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Short-term and Long-term Response of Planting Behavior to Climate in the U.S. Corn Belt *

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Abstract: Quantifying climate adaptation is important from the standpoint of effectively assessing the extent to which economic agents make adjustments to their behavior, thereby reducing damages from climate change. We conduct such an investigation in the context of planting behavior in the U.S. corn belt by leveraging a climate econometrics framework. Our estimation method not only distinguishes the short-run response and the long-run response of planting behavior of corn to temperature and precipitation effects during the pre-growing season but also tests for climate adaptation as part of the short-run response. We find evidence of early and delayed planting in response to temperature and precipitation effects, respectively, across the pre-growing season. In addition, our findings confirm long-term climate adaptation in planting behavior and highlight the importance of accounting for a location's advantage or disadvantage in terms of the extent of divergence between its climate normals and weather realization. These insights are informative for the policy efforts aimed at tailoring mitigation strategies to a region's unique climate. Our study also generates insights of practical utility to agronomic advisory services, given that our findings confirm that the planting behavior (contingent upon a location's climate) does leverage the flexibility provided by the pre-growing season window in response to temperature and precipitation effects.

Keywords: climate change, adaptation, agriculture, behavioral response, planting dates

JEL Codes: Q15, Q18, Q54

1. INTRODUCTION

The extant climate literature largely distinguishes climate extremes from weather shocks based on the time scale of such events. Weather extremes represent short-lived events such as episodes of excessive heat or frost, while climate variability refers to long-lived shifts

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in the meteorological averages (Chatzopoulos et al., 2020). This distinction is important to climate econometric methods that aim to estimate the extent to which economic agents adapt to short-run variations (i.e., weather shocks) versus long-run changes in climate (Burke and Emerick, 2016). Quantifying the impact of such adaptation strategies is particularly of significance to agriculture as they can mitigate the detrimental effects of climate change. The mitigation efforts can include a range of strategies, such as shifts in planting time, changes in cropping patterns, genotype improvements, etc. For instance, as a dynamic trait of agriculture systems, crop planting dates respond to both short-term and long-term climate signals, thereby indicating farmers' adaptation to weather and climate change (Deines et al., 2023). Identifying the extent to which farming practices adapt to climate variability can be vital to understanding the behavioral foundation of climate adaptation in agriculture.

Facilitated by the introduction of planting varieties more suitable for future climate conditions, farmers tend to adjust planting time to offset climate change-induced yield losses (IPCC, 2014). For example, Cui and Xie (2022) show that short-term response in the form of growing season adjustments results in earlier planting dates in China between 1993 and 2013. Till recently, the extant climate econometrics works relied on the panel approach that controls for both space and time fixed effects to relate the time series deviations from the average of location-specific climate to the deviations in the outcome variable of interest such as yield or planting dates (Auffhammer et al., 2013; Hsiang, 2016). However, the panel fixed effects approach used by such studies cannot explicitly capture the long-run response of planting behavior to changes in climate. Considering that long-term adaptation to climate mitigates the effects of short-term events, such as extreme variations in growing-season weather, it becomes crucial to distinguish the two responses to climate change. It is important to understand to what degree the planting window provides the flexibility to adjust to climate over the long run, conditional upon weather realized in the short term. To the best of our knowledge, no study so far has distinguished the short-run from the long-run responses of planting behavior to climate change in the U.S. corn belt.

Given that both meteorological extremes and agricultural-food systems are local in nature (Chatzopoulos et al., 2020), decomposing the agricultural impacts in terms of both short-term and long-term effects of regional climate-related events is crucial for regional and crop-centric risk management initiatives. In view of this, the region represented by the U.S. corn belt holds special significance as the Midwest U.S. alone accounts for close to 45% of global corn production (Urban et al., 2018). The region's agriculture is characterized by highly productive commercial-scale operations in crops such as corn (Deines et al., 2023). The question of whether climate drives planting adjustments deserves investigation in the context of this corn belt region, in particular, given the recent debate over the possibility of planting delays impacting average U.S. corn yields (Irwin, 2022).

By employing the innovative approach of Mérel and Gammans (2021), which includes a climate penalty in regressions to distinguish the short-run response from the long-run response to climate, we investigate both the short-term and long-term adjustments in planting behavior in response to climate variability in the major rain-fed areas of U.S. corn belt. The penalty term helps us assess the impact of the long-term adaptation in planting and pre-growing season weather relationship. We take planting dates required to complete 10% planting as a measure of planting behavior in the U.S. corn belt. We examine the effect of random inputs such as temperature and precipitation during the pre-growing season on crop progress, which is measured in terms of the planting behavior. We find a significant impact of pre-growing season weather on planting behavior. The temperature and precipitation effects on planting time vary across the twelve weeks period prior to planting. We find evidence for such effects to induce both early and delayed planting. Most importantly, as captured by the climate penalty term, we find strong evidence of long-term climate adaptation on planting behavior.

2. LITERATURE REVIEW

The warming climate threatens crop yields and farm incomes across the world. The vulnerability of agricultural systems to weather anomalies is evident in the negative response of U.S. crop yields to high temperatures (Schauberger et al., 2017; Kukal and Irmak, 2018). In Germany, droughts are the major cause of crop yield losses at the farm level, while waterlogging and frost show region-specific impacts on the country's crop production (Schmitt et al., 2022). However, the explanation for such interactions between biophysical conditions and crop outputs is incomplete without accounting for the possibility of farm management practices adapting to climate variabilities. Part of the challenge includes the statistical modeling of such relationships while accounting for the fact that economic agents respond and adjust to permanent baseline shifts in climate rather than to a temporary weather shock (Deschênes and Greenstone, 2007; Hagerty et al., 2022).

