Identifying climatic constraints of US agriculture

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Abstract

The paper estimates the countervailing climatic factors driving the timing of US corn planting decisions. We combine very diverse sources of data, including daily fine-scale satellite-derived information, to infer the timing of planting decisions over the past 30 years at the county-level. We match this information with daily data on temperature and soil moisture conditions to assess their contributions to the planting decision. Using a panel logit model we find that warmer spring temperatures increase the probability of planting, while extremely low or high levels of moisture reduce it. We find that the levels of moisture necessary to fully offset the season-expanding effect of a temperature rise of 3ºC would need to be very extreme, suggesting that the growing season for corn is likely to expand with climate change.

Keywords: agriculture, climate change, adaptation, planting dates, corn, temperature, soil moisture, panel logit

JEL codes: Q54, Q19

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1. Introduction

A large literature is focusing on assessing the potential of agricultural adaptation to climate change using statistical approaches. A common practice in this literature is to assume that weather is additive and growing seasons remain fixed. This is reflected in the construction of weather and climate variables aggregated over several months and climate projections that refer to same time period. If invalid, these assumptions impose restrictions on farmers' ability to adjust to a different climate and related studies may overstate projected climate change damages.

A growing body of work suggests that weather has different effects on crop production throughout the growing season and that sensitive periods are likely to be confined to relatively short periods of time (Ortiz-Bobea and Just, 2013). This has interesting implications for the analysis of agricultural adaptation to climate change. A first-order adaptive response resulting from non-additivity of weather is for farmers to change planting dates and cultivars to reduce the exposure of sensitive periods of the growing season to detrimental parts of the year.

Adaptive response in the timing of the growing season may be possible because a warmer climate results in a longer non-freezing period, which is arguably a limiting factor in many temperate areas across the country. Ortiz-Bobea and Just (2013) find that earlier corn planting across large parts of the Midwest could reduce yield losses from summer heat by 50 to 70 percent under a uniform warming scenario of 5ºF. As that study indicates, this could represent an important channel of adaptation in US crop agriculture. Interestingly, there is suggestive evidence that recent increases in corn yields in the Midwest may be partly attributed to earlier planting (Kucharik, 2008).

However, the encouraging adaptation possibilities of shifting growing seasons depend on farmers' ability to change planting dates, especially to earlier periods of the spring. It is well known that warmer springs result in earlier planting in the Midwest. Warm and appropriate moisture field conditions in the springs of 2010 and 2012 resulted in earlier corn planting by 1 to 2 weeks. On the other hand, cool and excessively wet conditions have the opposite effect. The wet springs of 1993 and 2013 resulted in corn planting delays of 1 to 2 weeks across the Midwest. Indeed, excessively moist soils reduce the number of available days of fieldwork for the agricultural machinery involved in planting operations. It remains unclear if farmers may be able to benefit from a longer growing season because excessive moisture might offset the effects of warmer spring.

Very few studies have empirically analyzed the driving factors of growing seasons and planting dates. Waha et al. (2012) use deterministic crop models to establish optimal planting dates for a number of crops across the world. While useful for assessments of climate change impacts and adaptation based on crop process models (e.g. Stehfest et al 2007), these approaches are poorly integrated with observational data. Sacks et al (2010) is the only study we've found attempting to assess the drivers of planting decisions empirically. The study assembles a large dataset of usual planting and harvesting dates for 19 major global crops and estimate how these are explained by 30-year climate normals for temperature, precipitation and potential evapotranspiration. The study finds that conditions at planting are fairly consistent in temperate areas, and that temperature is the major factor explaining the timing of planting. However, planting dates are found to be less predictable in tropical regions and the authors suggest that the timing of planting in these regions might be driven by an attempt to match the growing season to more beneficial portions of the year, rather than taking advantage of a longer growing season. However, the study is based on cross-sectional evidence and is therefore not able to provide evidence of how inter-annual variation in weather might be affecting planting decisions. Moreover, the study did not attempt to project how farmer might respond in response to climate change.

The objective of this paper is to provide, to our knowledge, the first estimates of the climatic factors driving the onset of the growing season for a major US crop. The study relies on a rich combination of data sources for estimating the drivers of planting decisions. We combine satellite data of various types to temporally and spatially downscale weekly state-level crop progress data to daily and fine-scale observations. We match corn planting behavior across the Midwest over the past 30 years with daily high resolution environmental data that includes temperature and soil moisture levels. We model the decision to plant as binary outcome under a latent-variable context and we use a panel logit model to estimate the climatic drivers of planting decisions. The paper is organized as follows. Section 2 provides a detailed description of the data sources and how the dataset for the regression analysis was constructed. Section 3 presents how the downscaling of satellite data was performed to infer fine scale planting behavior. The model and regression results are presented in sections 4 and 5 and section 6 concludes.

