertilizer and pesticide applications, respectively. In a similar manner, we also recover within-site variation in growing season adjustments by demeaning site-level planting dates and growing-season lengths, respectively. Because the agro-climatic monitoring sites are representative of the local agricultural production, we postulate that the within-site changes in planting dates and growing-season lengths can in general reflect the within-county variation in growing seasons in the county a site resides in. We further hypothesize that, if growing-season adjustments are accompanied by input adjustments, we would be able to detect systematic correlation between the changes in growing seasons and the changes in input applications at the same location.

Figure 5 visualizes these associations by pairing demeaned fertilizer and pesticide uses with demeaned planting dates and growing-season lengths. The dots present values of the demeaned variables, and the dashed line illustrates a simple line fit. The practice of demeaning effectively controls for location-specific time-invariant characteristics, and the line fit is essentially a fixed-effects estimate if we treat a site and its residing county as the same entity. For both fertilizer and pesticide

[21] After matching sites to counties, the final sample for analyzing input use only covers the period of 2001–2013.

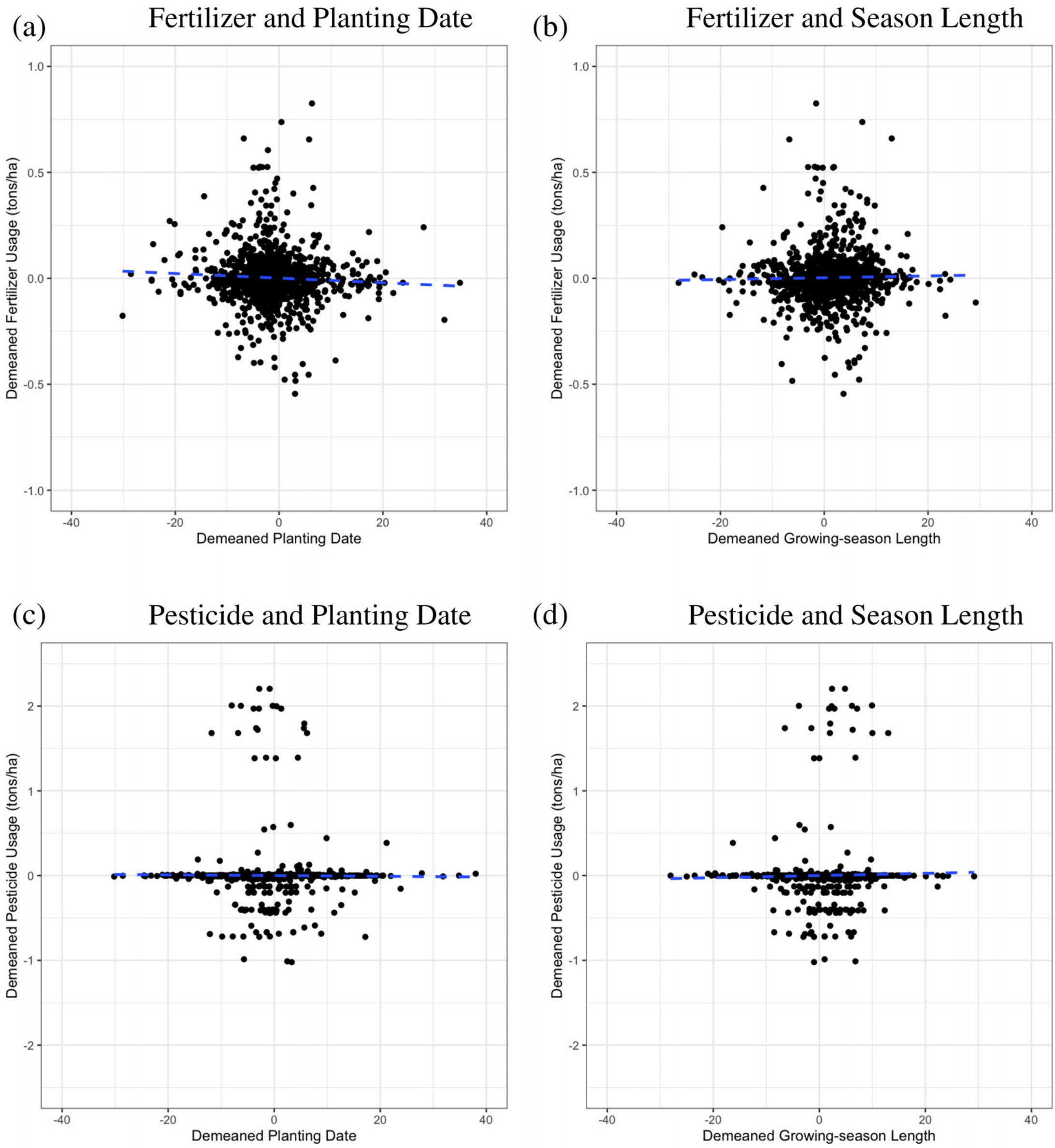

Figure 5. Association between input usage and growing season adjustments.