Climate unique to a particular region determines the comparative advantage that the region can leverage to respond to weather extremes. In a what-if scenario analysis, Malcolm et al. (2012) highlights the regional differences in the economic and environmental impacts of agricultural adaptation to climate change across the U.S. However, their analysis was limited to changes in crop patterns, as the Regional Environment and Agriculture Programming Model (REAP) they used did not account for other farm-level adaptation strategies, such as adjusting planting dates by Corn Belt farmers. Mérel and Gammans (2021) point out that locations experiencing weather closer to their climate can leverage more opportunities to adapt than the locations for which an extreme weather anomaly happens to be an outlier. For example, the warming of the climate in colder regions offers the opportunity for the farming systems to shift from single cropping to double cropping, thereby augmenting crop production (Kawasaki, 2019). Some of the previous phenological studies conjecture that longer-season corn hybrids (i.e., tolerant of sub-optimal temperatures) enable farmers to shift to early planting, in turn, boosting yields in the U.S. corn belt (Kucharik, 2006, 2008). On the other hand, Rizzo et al. (2022) show that the decadal climate trend and agronomic practices account for a higher proportion of corn yield gains in the temperate region of Nebraska than genotype improvements. However, these agronomy studies reach such conclusions by relating observed historical trends across planting, yield, and climate variables and do not necessarily represent causal relationships.

In addition to the phenological studies that document the relationship between planting or yield and climate, the recent literature in the area of remote sensing particularly highlights the importance of estimating and mapping planting dates, specifically in the U.S. corn belt. Urban et al. (2018) focus on mapping sowing dates of corn and soybean in the states of

Iowa, Indiana, and Illinois using algorithms that extract sowing dates from remotely sensed phenologies. Their results confirm that while the estimated sowing dates are not sensitive to variability in the ratio of corn to soybean area, they are sensitive to the weather variations during the sowing season of April and May in the area. For the same region, Deines et al. (2023) map planting dates at a finer field-level scale using non-parametric regressions and machine learning algorithms. They also confirm that early-season rainfall delays planting. Most of these studies underscore the importance of leveraging remote sensing technology to map planting dates while accounting for early season weather variations, they do not necessarily provide any clear evidence for the possible impacts of *climate adaptation* on the planting behavior in the region.

Another part of the challenge in establishing a causal interpretation of the impact of weather versus climate on planting behavior in a regional context is leveraging spatially disaggregated information on exposure to weather extremes and long-term climate patterns. Schmitt et al. (2022) draw our attention to this challenge by highlighting that spatial and temporal aggregations interact as crops require specific weather conditions during different phenological stages when growing windows do not necessarily match across a region or country. They find a way around this challenge by employing a panel method to estimate short-run responses of crop yield to extreme weather events while using a long-difference approach based on computing the cross-sectional observations as the five-year averages of farm-level yield and corresponding five-year averages of weather observations belonging to two time periods (i.e., 1995-1999 versus 2015-2019) in order to detect climate adaptation in yields. Auffhammer et al. (2013) rearticulate the dilemma over leveraging modeling approaches to capture short-run versus long-run responses of outcomes to climate variability as part of an econometrician's choice of a weather versus a climate measure that determines if the outcome is a true climate response or a short-run weather elasticity.

Most climate econometrics literature focuses on quantifying climate adaptation in crop yields and acreages. In a recent study, Cui (2020) finds that over the past 30 years, the rising temperature and precipitation encouraged the expansion of planted acres of corn and soybeans in cool and dry areas of the U.S. in contrast to the negative impact of climate on their acres in warm places. The evidence for crop yields is rather mixed. By including nonlinearities in explanatory weather variables in the panel data fixed-effects regressions to partially reflect long-run adaptation of productivity to climate, Schlenker and Roberts (2009) establish limited climate adaptability in the rainfed U.S. corn and soybean yields. Burke and Emerick (2016) corroborate this by accounting for the impact of variations in longer-term changes in temperature and precipitation on corn and soybean yields in the U.S. On the other hand, as a methodological improvement on the nonlinear panel model, Mérel and Gammans (2021) explicitly capture long-run adaptation by adding a climate penalty term to the nonlinear weather-crop yield relationship in panel fixed effects regressions. They define the climate penalty as "the squared distance between *contemporaneous* weather and a location's *normal* climate". Their findings confirm the long-run adaptation of corn and soybean yields to climate. In this study, we employ the estimation framework of Mérel and Gammans (2021) to establish both short-run and long-run responses of planting behavior (rather than crop yield) for corn to climate. By leveraging their augmented econometric framework, we aim to account for the possibility of economic agents, such as farmers, adjusting their actions in response to location-specific climate patterns. While Mérel and Gammans (2021) inspires our econometrics to capture climate adaptation in economic agent's behavior, Cui and Xie (2022) work on planting dates in China partially inspires us to acknowledge the actions of agents to adapt to weather variations in the form of planting time adjustments.

3. DATA

We apply our framework to examine the planting behavior of corn in rain-fed areas of the U.S. by combining publicly available high-resolution geospatial datasets of crop progress and weather. The planting dates of corn are derived from Crop Progress and Condition Reports (CPCR) published by the National Agriculture Statistical Service (NASS), U.S. Department of Agriculture (USDA). The information published in the CPCR can be used to monitor the crop status across major U.S. growing regions (Beguería and Maneta, 2020). These reports are published weekly during the growing season and, until recently, were available at the aggregate state level. However, the newly available crop condition and progress layers provide weekly crop progress and condition data since 2015 at a finer resolution as a 9 km x 9 km grid (Rosales, 2021). While this dataset is constructed using interpolation procedures from non-probabilistic surveys, the increased spatio-temporal resolution enables us to examine planting dates by using "fully synthetic representations of confidential, county-level data" (Rosales, 2021).

Each cell in the gridded crop progress layers contains the value of the crop progress index calculated using progress information about each phenological stage specific to a crop. As the first phenological stage is planting, we consider the first day of the week when 10% of planting was completed at a location as the planting date. The corresponding value of the crop progress index for 10% planting is 10/700, as planting is the first of the seven phenological stages of corn. This requires an assumption that 10% planting does not overlap with subsequent phenological stages. While the planting date calculated in this manner does not represent exact information about the planting dates at the location, it provides a workable alternative, given the scarcity of such data. In figure 1, we depict the planting days for 2023 in our study area constructed using the procedure. Note that we restrict our attention to the area of the conterminous U.S. to the east of the 100 °West meridian, following literature (Miao et al., 2016). This choice makes our study focus on rainfed areas where temperature and precipitation play an important role, and it includes the major corn-growing areas in the Midwestern U.S. In addition to the planting dates, we also need the usual planting dates to define pre-growing seasons at each location. We source the state-level normal planting dates of corn from the report, "Usual Planting and Harvesting Dates for U.S. Field Crops", published by the National Agricultural Statistics Service (2010). To our knowledge, this is the most recent time such information was published.