2. Methodology

The objective of the paper is to identify the climatic constraints that drive the growing seasons in US crop agriculture. The results are important for assessing climate change impacts of agriculture because shifting growing seasons is a potentially important and easy adaptive response. As suggested by Sacks et al (2010), the factors driving the timing of growing seasons are complex. Some of the factors influencing the decision to plant include the field and weather condition at planting (contemporaneous conditions) but also the expected conditions later in the season, especially during key stages of the crop cycle (expected conditions). Given the complexity of empirically assessing the role contemporaneous and expected field and environmental conditions in the planting decision, we confined ourselves, at this stage, to identifying the contemporaneous conditions. Future work might address the role of expected conditions during key parts of the season.

The approach we undertake is to estimate the decision of planting as explained by a set of daily environmental covariates. We construct a county-level panel dataset with a daily time step covering the 60 days surrounding the planting decision over the 1981 to 2010 period. Because planting date data is only available at the state-level and on a weekly basis, the use satellite data to “downscale” the planting date to much finer spatial (5-km) and temporal (daily) resolutions. We present this approach later in this paper and show a validation based on district level planting data available for the state of Illinois. We then proceed to aggregate the newly generated panting data to the county-level given the high degree of spatial correlation at such a fine scale. We then match the county-level planting data with temperature and soil moisture data, also available at the county and daily levels.

We model the planting decision as a climate-sensitive input decision that affects crop yield.[4] Empirically, we estimate a panel logit model where the dependent variable takes the value of 0 if planting has not occurred and 1 otherwise. The independent variables include minimum temperature and moisture conditions of the superficial soil layers. We consider several specifications allowing for the relevant conditions to span over time windows of varying lengths around panting time.

3. Data

3.1 Normalized Difference Vegetation Index data

We used remote sensing data for its spatial and temporal consistency and coverage as well. Daily, 0.05° resolution Normalized Difference Vegetation Index (NDVI) data from Long Term Data Record (LTDR) is used as an input data for its strong correlation with vigor, stress, green biomass and photosynthetic capacity of vegetation (Becker-Reshef et al., 2010). The LTDR is the data set made by processing the Advanced Very High Resolution Radiometer (AVHRR) GAC (Global

[4] This could happen either through the choice of longer season cultivars or by avoiding exposure to detrimental conditions later in the growing season, e.g. hot and dry summer spells during the sensitive flowering stage.

Area Coverage) and Moderate Resolution Imaging Spectroradiometer (MODIS) CMG (Climate Modeling Grid) time-series with vicarious calibration, Bidirectional reflectance distribution function (BRDF) correction, improved Quality Assessment, geo-location algorithms (Pedelty et al., 2007).

NDVI is most popular satellite derived vegetation index and successfully applied for many previous phenology studies (Tucker & Sellers, 1986).

$$NDVI = \frac{RED - NIR}{RED + NIR}$$

The NDVI is computed from the ratio of red and infrared reflectance. NIR and RED are the amounts of near-infrared and red light, respectively, reflected by the vegetation and captured by the sensor of the satellite (Pettorelli et al., 2005).

Median and Standard deviation from the NDVI time series data spanning from 1981 to 2010 are used to identify and filter erroneously high or low NDVI value. Then, weighted least squares linear fit model is applied to smooth NDVI time series. Weighted least squares linear fit model is a non-parametric function which performs a locally weighted linear regression to compute the smoothed value at each point based on a defined window size (Pouliot et al., 2008). Not like parametric functions, such as logistic functions, non-parametric method does not assume a priori shape of time series. This characteristic make the non-parametric function more appropriate for a range of land cover types (Bradely et al., 2007). In this research, a span of 0.2 was used with three iterations for a robust fitting.

3.2 Cropland Data Layer

National Agricultural Statistics Service Cropland Data Layer (NASS-CDL) from 2000 and 2010 are used to count target maize and soybean pixels within each NDVI pixels. The NASS-CDL classifies specific crop types and is generated using Landsat 5 Thematic Mapper (TM) and Landsat 7 Enhanced Thematic Mapper (ETM+) data.[5] The count of CDL pixels of the target crop within a NDVI pixel was used as a weighting factor representing the portion of the target crop within each NDVI pixels and as a guide to decide each of NDVI pixels as the pixel of the target crop with a selected threshold.

3.3 Crop Progress Data

State level crop progress data was obtained from USDA National Agricultural Statistics Service (NASS). The data is available on a weekly basis for major crops and producing states since the 1980s. These reports provide information on the share of state acreage that has undergone particular crop stages or farm operations, such as planting and harvesting. This state-level weekly data is used as the 'reference' for downscaling the satellite-derived information to infer planting behavior at a finer spatial (county) and temporal (daily) scale. Crop progress reports for Illinois were also obtained at the district level (a combination of counties smaller than the state) to carry out the out-of-sample validation of the downscaling routine described in the next section.

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[5] Available for download at: http://www.nass.usda.gov/research/Cropland/SARS1a.htm

3.4 Climate data

covering 1979 to present.

