

Three Essays on the Impact of Climate Change and Weather Extremes on the United States' Agriculture

by

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on the United States' Agriculture**

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Abstract

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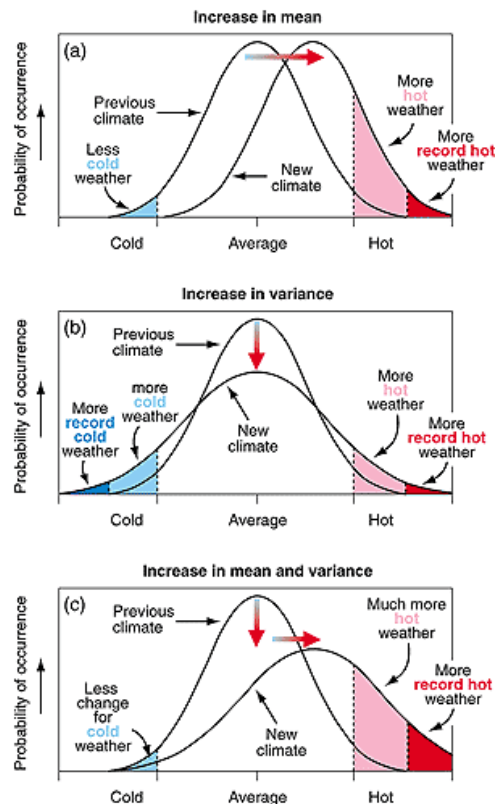
University of California, Berkeley

Professor Anthony C. Fisher, Chair

This dissertation incorporates three independent essays on the impact of climate change on the United States' agriculture, with each explores a different facet of climate change. There have been heated debates about the potential impact of climate change on the United States' agriculture. Several influential studies such as Schlenker, Hanemann, and Fisher (2005, 2006), Schlenker and Roberts (2006) suggest a potentially large negative impact of climate change on farmland values and crop yields, while others including Mendelsohn, Nordhaus, and Shaw (1994), and Deschenes and Greenstone (2007) believe that there is little impact or the US agriculture could be a major beneficiary of global warming. These opposing results inspired my work to examine another aspect of climate change that has not been carefully addressed in the current literature: the impact of climate and weather extremes.

While any individual extreme event cannot be causally linked to climate change, there could be a higher probability of more severe extreme events in the future. The figure (adapted from IPCC-WG1, AR4) demonstrates several potential scenarios in which we may expect more heating, less cooling, and less fluctuations between the extremes with different forms of distributional shifts in climatic conditions, all having the same change in the mean temperature. For example, climate change may result in increased precipitations in Northern America in the form of more droughts and more flooding events. These differential changes in the distribution of climatic conditions may have a subtle impact on agriculture, which could not be identified by studying moment variables such as the mean and the variance of temperatures or precipitations.

The three essays inherited two major empirical methods widely used in estimating the impact of climate change: hedonic regression and panel data. Hedonic regressions (also called the Ricardian approach) utilize cross-sectional variations to identify how climatic conditions such as the average temperature or precipitation capitalize in farmland values,



and panel estimations that employ within variations to link weathers with annual crop yields or farm profits. However, there is a situation in which both techniques are insufficient. If economic agents have forward-looking behaviors, and under uncertainties, the decision making process will involve a dynamic optimization problem whose a reduced-form approach as derived from either cross-sectional or panel data technique may not truly identify the actual behaviors. I devised an innovative dynamic programming approach built up on the Ricardian method to estimate the impact of natural disasters such as extreme drought events on cropland conversions.

In the first essay, using historical crop yield reports paired with high-resolution climate data, I discovered a small and positive effect of a decreasing diurnal temperature range on yields of five major crops including corns, wheat, cotton, soybeans, and sorghum. The asymmetric increases in observed maximum and minimum temperature have resulted in a falling diurnal temperature range across the United States. This effect could help mitigate some potential harmful impacts of climate change in the future, averaging up to a two percent yield offset for summer crops. Meanwhile, little impact on winter crops is expected. Moreover, the overall impact of climate change from a rising mean temperature and less fluctuations is dominantly harmful for most crops.

The second essay presents a structural model of cropland conversions with an application to the impact of extreme droughts. Droughts are perhaps the most destructive events to the US agriculture. Extended periods of severe droughts in the late 20th century caused widespread economic damages comparable to that of the Dust Bowl in 1930s. I showed that those events contributed to converting lands from agricultural production to urban uses by damaging soil productivity and lowering farming profits. I concluded the Ricardian approach to estimating climate change impacts is insufficient. Specifically, the Ricardian method works well for equilibrium adjustments by assuming that farm owners are able to make complete adaptations to a changing environment. However, the Ricardian approach fails to take into account the presence of climate extremes whose adaptations are neither possible nor costless. As a consequence, this method may underestimate the true cost of transient events related to climate change such as extreme droughts. This finding carries a significant implication for the future of the US' private croplands. As the US is predicted to experience more precipitations in the future with climate change, it seems that there would be a beneficial impact of more water for crops. It may not necessarily be the case, however. Even with increased precipitations, drought conditions may occur more frequently and intensively. Damages from potentially extreme drought events were not considered in the Ricardian estimates.

In the third essay, I examined the impact of extreme heating conditions on prime farmland conversions in California using the hedonic regression technique with a spatial dataset. I focused on the number of extreme heating days, defined as day with the recorded maximum temperature rises above 90 degree Fahrenheit. I found a small but significant nonlinear impact of extreme heating days on farmland conversions. A mild increase in the number of extreme heating days may be good for crops, thus helps keep farmlands in agricultural production. However, too excessive heating is harmful and accelerates conversions out of farming.

To my parents

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Essay 1

Decreasing Diurnal Temperature Range May Help Fight Climate Change: Evidence from US Crop Yields

Abstract

The asymmetric increase in the observed minimum and maximum temperature has resulted in a narrowing gap of the fluctuation range, the diurnal temperature range (DTR), in many places in the conterminous United States. Using an innovative non-parametric method that can overcome problems associated with unknown production functions, and county-level yield reports from 1940-2006, I discovered a statistically significant impact of decreasing DTR on yields of five major crops including corns, wheat, cotton, soybeans, and sorghum. The result indicates the existence of an optimal range for which crops may enhance yields from potential reductions in DTR. Importantly, the decreasing trend in DTR may help offset some potentially harmful effect from warming, averaging up to two percent offset in yields. Summer crops are projected to benefit the most from future DTR effects. Ignoring the potential impact of the changing DTR may result in overestimating the damage of climate change. However, this DTR effect is significantly smaller than the damage caused by rising mean temperature. Predictions under two medium climate change scenarios all point to overwhelming agricultural damages from global warming.

Key words: Diurnal temperature range, climate change impact on agriculture

1 Introduction

While global warming often implies a higher mean temperature, important information is often ignored, such as the difference between maximum and minimum temperature extremes, or the diurnal temperature range. A decreasing DTR signal was first mentioned in Karl et al. (1984), followed up Easterling et al. (1997), Dai et al. (1999). Lately, Vose et al. (2005) suggest that the global trend of a falling DTR has stalled since 1979. With a focus on the conterminous US, a falling DTR trend is still uncertain. A more recent study by Portmann et al. (2009) suggest a large difference in trends in maximum and minimum temperatures in the southeastern US, implying a decreasing DTR trend. I present evidence that a falling DTR trend has not been reversed, and at the same time, become more spatially divergent, in contrast to the rising mean temperature trend in the

conterminous US by analyzing high resolution data (details in Appendix). Since DTR is an important indicator of climate change (Braganza et al., 2004), one has to question whether such a narrowing range of temperature fluctuations has any impact on crops. Consequently, does omitting DTR from an analysis result in a loss of useful information and possibly, missing some potential impacts?

DTR can be an important factor to agronomics beyond other frequently used weather inputs such as the mean temperature or precipitation. Crop biology stipulates that there is a limit to crop endurance when exposed to temperature fluctuations. A faster rising minimum temperature and narrowing DTR can have a significant effect if warmer nighttime temperatures allow for a longer growing season. Using a crop simulation model, earlier attempt by Rosenzweig and Tubiello (1996) suggest a higher wheat yield in a controlled environment with the minimum temperature increasing three times as much as the maximum temperature. For other crops including corn and soybeans, Dhakhwa and Campbell (1998) also conclude that impacts under differential warming may be less severe than under equal warming.

However, empirical evidence is inconclusive. This raises the question whether such DTR effects, if they exist, are insignificant or whether inadequate methods were used in the predictions of these results. For example, Lobell (2007), analyzing national cereal yields, found that a changing DTR has an inconsistent impact on cereal yields. It is not surprising, for several reasons. First, besides the small sample size issue as admitted by the author, the observations were averaged countrywide, which shows little variations on a national scale. Second, Lobell employs a linear model of yield response to changing mean temperatures and DTR, which cannot capture nonlinear effects of weather on yields. A linear model with a negative coefficient of the mean temperature will always predict a harmful impact from warming, regardless of the degree of future warming. This contradicts a general premise that mild climate change may initiate optimal growing conditions, likely yielding short term benefits. Schlenker and Roberts (2008) emphasizes the importance of a non-linear relationship between crop yields and temperatures, with special attention to the harm created by extreme heating conditions after the optimal temperature threshold has been reached.

Looking solely at the US, DTR data varies significantly both east and west of the 100th meridian. Using high resolution data, I find that temporal and spatial aggregation may suppress opposing local trends therefore underestimating the true magnitude of the changing DTR. While it is not possible to exclusively link locally observed DTR trends to global climate change, the effect of changing DTR on yields can be accurately determined.

I present a new, nonparametric approach using a multivariate local regression technique, which best models complicated production functions. I find that the impact of changing DTR is statistically significant for all five major crops in the US, including corns, winter wheat, cotton, soybeans, and sorghum. The implication is significant: climate change with a higher mean temperature and less fluctuations may be less harmful for crops than if DTR was to remain the same. Predictions that do not account for changes in DTR may overestimate damages to crop yields. The magnitude of the falling DTR effect was estimated at a few percent of the current yields, with a higher value for summer

crops when a falling DTR trend manifests more clearly than in winter growing seasons. However, these results are conditional on the persistence of the falling DTR trend in the future.

Lastly, even with the effect of DTR accounted for, projected impacts based on two medium and low emission trajectories are dominantly harmful, especially for the rain-fed agricultural region in the US. Significantly negative impacts are expected for all crops in the lower latitudes. These results are comparable with projected severely harmful impacts of climate change as reported by Schlenker and Roberts (2008) up to a 43 percent yield reduction under the slowest warming, and up to almost 80 percent reduction under the most intensive warming scenario by the end of the 21st century. However, the higher latitude states from 40-45 degree north and above may experience increased yields consistently. Cotton crops are expected to thrive particularly in the mid to high latitudes. Lower Corn Belt states would be hit hard under a higher emissions scenario with expected reduced corn yields up to 40 percent by the mid-21st century.