We then construct weekly temperature and precipitation variables to represent the pre-growing season weather of corn at each cell, which includes the normal planting weeks at the location and the twelve weeks preceding it. The weather data comes from the PRISM-climate group at Oregon State University (PRISM Climate Group, Oregon State University, 2024). We employ three alternative temperature measures: weekly mean temperature, growing degree days (i.e., temperature threshold considered suitable for initiating corn growth in the

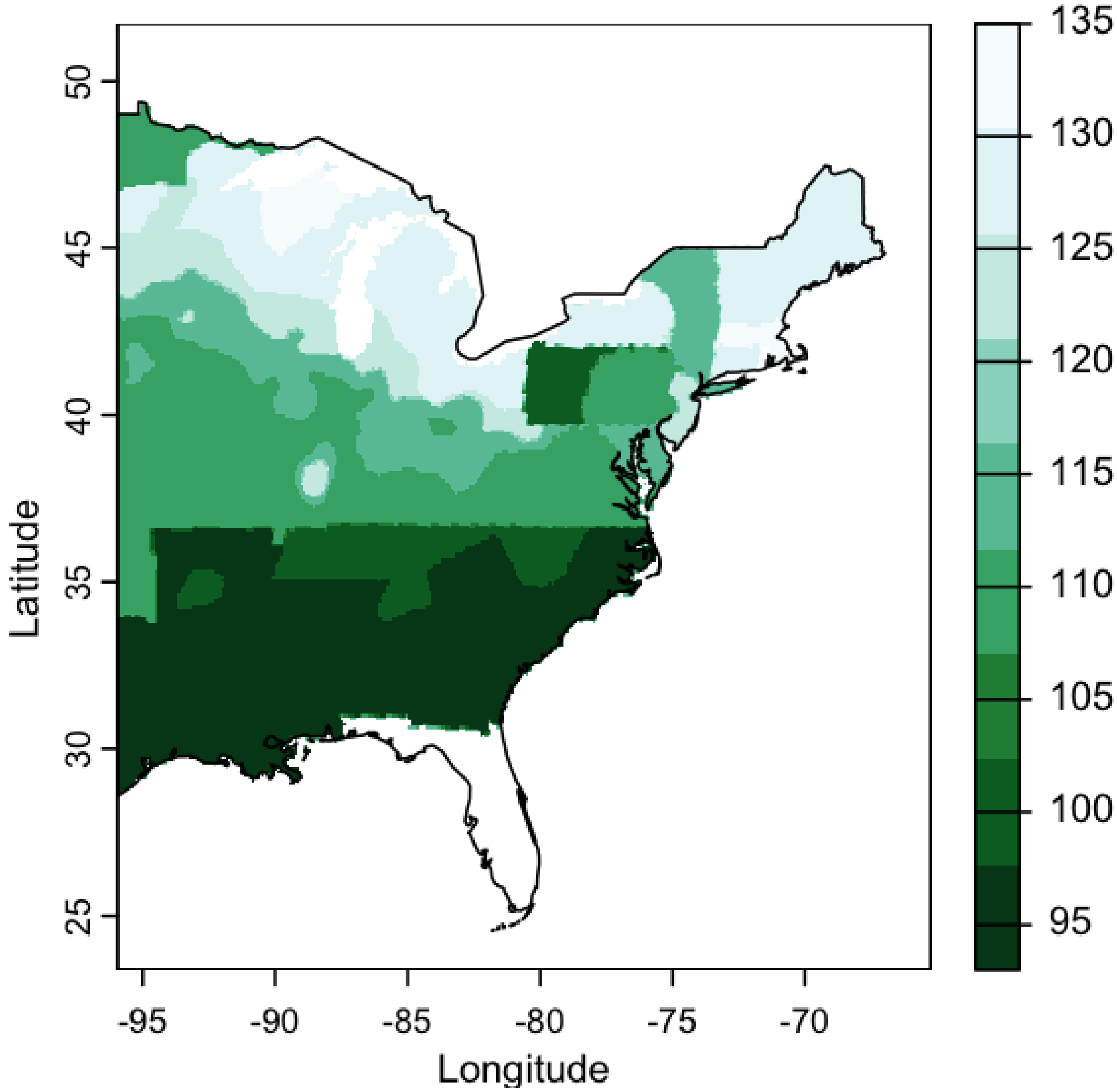

Figure 1: Planting days of corn in 2023 in the study area, in terms of number of days from the start of the year

