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Effects of water surplus on prevented planting in the US Corn Belt for corn and soybeans

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Effects of water surplus on prevented planting in the US Corn Belt for corn and soybeans

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Seunghyun Lee¹ and John T Abatzoglou² ¹ Department of Agricultural Economics and Economics, Montana State University, MT, United States of America² Management of Complex Systems, University of California, Merced, CA, United States of AmericaE-mail: seunghyun.lee@montana.edu**Keywords:** prevented planting, excess moisture, US Corn Belt, climate changeSupplementary material for this article is available [online](#)**Abstract**

Record-high prevented planting of staple crops such as corn and soybeans in the United States (US) Corn Belt due to heavy rainfall in recent years has spurred concern over crop production, as growing evidence suggests winter and spring precipitation extremes will occur more frequently in the coming decades. Using county-level data, we examine the effects of planting-season water surplus—precipitation minus evaporative demand—on prevented planting of corn and soybeans in the US Corn Belt. Using monthly water surplus data, we show significant impacts of excess moisture on preventing planting and suggest a 58%–177% increase in prevented planting during the months of April–June per standard deviation increase in water surplus. Downscaled climate change projections are used to estimate future changes in prevented planting during the mid-century (2036–2065) under the moderate emission scenario (RCP4.5). Our model predicts a *decrease* in prevented planting of approximately 111,000 acres (12%) for corn and 80,000 acres (16%) for soybeans in the US Corn Belt, relative to historical levels from 1950 to 2005. However, if we consider only precipitation and disregard evaporative demand, the alternative model indicates an *increase* of approximately 260,000 acres (30%) for corn and 86,000 acres (19%) for soybeans. Geographically, we find that prevented planting will slightly increase in some parts of Iowa, Minnesota, and Wisconsin and generally decrease in the other parts of the US Corn Belt. This work collectively highlights the value of incorporating water surplus data in assessing prevented-planting impacts and is the first known study to examine changing risk of prevented planting under future climate scenarios that may help inform adaptation efforts to avoid losses.

1. Introduction

Springtime adverse weather conditions, such as excess moisture, can prevent crops from being planted. For example, in 2019, anomalously high precipitation in the spring across the US Corn Belt led to a record-high of nearly 20 million acres of prevented-planting cropland, according to the U.S. Department of Agriculture (USDA). As agricultural production relies highly on climatic factors, there is a rich literature on the link between climatic conditions and agricultural outcomes. Most of the prior research focuses on the impacts of growing-season weather on crop yields (e.g. Lobell and Field (2007), Schlenker and Roberts (2009), Gammans *et al* (2017), Ortiz-Bobea *et al* (2019)). Another strand of literature has sought to understand acreage responses to past local growing-season weather (Cui 2020, Ramsey *et al* 2021). Although planting-season weather can also have a significant impact on crop production by reducing the planted area, the effects of planting-season weather on prevented planting have been understudied.

Previous studies (e.g. Miao *et al* 2016, Hendricks *et al* 2014) have documented that springtime heavy rainfall tends to reduce planted acreage, for example, due to the difficulty of operating machinery in wet soils (Sacks *et al* 2010). These studies include planting-season weather variables as controls in estimating acreage responses to

economic variables (e.g. crop prices). For example, Miao *et al* (2016) used monthly cumulative precipitation in March-May, and Hendricks *et al* (2014) used a dummy variable which equals one if precipitation in April is above a certain threshold level (e.g. 75th percentile). To our knowledge, Boyer *et al* (2022) is the only study that seeks to statistically characterize the relationship between planting-season weather and prevented planting. Using monthly precipitation and temperature data, they found that monthly precipitation from January to May affects prevented planting of corn while only precipitation in May and June impacts prevented planting of soybeans.

In this study, we leverage water surplus defined herein as precipitation minus evaporative demand to shed light on prevented planting of corn and soybeans in the US Corn Belt, which produces around 20% of the world's corn and soybeans. This measure can be viewed as a non-standardized version of the Standardized Precipitation Evapotranspiration Index (SPEI) (Vicente-Serrano *et al* 2010). The motivation for using a water surplus approach, as opposed to relying solely on precipitation data, is as follows. The ability of farmers to plant their intended crop depends not only on precipitation but also on evaporative demand, which is the rate at which water transfers from the land to the atmosphere and ultimately determines the near-surface soil moisture. Accounting for evaporative demand is essential because farmers have to wait until fields are dry enough for the planter to operate properly without causing soil compaction (Sacks *et al* 2010).

Accounting for evaporative demand is also important for assessing climate change impacts. Considering only precipitation may overestimate the impacts of planting-season weather on prevented planting in a changing climate and may lead to misleading adaptation strategies as evaporative demand is generally projected to increase (Vicente-Serrano *et al* 2020). Water surplus also provides a climatologically intuitive interpretation of parameter estimates in a statistical framework by simultaneously accounting for precipitation and evaporative demand. Most relevant to our study, Boyer *et al* (2022) separately estimated parameters on precipitation, precipitation squared, temperature, and the interaction of precipitation and temperature, making it difficult to interpret their empirical results. Using modeled soil moisture data could be an alternative appealing approach for our research questions, although projections of near-surface soil moisture at pertinent scales are limited. We opted to use water surplus because there are more extensive downscaled climate change projections on precipitation and evaporative demand than on soil moisture.

In the US Corn Belt, the most common cause (>90%) of prevented planting has been excess moisture (USDA Risk Management Agency 2021). Growing evidence suggests that parts of the US Corn Belt are projected to experience more frequent precipitation extremes as anthropogenic global warming continues (e.g. Zhou *et al* 2022). However, warming temperature in spring due to global warming can increase evaporative demand and can offset increases in precipitation, making net effects on water surplus and prevented planting less clear. To the extent that changes in water surplus over the planting season leave more land unplanted, efforts to meet the future food demand will be undermined.

This study consists of two main parts. In the first part, we ask how monthly water surplus in the planting season affects prevented planting in the US Corn Belt. In the second part, using a model developed from observations and downscaled climate change projections, we ask how the risk of prevented planting of corn and soybeans will change during the mid-21st century (2036–2065) to identify at-risk areas. Answers to these questions will help stakeholders and policymakers to make informed decisions to reduce the impacts of prevented planting.