2 Data Sources

2.1 Historical Climate Dataset and Growing Seasons

The data used for calibration of the coefficients is provided by the USDA Forest Service (Coulson and Joyce, 2010). The data covers monthly minimum, maximum temperature, and precipitation from 1940 to 2006, at the county level, for all conterminous counties in the US. This dataset was derived by integrating and spatially weighting high-resolution PRISM climate grids. More details are available in the Appendix.

Crop growing seasons are determined by the major planting dates and harvesting dates reported by the USDA. Because planting and harvesting dates vary between regions and years, the choice of growing seasons used in this study applies to the broad picture as opposed to a specific county. The following growing seasons were used: corns from May to August, winter wheat from September to June of the year after, cotton from May to September, and soybeans and sorghum from May to October. Flexing the growing seasons by moving the starting and harvesting date forward or backward by one month does not result in any significantly different estimate.

These variables are calculated from monthly minimum and maximum temperature:

Mean temperature

$$T_m = \frac{T_{max} + T_{min}}{2} \quad (1)$$

Diurnal temperature range

$$DTR = T_{max} - T_{min} \quad (2)$$

For a crop's growing season spreading over a period of several months, then T_m and DTR

is averaged over the period. Precipitation is totalled over all months in a cropping season.

2.2 Crop Yields

Annual crop yields for five major crops including corns for grain, winter wheat, upland cotton, soybeans, and sorghum were extracted from the USDA’s National Agricultural Statistics Service, USDA, data from 1940 to the most recent year in 2012. Total production, acres planted, and acres harvested were used as weights in the regression analysis. Details are provided in the Summary Statistics.

3 Methodology

The production approach models crop yields as a function of weather inputs such as temperature and precipitation:

$$Yield = f(\textit{productivity}, \textit{temperature}, \textit{precipitation}, \textit{unobservables}) \quad (3)$$

where $f(.)$ describes a functional relation between inputs and yields. Inputs can be either observable such as weather conditions, such as temperature and precipitation, or unobservable such as labor and farming efforts. Yields are measured as the total production per acreage planted or harvested. The factor productivity is supposed a constant. In a longitudinal analysis, the total factor productivity, which measures output per one *generalized* unit of inputs, grows over time¹. The factor productivity is a scale parameter (thus having no unit of measurement) and can be approximated by a time trend. Since the Green revolution in 1940s, many crop yields have almost doubled. The effect of increasing factor productivity has to be removed prior to any analysis so as not to confuse the explanation of the weather coefficients. Regressing yields on a time trend can be used to remove time-dependent variations from supposedly random year-to-year weather fluctuations.

$f(.)$ is often assumed a quadratic function of inputs, implying a nonlinear relation between inputs with yields, and an optimal level of inputs for which yields peak as in Figure 1. If the left-hand side is in the logarithm of yields, the above model explains the influence of inputs on the percentage change in yields. The canonical function to be estimated is:

$$\log Y_{it} = \beta_0 + \beta_1 T_{mit} + \gamma_1 T_{mit}^2 + \beta_2 Prec_{it} + \gamma_2 Prec_{it}^2 + \beta_3 DTR_{it} + \gamma_3 DTR_{it}^2 + C_i + T_t + \varepsilon_{it} \quad (4)$$

in which

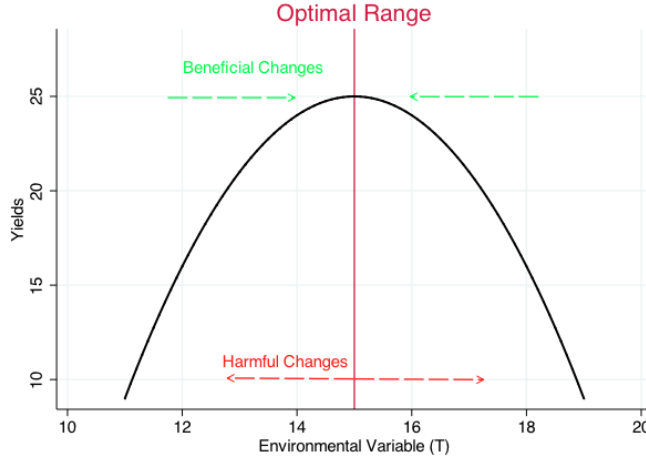
Y_{it} is the average crop yields of county i at year t

T_m is mean temperature

¹Due to changing input mixes and input qualities, which could be a result of changing prices, availability, and technological improvements, productivity measurements are not comparable without adjustments to the input side.

$Prec$ is precipitation
 DTR is diurnal temperature range
 C_i is county i fixed effect
 T_t is year t fixed effect

Figure 1: Agronomy of Crop Growth with a Changing Environment.



The inclusion of a set of county and time fixed effects will capture county-level difference such as soils, local infrastructures, and time-dependent shocks such as a more productive variety, more efficient machineries, or irrigation being introduced. What differs from the traditional production approach is that DTR is also assumed an input to the production, and behaves in the same way as other weather inputs such as the mean temperature and precipitation. Of course, a real world production function may be far more complicated since farm owners are reactive to changes in weather conditions as well as input or output price. Farm owners with insurance may abandon low-yield fields, which results in a bias in reported yields. Sensitivity analysis will look at different yield measures and weighting schemes. Lack of data at the field level does not allow for a sub-county analysis.

Marginal Impacts of Changing Mean Temperature and DTR

The marginal effect in percentage change of one degree increase in mean temperature in county i , holding all other variables constant, is computed as :

$$\frac{dY_i}{Y_i} = \beta_1 + 2\gamma_1 \bar{T}_m \quad (5)$$

where \bar{T}_m is the baseline temperature at county i .

To estimate the impact of climate change, it is assumed that the marginal impact is constant. For example, the predicted impact from rising mean temperature is:

$$\Delta D_{T_m} = (\beta_1 + 2\gamma_1 \bar{T}_m) \times \Delta T \quad (6)$$

with ΔT is the deviation of mean temperature from the baseline value.

The same analogy is applied to calculating the marginal impact and the projected impact of changes in DTR.

Although it is better to account for the curvature of the quadratic function, the difference may not be large, given such a small deviation in projected changes in mean temperature or DTR. The projected total impact is the sum of impacts from changes in mean temperature and DTR, assuming no interaction between those variables. The regressions were weighted by the total harvested acreage in each county to correct for the influence of heterogeneous observations. Replacing weights by the total production or the total planted acreage does not cause any significant change in the results.

I keep the potential impact of increasing precipitation on crop yields unchanged for several reasons. First, the objective of this study is to investigate the potential change in temperature patterns, with a possible impact of falling DTR, on yields. Second, even precipitation is predicted to increase in North America with climate change, shifting precipitation patterns toward more rainfalls, less snowfalls, and early snowmelts (Knowles et al., 2005) may adversely effect soils and crops, which is difficult to discern through an empirical model. And third, the effect of precipitation is not large enough to change the claimed findings. Based on the estimates in Tables 1 and 2, even a large increase of up to 25 percent in precipitation during growing seasons will only offset approximately 2 percent reductions in corn yields on average, close to a 3 percent increase in yields due to precipitation effects as suggested by Changnon and Hollinger (2003)'s field study. Thus, the calculated impacts in Tables 4 and 5 may be slightly higher than actual impacts due to precipitation effects, but the difference is not large enough to significantly affect the overall results. Finally, the analysis is applicable only east of 100th meridian, the perceived boundary of the arid west and humid east. The agriculture of the west is dependent on irrigated water, which is not accounted for in this analysis. I also consider neither adaptations nor carbon fertilization effects.

4 Empirical Results

4.1 Parametric Estimates of the Impact of Rising Mean Temperature and DTR

The estimated production function in (4) is presented in Table 1, for all five crops using all available data from 1940-2006. Given such a large sample size, it is not surprising that a significant nonlinear relation is found between all weather variables such as the mean temperature and precipitation and yields as predicted in agronomics: the positive linear term indicates an initial yield-enhancing impact of increasing temperature or precipitation, but once an optimal threshold has been reached, further increase would be yield-decreasing. The optimal thresholds of temperature and precipitation for crop growth

are very close to field experiments, such as the optimal mean temperature for corns, soybeans and sorghum is around 20 degree Celsius, while cotton peaks at 23 degree. To produce the highest yields, corn crops need around 50 centimeters of precipitation during a growing season. Meanwhile, wheat needs 65 centimeters. Soybean and sorghum yields maxes out at slightly more than 70 centimeters of precipitation. The model does not predict water requirement for cotton well. The optimal mean temperature for winter wheat is surprisingly low, at around 6.5 degree Celsius, probably due to an extended growing season of 10 months from September to June of the year after, or data irregularity.

Most importantly, the impact of DTR follows the exact same pattern as the mean temperature and precipitation. This confirms limited crop endurance to a temperature fluctuation window. The optimal range of DTR for corns is 12.3 degree Celsius, winter wheat and cotton 12.2 degrees, soybeans 10.5 degree, and sorghum 11.5 degree. A test for the coefficients of DTR and DTR-squared jointly insignificant $\beta_3 = \gamma_3 = 0$ was comfortably rejected with 99 percent confidence for all crops.

It is important to confirm that the obtained result is not driven by unobservables that may be correlated with DTR, or outliers. For example, one may be concerned that the introduction of irrigation in some specific locations in more recent years may have increased yields, and at the same time caused DTR to fall. Such an unobservable effect of irrigation can be addressed by neither county fixed effects nor year fixed effects. When unobservables are correlated with both the regressor (DTR) and yields, the usual interpretation of the DTR coefficient may be fallacious. I implemented a scheme to check for possible structural changes in the production function which may be caused by unknown confounding factors.

I select a 30-year window from the available 67-year data length (1940-2006), and estimate a separate model for each possible window, starting from 1940-1970, 1941-1971 to 1986-2006 window. If there were structural changes in the production functions, one might expect gradual shifts in the estimated coefficients over time. The result of rolling regressions is presented in Figure 2. It is interesting to see that the estimated optimal DTR does not vary with sub-samples as in the case of corns, wheat, and soybeans, and has only decreased slightly for cotton and sorghum crops. There is also evidence that the optimal amount of precipitation has increased slightly as in the case of corns, wheat, and soybeans. This could be due to increasing temperatures, or new water-demanding crop varieties. The relatively flat optimal mean temperature trend lines are evidence that most crops have not become more heat resistant since 1940. As mentioned earlier, estimates of precipitation for cotton were not reliable, and require further examination. A few jumps in the graphs of cotton and wheat at the midpoint in around 1970 are possibly due to data irregularity. The estimates were much more stable after that specific segment.