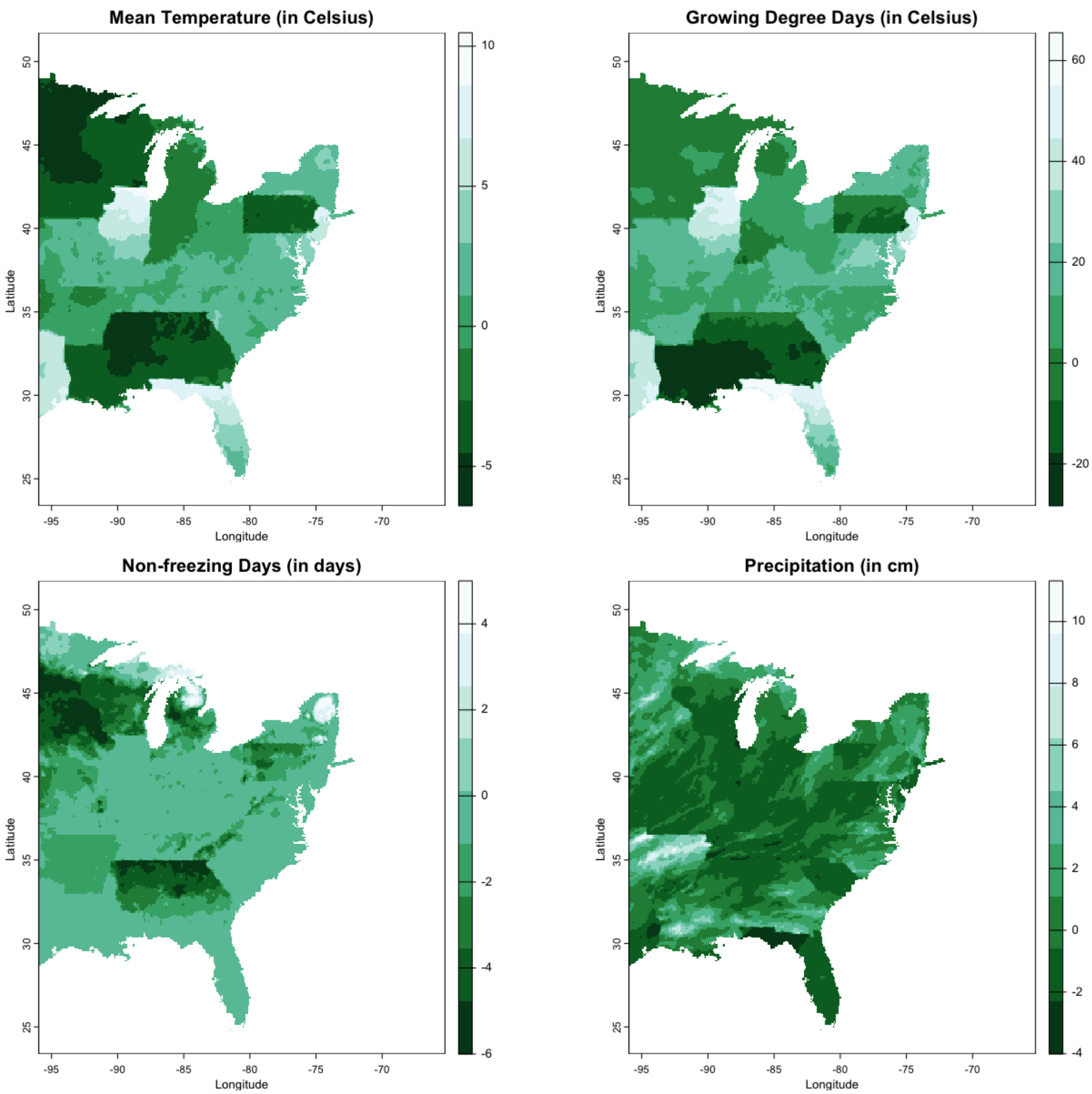

Figure 2: Mean temperature, growing degree days, number of non-freezing days, and precipitation on normal planting weeks in the study area during 2023, expressed in terms of deviation from their 30-year long-term averages in that week

U.S. corn belt), and the number of non-freezing days in the week. The growing degree days for corn is calculated using the equation (1):

$$GDD = \sum_{i=1}^{n} \frac{[T_{max} + T_{min}]}{2} - T_b \tag{1}$$

where, T_{max} is the maximum temperature, T_{min} is the minimum temperature, and T_b is the base temperature. Following the agronomy literature (Kucharik, 2006, 2008), we use 10 °C as the base temperature of corn. To calculate the number of non-freezing days, we count the number of days during which minimum temperature was above 0 °C. For precipitation, we use the cumulative precipitation over the week in centimeters. In addition, we use 30-year normals that provide long-term averages for both temperature and precipitation variables. These long-term averages serve as the baseline "normals" from which we calculate the deviation of temperature measures and precipitation. We then use the square of this deviation to define the climate penalty term in our regressions, according to the econometric framework in equations (2) and (3). We merge the temperature and precipitation variables with planting day estimates from the crop progress data layers to construct a balanced panel dataset between the years 2016 and 2023. In figure 2, we depict this deviation from the long-term average for weekly mean temperature, growing degree days, non-freezing days, and weekly precipitation for the normal planting week in 2023 within the study area.

4. METHODS

We adopt the panel approach to data analysis that controls for space and time fixed effects to estimate weather or climate response in planting behavior. The fixed effects approach relies on time series deviations in climate indicators within a spatial unit or location as a source of variability in the outcome of interest. With the ability to control for time-invariant omitted variables that may give biased estimates for climate effect on economically relevant outcomes in cross-sectional studies, the panel approach is still criticized for its inability to capture climate adaptation due to its heavy reliance on weather fluctuations rather than climatic differences (Auffhammer et al., 2013; Burke and Emerick, 2016; Mérel and Gammans, 2021). Given this drawback of the panel fixed effects framework, we adopt the Mérel and Gammans (2021) approach to add a *climate penalty* term to the quadratic-weather and planting behavior relationship with fixed effects. The addition of the climate penalty term helps us with two things: 1) to distinguish the short-run response of planting behavior to weather and climate indicators from its long-run response to them, and 2) to confirm long-term climate adaptation in planting behavior for corn. We explain our methodology below with details centered on designing the climate penalty-augmented nonlinear panel approach.

The short-run response of planting dates to weather can be estimated by the following equation (2),

$$\begin{aligned}
y_{i,t} = {} & \alpha_i + \lambda_t + \beta_1 T_{it,[N_i-1,N_i-4]} + \beta_2 T_{it,[N_i-5,N_i-8]} + \beta_3 T_{it,[N_i-9,N_i-12]} + \beta_4 T^2_{it,[N_i-1,N_i-4]} \\
& + \beta_5 T^2_{it,[N_i-5,N_i-8]} + \beta_6 T^2_{it,[N_i-9,N_i-12]} + \beta_7 (T_{it,[N_i-1,N_i-4]} - \mu^T_{i,[N_i-1,N_i-4]})^2 \\
& + \beta_8 (T_{it,[N_i-5,N_i-8]} - \mu^T_{i,[N_i-5,N_i-8]})^2 + \beta_9 (T_{it,[N_i-9,N_i-12]} - \mu^T_{i,[N_i-9,N_i-12]})^2 \\
& + \gamma_1 P_{it,[N_i-1,N_i-4]} + \gamma_2 P_{it,[N_i-5,N_i-8]} + \gamma_3 P_{it,[N_i-9,N_i-12]} + \gamma_4 P^2_{it,[N_i-1,N_i-4]} \\
& + \gamma_5 P^2_{it,[N_i-5,N_i-8]} + \gamma_6 P^2_{it,[N_i-9,N_i-12]} + \gamma_7 (P_{it,[N_i-1,N_i-4]} - \mu^P_{i,[N_i-1,N_i-4]})^2 \\
& + \gamma_8 (P_{it,[N_i-5,N_i-8]} - \mu^P_{i,[N_i-5,N_i-8]})^2 + \gamma_9 (P_{it,[N_i-9,N_i-12]} - \mu^P_{i,[N_i-9,N_i-12]})^2 \\
& + \epsilon_{i,t} \qquad (2)
\end{aligned}$$