The climate data used in this study was obtained from the North American Land Data Assimilation System (NLDAS). NLDAS is a framework developed by NASA, NOAA, Princeton University and University of Washington, that incorporates atmospheric forcing and land parameter values along with land surface models to diagnose and predict the state of the land surface (Mitchell et al 2003). The dataset provides hourly data based for every 14-km grid over the lower 48 states since 1979. We obtain air temperature and soil moisture for the top soil layer (0-10cm) from this dataset. It is worth mentioning that the NLDAS data has been validated and found to closely match observations for both weather and soil moisture readings (Luo et al 2003 and Xia et al 2012, respectively). For the purpose of our study we aggregated the hourly information to the day and obtain minimum and maximum air temperature as well as average soil moisture content. The data was subsequently aggregated to the county level for each day by weighting each NLDAS data grid by average amount of cropland planted in corn during the 2008-2012 time period based on the CDL.

4. Inferring planting behavior from satellite data

4.1 Objective

In order to do our empirical analysis, we first need to identify our dependent variable (planting behavior of farmers) very precise level. However, the data of planting behavior is only available in state level in government data. Therefore we need a method to identify planting behaviors of farmers in a more precise level.

One possibility is to infer planting behavior of farmers from satellite data. First we could define a resolution level (for example, a pixel is defined as a circle with 15 meters radius) in using the satellite data. Then secondly we could observe the level of greenness for each pixel across the whole year. Through observations of the level of greenness in a particular year, we could then infer planting behaviors of farmers. For example, for a particular pixel, when level of greenness reaches a certain level, we infer that a particular stage of crops starts in that pixel. We repeat the same process for every stage of crops, then we could extract the exact day of year when crops in that particular pixel planted, emerged, etc. Eventually for each stage of the crops, we could predict the exact day of year when that stage happened for every pixel in the U.S. i.e., we could study planting decisions of farmers in pixel level instead of state level.

The main question in this method is how to find an optimal way in matching satellite data with actual government data. This question could be interpreted as (for example), for each pixel how should we choose the threshold of level of greenness that determines when crops are planted? We proposed two approaches to answer this question. In brief, those two approaches implemented a similar optimization routine (with different parameters) in minimizing the difference between predicted data and actual data collected by the government (in aggregate level). To be more specific, for every state in the U.S. the government data records the advancement of crops in a particular stage.

For example, figure 1 explains in state “47” the advancement of Corn in stage silking in year 2005. Then with the help of two different approaches, we could obtain when silking starts for every pixel in state “47”. Afterwards we use the information of when silking starts for each pixel to derive the predicted aggregate-level advancement of Corn in state “47”. At last we change the value of parameters in the two approaches mentioned above to minimize the difference between actual aggregate-level data (USDA data) and our predicted aggregate-level data (NDVI data).