2. Data and methods

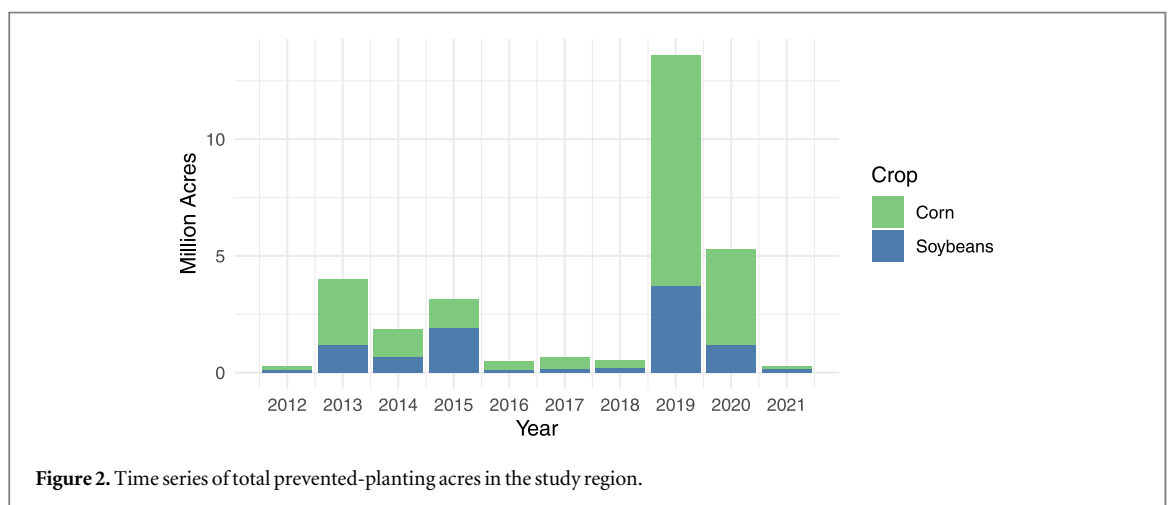
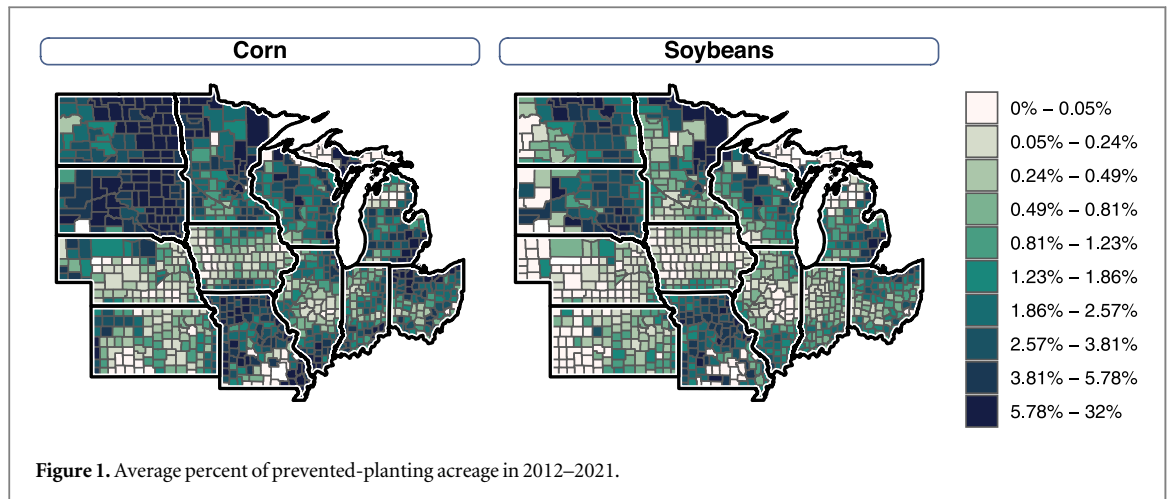
2.1. Study region

We focus our analysis on 12 states in the Midwestern US, which produce the majority of US corn and soybeans (See figure S1). In the region, the most active planting season is around May for both crops, although corn tends to be planted a few weeks earlier. To explore potential heterogeneous responses between regions, we divided the area into northern and southern regions, equally spaced by latitude, as shown in figure S1.

2.2. Data

2.2.1. Acreage

We source annual county-level crop acreage data from the USDA Farm Service Agency (FSA) for 2012–2021 (USDA Farm Service Agency 2021). The USDA FSA requires producers who participate in federal programs including crop insurance to file an annual report of all cropland use on their farms. Producers are required to report *prevented*, *planted* (and successfully harvested), and (planted but) *failed* acres by crop. Failed acreage is acreage that was timely planted with the intent to harvest but failed before it could be brought to harvest because of adverse conditions. Because prevented acreage is highly linked to the prevented planting provision of the US federal crop insurance program, it is worth describing prevented-planting acreage in the context of the program.



Under the program, prevented planting refers to the failure to plant an insured crop with the proper equipment by the final planting date. In our study region, the final planting dates are around the end of May for corn and mid-June for soybeans.

For the dependent variable, we calculate the ratio of prevented-planting acres to total acres—the sum of prevented, planted, and failed acres—for each crop and year. We refer to this measure as the prevented-planting share. It is worth emphasizing that the dependent variable has a non-zero value only when farmers file a claim for prevented planting. Thus, it is important to avoid interpreting our findings as being solely impacted by natural factors. Figure 1 presents the average prevented-planting shares in percentage terms for each crop and county from 2012 to 2021, while figure S2 displays maps of the average planted acres during the same period. Both for corn and soybeans, the prevented-planting share is high in the Prairie Pothole Region, which encompasses parts of North Dakota, South Dakota, and Minnesota. Figure 2 illustrates temporal variation in the total prevented-planting acres for corn and soybeans in the study region over the period. Prevented-planting acres were highest in 2019, reaching 13.6 million acres in the region (9.9 million for corn and 3.6 million for soybeans). In percentage terms, these numbers account for about 12% of the total corn acres (i.e. the sum of planted, prevented, and failed acres) and 5.6% of the total soybean acres (See figure S3).