where $y_{i,t}$ is the planting date coded as the number of days since the first day of year t in location or grid i. For example, the planting day for the week when 10% planting is completed can be taken as the date when the reporting week for the crop progress index ends, and the planting date is calculated as the number of days from the first day of the year up till the planting day. $T_{it,[N_i-\phi_1,N_i-\phi_2]}$ and $P_{it,[N_i-\phi_1,N_i-\phi_2]}$ represent weekly mean temperature and weekly cumulative precipitation at location i in year t averaged over the $\phi_1-\phi_2$ weeks prior to the grid-specific normal planting date, represented by N_i. Auffhammer et al. (2013) emphasize that to ensure unbiasedness of the estimates for the impact of two weather variables, such as temperature and precipitation, which are historically correlated, one should control for both in the regression equation. Along with the weekly average temperature indicators and weekly cumulative precipitation, we also include the squares of these terms to allow for nonmonotonicity in the weather and planting behavior relationship in line with the extant climate econometrics literature. Including non-linearity in explanatory weather variables also helps account for different marginal responses to weather or climate indicators across different locations (Mérel and Gammans, 2021). The term $(T_{it,[N_i-\phi_1,N_i-\phi_2]} - \mu^T_{i,[N_i-\phi_1,N_i-\phi_2]})^2$ is the climate penalty in which $T_{it,[N_i-\phi_1,N_i-\phi_2]}$ is the realized weather for location i, and $\mu^T_{i,[N_i-\phi_1,N_i-\phi_2]}$ is the underlying climate captured by the 30-year normals for the set of $\phi_1 - \phi_2$ weeks in the year t. The same explanation applies to the precipitation penalty term i.e., $(P_{it,[N_i-\phi_1,N_i-\phi_2]} - \mu^P_{i,[N_i-\phi_1,N_i-\phi_2]})^2$. The penalty terms capture to what extent climate influences agents' committed actions. We also estimate alternative versions of these regressions by substituting the mean temperature with the number of growing degree days and non-freezing degree days. When all actions can be varied relative to the prevalent weather conditions, the penalty term vanishes, and the long-run response can be expressed as:

$$\begin{aligned}
y_{i,t} = {} & \alpha_i + \lambda_t + \beta_1 T_{it,[N_i-1,N_i-4]} + \beta_2 T_{it,[N_i-5,N_i-8]} + \beta_3 T_{it,[N_i-9,N_i-12]} + \beta_4 T^2_{it,[N_i-1,N_i-4]} \\
& + \beta_5 T^2_{it,[N_i-5,N_i-8]} + \beta_6 T^2_{it,[N_i-9,N_i-12]} + + \gamma_1 P_{it,[N_i-1,N_i-4]} + \gamma_2 P_{it,[N_i-5,N_i-8]} \\
& + \gamma_3 P_{it,[N_i-9,N_i-12]} + \gamma_4 P^2_{it,[N_i-1,N_i-4]} + \gamma_5 P^2_{it,[N_i-5,N_i-8]} + \gamma_6 P^2_{it,[N_i-9,N_i-12]} + \epsilon_{i,t} \qquad (3)
\end{aligned}$$

where α_i is the time-invariant grid-level fixed effect that controls for time-invariant heterogeneity. As Cui and Xie (2022) points out, soil productivity or quality can be one source of such heterogeneity. λ_t represents state-level time trends of the year that can capture effects related to technological changes and any arbitrary socio-economic shocks. Given that the errors in the econometrics framework leveraging gridded-datasets can be prone to spatial correlations across adjacent grids (Auffhammer et al., 2013), we allow the error terms $\epsilon_{i,t}$ to be spatially correlated by using the nonparametric routine of Conley (1999), which uses a cutoff distance to calculate standard errors (Conley, 2008; Düben, 2022). We also take an alternative route to allow for spatial as well as temporal heteroscedasticity and autocorrelations by adopting the two-way clustering strategy, i.e., cluster standard errors at the location or grid level and allow for heteroscedasticity across time. We have the estimates for each regression (i.e., short-run and long-run specifications) with the two-way clustering strategy in table 1 and the estimates with the Conley (1999) routine in table 2. Both sets of our results come from balanced panel regressions.

Taking equation (2) as a test for long-run climate adaptation, i.e., captured by the climate penalty, we assess if the exposure to climate normals over the years impacts outcomes such as planting behavior given that farmers vary their actions as per prevalent environmental conditions. Further, we compare the evidence on the short-run response of planting to temperature and precipitation in equation (2) to that estimated by the naive model in equation (3). Mérel and Gammans (2021) refer to the latter equation as a naive model of estimation and acknowledge the former short-run response model with climate penalty as an improvement in establishing the behavioral foundation of climate adaptation efforts.[1]

5. RESULTS AND DISCUSSIONS

We estimate three versions of our short-run and long-run regression equations, each with a different measure of weekly temperature: the weekly mean temperature, growing degree days, and the number of non-freezing days in three phases of the pre-growing period. We present two versions of the estimates. In table 1, we present the fixed effect estimates with two-way clustering across state and year. In table 2, we present the short-run and long-run estimates by using Conley standard errors that correct for the spatial correlation (Conley, 1999). As the estimation is computationally intensive, we choose a cut-off distance of 100 km to estimate the distance matrix for addressing cross-sectional spatial correlation while also allowing one period lag for serial correlation (Düben, 2022). We take the results in table 1 to be our main results while table 2 provides the robustness check for our set of main results. In the following discussion, each time we discuss the interpretation of estimates, we refer to the table 1 results while we only mention the consistency of our estimates' statistical significance when we refer to table 2.