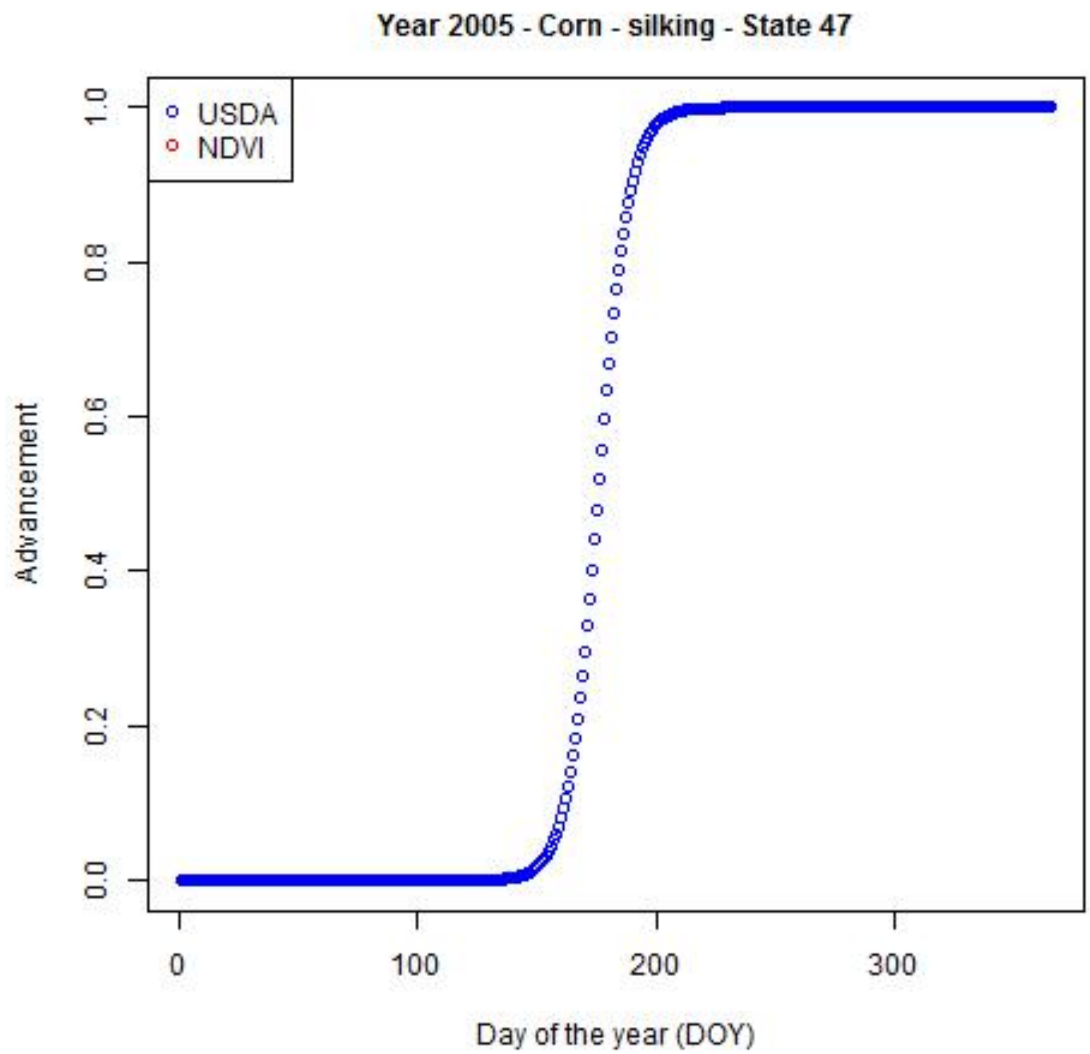

Figure 1 State-level progress for the corn "silking" stage in Tennessee in 2005

Figure 2 below illustrates how we compare actual and predicted data. In each approach a parameter is used to determine the threshold of levelof greenness for each stage of the crops. The parameter is contemporarily homogeneous for a certain crop in a particular state and stage. It varies across time, type of crops, state and stages of a particular crop. In the subsection below we will discuss how we could obtain an optimal value of parameters in each approach.

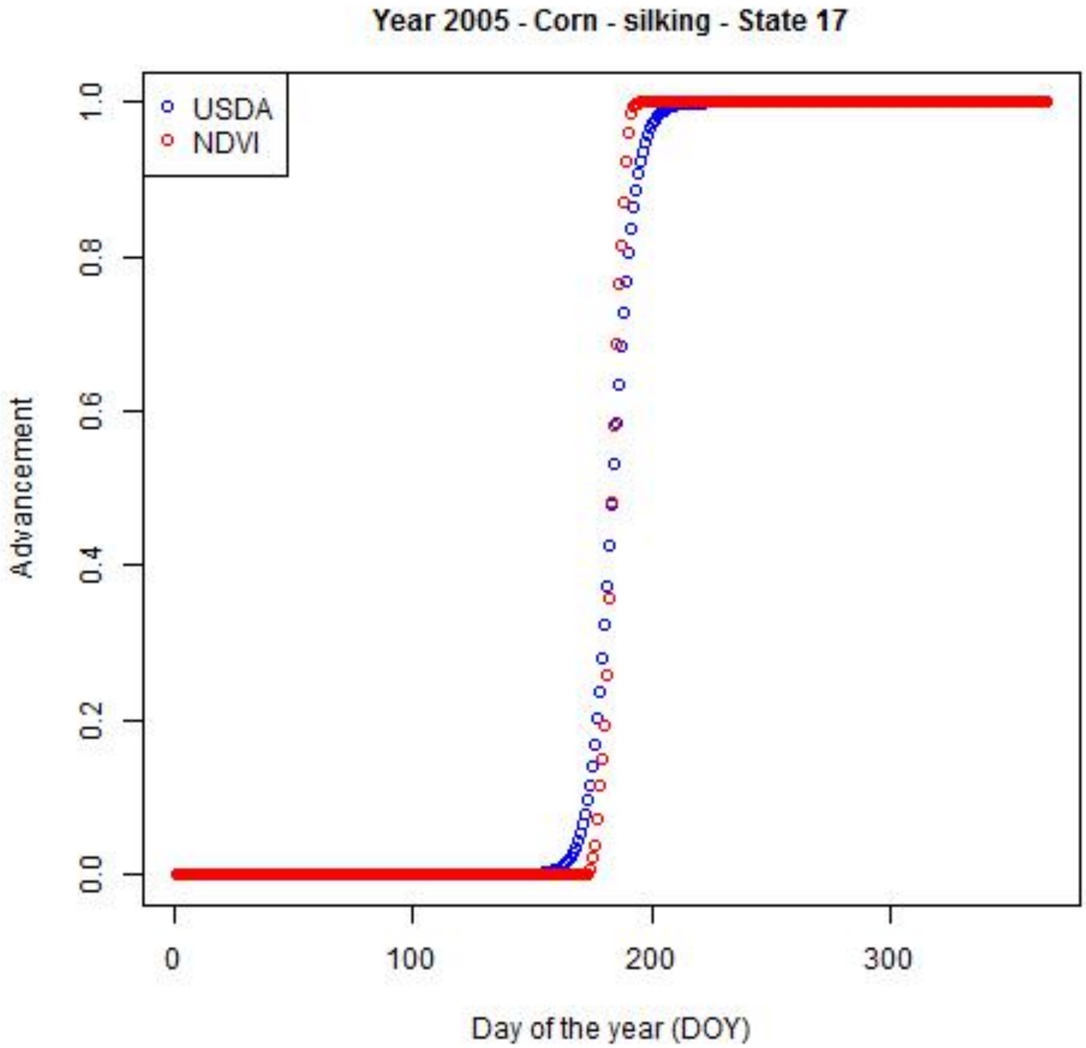

Figure 2 Comparison of state-level US crop progress and state-level NDVI variable for Illinois in 2005