2.2.2. Water surplus

We obtain daily (4km-resolution) gridded data on precipitation and evaporative demand from gridMET (Abatzoglou 2013). Evaporative demand was calculated using the Penman-Monteith equation for a reference grass crop. We define water surplus as precipitation (mm) minus evaporative demand (mm). To match the acreage data, we aggregate the gridded data to the county level using the fraction of cropland as weight in each gridMET grid. We identified cropland using land cover data from the National Land Cover Database (NLCD) (Dewitz 2019). For empirical analysis with monthly water surplus data, we compute water surplus for a month as the sum of daily water surplus in that month. Water surplus is essentially a non-standardized version of the Standardized Precipitation Evapotranspiration Index (SPEI) with a one-month time window

(Vicente-Serrano *et al* 2010). We use raw water surplus rather than SPEI because we are interested in approximating the actual soil moisture level, which biophysically may be a more accurate assessment of local water surplus than SPEI. Table S1 shows descriptive statistics of the data for empirical analysis.

2.2.3. Multivariate Adaptive Constructed Analogs (MACA)

To assess climate change impacts, we utilize 20 downscaled Global Climate Models (GCMs) of Coupled Model Intercomparison Project Phase 5 (CMIP5) from the Multivariate Adaptive Constructed Analogs (MACA) dataset (Abatzoglou and Brown 2012). MACA is a statistical method for downscaling GCMs from their native coarse resolution to a higher spatial resolution that reflects observed patterns of daily near-surface meteorology and simulated changes in GCMs experiments. We first obtain 4km-resolution monthly precipitation and evaporative demand data for the historical period (1950–2005) and the mid-century (2036–2065) under the moderate emission scenario (RCP4.5). We calculate monthly water surplus data as input into the aforementioned models that were empirically developed with observed data. Downscaled MACA data allow for interoperable use in climate impact assessments as they were created using gridMET as training data. As we did for observed weather data, we aggregate the gridded data to the county level using the fraction of cropland as weight in each MACA grid.

2.3. Regression model

To investigate the relationship between planting-season weather and prevented-planting share, we use the fixed-effects Poisson pseudo-maximum likelihood (PPML) estimator for the following consideration (Hausman *et al* 1984, Wooldridge 1999). More than 40% of the observations in the dependent variable of our data are zero. By naturally accommodating zero values without any transformation, the Poisson model produces consistent estimates that are interpretable as semi-elasticities. Even if the data generating process does not follow a Poisson distribution, the estimator is still consistent as long as the conditional mean is correctly specified. Admittedly, this robustness does not extend to estimated covariance matrices, but bootstrap could resolve this concern. In addition, the PPML does not suffer from the incidental parameter problem in the presence of fixed effects unlike other maximum likelihood estimators. The model can be also applied to a fractional or continuous variable (Silva and Tenreiro 2006, Gaule and Piacentini 2013, Zhao *et al* 2013).

2.3.1. Parametric estimation using monthly water surplus data

Our initial step is to estimate the following simple model:

$$a_{it} = \exp\left(\sum_{m \in M} \beta_m w_{mit} + \lambda_i + f(t)\right) \epsilon_{it}, \quad (1)$$

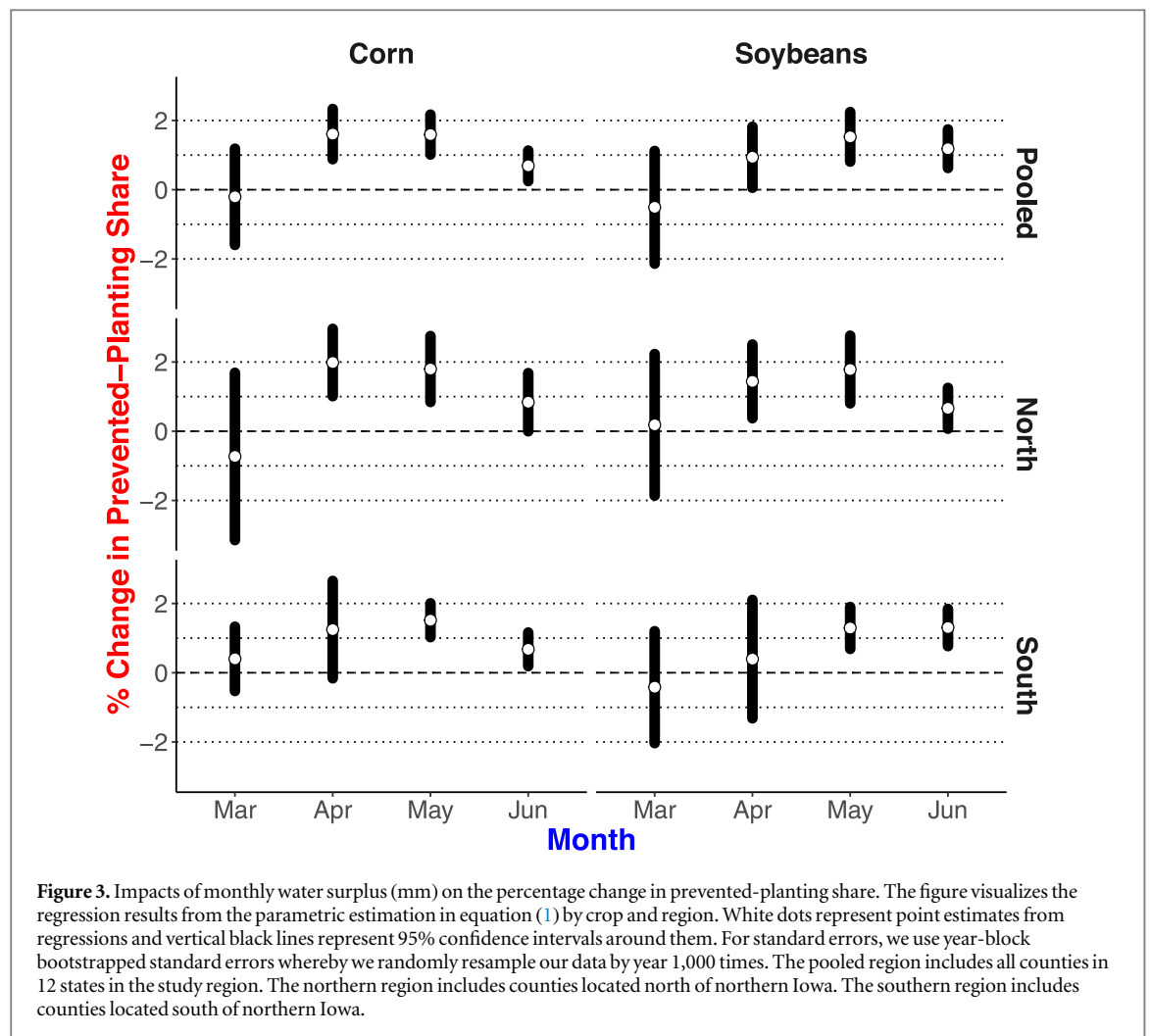
where a_{it} is the prevented-planting share in county i in year t . w_{mit} is monthly water surplus in month m in year t , and $M \equiv \{\text{March, April, May, June}\}$. λ_i is the county fixed effects, and $f(t)$ denotes a linear time trend, and ϵ_{it} is the error term. We will use this model in the next section when we assess climate change impacts on prevented planting. We run equation (1) separately for each crop and region. All of our regressions are weighted by crop-by-county total acres. For standard errors, we use year-block bootstrapped standard errors whereby we randomly resample our data by year 1,000 times. Resampling data by year assumes independence between years but accounts for any cross-sectional correlation.