Marginal Impact from Changing Mean Temperature and DTR

In Table 2, on average, most crops expect harmful impact from rising mean temperature, ranging from significantly damaging impact up to 8 percent for each degree increase for corn and sorghum to a lesser impact on soybean, and wheat. Evidently, the extent of damage from a one-degree increase in mean temperature is not as harmful as Lobell and

Asner (2003)'s estimated damage, which they found to be up to a 17 percent reduction in cereal yields. Possibly the higher damage was the result of a linear damage function often seen in their studies. However, there is a large variation between counties with some expecting heavy losses while others expect substantial gains. In contrast, temperate crops such as cotton are expected to experience higher yields due to rising mean temperatures. Precipitation increase is yield-enhancing on average, especially for summer crops, except cotton and winter wheat. The impact of falling DTR is positive for all crops, with the highest impacts observed on corns and soybeans, and little impacts on wheat and cotton. Yet, variations are large, especially for corns and wheat. The actual DTR impact is either yield-enhancing or yield-decreasing, depending on the initial baseline condition.

For example, the direction of potential effects is shown in Figure 3 and 4, based on the sign of marginal impacts. If climate change is restricted to increasing mean temperature alone, one can say that mid to low latitudes should expect reduced yields in all crops. Higher latitude states (about 40 degree north and above) will expect increased yields, as temperatures rise in the direction of the optimal range as indicated in Figure 1. This is consistent with the general understanding that agriculture will move to the north to benefit from longer growing seasons. However, the impact of a falling DTR is less spatially coherent, with a positive impact on all summer crops almost everywhere, while only the mid to low latitude and central Plain states may expect a positive effect on winter wheat. As shown in the Appendix, the eastern US has consistently seen a falling DTR in summers. It is appealing to suggest that the DTR effect may have played an important role in observed yield growth of summer crops in the past several decades.

4.2 Nonparametric Evidence of Decreasing DTR Offsetting Rising Mean Temperature Impacts Using Multi-stage Multivariate Local Fitting

The most convincing evidence of the impact of falling DTR on yields comes from a new nonparametric multivariate local fitting technique which does not impose any restriction on the functional form of the yield equation. A quadratic production function implies that there is a unique optimal weather condition, and the marginal impact is constant, which is rather restrictive. Other authors such as Schlenker and Roberts (2008) have used a nonlinear corn yield response function that depicts an initially slowly rising segment with increasing temperature, then yields decrease dramatically at extreme temperatures.

A two-stage procedure is proposed. First, random fluctuations in yields are filtered out from other factors such as changing precipitation, time and location fixed effects. In the second stage, I examine the residual yields from the first stage on changes in mean temperature and DTR. Since the mean temperature and DTR is not included in the first stage, the first-stage regression therefore suffered from an omitted variable bias. Our primary concern is not relegated to the first stage itself, however, as the residuals extracted from the first stage regression are used for the second stage multivariate local fit. Ideally, the residuals will only contain yield variations due to the missing variables,

the mean temperature and diurnal temperature range. However, it will also pick up any remaining variables left unaccounted for, such as the impact of any localized event.

Formally, suppose \tilde{Y}_{it} is the yield residual of county i at time t extracted from the first stage regression of the logarithm of yields on precipitation with location and time fixed effects:

$$\log Y_{it} = \beta_0 + \gamma_1 \text{Prec}_{it} + \gamma_2 \text{Prec}_{it}^2 + C_i + T_t + \tilde{Y}_{it} \quad (7)$$

In the second stage, a nonparametric function $\mu(T_{mit}, DTR_{it})$ is estimated from mean temperature and DTR in the neighborhood of any pair of (T_{mit}, DTR_{it}) by a local polynomial:

$$\tilde{Y}_{it} = \mu(T_{mit}, DTR_{it}) + \nu_{it} \quad (8)$$

For example, a second order polynomial of μ in the neighborhood (T_{mit}, DTR_{it}) can be written as:

$$\mu(x, y) = a_0 + a_1(x - T_{mit}) + a_2(y - DTR_{it}) + \frac{1}{2}a_3(x - T_{mit})^2 + \frac{1}{2}a_4(y - DTR_{it})^2 + a_5(x - T_{mit})(y - DTR_{it})$$

The bandwidth is arbitrary in local regression estimation so various bandwidths were used to check the overall fit. This study employed a quadratic local fit. Although a higher order polynomial could be implemented with ease, it does not produce any extra benefit.

The results are presented in Figures 5 and 6. The contour lines indicate the extent of impacts in a two-dimensional coordinate of mean temperature and DTR. Each point in the graph corresponds to a yield residual extracted from the first stage regression. Most crops exhibit a similar response pattern towards mean temperature-DTR interactions. A lower DTR can help offset negative impacts from a higher mean temperature, as illustrated by a movement along the contour lines. Thus, the impact of a warmer climate is partially mitigated by a narrower temperature fluctuation range. This offsetting pattern can be seen in all summer crops, most clearly with corns, cotton, and soybeans. For wheat and soybeans, the graphs clearly show the optimal range of the mean temperature and DTR which maximizes yields as identified by the inner most contour line. Deviations from the optimal ranges, whether the mean temperature or DTR, will result in lower yields.

To see the importance of these mean temperature-DTR interaction patterns in relation to climate change impacts, a shift from the north-west corner to the south-east direction, underlying a simulated increase in mean temperature accompanied by less variations, will not cause the same level of damage as would be resulted from a west-east horizontal movement, underlying an increase in mean temperature only. In contrast, a higher mean temperature plus more fluctuations is more damaging than a rising mean temperature alone, represented by a movement from the south-west to the north-east corner. The difference between east and west of the 100th meridian patterns is noteworthy; without accounting for irrigation, the impact of changing mean temperature and DTR can be very complicated to predict.

5 Projected Impacts with Climate Change

Climate Models

The Community Climate System Model (CCSM), a fully coupled global climate model, was used to derive the projected changes in the mean temperature and DTR in the 21st century. The projections are based on two Special Report on Emissions Scenarios (SRES) balanced-energy resource A1B and the environmental-friendly B1 emission scenarios with CO₂ level stabilizes at 720 and 550 ppm by 2100, respectively. The model was used in the IPCC Fourth Assessment Report (2007)². I used a downscaled version at a resolution of 5-arc minute provided by the USDA Forest Service to calculate potential changes in mean temperature and DTR³. I calculated the shifts in both mean temperature and DTR for three time intervals: Short Run (SR, 2010-39), Medium Run (MR, 2040-69), and Long Run (LR, 2070-99), from the 20th century baseline climate simulation for the period 1970-1999.

The predicted warming is comparable with SRES projections about an increase in mean temperature of around 1.5 degrees Celsius globally for both scenarios A1B and B1 in the short run (Table 3). This is as expected because of the long carbon cycle in the atmosphere, short run predictions are not affected by current or near-term emissions. However, the predictions divert substantially for the latter half of the 21st century. Under B1 scenario, mean temperature remains at an increase of around 2 degrees compared to the baseline for all cropping seasons. Yet, mean temperature would rise by approximately 3 degrees or higher under the A1B scenario. Mean temperature is predicted to rise faster in winters. DTR decreases in all seasons, with the largest reductions to happen in summers, in agreement with the exploratory analysis in the Appendix.

Spatial patterns of mean temperature and DTR can be recognized in Figures 9-16. The most serious warming is expected at high latitudes, and warming regions extend further to the south by the end of the 21st century. DTR is expected to decrease more in the southeast in summers, and at high latitude in winters. Large variations suggest that potential impacts will be diverse. Note that not all climate models agree on the magnitude of warming, and of DTR in particular.

Projected Impacts

Projected impacts from changing mean temperature relative to DTR are shown in Figure 7, with the projected total impacts in Figure 8. Details for all crops are in Tables 4 and 5. I calculated the impact of changing mean temperature and DTR on crop yields at every grid of the climate model covering the eastern US by first order approximation as in formula (6), without weighting. These numbers should show all possible impacts if all crops are grown at every location. It is not the same as the actual impact since crops are specific to certain climates. For example, cottons are grown primarily in temperate states at lower latitudes, thus more warming at higher latitude may not help, and the actual impact on biggest cotton producers including Arizona, California, Mississippi, and Texas

²Available at <http://www-pcmdi.llnl.gov/>

³<http://dx.doi.org/10.2737/RDS-2011-0023>

would be already harmful even in the short run, rather than beneficial if just looking at the mean value in Tables 4 and 5.

Evidently, negative impacts from the rising mean temperature are expected for most crops under all emission scenarios, except cotton. Impacts are substantially more damaging in the A1B than in the B1 scenario in the medium and long runs. Corn yields are expected to decrease about 19 percent on average under the A1B, and more than 7 percent under the B1 scenario. The most extreme locations should expect more than 80 percent yield reduction under the A1B, and 48 percent reduction under the B1, consistent with Schlenker and Roberts (2008). The same damages are expected for sorghum, while impacts on wheat appear to be slightly less, at an average yield reduction of up to 10 percent. Soybeans may fare better than other crops with the expected damage averaging 3 percent in the long term for the high emissions scenario.

The impact of changing DTR is small due to the relatively small changes in predicted DTR, but positive for most crops on average, except winter wheat whose DTR effect is negligible. As mentioned earlier, the impact of changing DTR can be a further damage to crop yields or a benefit, depending on the baseline condition. Lower latitude regions are already above the optimal mean temperature threshold for growing wheat and corn as seen in Figure 3-4, thus more warming will be damaging, especially under the A1B scenario. At the same time, the current DTR is higher than optimum for most summer crops almost everywhere, except coastal or lake states whose DTR tends to be smaller than landlocked states', potential decreases in DTR will be beneficial. The average value of the DTR effect is around one to two percent, with the highest values expected for summer crops like corns and soybeans, and to a lesser extent, sorghum. Cotton may gain up to a half of a percent. Though, the total impact of both changes in mean temperature and DTR is largely dominated by the effect of rising mean temperature, as seen in Figure 7 comparing relative impacts. Cotton is expected to gain consistently, in all periods and emissions trajectories.

Spatial Distribution of Impacts

Distributions of impacts from simultaneous changes in mean temperature and DTR are presented in Figure 17-26. Low to mid latitude regions may expect harmful rising mean temperatures, while there are expected gains at higher latitudes, for all crops and all periods. Particularly, corns grown in the southern most states such as Texas may see more than a 40 percent yield reduction following the A1B emissions scenario. Even under a low emissions trajectory, lower Corn Belt states may experience a moderate yield reduction between 10 to 20 percent in the long run. Meanwhile upper states would benefit from warming throughout the 21st century. North-central Plain states may also expect increased wheat yields throughout the century, but other major wheat producing states in the south including Texas, Oklahoma, and Arkansas would likely suffer. Sorghum grown mostly in south-central states would see the largest impact from warming.

The comfort zone for all crops is projected to gradually shift to the north, with the lower half of the country becoming very intolerant to agriculture by the end of 21st century. The damage region is predicted to expand to the north, narrowing most crop

acreage. These conclusions are consistent with established scientific understandings of the future impact of climate change on US agriculture. Even in the short run, the impact is predominantly negative, especially for lower latitude regions. However, upper latitudes from 40-45 degree north are predicted to benefit from future warming.