Note: The dots are values of the demeaned variables, and the dashed lines are line-fits of simple linear regressions. Fertilizer and pesticide uses are demeaned within counties, and planting dates and growing-season lengths are demeaned within agro-climatic monitoring sites. Corn sites are matched to the counties in which they are located. The sample period covers 2001–2013.

uses, we do not find them to be systematically correlated with adjustments in planting dates and growing-season lengths. This finding is further supported by regressions with additional controls of provincial trends or province-by-year fixed effects. As shown in all columns in table 5, there is no evidence that the within-variation in fertilizer and pesticide usage is significantly correlated with the within-variation in planting dates or growing-season lengths.

Several reasons could explain this result. On one hand, the adjustments in growing seasons may not be sufficiently large to incur necessary input adjustments. On the other hand, farmers may not be well informed to realize the necessity to adjust input uses along with growing-season adjustments. Besides, even if farmers would like to adjust, input markets in rural China may also be incomplete so that farmers are unable to make adjustments contemporaneously. It is also worth noting that there are

Table 5. Association between Input Usage and Growing Season Adjustments

	Demeaned fertilizer usage			Demeaned pesticide usage		
	(1)	(2)	(3)	(4)	(5)	(6)
Demeaned planting date	−0.0009 (0.0007)	−0.0003 (0.0007)	−0.0005 (0.0007)	0.0004 (0.0007)	−0.0006 (0.0009)	0.0013 (0.0009)
Demeaned growing-season length	−0.0001 (0.0007)	0.0001 (0.0007)	−0.0003 (0.0007)	0.0016 (0.0014)	0.0005 (0.0013)	0.0016 (0.0013)
Provincial quadratic time trends	No	Yes	No	No	Yes	No
Province-by-year FE	No	No	Yes	No	No	Yes
Observations	1,166	1,166	1,166	1,243	1,243	1,243

Note: Fertilizer and pesticide uses are demeaned within counties, and planting dates and growing-season lengths are demeaned within agro-climatic monitoring sites. Corn sites are matched to the counties in which they are located. The sample period covers 2001–2013. Standard errors in parentheses are clustered at the county level.

a few caveats in the analysis above. Our growing-season data are at the site level, whereas input data are at the county level, and the information on input usage is not crop-specific. These data limitations have prevented us from rigorously identifying the causal relationship between growing-season adjustments and input use. Future analysis with better data is still needed for further improving the understanding of this relationship.

Regional Heterogeneity

The baseline estimates we have identified on planting dates and growing-season lengths can be interpreted as average effects of all sites. Considering that China is a country with a vast territory, it is reasonable to believe response heterogeneity exists across space, given the spatial heterogeneity in environmental and resource endowments. We therefore evaluate regional heterogeneity in growing-season adjustments by utilizing supplementary information on agricultural region divisions officially publicized by the government.

We explore regional heterogeneity in growing-season adjustments by allowing for regionally heterogeneous coefficients in our four-week version regressions represented by equations (2) and (4). Tables 6 and 7 present the results of regional heterogeneity for the planting date regression and the growing-season length regression, respectively. In each table, the estimates in all columns are obtained from a single regression, and each column presents a set of region-specific coefficients.

Based on the temperature estimates in table 6, we observe a north–south gradient in how pre-planting temperature affects planting dates. In the northern regions including the Northeast and the Northwest, warming during the first-fourth weeks before median planting dates significantly advances the actual growing seasons, but warming occurred even earlier has no significant impact. In the Huang-huai-hai, an earlier planting date is associated with warming during the fifth–twelfth weeks prior to the normal planting time. But warming that occurs right before the median planting date does not have a significant impact. In the southern regions including the Southwest and the Yangtze River Delta, warming effects are found to be statistically insignificant throughout the twelve pre-planting weeks.