2.3.2. Nonparametric estimation using binned monthly water surplus data

We have been assuming that the response of prevented-planting share to water surplus remains constant regardless of the level of water surplus, as long as the timing of water surplus is considered. However, the response could be nonlinear. For example, extremely wet conditions could have a more detrimental effect than moderately wet conditions. We explore potential nonlinear responses nonparametrically using a binned model. To do so, we bin monthly water surplus data into ten indicator variables using deciles of county-specific historical (1979–2021) distribution of monthly water surplus and estimate the following model:

$$a_{it} = \exp\left(\sum_{m \in M, d \in \{1, 2, 3, 4, 6, 7, 8, 9, 10\}} \beta_{m,d} \mathbb{I}\{w_{mit} \in Q_{mi,d}\} + \lambda_i + f(t)\right) \epsilon_{it}, \quad (2)$$

where \mathbb{I} is an indicator function that equals 1 if $w_{mit} \in Q_{mi,d}$ and 0 otherwise. $Q_{mi,d}$ denotes the interval of the d th decile of the historical distribution of water surplus for month m in county i . To avoid perfect multicollinearity, we drop the bin for the 5th decile in each month.



2.3.3. Semiparametric estimation using daily water surplus data

To investigate more detailed time-varying effects, we perform our analysis using daily water surplus. We estimate the regression of the form:

$$a_{it} = \exp(g(w_{1it}, \dots, w_{Dit}) + \lambda_i + f(t)) \epsilon_{it}, \quad (3)$$

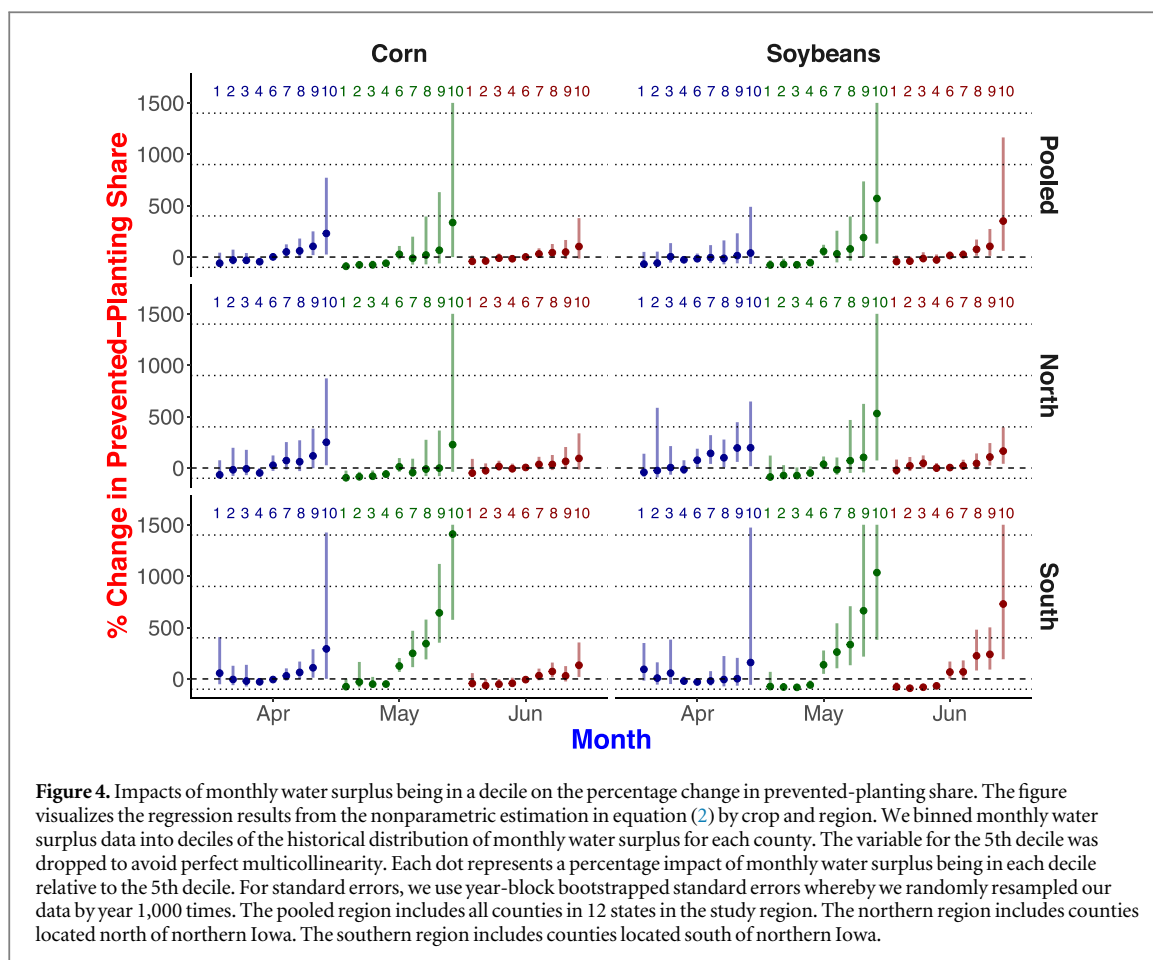
where D is the number of days between March 1 and July 30. We include July simply because estimated parameters are sometimes sensitively influenced by boundary values in semiparametric estimation. $g(\cdot)$ is a natural cubic spline. Unlike in the analysis using monthly water surplus variables, equation (3) restricts coefficients to vary smoothly over the planting season (See Supplementary Material for more details). We optimally choose the degrees of freedom ($df \in \{3, 4, 5, 6, 7, 8\}$) for $g(\cdot)$ for each crop and region using the root mean square error (RMSE) of year-block 10-fold cross validation.