6 Concluding Remarks

This study demonstrates that the falling DTR trend has a significant effect on yields of five major crops in the conterminous United States, and that a possibility of trade-off between a future higher mean temperature and a smaller diurnal temperature range can help mitigate some of the potential negative impacts of future warming. The estimated benefit of falling DTR may amount up to a few percent offset in yields for most summer crops, and less for winter crops. If the falling DTR trend continues in the future, then this effect is not negligible in economic terms. However, calculated damages under a modest emission scenario B1 or a balanced-energy scenario A1B still indicate significantly harmful impacts of climate change on the rain-fed agricultural region in the U.S.

Appendix 1

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Summary Statistics (Mean)(Min)(Max)(Std.Dev.), All Conterminous Counties

Dependent Variable	Corn	Wheat	Cotton	Soybean	Sorghum
Yields					
Unit	(72.18)(-30)(246)(38.59) bu/acre	(33.18)(1.50)(127.80)(15.01) bu/acre	(436.96)(8)(3422)(235.26) lb/acre	(26.67)(1.7)(249)(9.82) bu/acre	(49.88)(2)(144)(21.29) bu/acre
Explanatory Variables	(Seasonal Average)				
Mean Temperature (C)	(21.52)(8.70)(32.06)(2.99)	(9.39)(-3.51)(23.21)(4.51)	(24.62)(16.48)(31.94)(1.51)	(20.25)(12.01)(29.23)(2.68)	(21.49)(8.29)(30.16)(2.58)
DTR (C)	(13.35)(7.44)(21.58)(1.65)	(12.87)(7.28)(20.98)(1.70)	(13.12)(7.19)(20.42)(1.50)	(13.03)(7.54)(19.24)(1.18)	(13.78)(6.95)(20.84)(1.69)
Precipitation (cm)	(38.50)(0.00)(120.06)(13.49)	(74.23)(-39)(370.11)(34.01)	(49.56)(0.00)(145.12)(17.04)	(57.11)(10.68)(151.51)(15.17)	(52.34)(-.42)(145.32)(18.10)
Auxiliary Variables					
Acres Planted	(33,374)(10)(395,300)(46,599)	(36,741)(10)(764,400)(67,447)	(22,154)(1)(465,200)(40,917)	(35,421)(5)(540,000)(46,376)	(na)
Acres Harvested	(31,508)(10)(394,700)(43,840)	(28,126)(5)(642,600)(56,434)	(18,970)(1)(455,000)(35,660)	(30,465)(3)(539,000)(42,375)	(na)
Production	(2,772,508)(60)(6.18e7)(5,073,463)	(845,188)(50)(4.31e7)(1,807,126)	(35,070)(3)(461,889)(57,401)	(974,446)(30)(1.93e7)(1,554,139)	(11,262)(2)(331,300)(22,057)
Observations (Eastern US)	137,362	128,789	36,547	97,607	50,247
Year	122,248	97,957	32,222	95,229	41,221
Counties	1940-2006	1940-2006	1940-2006	1940-2006	1940-2006
	2,860	2,858	1,012	2,280	1,993

Table 1: **Parametric Estimations. East of 100th Meridian.** +, *, and - denotes significant at 99, 95 and 90% level. These models were estimated with robust clustered standard errors, weighted by harvested acreages. The dependent variable is the logarithm of crop yields. DTR and mean temperature is measured in degree Celsius. Precipitation is in centimeter.

	Corn	Wheat	Cotton	Soybean	Sorghum
T_m	.5975 ⁺	.0732 ⁺	.9670 ⁺	.5954 ⁺	.3337 ⁺
T_m^2	-.0155 ⁺	-.0056 ⁺	-.0212 ⁺	-.0156 ⁺	-.0103 ⁺
$Prec$.0168 ⁺	.0060 ⁺	.0023	.0087 ⁺	.0105 ⁺
$Prec^2$	$-1.792e - 4^+$	$-.461e - 4^+$	$-.606e - 4^+$	$-.604e - 4^+$	$-.763e - 4^+$
DTR	.8042 ⁺	.491 ⁺	.1761 ⁺	.2238 ⁺	.1777 ⁺
DTR^2	-.0328 ⁺	-.0201 ⁺	-.0072 ⁺	-.0107 ⁺	-.0077 ⁺
F-Test					
$DTR = DTR^2 = 0$	$F_{(2,2347)} = 280^+$	$F_{(2,2210)} = 156^+$	$F_{(2,861)} = 7.43^+$	$F_{(2,2121)} = 256^+$	$F_{(2,1658)} = 22.86^+$
Fixed Effects					
Counties	2,348	2,211	862	2,122	1,659
Year	Yes	Yes	Yes	Yes	Yes

Note: Due to data irregularity suggested in Figure 2, wheat coefficients were estimated for the period 1970-2000 only. Other estimates include all observations from 1940-2006.

Table 2: **Marginal Impacts. East of 100th Meridian.** Percentage change in yields from one degree Celsius increase in mean temperature, one degree Celsius *decrease* in DTR, and one centimeter increase in precipitation from the baseline climate in 1970-1999, calculated based on (6). The mean value (column 2) is the simple average of the marginal impacts from all grids covering the East of the 100th meridian at a 5-arc minute resolution.

Variable	(Mean)	(Std. Dev.)	(Min)	(Max)
<u>Corn</u>				
Mean Temperature	-7.80	10.71	-32.80	21.85
DTR	3.55	7.34	-47.10	27.21
Precipitation	.17	.25	-1.03	.90
<u>Wheat</u>				
Mean Temperature	-3.82	6.25	-20.26	8.44
DTR	.30	4.78	-25.30	16.54
Precipitation	-.28	.27	-1.17	.40
<u>Cotton</u>				
Mean Temperature	11.84	15.92	-24.81	52.81
DTR	.92	1.60	-9.85	6.87
Precipitation	-.39	.11	-.93	-.13
<u>Soybean</u>				
Mean Temperature	-2.90	11.71	-29.88	27.25
DTR	5.15	2.37	-10.85	14.00
Precipitation	.15	.12	-.39	.47
<u>Sorghum</u>				
Mean Temperature	-7.86	7.73	-25.67	12.05
DTR	2.05	1.71	-9.47	8.41
Precipitation	.14	.15	-.55	.54

To find the impact of increasing precipitation on corn yields, for example, with a 25 percent increase from the baseline, the absolute change in precipitation has to be converted to percentage. Since the mean precipitation in corn's growing seasons is 45cm, $1\text{cm} \approx 1/45 \approx 2.22\%$. Thus a 25% increase in precipitation would result in $\approx \frac{25}{2.22} \times .17 = 1.93\%$ increase in corn yields on average.

Table 3: **Projected Changes in Mean Temperature and DTR, for Eastern US, (Mean)(Std.Dev.)(Min)(Max), Degree Celsius.**

For two major summer and winter growing seasons, for three time intervals: Short Run (SR, 2010-2039), Medium Run (MR, 2040-69), and Long Run (LR, 2070-99). The projected changes are derived as anomalies from the baseline 1970-2000 PRISM dataset, at a 5-arc minute resolution, totaling 62,419 grids. Only results from CCSM climate model is presented.

Scenario	Interval	Mean Temperature							
		Corn		Winter Wheat					
A1B	SR	(1.28)	(0.30)	(0.72)	(2.19)	(1.70)	(0.30)	(0.90)	(2.46)
	MR	(2.37)	(0.33)	(1.61)	(3.46)	(2.59)	(0.46)	(1.43)	(3.94)
	LR	(2.99)	(0.49)	(2.04)	(4.30)	(3.20)	(0.44)	(1.98)	(4.27)
B1	SR	(1.19)	(0.33)	(0.67)	(2.16)	(1.39)	(0.43)	(0.64)	(2.57)
	MR	(1.73)	(0.33)	(1.08)	(2.73)	(1.93)	(0.37)	(1.04)	(2.85)
	LR	(1.56)	(0.41)	(0.97)	(2.80)	(2.10)	(0.43)	(1.07)	(3.41)

Scenario	Interval	DTR							
		Corn		Winter Wheat					
A1B	SR	(-0.64)	(0.31)	(-1.54)	(0.04)	(-0.40)	(0.11)	(-0.62)	(0.00)
	MR	(-0.57)	(0.28)	(-1.20)	(0.28)	(-0.41)	(0.25)	(-1.00)	(0.08)
	LR	(-0.57)	(0.40)	(-1.59)	(0.22)	(-0.49)	(0.21)	(-1.13)	(-0.03)
B1	SR	(-0.27)	(0.22)	(-0.84)	(0.17)	(-0.27)	(0.08)	(-0.50)	(-0.01)
	MR	(-0.49)	(0.33)	(-1.32)	(0.18)	(-0.38)	(0.16)	(-0.81)	(-0.01)
	LR	(-0.57)	(0.38)	(-1.62)	(0.09)	(-0.40)	(0.14)	(-0.77)	(-0.01)

Table 4: **Projected Impacts, by Mean Temperature, DTR, and Total, for Eastern Grids, Percents from 1970-2000 Baseline, (Mean)(Min)(Max).**

The impacts are approximated from first order change as in formula (6), according to the projected changes in mean temperature and DTR shown in Table 3.

Corn - A1B			
	Mean Temperature	DTR	Total
SR	(-8.70)(-32.96)(31.40)	(2.34)(-20.00)(23.54)	(-6.36)(-40.72)(30.63)
MR	(-15.96)(-58.50)(54.10)	(2.10)(-19.39)(20.76)	(-13.86)(-62.47)(53.55)
LR	(-20.70)(-78.88)(65.55)	(1.93)(-19.43)(21.60)	(-18.77)(-81.44)(67.79)

Corn - B1			
	Mean Temperature	DTR	Total
SR	(-7.44)(-25.35)(30.96)	(1.00)(-9.84)(11.61)	(-6.45)(-28.42)(33.43)
MR	(-11.37)(-45.36)(40.98)	(1.67)(-18.95)(21.59)	(-9.71)(-46.80)(43.69)
LR	(-9.22)(-39.39)(40.54)	(2.02)(-18.20)(25.40)	(-7.20)(-48.64)(41.42)

Winter Wheat - A1B			
	Mean Temperature	DTR	Total
SR	(-4.82)(-23.79)(19.81)	(0.07)(-8.70)(5.85)	(-4.75)(-24.14)(22.31)
MR	(-7.31)(-39.77)(31.59)	(-0.36)(-13.58)(6.14)	(-7.67)(-39.96)(35.19)
LR	(-9.65)(-48.09)(34.47)	(-0.11)(-14.62)(6.85)	(-9.76)(-47.21)(39.18)

Winter Wheat - B1			
	Mean Temperature	DTR	Total
SR	(-2.79)(-13.47)(20.82)	(0.01)(-6.32)(5.59)	(-2.78)(-15.68)(21.62)
MR	(-5.24)(-24.01)(22.97)	(-0.02)(-10.95)(7.35)	(-5.26)(-23.87)(26.46)
LR	(-5.70)(-29.31)(27.61)	(0.00)(-10.61)(5.75)	(-5.70)(-29.39)(28.44)

Cotton - A1B			
	Mean Temperature	DTR	Total
SR	(20.24)(-30.36)(93.36)	(0.50)(-3.49)(4.25)	(20.74)(-29.94)(93.31)
MR	(33.27)(-49.97)(146.39)	(0.51)(-3.96)(4.32)	(33.78)(-49.43)(146.31)
LR	(40.04)(-63.79)(175.26)	(0.55)(-3.81)(4.88)	(40.60)(-63.21)(175.04)

Table 5: Projected Impacts, by Mean Temperature, DTR, and Total, for Eastern Grids, Percents from 1970-2000 Baseline, (Mean)(Min)(Max). (Continued)

The impacts are approximated from first order change as in formula (6), according to the projected changes in mean temperature and DTR shown in Table 3.