In table 1, for our short-run response model, we observe that not only the temperature and precipitation across the pre-growing season have a significant impact on planting behavior but also that this impact varies across the sets of four-weeks characterized as first to fourth

[1]Even though Mérel and Gammans (2021) take the long-run response to be an upper envelope of the set of short-run responses of crop yield to climate effects as climate mitigation efforts in the long-term will reduce damages. In our setting, we take this to be an empirical question where the long-run response of the outcome variable, i.e., planting behavior, might not necessarily be the upper envelope of its short-term response to temperature and precipitation effects. We acknowledge this to be a result of the nature of planting behavior, which when adjusted, may confirm adaptation either way: earlier planting and delayed planting.

Table 1: Short-run and long-run response of planting day to temperature and precipitation, Cluster Robust Standard Errors

	Short-run			Long-run		
	(1)	(2)	(3)	(1)	(2)	(3)
Temperature						
$T_{it,[N_i-1,N_i-4]}$	0.275***	−0.119***	−0.125***	−0.271***	−0.077***	−0.093***
	(0.017)	(0.001)	(0.010)	(0.015)	(0.001)	(0.009)
$T^2_{it,[N_i-1,N_i-4]}$	−0.042***	0.000***	0.002***	−0.007***	0.000***	0.000
	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
$(T_{it,[N_i-1,N_i-4]} - \mu^T_{i,[N_i-1,N_i-4]})^2$	0.138***	0.001***	0.006***			
	(0.002)	(0.000)	(0.000)			
$T_{it,[N_i-5,N_i-8]}$	−0.599***	−0.031***	−0.651***	−0.648***	−0.014***	−0.798***
	(0.006)	(0.001)	(0.009)	(0.005)	(0.001)	(0.009)
$T^2_{it,[N_i-5,N_i-8]}$	0.040***	0.000***	0.026***	0.030***	0.000***	0.030***
	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
$(T_{it,[N_i-5,N_i-8]} - \mu^T_{i,[N_i-5,N_i-8]})^2$	−0.047***	−0.000***	−0.006***			
	(0.002)	(0.000)	(0.000)			
$T_{it,[N_i-9,N_i-12]}$	−0.504***	0.048***	0.122***	−0.607***	0.025***	0.225***
	(0.008)	(0.001)	(0.012)	(0.007)	(0.002)	(0.011)
$T^2_{it,[N_i-9,N_i-12]}$	0.011***	−0.000***	−0.005***	0.005***	−0.000***	−0.009***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$(T_{it,[N_i-9,N_i-12]} - \mu^T_{i,[N_i-9,N_i-12]})^2$	−0.033***	−0.000	0.006***			
	(0.002)	(0.000)	(0.000)			
Precipitation						
$P_{it,[N_i-1,N_i-4]}$	1.918***	1.669***	1.986***	0.744***	0.989***	1.004***
	(0.040)	(0.042)	(0.042)	(0.025)	(0.025)	(0.025)
$P^2_{it,[N_i-1,N_i-4]}$	−0.319***	−0.263***	−0.314***	−0.094***	−0.120***	−0.113***
	(0.007)	(0.008)	(0.008)	(0.003)	(0.003)	(0.003)
$(P_{it,[N_i-1,N_i-4]} - \mu^P_{i,[N_i-1,N_i-4]})^2$	0.317***	0.244***	0.304***			
	(0.010)	(0.010)	(0.011)			
$P_{it,[N_i-5,N_i-8]}$	0.431***	0.293***	0.632***	0.360***	0.569***	0.709***
	(0.031)	(0.032)	(0.031)	(0.023)	(0.024)	(0.024)
$P^2_{it,[N_i-5,N_i-8]}$	−0.043***	−0.041***	−0.080***	−0.046***	−0.098***	−0.092***
	(0.006)	(0.006)	(0.007)	(0.003)	(0.003)	(0.003)
$(P_{it,[N_i-5,N_i-8]} - \mu^P_{i,[N_i-5,N_i-8]})^2$	−0.050***	−0.057***	−0.013			
	(0.009)	(0.009)	(0.010)			
$P_{it,[N_i-9,N_i-12]}$	2.110***	3.167***	3.046***	1.454***	1.761***	1.904***
	(0.045)	(0.044)	(0.042)	(0.029)	(0.030)	(0.031)
$P^2_{it,[N_i-9,N_i-12]}$	−0.283***	−0.502***	−0.478***	−0.137***	−0.181***	−0.195***
	(0.008)	(0.008)	(0.008)	(0.004)	(0.004)	(0.004)
$(P_{it,[N_i-9,N_i-12]} - \mu^P_{i,[N_i-9,N_i-12]})^2$	0.230***	0.516***	0.453***			
	(0.009)	(0.009)	(0.009)			
R^2	0.160	0.096	0.097	0.136	0.061	0.077
Adj. R^2	0.040	−0.033	−0.032	0.013	−0.074	−0.055
N	285704	285704	285704	285704	285704	285704

Notes: a) Standard errors are in parentheses. Significance levels are *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. b) The dependent variable is the planting day. c) Model (1) uses weekly mean temperature, while models (2) and (3) uses growing degree days (GDD) and number of non-freezing days as temperature measures, respectively. d) $T_{it,[N_i-\phi_1,N_i-\phi_2]}$ and $P_{it,[N_i-\phi_1,N_i-\phi_2]}$ represent location or grid i in year's t's weekly mean temperature and weekly cumulative precipitation averaged over the $\phi_1 - \phi_2$ weeks prior to the grid-specific normal planting date, represented by N_i. e) The models control for cell and year fixed effects in a balanced panel, and use cluster-robust standard errors at the state and year levels.