3. Results

3.1. Regression results

Figure 3 shows the response of prevented-planting share to monthly water surplus with 95% confidence intervals. The figure suggests that water surplus in April–May (May–June) has large and statistically significant positive effects on the prevented-planting share of corn (soybeans) while water surplus in March has limited effects. We first interpret our results for the pooled region. Specifically, we find that a one standard deviation increase in water surplus in April (53 mm), May (64 mm), and June (66 mm) leads to an increase in the prevented-planting share of corn by 139%, 177%, and 58%, respectively. We calculated these numbers using the following formula:

$[e^{\hat{\beta}_m \sigma_m} - 1] \times 100\%$, where σ_m is the standard deviation of water surplus for month m in 1979–2021. These percentage effects correspond to 2.8 million, 3.7 million, and 1.2 million acres, assuming the total acres (the sum of planted, failed, and prevented acres) are fixed at the level of the last decade (2012–2021). Interestingly, based on the pooled model for corn, the coefficient on water surplus in June is also statistically significant at the 5% significance



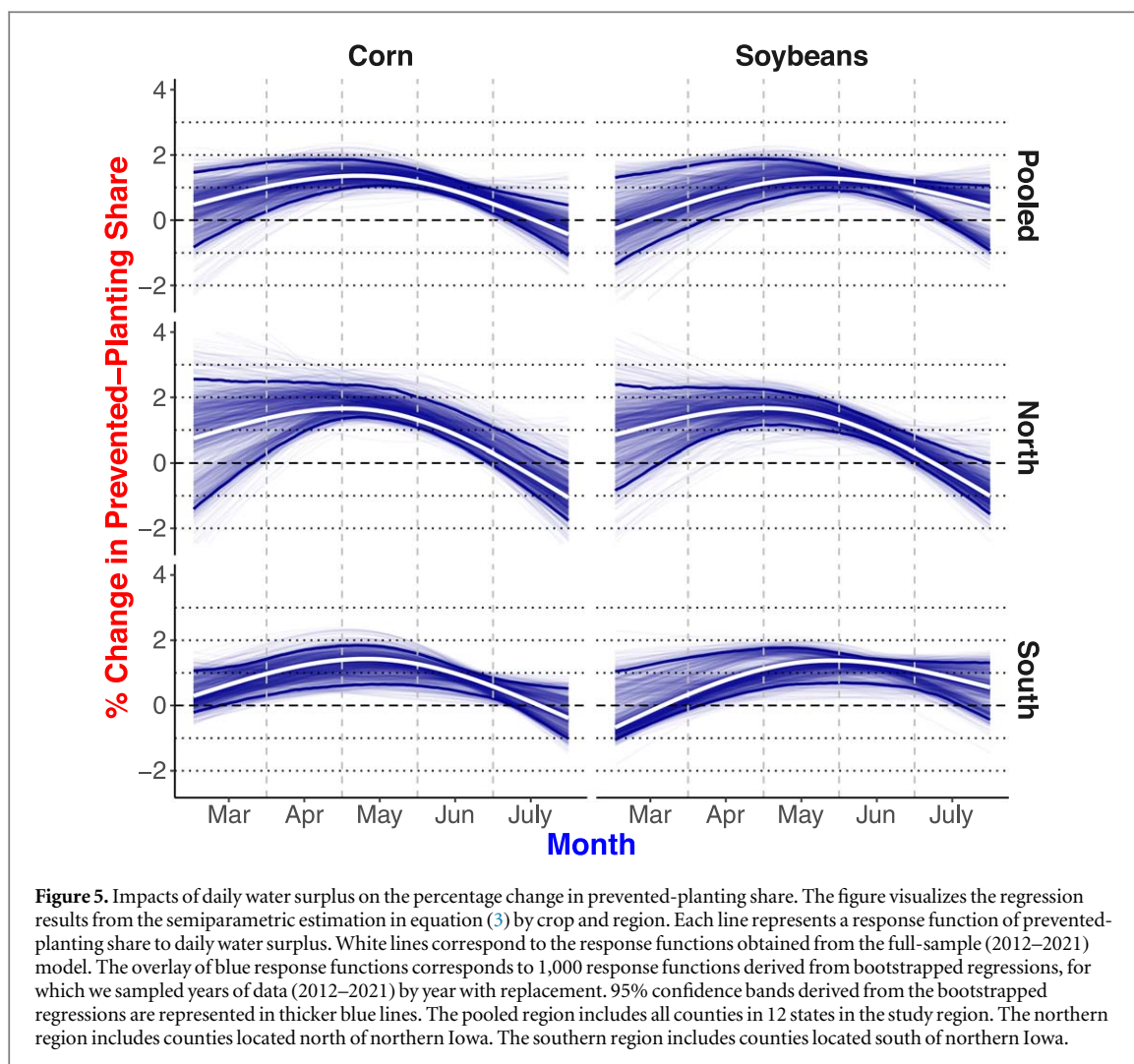
level although the magnitude is much smaller than that in April and May. One possible explanation is that the final planting dates for corn are early June in some southern parts of the study region.