4.2 Approach

In a certain state, for a particular pixel we need to define the threshold of level of greenness to determine when each stage of a crop starts. Two approaches are proposed to determine the threshold.

The first approach (approach alpha) uses the cumulative level of greenness to determine when each stage of a crop starts. As shown in figure 3, when the cumulative level of greenness exceeds certain threshold (parameter a), we define the corresponding day of year as the start of that stage. For example in figure 3, for pixel #33 in Illinois, corn emerged at the 100th day of year in 2005. The parameter a varies across time, type of crops, state and stages of a particular crop. i.e. In determining when corn emerged in Illinois in year 2005, the value of parameter a is unique and holds the same for all pixels inside Illinois in year 2005. The value of a changes in all other cases. Given the value of parameter a, we could derive when each stage of a crop starts for every pixel inside a state. Afterwards we could use this information to derive the predicted planting behaviors in aggregate-level. The last step is to use an optimization algorithm to obtain the optimal value of parameter a which minimizes the difference between predicted aggregate-level data and actual aggregate-level data (figure 4).

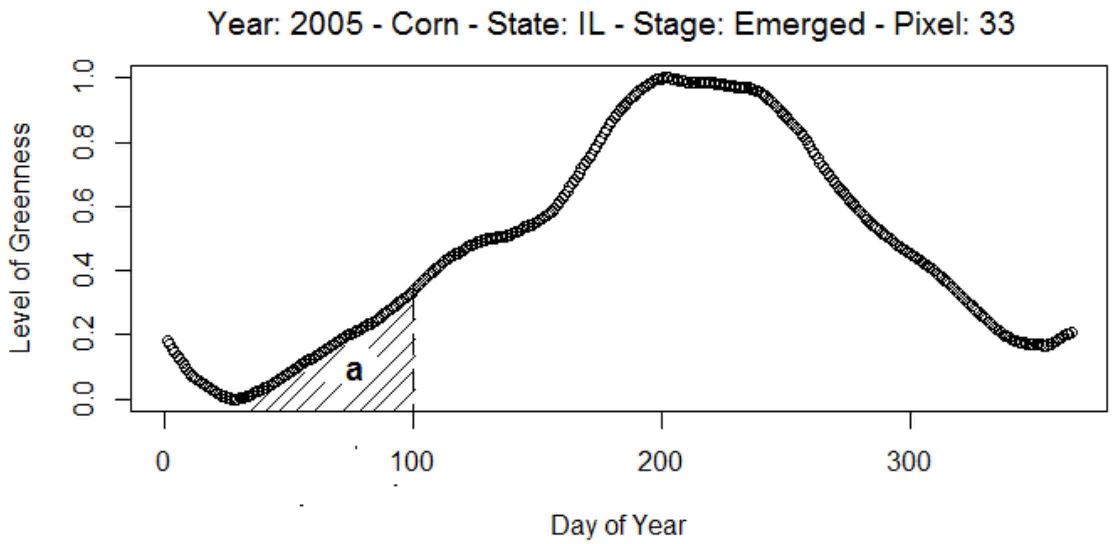

Figure 3 The alpha method

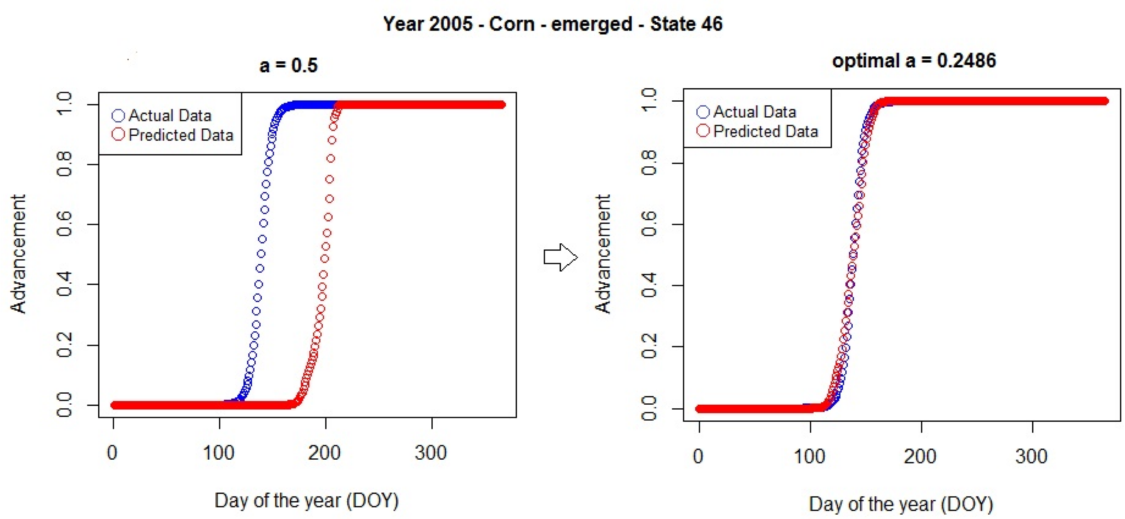

Figure 4 The alpha method at work

The second approach (approach beta) uses the magnitude of level of greenness to determine when each stage of a crop starts. In approach beta, for each pixel we first normalize its level of greenness to make the level of greenness always start from level 0 and ends at level 1. Then for each pixel we rescale its level of greenness to assure monotonicity of its level of greenness (figure 5). (No rescaling or normalization is implemented in approach alpha). In approach beta, when the absolute magnitude of level of greenness exceeds certain threshold (parameter b), we define the corresponding day of year as the start of that stage. Then similar to approach alpha, we use an optimization algorithm to find the optimal value of parameter b.

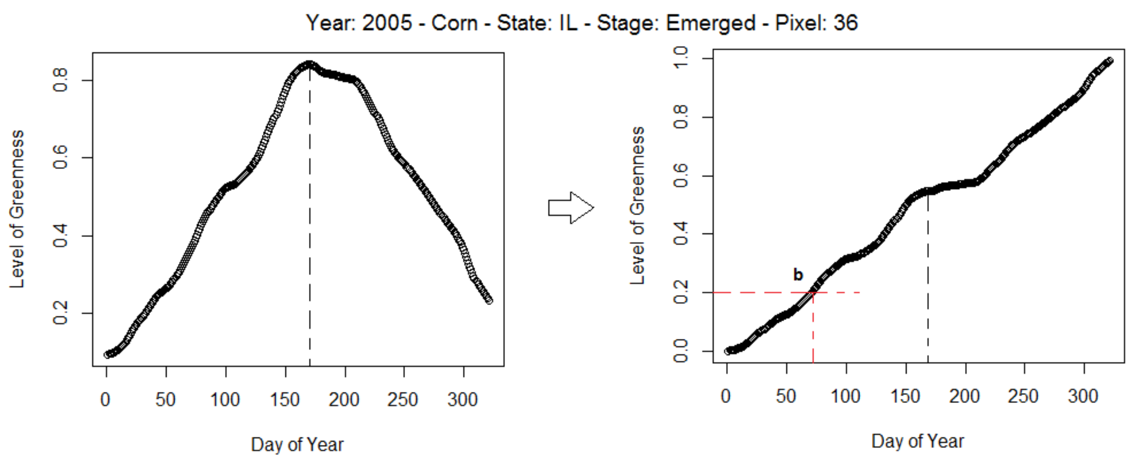

Figure 5 The beta method

4.3 Results