Cotton - B1			
	Mean Temperature	DTR	Total
SR	(18.03)(-21.72)(85.33)	(0.22)(-2.00)(2.18)	(18.25)(-21.37)(85.11)
MR	(22.79)(-37.48)(100.89)	(0.49)(-4.02)(4.74)	(23.28)(-37.33)(101.03)
LR	(23.83)(-37.98)(114.87)	(0.41)(-2.28)(4.05)	(24.24)(-37.61)(114.70)

Soybean - A1B			
	Mean Temperature	DTR	Total
SR	(-2.64)(-36.64)(42.30)	(2.57)(-2.90)(9.69)	(-0.08)(-34.73)(42.13)
MR	(-4.45)(-60.16)(70.22)	(2.67)(-3.29)(9.99)	(-1.78)(-57.78)(70.15)
LR	(-5.91)(-77.00)(84.49)	(2.89)(-3.26)(12.84)	(-3.02)(-74.32)(83.99)

Soybean - B1			
	Mean Temperature	DTR	Total
SR	(-1.94)(-27.95)(38.66)	(1.13)(-1.68)(5.50)	(-0.81)(-27.21)(37.92)
MR	(-3.09)(-45.24)(48.38)	(2.53)(-3.31)(10.31)	(-0.56)(-44.53)(48.01)
LR	(-2.63)(-45.84)(52.04)	(2.10)(-2.06)(10.65)	(-0.53)(-44.13)(51.70)

Sorghum - A1B			
	Mean Temperature	DTR	Total
SR	(-10.72)(-32.03)(18.15)	(1.05)(-3.09)(5.20)	(-9.67)(-32.17)(17.95)
MR	(-17.74)(-51.72)(31.05)	(1.08)(-3.50)(5.41)	(-16.66)(-51.15)(30.11)
LR	(-22.00)(-66.21)(37.36)	(1.17)(-3.27)(6.78)	(-20.82)(-65.08)(36.10)

Sorghum - B1			
	Mean Temperature	DTR	Total
SR	(-9.06)(-26.20)(14.99)	(0.46)(-1.78)(2.97)	(-8.60)(-26.30)(14.93)
MR	(-12.20)(-38.90)(21.39)	(1.03)(-3.55)(5.92)	(-11.17)(-38.60)(20.58)
LR	(-12.05)(-39.42)(22.94)	(0.86)(-2.02)(5.63)	(-11.19)(-38.70)(22.48)

Figure 2: Stability of Estimated Coefficients.

The trend line is the estimated optimal growing condition. Each point was estimated from a 30-year sample, forward and backward by 15 years.

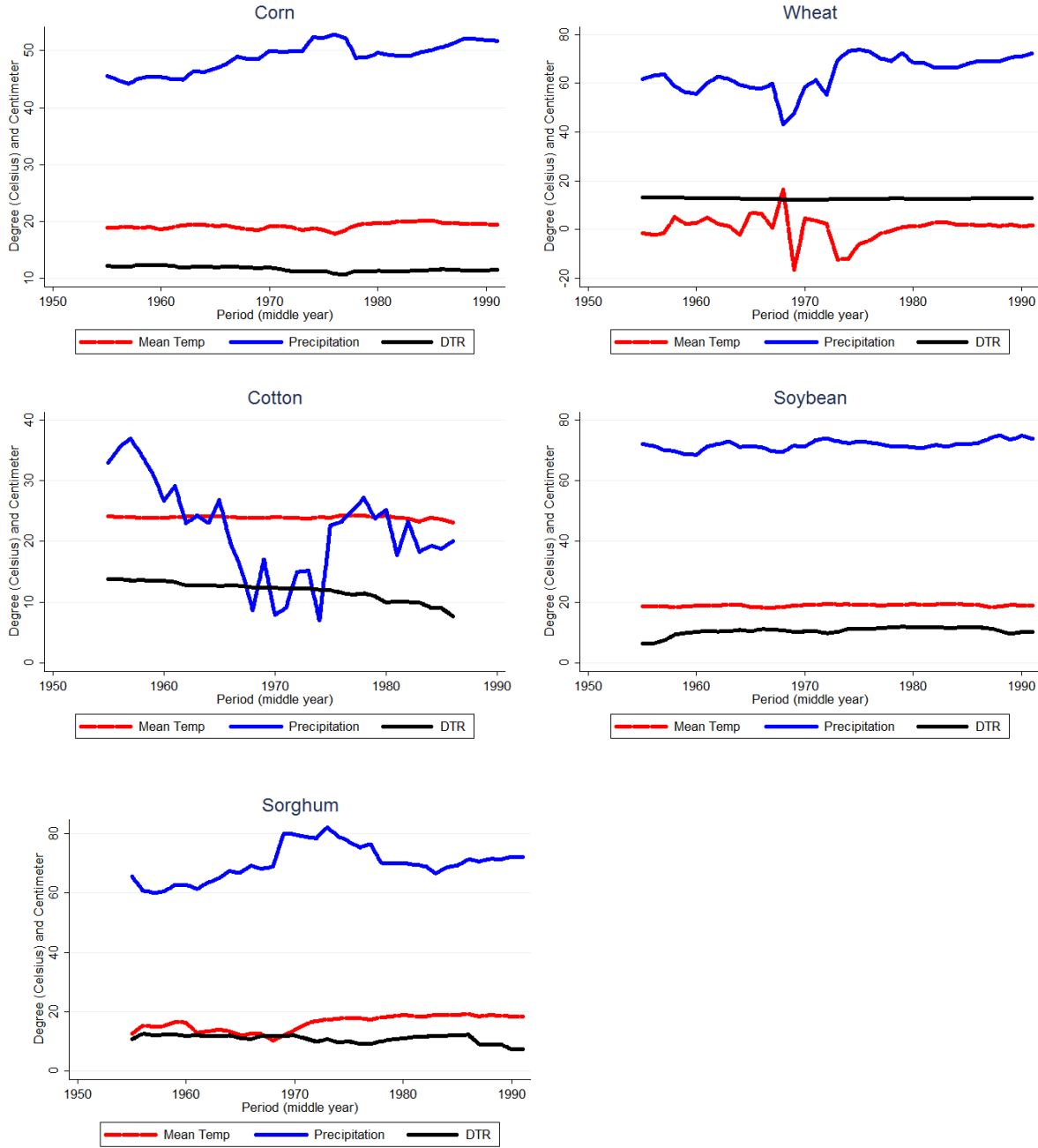


Figure 3: Marginal Impact from Rising Mean Temperature and Falling DTR on Corn Yields.

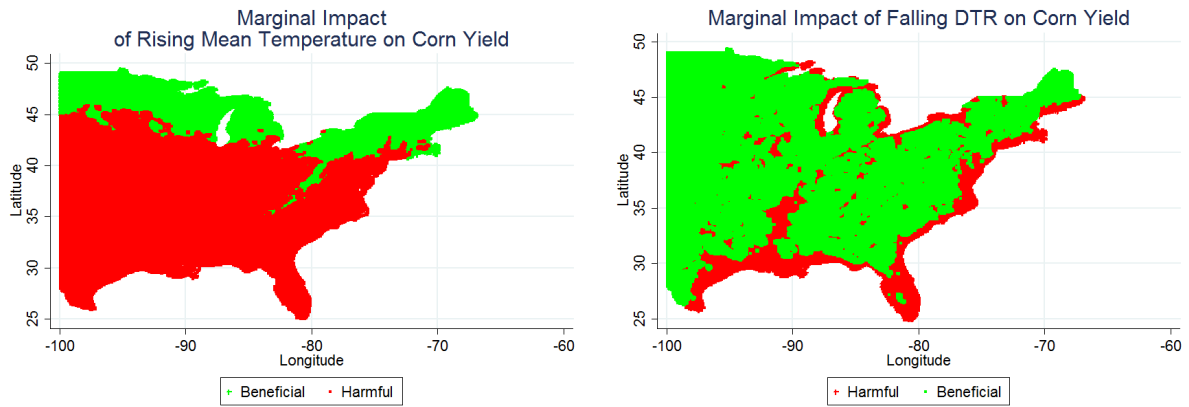


Figure 4: Marginal Impact from Rising Mean Temperature and Falling DTR on Wheat Yields.

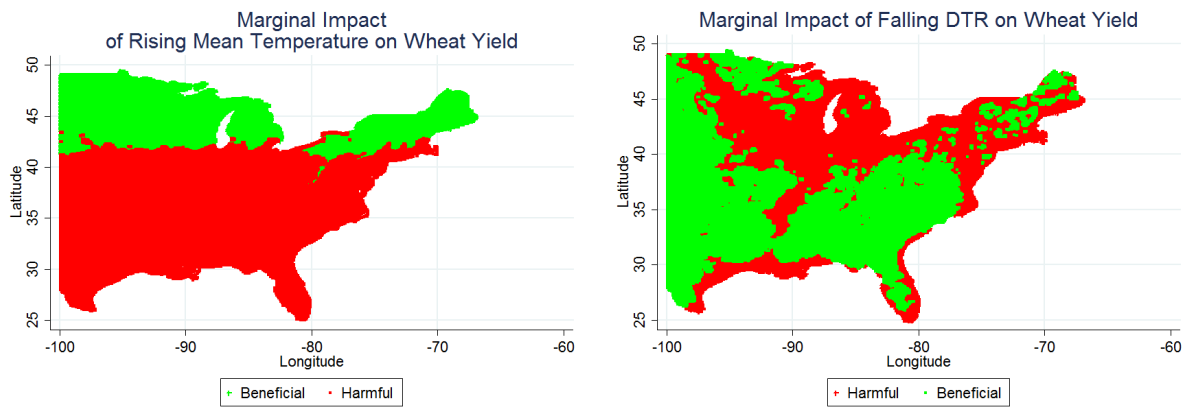


Figure 5: Multivariate Local Fit of Yield Residuals on Mean Temperature and DTR. East of 100th Meridian.