We also find that soybeans are less susceptible than corn to high water surplus in April and more susceptible to that in June than corn. Specifically, for soybeans, a one standard deviation increase in water surplus in April, May, and June would lead to an increase in prevented-planting share by 65% (~0.6 million acres), 165% (~1.5 million acres), and 120% (~1.1 million acres), respectively. Our results also suggest that, when we use monthly water surplus rather than precipitation, goodness of fit—measured by McFadden’s pseudo R^2 —increases by 5%–7% (McFadden 1974). Similarly, the goodness of fit also increases by 5% when we use monthly water surplus rather than the total water surplus from March to June.

The results for the pooled region obscure heterogeneous responses between regions. In general, the northern region shows a stronger positive relationship between water surplus and prevented-planting share in April and May for both crops than its counterpart. On the other hand, in the southern region, the effect of water surplus remains relatively salient even in June and this tendency is particularly true for soybeans.

Figure 4 shows the percentage impacts of monthly water surplus being each decile relative to the 5th decile from the nonparametric estimation in equation (2). The numbers from 1 to 10 in each month represent the bins of the 1st to 10th decile of the historical distribution of monthly water surplus. (In figure S4, we show the coefficients and confidence intervals used to calculate the percentage impacts). The figure indicates that an extremely wet condition in the southern region can be highly damaging for both crops. To be specific, an event of monthly water surplus in the 10th decile in May increases prevented-planting share by 15 times for corn and by 11 times for soybeans relative to an event of the 5th decile. In the northern region, extremely wet conditions appear to be less damaging than those in the southern region. However, for soybeans in the northern region, an extremely wet condition in May (i.e. 10th decile) could increase prevented-planting share more than 6 times relative to an event of the 5th decile in May.

Figure 5 shows the time-varying effects of daily water surplus on prevented-planting share. The results for the pooled region suggest that corn is most sensitive to water surplus around early May whereas soybeans are most sensitive to water surplus around late May. To be specific, a one standard deviation increase in water surplus on the estimated most critical date for corn, May 6, increases prevented-planting share by 8.7% (~180,000 acres), while a one standard deviation increase in water surplus on the estimated most critical date for



soybeans, May 23, increases prevented-planting share by 9% (~84,000 acres) (See table S3 for more detailed calculation and results). Based on the results for subregions, we also find that, while early May is the most critical time window for corn and soybeans in the northern region and corn in the southern region, late May is the most critical time window for soybeans in the southern region.

3.2. Climate change impact assessment

To assess the impacts of climate change on prevented planting, we utilize 20 downscaled climate projections from MACA and the crop-specific regression results for the pooled region from parametric estimation using monthly water surplus data. In this paper, we focus on climate change impacts under the moderate emission scenario (RCP4.5) during the mid-century (2036–65). In Supplementary Material, we additionally consider the high emission scenario (RCP8.5) and the end of the century (2070–99) (See figures S7 and S8 and table S4).

We begin by presenting the aggregate-level projected impacts. Based on the median of the 20 downscaled climate projections, our model predicts a decrease in prevented planting of approximately 12% (equivalent to 111,000 acres assuming intended acreage fixed at the level of the last decade (2012–2021)) for corn and 16% (~80,000 acres) for soybeans in the US Corn Belt under the moderate emission scenario (RCP4.5) during the mid-21st century (2036–65), relative to historical levels from 1950 to 2005. However, if we consider only precipitation and disregard evaporative demand, the alternative model predicts an increase of approximately 30% (~260,000 acres) for corn and 19% (~86,000 acres) for soybeans (See table S4 for additional results and details). Furthermore, as table S4 shows, the precipitation model indicates that prevented planting will be larger under the high emission scenario (RCP8.5) than under the moderate emission scenario (RCP4.5), while the water surplus model suggests the opposite trend. These findings suggest that despite the projected increase in precipitation in a changing climate, the rise in evaporative demand is expected to surpass the effects of increased precipitation in the US Corn Belt during spring planting. Our findings collectively highlight the significance of considering evaporative demand when assessing climate change risks associated with prevented planting.