In average, approach alpha results in a difference of 21 days between predicted aggregate-level data and actual aggregate-level data. i.e., if in Illinois corn emerged at 121th day of the year in 2005, in average our predicted day of year (obtained from approach alpha) is 21 days away from the actual number. In average approach beta results in a difference of 16 days. Table 1 below shows the average difference of day of the year in more details (in terms of crops and stages of crops).

Table 1: Average difference of day of the year

Crops	**Stage**	**Approach Alpha**	**Approach Beta**	**Diff (alpha - beta)**
Corn	planted	10.361786	11.058032	-0.6962463
Corn	emerged	8.751211	9.255086	-0.5038755
Corn	silking	9.634099	18.594513	-8.9604135
Corn	doughing	23.822883	18.404417	5.4184656
Corn	dented	24.414729	19.02832	5.3864084
Corn	mature	23.669914	14.751909	8.9180045
Corn	harvested	36.146523	18.600104	17.5464188
Cotton	planted	15.156962	18.738771	-3.5818087
Cotton	squaring	20.120397	19.742949	0.377448
Cotton	setting.bolls	25.417201	22.134843	3.282358
Cotton	bolls.opening	32.23684	22.62056	9.6162801
Cotton	harvested	44.14488	28.763233	15.3816461
Soybeans	planted	16.850976	12.534787	4.3161895
Soybeans	emerged	15.672941	10.082173	5.5907679
Soybeans	blooming	19.555364	10.820406	8.7349584
Soybeans	setting.pods	23.35373	14.342997	9.0107332

Soybeans	dropping.leaves	23.442652	16.277868	7.1647847
Soybeans	harvested	24.110464	15.33762	8.7728437

4.4 Validation

In order to check the robustness of our approaches, we implement out-of-sample tests for both approach alpha and approach beta. In our sample, actual data is collected in state level. For example, from actual data we know the advancement of corn that silks in state "47" (figure 1). As a comparison, in our out-of-sample test, our out-of-sample data describes the advancement of crops in a certain stage in sub-state regions. To be more specific, our out-of-sample data includes aggregate-level data for sub-state regions of Illinois (details of sub-state regions is described in figure 6). With the help of approach alpha and beta, we could first obtain an optimal value of a and b from our sample data. Given values of a and b and location of sub-state regions of Illinois, we could then derive the predicted aggregate-level advancement of crops in a certain stage in sub-state level of Illinois. Lastly we could compare predicted data with actual data in sub-state level in Illinois.