Table 6. Effects of Pre-Planting Weather on Planting Dates: Regional Heterogeneity

	Northeast (1)	Northwest (2)	Huang-Huai-Hai (3)	Southwest (4)	Yangtze River Delta (5)
Temperature before median planting date:					
First–fourth weeks	−0.793*** [0.169]	−1.122*** [0.188]	0.080 [0.221]	−0.134 [0.275]	−0.999 [0.562]
Fifth–eighth weeks	−0.377 [0.267]	−0.320 [0.202]	−0.994*** [0.249]	−0.413 [0.313]	−0.885 [0.739]
Ninth–twelfth weeks	−0.099 [0.058]	0.194 [0.165]	−0.657* [0.264]	−0.112 [0.417]	−0.177 [0.501]
Precipitation before median planting date:					
First–fourth weeks	1.116** [0.406]	−1.221* [0.542]	−0.877 [0.648]	−0.961 [0.597]	0.121 [0.673]
Fifth–eighth weeks	1.109 [1.247]	−2.288 [1.654]	−0.971 [0.544]	−2.432 [1.565]	−0.041 [1.089]
Ninth–twelfth weeks	1.259 [1.906]	1.313 [2.316]	0.468 [1.301]	2.888 [1.821]	−0.016 [1.241]

Note: Results are obtained by a single regression with regional heterogeneous coefficients. The total number of observations is 3,225. Temperature variables are weekly average temperatures, measured in degrees Celsius. Precipitation variables are weekly cumulative precipitations, measured in centimeter. The regression controls for site fixed effects and provincial quadratic time trends. Standard errors in brackets are two-way clustered at sites and province-by-year pairs.
Significance: * <0.05, ** <0.01, *** <0.001.

Table 7. Effects of Post-Planting Weather on Growing-Season Lengths: Regional Heterogeneity

	Northeast (1)	Northwest (2)	Huang-Huai-Hai (3)	Southwest (4)	Yangtze River Delta (5)
Temperature after planting date:					
First–fourth weeks	−0.803*** [0.129]	−1.080*** [0.210]	−0.604** [0.226]	−0.831*** [0.191]	−1.755*** [0.248]
Fifth–eighth weeks	−1.020*** [0.184]	−0.248 [0.202]	−0.241 [0.501]	−1.591*** [0.292]	−0.777 [0.401]
Ninth–twelfth weeks	−1.757*** [0.251]	−0.999*** [0.244]	−0.634* [0.285]	−1.241*** [0.279]	−1.434*** [0.289]
Thirteenth–sixteenth weeks	0.143 [0.218]	−0.005 [0.190]	0.769*** [0.197]	−0.086 [0.279]	−0.171 [0.568]
Seventeenth–twentieth weeks	0.543* [0.228]	0.717** [0.251]	0.363* [0.176]	0.411 [0.325]	−0.601 [0.430]
Twenty-first–twenty-fourth weeks	0.446* [0.180]	0.900*** [0.168]	0.063 [0.151]	0.692 [0.414]	0.137 [0.303]
Precipitation after planting date:					
First–fourth weeks	−1.146** [0.358]	−1.592*** [0.396]	−0.468 [0.244]	−1.309** [0.436]	−0.803** [0.271]
Fifth–eighth weeks	−0.688** [0.251]	−0.522 [0.319]	0.009 [0.159]	−1.021*** [0.301]	0.133 [0.249]
Ninth–twelfth weeks	−0.431** [0.158]	−0.279 [0.157]	0.002 [0.172]	−0.314 [0.226]	−0.378 [0.212]
Thirteenth–sixteenth weeks	0.260 [0.132]	0.723*** [0.170]	0.738*** [0.175]	0.174 [0.255]	−0.081 [0.218]
Seventeenth–twentieth weeks	0.238 [0.250]	1.251** [0.378]	0.799*** [0.229]	0.262 [0.169]	−0.151 [0.418]
Twenty-first–twenty-fourth weeks	0.838* [0.343]	0.620* [0.268]	0.968 [0.495]	0.148 [0.203]	0.052 [0.315]

Note: Results are obtained by a single regression with regional heterogeneous coefficients. The total number of observations is 2,759. Temperature variables are weekly average temperatures, measured in degrees Celsius. Precipitation variables are weekly cumulative precipitations, measured in centimeter. The regression controls for site fixed effects and provincial quadratic time trends. Standard errors in brackets are two-way clustered at sites and province-by-year pairs.
Significance: * <0.05, ** <0.01, ***<0.001.