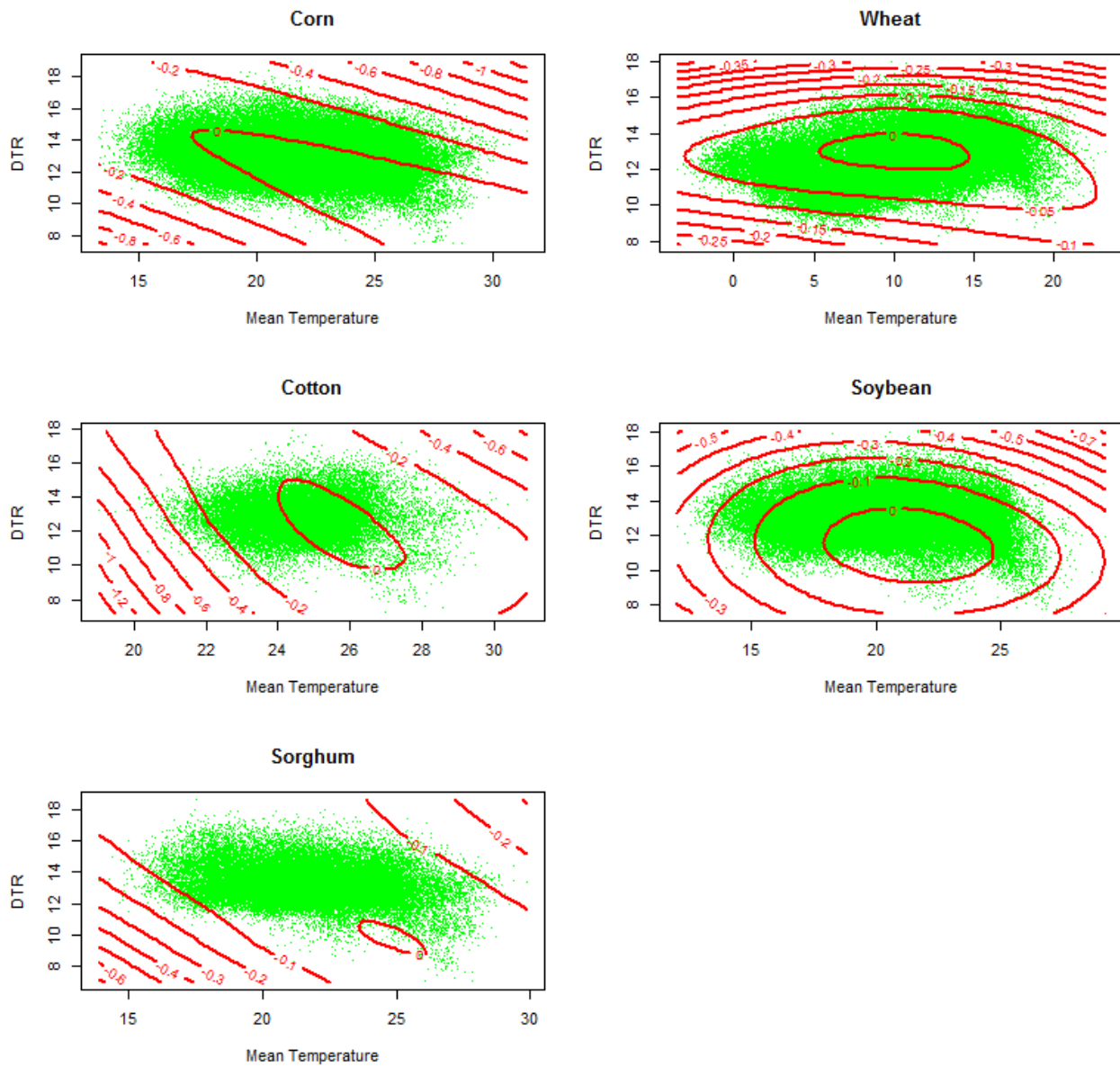


Figure 6: Multivariate Local Fit of Yield Residuals on Mean Temperature and DTR. West of 100th Meridian.

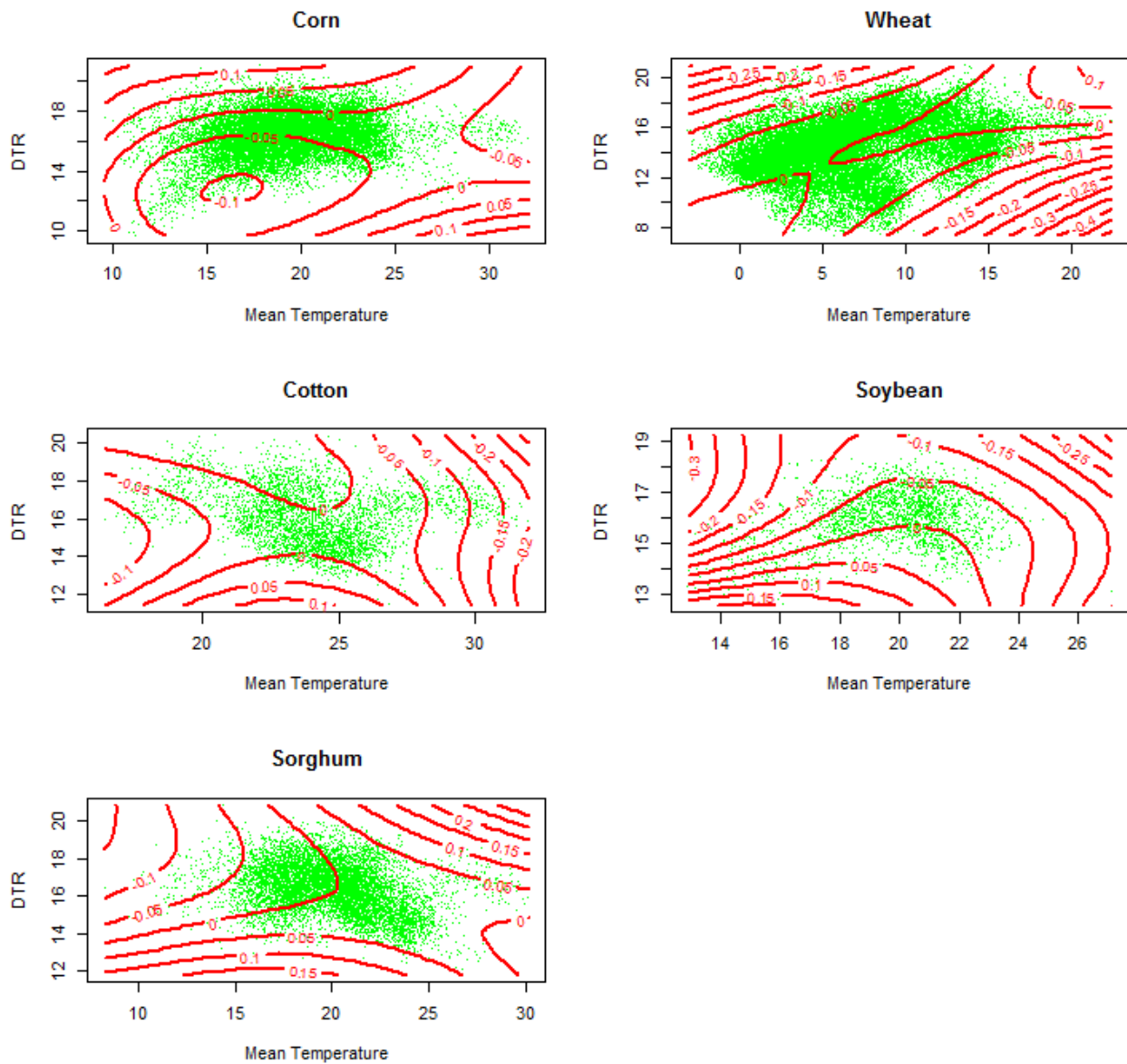


Figure 7: **Relative Impacts of Mean Temperature and DTR in 21st Century.** For each crop, the first three plots are projected impacts in percent from the baseline due to rising mean temperature in the SR, MR, and LR. The last three plots are impacts due to changing DTR. Short Run (SR, 2010-39), Medium Run (MR, 2040-69), and Long Run (LR, 2070-99), corresponding to CCSM A1B and B1 scenario.

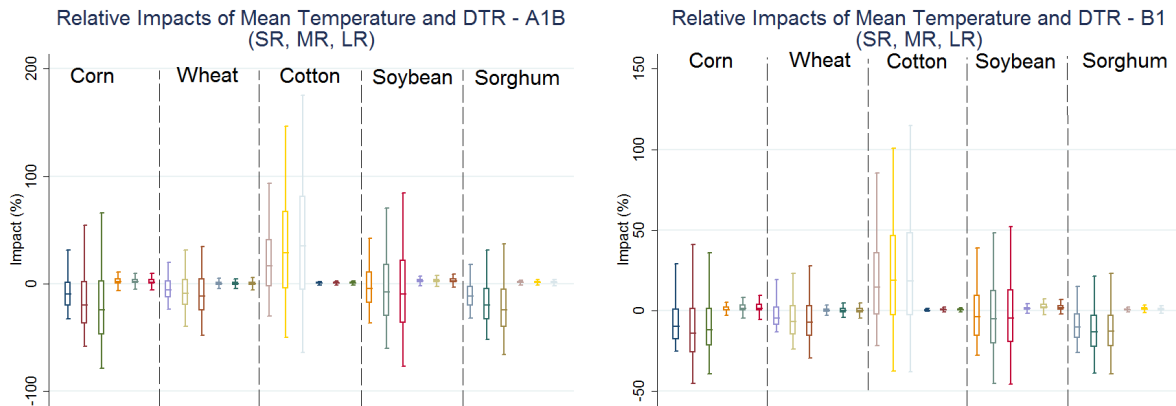


Figure 8: **Projected Total Impacts in 21st Century.** For each crop, the boxes indicate projected total impacts in percent compared to the baseline in the SR, MR, and LR, from simultaneous change in mean temperature and DTR.

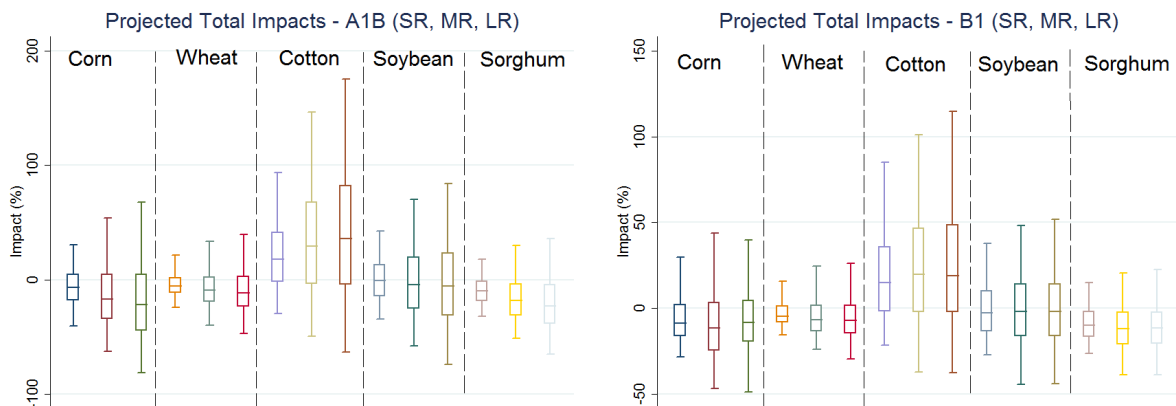


Figure 9: Projected Change in Mean Temperature (Degree Celsius), Corn's Growing Season, A1B.