In our out-of-sample test, in average approach alpha results in a difference of 15 days between predicted data and actual data. Approach beta results in a difference of 11 days in average. Table 2 below shows the average difference of day of the year in more details (in terms of crops and stages of crops).

Table 2: Average difference of day of the year (out-of-sample validation)

Crops	Stage	Approach Alpha	Approach Beta	Diff (alpha - beta)
Corn	planted	14.58964	12.13902	2.4506207
Corn	emerged	13.26934	10.60611	2.6632315
Corn	silking	8.599782	13.45941	-4.859625
Corn	doughing	23.24686	11.62795	11.618903
Corn	dented	21.30699	20.48219	0.8248028
Corn	mature	13.82438	9.554442	4.2699383
Corn	harvested	18.43608	10.12703	8.3090497
Soybeans	planted	12.21762	10.21513	2.00249
Soybeans	emerged	10.65763	9.333995	1.3236399
Soybeans	blooming	15.31001	12.05194	3.2580694
Soybeans	setting.pods	23.63743	15.4635	8.1739366
Soybeans	dropping.leaves	8.877612	9.583597	-0.7059846
Soybeans	harvested	11.11709	8.966265	2.1508226

The validation results reveal that both approach alpha and approach beta is robust, because predicted value in both approaches didn't deviate much from the actual data. In average out-of-sample result even performs better than results in in-sample optimization. In average approach alpha results in a deviation of 21 days in in-sample optimization, but the deviation is reduced to be 15 days in out-of-sample test. Similar pattern could also be observed in the results of approach beta.

In this paper we use approach beta to identify planting behaviors of farmers. This is because in both in-sample optimization (a difference of 21 days versus 16 days) and out-of-sample validation (a difference of 15 days versus 11 days), approach beta always results in smaller difference between predicted data and actual data. Moreover, from both table 1 and table 2 we could observe that in most cases approach beta generates less difference in a comparison between predicted data and actual data.

5. Empirical estimation and results

We model the planting decision as a binary outcome y and we estimate the model using both pooled and fixed-effect logit models. The fixed-effect specification is:

$$y_{it} = \alpha_i + f(T_{it}) + g(M_{it}) + \epsilon_{it}$$

where y_{it} takes the value of 0 if planting has not occurred in time period t in county i and α_i is a county fixed effect that reduces to an single parameter in the pooled model. Flexible representations of minimum temperature and soil moisture are presented by $f(T)$ and $g(M)$, respectively, and ϵ_{it} is an error term that is contemporaneously correlated. Our preferred specification is based on step functions for $f(T)$ and $g(M)$ which allow for non-linear effects of these variables.

Regression results are represented in figure 6. The first row presents the marginal effects of temperature and moisture on the probability of the planting decision in the pooled model. The second row presents results for the fixed-effect model. The last row presents the distribution of the climatic factors in the sample. As expected warmer temperatures increase the probability of planting. The relationship is almost linear with a slope of 0.102 and 0.132 per $^{\circ}$C in the pooled and fixed-effect models, respectively. This seems to indicate there isn't a specific threshold over which planting has a greater chance of occurring.

On the other hand, the response function for soil moisture is nonlinear and the fixed-effect specification reveals that excessively wet (>360 g/L) or dry (<150 g/L) conditions reduce the probability of planting. These conditions are fairly rare in the sample and occur 1.2 and 2.2% percent of the time, respectively. Moisture conditions over a wide range of condition (150 to 360 g/L) seem suitable for planting. The decision to plant seems to be delayed by fairly extreme moisture conditions.