Table 2: Short-run and long-run response of planting day to temperature and precipitation, Conley Standard Errors

	Short-run			Long-run		
	(1)	(2)	(3)	(1)	(2)	(3)
Temperature						
$T_{it,[N_i-1,N_i-4]}$	0.275*	−0.119***	−0.125	−0.271*	−0.077***	−0.093
	(0.124)	(0.009)	(0.077)	(0.107)	(0.008)	(0.075)
$T^2_{it,[N_i-1,N_i-4]}$	−0.042***	0.000	0.002	−0.007	0.000***	0.000
	(0.006)	(0.000)	(0.002)	(0.005)	(0.000)	(0.002)
$(T_{it,[N_i-1,N_i-4]} - \mu^T_{i,[N_i-1,N_i-4]})^2$	0.138***	0.001***	0.006**			
	(0.017)	(0.000)	(0.002)			
$T_{it,[N_i-5,N_i-8]}$	−0.599***	−0.031**	−0.651***	−0.648***	−0.014	−0.798***
	(0.047)	(0.011)	(0.074)	(0.047)	(0.010)	(0.070)
$T^2_{it,[N_i-5,N_i-8]}$	0.040***	0.000***	0.026***	0.030***	0.000**	0.030***
	(0.005)	(0.000)	(0.002)	(0.004)	(0.000)	(0.002)
$(T_{it,[N_i-5,N_i-8]} - \mu^T_{i,[N_i-5,N_i-8]})^2$	−0.047***	−0.000	−0.006***			
	(0.013)	(0.000)	(0.001)			
$T_{it,[N_i-9,N_i-12]}$	−0.504***	0.048***	0.122	−0.607***	0.025*	0.225**
	(0.055)	(0.012)	(0.083)	(0.055)	(0.011)	(0.077)
$T^2_{it,[N_i-9,N_i-12]}$	0.011**	−0.000**	−0.005	0.005*	−0.000**	−0.009***
	(0.004)	(0.000)	(0.003)	(0.002)	(0.000)	(0.003)
$(T_{it,[N_i-9,N_i-12]} - \mu^T_{i,[N_i-9,N_i-12]})^2$	−0.033*	−0.000	0.006***			
	(0.016)	(0.000)	(0.002)			
Precipitation						
$P_{it,[N_i-1,N_i-4]}$	1.918***	1.669***	1.986***	0.744***	0.989***	1.004***
	(0.279)	(0.309)	(0.299)	(0.167)	(0.183)	(0.170)
$P^2_{it,[N_i-1,N_i-4]}$	−0.319***	−0.263***	−0.314***	−0.094***	−0.120***	−0.113***
	(0.049)	(0.056)	(0.054)	(0.018)	(0.021)	(0.019)
$(P_{it,[N_i-1,N_i-4]} - \mu^P_{i,[N_i-1,N_i-4]})^2$	0.317***	0.244***	0.304***			
	(0.063)	(0.072)	(0.070)			
$P_{it,[N_i-5,N_i-8]}$	0.431	0.293	0.632*	0.360	0.569**	0.709***
	(0.270)	(0.288)	(0.279)	(0.192)	(0.209)	(0.204)
$P^2_{it,[N_i-5,N_i-8]}$	−0.043	−0.041	−0.080	−0.046	−0.098***	−0.092***
	(0.050)	(0.053)	(0.052)	(0.024)	(0.026)	(0.026)
$(P_{it,[N_i-5,N_i-8]} - \mu^P_{i,[N_i-5,N_i-8]})^2$	−0.050	−0.057	−0.013			
	(0.064)	(0.067)	(0.065)			
$P_{it,[N_i-9,N_i-12]}$	2.110***	3.167***	3.046***	1.454***	1.761***	1.904***
	(0.351)	(0.343)	(0.340)	(0.222)	(0.235)	(0.240)
$P^2_{it,[N_i-9,N_i-12]}$	−0.283***	−0.502***	−0.478***	−0.137***	−0.181***	−0.195***
	(0.060)	(0.061)	(0.058)	(0.026)	(0.030)	(0.030)
$(P_{it,[N_i-9,N_i-12]} - \mu^P_{i,[N_i-9,N_i-12]})^2$	0.230***	0.516***	0.453***			
	(0.067)	(0.068)	(0.065)			
R^2	0.160	0.096	0.097	0.136	0.061	0.077
Adj. R^2	0.160	0.096	0.097	0.136	0.061	0.076
N	285704	285704	285704	285704	285704	285704

Notes: a) Standard errors are in parentheses. Significance levels are *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. b) The dependent variable is the planting day. c) Model (1) uses weekly mean temperature, while models (2) and (3) uses growing degree days (GDD) and number of non-freezing days as temperature measures, respectively. d) $T_{it,[N_i-\phi_1,N_i-\phi_2]}$ and $P_{it,[N_i-\phi_1,N_i-\phi_2]}$ represent location or grid i in year's t's weekly mean temperature and weekly cumulative precipitation averaged over the $\phi_1 - \phi_2$ weeks prior to the grid-specific normal planting date, represented by N_i. e) The models control for cell and year fixed effects in a balanced panel.

week, fifth to eighth weeks, and ninth to twelfth week prior to the normal planting date. For instance, the significant and positive estimate for the temperature variable during the first four-weeks suggests that a 1°C higher mean temperature during the first four-weeks delays planting by 0.28 days. In contrast, we find that significant and negative estimates for the temperature variable during the second four-week and the third four-week prior to normal planting dates suggest that a 1°C higher mean temperature during the four-week periods leads to advancement in planting by 0.60 days and 0.50 days, respectively. Combining these observed impacts highlights that if the mean temperature during the first to twelfth weeks prior to the normal planting date increases by 1°C, then corn is planted at least 0.82 days earlier in that year. For the alternative measure of growing degree days in column (2), we observe that negative and significant estimates for the temperature variable during the first to fourth and the fifth to eighth week sets suggest pre-planting. Specifically, combining the observed effects for the three four-week sets prior to the normal planting date shows that an additional degree Celsius day of heat accumulation during these twelve weeks prior to the normal planting date leads to advancement in planting time by roughly 0.1 days. In column (3), for the alternative temperature measure of non-freezing days, we again observe that one additional non-freezing day in the first to fourth and fifth to eighth weeks leads to advancement in planting by roughly 0.12 and 0.65 days, respectively. Overall, combining the observed effects over the twelve week period prior to the normal planting date confirms that an additional non-freezing day in the period leads to an advancement of planting by roughly 0.65 days. Except for a couple of cases, the significance for most of the results also holds for the estimations obtained from the Conley (1999) routine in table 2. We interpret these results to mean that the reduction in freezing days caused due to warming, in turn, leads to earlier planting of corn, which is also consistently captured by alternative temperature measures such as the non-freezing days.