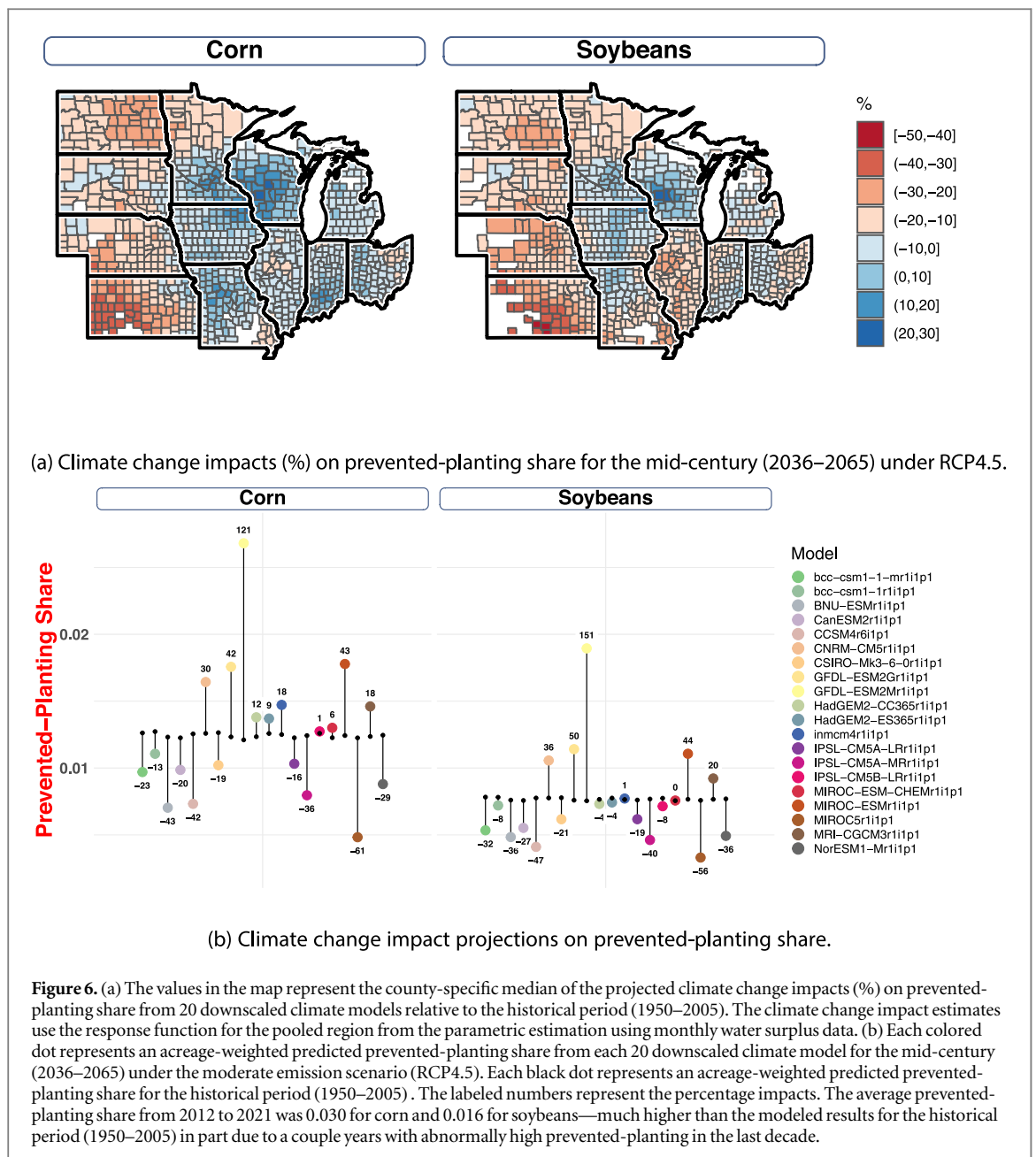


Figure 6(a) shows the spatial distribution of the percentage impacts of climate change on prevented-planting share. Based on the county-specific median of the 20 downscaled climate projections, our results indicate that prevented planting will decrease in many parts of the US Corn Belt. For example, the prevented-planting share of corn is projected to decrease by 10%–40% (~1–6,649 acres) in North Dakota and South Dakota where prevented planting has been historically a major concern. This finding is of great importance and relevance in a changing climate given that the two states have seen the most extensive growth of corn and soybean acreage in the past decades due to a warming trend (Cui 2020). Our modeled results also suggest that prevented planting is projected to increase in some parts of Iowa, Minnesota, and Wisconsin by 0%–30% (~0–267 acres), particularly for corn.

Anticipating heightened precipitation levels during the spring in many areas of the northern region, the projected decrease in prevented planting across multiple parts of the US Corn Belt can be attributed to an accompanying rise in evaporative demand in a changing climate. This increased evaporative demand would lead to drier planting conditions, ultimately reducing the occurrences of prevented planting. Figure S6 shows the county-specific medians of the projected changes in water surplus under the moderate emission scenario in the mid-century. As the figure shows, many parts of North Dakota and South Dakota are expected to see a decrease in water surplus in April and May. The opposite is true for the region expected to see an increase in prevented planting.

One might wonder if the statistical model we employ to assess the impacts of climate change varies across space and time, given that prevented planting tends to be concentrated in wet regions and years. To address this question, we calculate out-of-sample errors measured by Normalized Root Mean Square Errors (NRMSE) on a

yearly basis. In other words, we utilize all years except one as a training dataset and assign the unused year as an out-of-sample year. The use of this normalized measure is motivated by the significant variability in prevented planting across various regions and crops. Figure S5(a) illustrates the average out-of-sample errors across test years for individual counties. The figure suggests that the model's performance is noticeably lower in certain parts of the southern region where prevented planting is uncommon. Figure S5(b) displays the average out-of-sample errors across counties for each test year. It indicates that when data from typical years (i.e. all years from 2012 to 2021 except for 2019) are used, the model struggles to predict prevented planting in an unusually wet year, such as 2019. This outcome underscores the importance of including the wet year in the training dataset to enhance predictions for future years prone to flooding.

It is worth emphasizing that farmers' adaptive responses to a changing climate could mitigate potential acreage losses. For example, warmer temperatures during late winter or early spring may allow farmers to start planting a few weeks earlier. This shift in timing could potentially provide farmers with greater flexibility to adjust their planting dates. Besides planting date adjustments, farmers can take a variety of adaptation strategies to reduce acreage losses: planting cover crops to improve water infiltration of the soil, installing drainage tiles, outsourcing some planting operations to a custom operator, and investing in machinery that could reduce the total hours of planting time (Edwards and Hanna 2020).

It should be also noted that we assessed climate change impacts using the median projections but there are substantial differences in projected impacts across climate models. Figure 6(b) shows aggregate-level impacts for the study region across 20 downscaled climate models under the moderate emission scenario (RCP4.5) during the mid-century (2036–2065). The figure suggests that there is substantial climate uncertainty about how changes in water surplus during the springtime period would affect prevented planting.

4. Conclusion

In this paper, we sought to establish the relationship between planting-season water surplus and prevented planting of corn and soybeans in a wide expanse of the US Corn Belt. Using water surplus that accounts for both precipitation and evaporative demand, we find that wet conditions in April-May (May-June) tend to significantly increase prevented planting for corn (soybeans). Using nonparametric estimation, we also document that extremely wet events in the critical planting window can detrimentally increase prevented planting, particularly in the southern portion of the region.

We have a caveat. Our study region has a unique institutional context not to mention biophysical environments. Thus, our results might not hold in other contexts or regions. A large portion of farmers participates in the federal crop insurance program, which has its unique prevented-planting provisions. This means that our results reflect farmers' behavioral responses driven by incentives they face under the current prevented-planting provisions in the federal crop insurance policies, although, of course, weather is the key driver of prevented-planting acreage (Rejesus *et al* 2005, Kim and Kim 2018, Wu *et al* 2020).