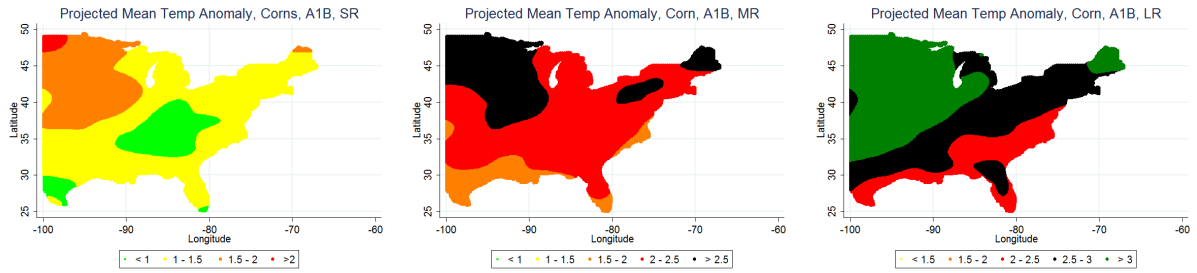


Figure 10: Projected Change in Mean Temperature (Degree Celsius), Corn's Growing Season, B1.

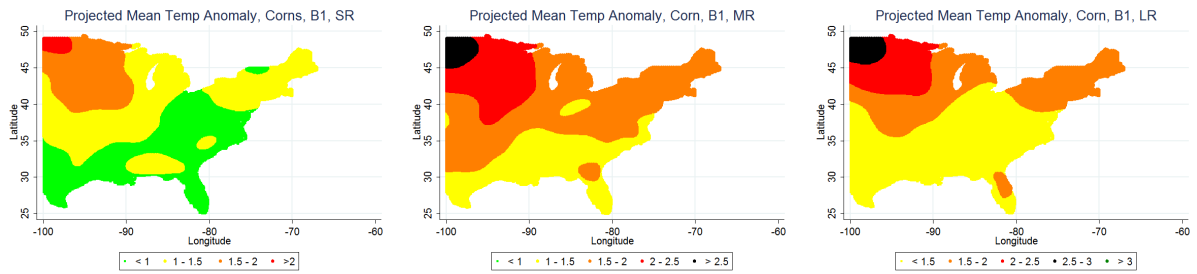


Figure 11: Projected Change in DTR (Degree Celsius), Corn's Growing Season, A1B.

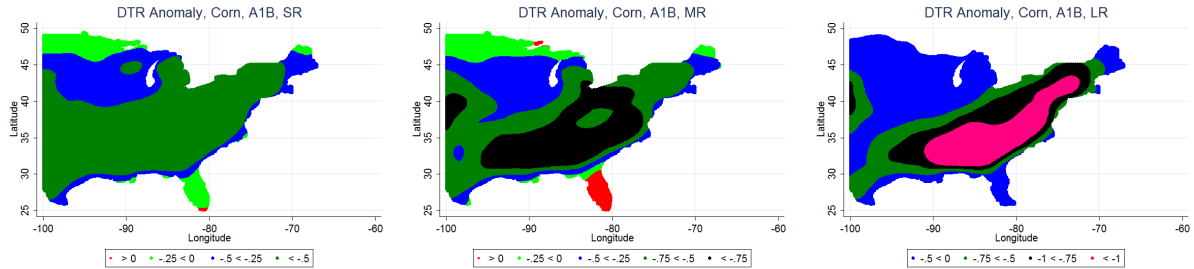


Figure 12: Projected Change in DTR (Degree Celsius), Corn's Growing Season, B1.

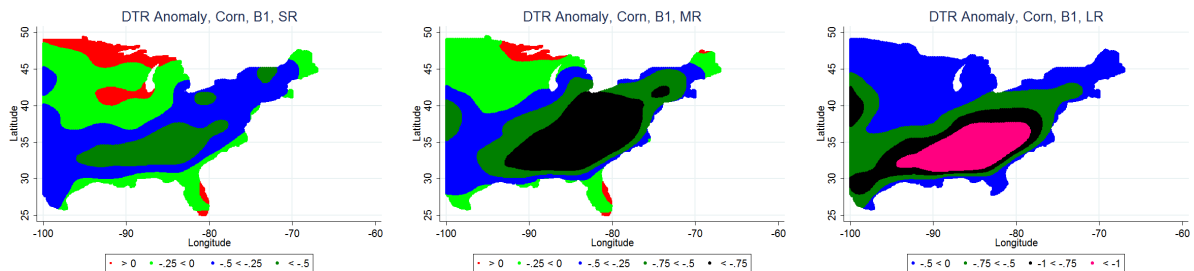


Figure 13: Projected Change in Mean Temperature (Degree Celsius), Wheat's Growing Season, A1B.

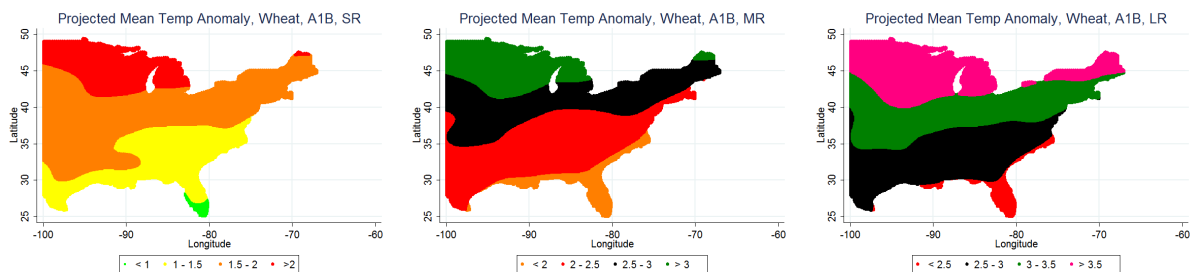


Figure 14: Projected Change in Mean Temperature (Degree Celsius), Wheat's Growing Season, B1.

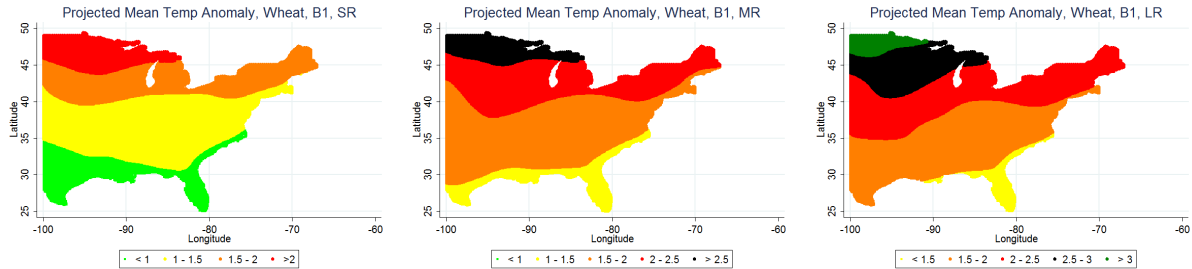


Figure 15: Projected Change in DTR (Degree Celsius), Wheat's Growing Season, A1B.

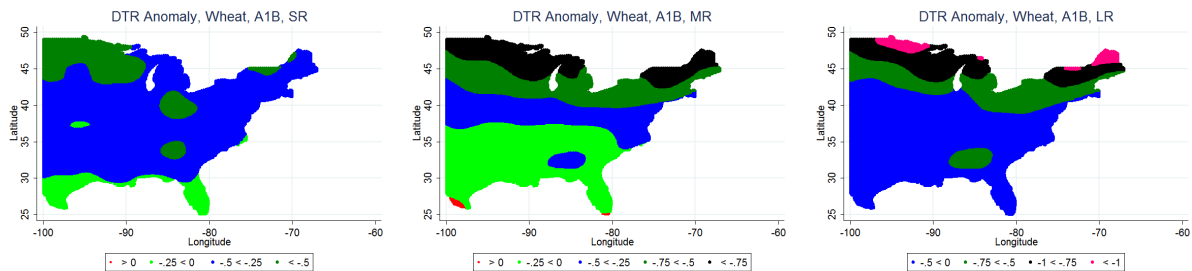


Figure 16: Projected Change in DTR (Degree Celsius), Wheat's Growing Season, B1.

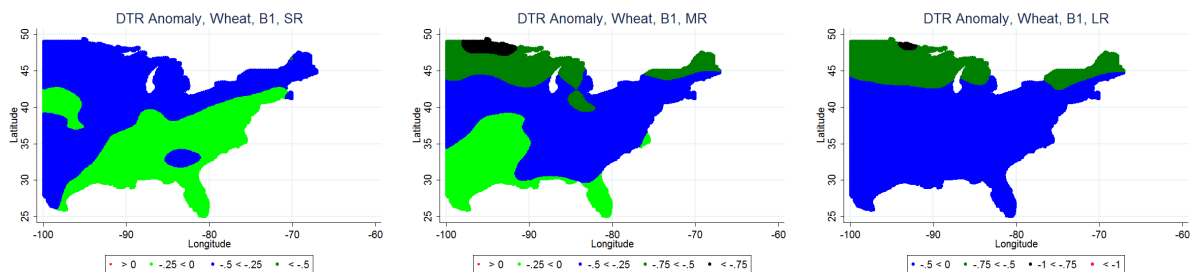


Figure 17: Projected Impact on Corn - A1B.

Impacts are projected in percentage changes from the baseline in 1970-1999. SR, MR, and LR denotes Short Run (2010-39), Medium Run (2040-69), and Long Run (2070-99).

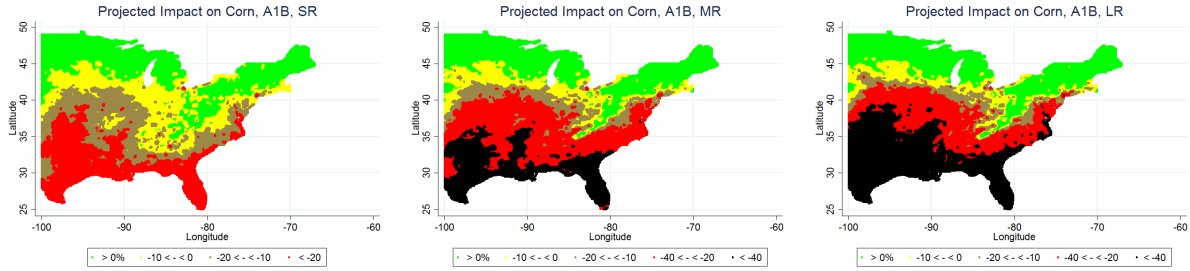


Figure 18: Projected Impact on Corn - B1.