Overall, our results for temperature effects do not find much support for delayed planting. These results are also in line with the findings in agronomy literature, which confirm a trend over time for earlier planting to have contributed to yield increases in the U.S. corn belt (Kucharik, 2008). The precipitation effects across columns (1) to (3) consistently suggest that an increase of cumulative precipitation by 1cm in the respective first to fourth, fifth to eighth, and ninth to twelfth weeks prior to the normal planting date leads to a delay in planting. For example, in column (1), combining these observed impacts highlights that an increase of 1 cm in cumulative precipitation in the first to twelfth weeks prior to the normal planting date delays planting by 4.46 days. These results hold for the majority of the cases in table 2. These findings for precipitation effects are consistent with the extant literature spanning from agronomy to remote sensing literature, which time and again have related delayed planting to an increase in cumulative precipitation (Kucharik, 2006, 2008; Urban et al., 2018; Deines et al., 2023).

In table 1 , we also find that both temperature and precipitation effects show evidence of nonmonotonicity in the short-run response model across the three four-week sets of the pre-growing season. For instance, evidence of opposite signs of the estimates for the temperature and the squared temperature variables suggests nonmonotonicity in the short-run response model. Similarly, for precipitation effects, we find consistent evidence of nonmonotonicity across columns (1) to (3). These results hold for most of the parameters in table 2.

As evident from the short-run response model's estimates for the climate penalty term in table 1, we find consistently positive and significant estimates across columns (1) to (3) for the temperature climate penalty in the first to fourth weeks prior to the normal planting time. During the fifth to eighth and ninth to twelfth weeks, we establish negative and significant estimates for the temperature climate penalty term across the regressions using alternative temperature measures. Similarly, for the precipitation climate penalty, we find significant positive estimates in the first to fourth and ninth to twelfth weeks prior to normal planting, in contrast to significant negative estimates for fifth to eight weeks prior to normal planting. We interpret these results to confirm climate adaptation of planting behavior to both temperature and precipitation effects. These findings hold for the majority of the parameters in table 2 except for the fifth to twelfth four-week set.

Lastly, the results in table 1 confirm that the short-run responses of planting behavior differ from the long-run responses to temperature and precipitation across the pre-growing season. For instance, during the first to twelfth weeks combined prior to the normal planting day, a 1°C increase in mean temperature results in an earlier planting by 0.82 days as a short-run response in contrast to 1.53 days as a long-run response. Similarly, the differences in the magnitude of temperature effects are also evident in the short-run and long-run responses to the alternative measures of temperature in columns (1) to (3). For precipitation effects, we observe consistent differences in the magnitude of short-run and long-run responses across the pre-growing season. For example, for the combined observed effects across the first to twelfth weeks prior to the normal planting day, we find that an increase of 1 cm in the cumulative precipitation during this period leads to a delay of 4.46 days as a short-run response versus a delay of 2.56 days as a long-run response. These findings hold for the majority of temperature and precipitation effects in table 2. These findings highlight that estimating the impact of climate variables on planting time with the naive model of long-run response risks accounting for just partial long-term response of planting behavior to climate. By accounting for climate information's influence on the outcome-weather relationship, our estimation method and empirical findings support the growing consensus on the behavioral aspect of climate mitigation efforts that can alter outcomes.

Overall, our results provide insights into temperature and precipitation effects on the planting time of corn when accounting for climate adaptation such as that by farmers. This should be informative for the agronomists in the U.S. corn belt who can continue to encourage more flexibility in corn planting as continued warming of climate induces earlier planting behavior. Moreover, the warming-induced early planting date might also support corn planting in places that were earlier considered to be too cold for corn in order to compensate for the loss of corn production in places exposed to more abnormal extreme heat events. For the policymakers, our results emphasize to account for the possibility of the comparative advantage that certain locations can leverage to respond to weather extremes. The risk management initiatives designed taking into consideration the ability of economic agents to adapt to location-specific climate might prove to be more effective as part of larger regional climate mitigation efforts.

6. CONCLUSIONS

In this study, we use an innovative econometric approach to comprehensively examine the adaptation of planting behavior of corn in the U.S. Our work is the first to account for *climate adaptation* in planting behavior in the rain-fed corn belt of the U.S. Moreover, we empirically establish a causal relationship between weather and advancement/delay of planting. Our findings confirm that farming behavior leverages a location's climate information for adaptation purposes. By employing Mérel and Gammans (2021) strategy to include climate penalty in the quadratic-in-weather model, we explicitly capture the planting time's adaptation to climate and accommodate the fact that prior periodic exposure to specific environmental conditions provides agents such as farmers with more opportunities to adapt to similar occurrences in the future. These insights also highlight the fact that a location's historical climate shapes its agency to counter negative weather impacts by exploiting the flexibility that the planting window provides.

Our findings inform current and future climate mitigation efforts, such as extension-based advice on the timing of planting, as farmers can leverage favorable weather and systematically adjust their planting time with access to potential hybrid varieties. Furthermore, it highlights the importance of accounting for the climate's impact on the planting behavior-weather relationship for policy-level implications, especially those concerning the region-specific assessment of the cost-effectiveness of adaptation measures employed against climate change. It can help tailor climate adaptation plans to a location's climate-related history and current weather-related challenges. The effects of early and delayed planting on corn yield are well-documented in the literature and frequently discussed in agricultural extension circles (Irwin, 2022). The convention wisdom is that delaying planting beyond an optimal window, typically from late April to early May in the Midwest, can significantly reduce yields. In addition, news about delayed planting across a large area can cause volatility in commodity markets due to concerns about potential supply shocks. The findings can be useful for extension educators to advise farmers on optimal planting schedules and risk management strategies, including crop insurance options like prevented planting coverage. Therefore, the findings of our study offer valuable insights for developing extension programming in corn-growing regions.

Our study is not without limitations. A critical barrier in investigating the adaptation of cropping behavior to climate is the limited availability of quality datasets in finer spatio-temporal resolution. While the newly released NASS crop condition and progress layers are a welcome addition, their synthetic nature to protect the confidentiality of county-level information presents unique challenges in using them in research. Nevertheless, we overcame this limitation in our study by using a simple workaround of creating a proxy of the planting date. Future studies may extend our approach to the advanced stages of the growing season and potentially examine the impact of a warming climate on growing season length, much in the spirit of Cui and Xie (2022).

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