Unlike Boyer *et al* (2022), we do not find that planting-season weather in March plays an important role in determining the prevented-planting share of corn. One possible explanation is that their standard errors do not account for the correlation across cross-sectional units (here, counties) in the data even though the amount or fraction of prevented-planting area is highly spatially correlated. Their assumption of spatially uncorrelated errors could have led to over-rejection of the null hypothesis of no effect in March. In addition, our result indicates that monthly water surplus in June has a statistically significant effect on the prevented-planting share of soybeans, although Boyer *et al* (2022) finds mixed results for precipitation and temperature in June. We posit that our different result stems from the fact that we harness a weather variable that simultaneously accounts for precipitation and evaporative demand.

Our climate change impacts assessments suggest that prevented planting is projected to decrease in the Prairie Pothole Region—where prevented-planting acres tended to be high—in a changing climate. Such decline is due to a warming trend that increases evaporative demand. In some northern parts of the US Corn Belt, it appears that rising evaporative demand is not enough to offset the effect of increasing precipitation in the planting season on prevented planting. As a result, prevented planting is projected to increase in the region relative to their historical levels.

It should be noted that these assessments are based on the median projected impacts among 20 climate models and there is a substantial difference among the projected impacts from different climate models. In addition, our projections target an average future planting season, meaning that our results are silent about how potential increases in inter-annual variability of planting season weather would affect prevented planting. A potential avenue for future research is to examine the effects of changes in extreme weather intensity and frequency during the planting season on prevented-planting cropland. Another potential area for future research is the use of modeling to investigate how soil properties and other biophysical factors influence soil saturation and its relation to prevented planting.

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Data availability statement

No new data were created or analysed in this study.

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References

- Abatzoglou JT 2013 Development of gridded surface meteorological data for ecological applications and modelling *Int. J. Climatol.* **33** 121–31
- Abatzoglou JT and Brown T J 2012 A comparison of statistical downscaling methods suited for wildfire applications *Int. J. Climatol.* **32** 772–80
- Boyer C N, Park E and Yun S D 2022 Corn and soybean prevented planting acres response to weather *Applied Economic Perspectives and Policy* **45** 970–83
- Cui X 2020 Climate change and adaptation in agriculture: evidence from US cropping patterns *Journal of Environmental Economics and Management* **101** 102306
- Dewitz J 2019 National Land Cover Database (NLCD) 2016 Products: U.S. Geological Survey data release, Available at <https://doi.org/10.5066/P96HHBIE>, accessed: December 10, 2021.
- Edwards W and Hanna M 2020 Iowa State University Extension and Outreach, Available at <https://extension.iastate.edu/agdm/crops/html/a3-25.html/>, accessed on January 05, 2022.
- Gammans M, M  rel P and Ortiz-Bobea A 2017 Negative impacts of climate change on cereal yields: statistical evidence from France *Environ. Res. Lett.* **12** 054007
- Gaule P and Piacentini M 2013 Chinese graduate students and US scientific productivity *Review of Economics and Statistics* **95** 698–701
- Hausman J, Hall B H and Griliches Z 1984 Econometric models for count data with an application to the patents-R&D relationship *Econometrica* **52** 909–38
- Hendricks N P, Smith A and Sumner D A 2014 Crop supply dynamics and the illusion of partial adjustment *American Journal of Agricultural Economics* **96** 1469–91
- Kim T and Kim M-K 2018 Ex-post moral hazard in prevented planting *Agricultural Economics* **49** 671–80
- Lobell D B and Field C B 2007 Global scale climate-crop yield relationships and the impacts of recent warming *Environ. Res. Lett.* **2** 014002
- McFadden D 1974 Conditional logit analysis of qualitative choice behavior *Frontiers in Econometrics*
- Miao R, Khanna M and Huang H 2016 Responsiveness of crop yield and acreage to prices and climate *American Journal of Agricultural Economics* **98** 191–211
- Ortiz-Bobea A, Wang H, Carrillo C M and Ault T R 2019 Unpacking the climatic drivers of US agricultural yields *Environ. Res. Lett.* **14** 064003
- Ramsey S M, Bergtold J S and Heier Stamm J L 2021 Field-level land-use adaptation to local weather trends *American Journal of Agricultural Economics* **103** 1314–41
- Rejesus R M, Escalante C L and Lovell A C 2005 Share tenancy, ownership structure, and prevented planting claims in crop insurance *American Journal of Agricultural Economics* **87** 180–93
- Sacks W J, Deryng D, Foley J A and Ramankutty N 2010 Crop planting dates: an analysis of global patterns *Global Ecol. Biogeogr.* **19** 607–20
- Schlenker W and Roberts M J 2009 Nonlinear temperature effects indicate severe damages to US crop yields under climate change *Proc. Natl Acad. Sci.* **106** 15594–8
- Silva J S and Tenreiro S 2006 The log of gravity *Review of Economics and Statistics* **88** 641–58
- USDA Farm Service Agency (2021): Crop Acreage Data, Available at <https://fsa.usda.gov/news-room/efoia/electronic-reading-room/frequently-requested-information/crop-acreage-data/index>, accessed: December 10, 2021.
- USDA Risk Management Agency (2021): summary of Business, Available at <https://rma.usda.gov/SummaryOfBusiness/CauseOfLoss>, accessed: December 06, 2021.
- Vicente-Serrano S M, Beguer  a S and L  pez-Moreno J I 2010 A multiscale drought index sensitive to global warming: the standardized precipitation evapotranspiration index *J. Clim.* **23** 1696–718
- Vicente-Serrano S M, McVicar T R, Miralles D G, Yang Y and Tomas-Burguera M 2020 Unraveling the influence of atmospheric evaporative demand on drought and its response to climate change *Wiley Interdiscip. Rev. Clim. Change* **11** e632
- Wooldridge J M 1999 Distribution-free estimation of some nonlinear panel data models *Journal of Econometrics* **90** 77–97
- Wu S, Goodwin B K and Coble K 2020 Moral hazard and subsidized crop insurance *Agricultural Economics* **51** 131–42
- Zhao Y, Tang K K and Wang L-L 2013 Do renewable electricity policies promote renewable electricity generation? Evidence from panel data *Energy Policy* **62** 887–97
- Zhou W, Leung L R and Lu J 2022 Seasonally dependent future changes in the US Midwest hydroclimate and extremes *J. Clim.* **35** 17–27