This north–south gradient indicates that the warming-induced advancement in planting dates is more likely realized in the northern cool area because cold weather in spring is a major constraining factor for planting corn. In contrast, the southern hot area has not been constrained by heat deficits in planting corn. The timing difference between the northern regions and the Huang-huai-hai likely reflects how uncertainty influences planting decisions. In the northern regions, even temperature becomes warmer in more than one month prior to normal planting time, farmers may still be reluctant to plant earlier because of the likelihood of a later cold spell. However, this is not a severe concern in the Huang-huai-hai as climate is much milder in this region.

Increasing precipitation before the normal planting time advances planting dates in the Northwest. The geological and hydrological features in some parts of this region determines that it is short in rainfall and irrigation with relatively low water retention in soil. A timely increase in precipitation can improve soil moisture so that earlier planting becomes feasible. In contrast, more rainfall near the planting time in the Northeast is found to postpone corn planting. Because corn planting in this region is highly mechanical, high precipitation can temporarily prevent machines from entering the field as soil moisture becomes exceedingly high. A similar effect has also been found in the US Midwest (Miao, Khanna, and Huang 2016).

On growing season lengths, table 7 shows that warmer temperatures during the first half of the season reduce the length of a growing season in all regions, but the stage-specificity and the magnitude of the effects vary across regions. In the Northeast and the Southwest, high temperatures significantly shorten the growing seasons in almost all stages of the - twelve-week post-planting period. A 1°C warming over this period would amount to a roughly 3.6 days reduction of the growing season in these two regions. Warming in the later course of the growing season lengthens the duration of corn growth in the Northeast, the Northwest, and the Huang-huai-hai. In contrast, this lengthening effect is insignificant in the southern region, suggesting that the specific cultivars adopted in this relatively warmer region has better adaptability to higher temperatures.

Increasing precipitation in the early course of the growing season significantly reduces the season lengths in all regions except for the Huang-huai-hai, and this effect is most substantial during the first four weeks. In the Northwest and the Yangtze River Delta, the shortening effect of increasing precipitation become insignificant since the fifth post-planting week. In the Northeast and the Southeast, this effect still exists after the fifth week, and the combined effect over the first twelve weeks amounts to roughly 2.3 days. Lowered precipitation in the late course of the growing season significantly accelerates the growth duration in the Northeast, the Northwest, and the Huang-huai-hai. This stress-induced accelerating effect is the largest in the Northwest, where a 1 cm reduction in weekly precipitation over the second twelve post-planting weeks is associated with a nearly 2.6 days shorter growing season.

As discussed above, the regional heterogeneity in induced growing-season adjustments reflects the uneven distribution of environmental endowments over space. The pattern of north–south gradient in planting date responses also corroborate with our rationale that warming in cool areas helps relax the heat constraint and provides more flexibility for crop planting. It is also somewhat reassuring to discover that the important corn region in northern China, especially the Northeast, also exhibits the highest adaptability to contemporaneous weather through growing season adjustments.

Concluding Remarks

Recent studies have shown that climate change will seriously damage future crop production based on panel estimates of weather shocks. Although an optimally rearranged growing season could be effective in mitigating potential yield losses, causal estimates on the extent to which farmers actually make adjustments on growing seasons are still lacking. In this article, we empirically quantify the causal effects of temperature and precipitation on affecting planting dates and growing-season lengths. Utilizing a novel panel dataset of agro-climatic monitoring sites in China, we show that both planting dates and growing-season lengths respond to changes in contemporaneous temperature and precipitation. Relying on our estimates, we show that the adaptive behavior in growing-season adjustments can result in a shift of growing season under future climate and partially mitigate potential yield losses.

In addition to making an important contribution to understanding climatic impacts on agricultural production, the findings in this article also provide meaningful implications on policy discussions centering around agricultural adaptation to climate change. On one hand, the induced growing-season adjustments should be incorporated in evaluating the cost effectiveness of adaptation-related investments on, for instance, protective farm infrastructure and adaptive seed breeding. On the other hand, the behavioral response found in this article, especially on planting date decisions, highlights the potential value of improving weather forecasts and practical guidance so that crop growers can better utilize favorable weather and more effectively adjust their planting dates.

We acknowledge that this research also has some limitations. The impacts we successfully identified in this article are still short-run effects, and future research on identifying long-run adjustments are still needed. Our estimates also do not fully capture the impacts on some other related margins like the switch in seed varieties. Besides, our empirical analysis focuses on corn in China, but the behavioral response in growing-season adjustments could differ in other contexts for reasons related to crop biology, technology, and institutions. Therefore, a more comprehensive understanding of the issue requires further studies on growing-season adjustments of other crops (like wheat and rice) and in other country contexts.

Supplementary Material

Supplementary material are available at American Journal of Agricultural Economics *online.*

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