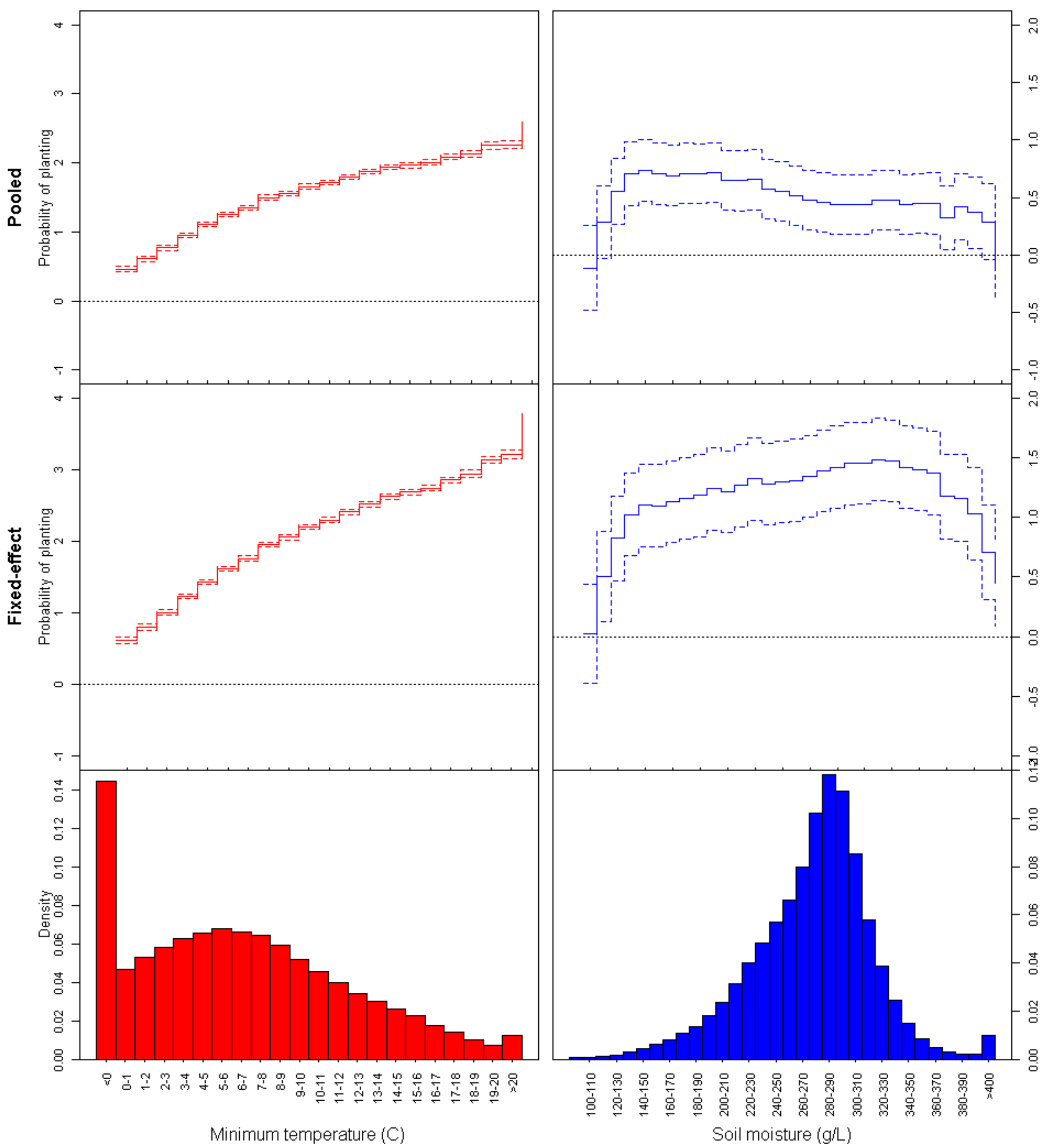

Figure 6 Influence of climatic factors on corn planting probability

A useful way to interpret the relative magnitude regression coefficients is to compute the necessary moisture changes necessary to fully offset the effects of warmer conditions. For the median moisture condition (270-280g/L), a 3°C warming would be offset by either a decrease of 40% or an increase of 22% in soil moisture. These offsetting moisture levels correspond to 2nd and 98th percentiles of the current moisture distribution. In other words, farmers would not be able to plant earlier with a 3^{o}C warmer spring only if moisture levels exhibit dramatic changes that are rarely observed in the sample. However, regions that already experience fairly wet conditions would require lower increases in moisture to offset the season-expanding potential of warmer springs.

6. Conclusion

To our knowledge, this is the first study seeking to estimate the influence of climatic factors on the timing of crop planting date using large-scale observational data. We combine a rich set of data sources to infer planting dates at the county level over a 30-year period. We model the planting decision as a binary outcome using a panel logit model in which we allow nonlinearities in the response function of key climatic factors.

As expected, we find that warmer temperature increase the probability of planting. We find no evidence of a threshold over which planting is more likely to occur. On the other hand, we find that extremely dry or wet conditions decrease the probability of planting, which is consistent with the conventional wisdom that appropriate soil moisture conditions are necessary for carrying out planting operations. However, these extreme moisture conditions are fairly rare in the sample. We find that spring would need to be 40% drier or 22% wetter in a place with median moisture conditions, in order to offset the effect of a 3^{o}C warming. Although more thorough explicit analysis is needed to understand the regional implications of the projected changes of climatic factors on planting behavior, these preliminary results suggest that the growing season is likely to expand through earlier planting.

Future work will incorporate climate change projection under various scenarios and climate models, as well the analysis of additional crops. The goal is to infer how much may the growing seasons of various important crops expand under a different climate using the current sensitivity of planting behavior to climatic factors as a guide. Other climatic factors, such as the length off the day could be incorporated and a more detailed treatment of standard errors is needed to account for contemporaneous correlation of the data.

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