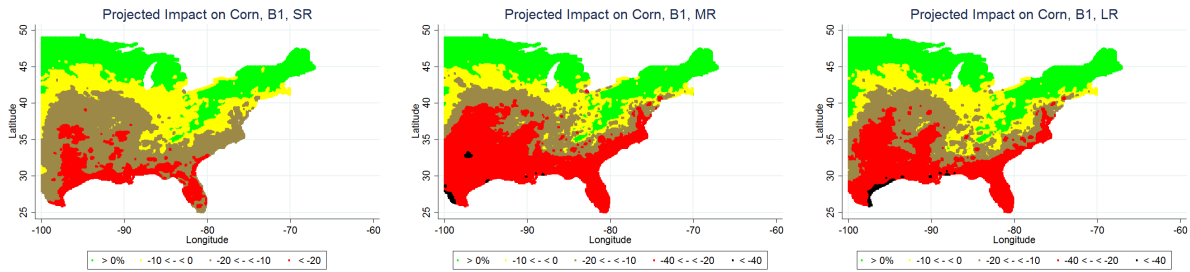


Figure 19: Projected Impact on Winter Wheat - A1B.

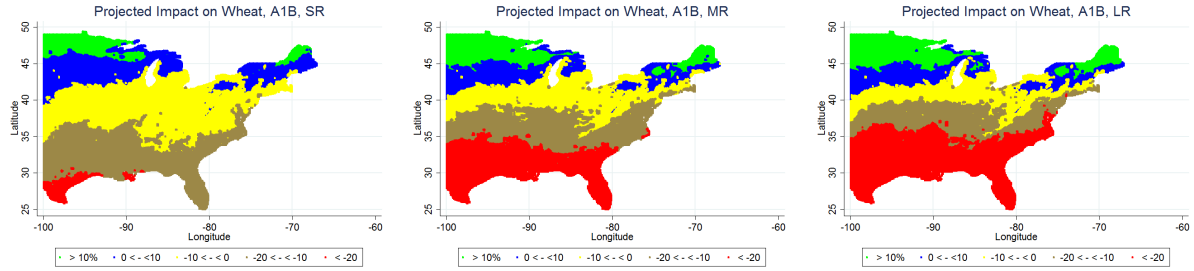


Figure 20: Projected Impact on Winter Wheat - B1.

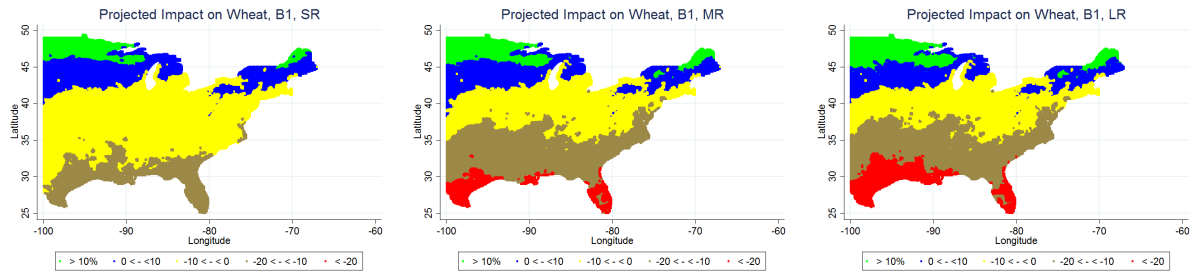


Figure 21: Projected Impact on Cotton - A1B.

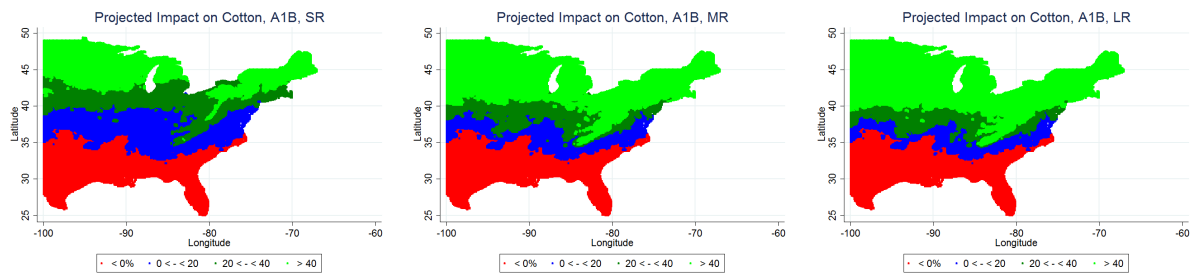


Figure 22: Projected Impact on Cotton - B1.

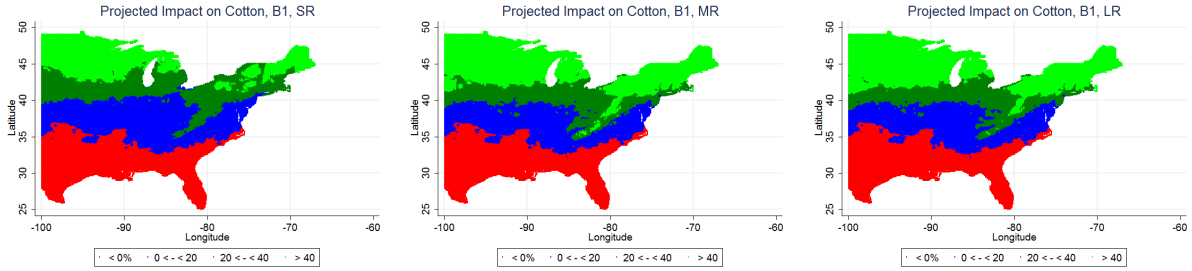


Figure 23: Projected Impact on Soybean - A1B.

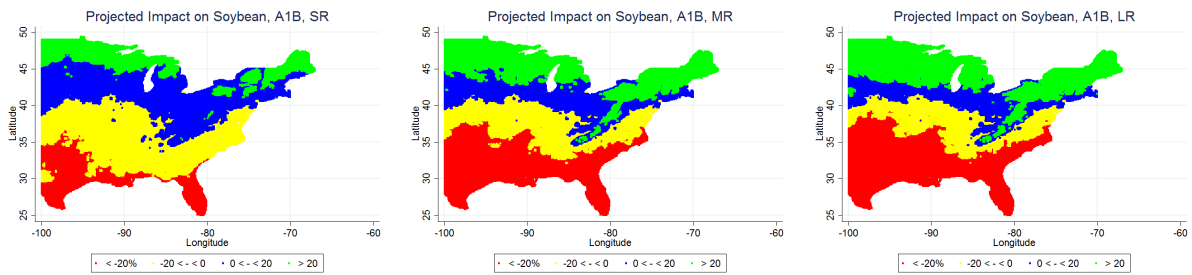


Figure 24: Projected Impact on Soybean - B1.

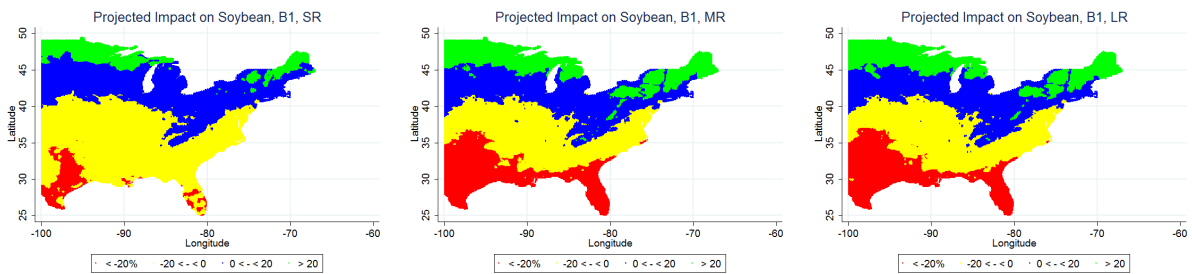


Figure 25: Projected Impact on Sorghum - A1B.

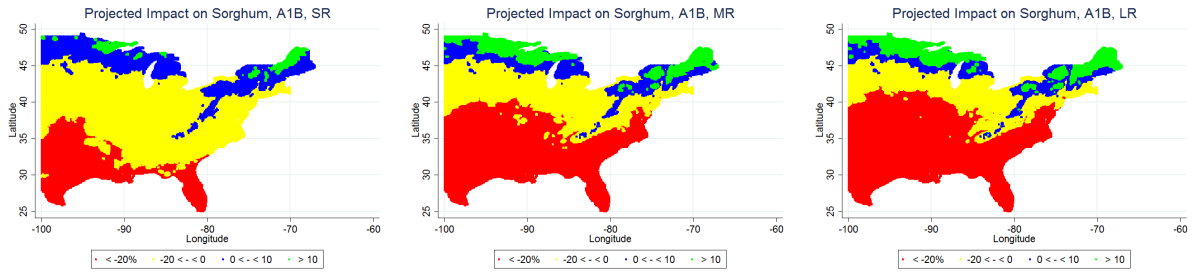
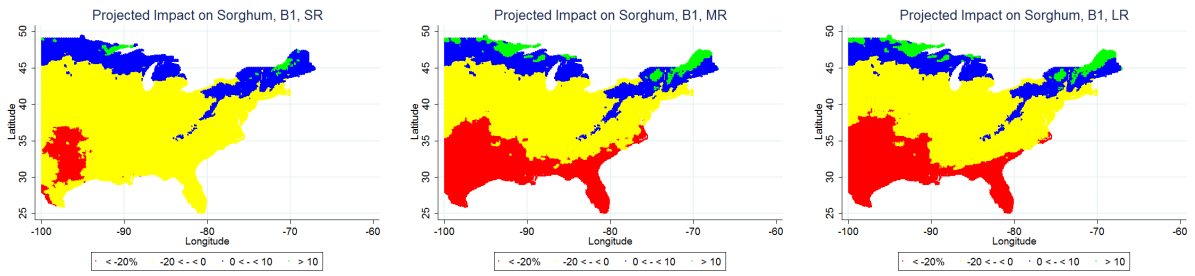


Figure 26: Projected Impact on Sorghum - B1.



Appendix 2

Decreasing Diurnal Temperature Range in the United States: Evidence from High-Resolution Climate Data

Abstract

I examine two temperature indicators, the mean temperature and diurnal temperature range (DTR), the fluctuation range between the maximum and minimum temperature, measured in monthly and yearly intervals. The availability of high-resolution data in the US allows for detecting trends and patterns that are identifiable at the county and sub-county level. Utilizing non-parametric approaches, I present evidence that a falling DTR trend is strong and consistent across the conterminous US, using most recent data up to 2012. While the overall decreasing trend is consistently observed with aggregate data since 1950s, DTR patterns vary greatly between seasons, geographical locations, and over time from disaggregate data. A consistently falling DTR during summers has been observed, while little change occurred over winters. Notably, spatial variations in DTR tend to widen, caused by particularly large reductions in the eastern US in summers. Such diverse spatial variations may be a significant source of bias in modeling the impact of climate change using national aggregate data. The attributes and processes of the observed changes are beyond the scope of this study.

1 Introduction

Asymmetric changes in the observed minimum and maximum temperature have been observed on the global scale since early the 20th century. Karl et al. (1984) noted a statistically decreasing DTR using weather stations' observations at many locations in North America. More recent studies including Karl et al. (1993), Easterling et al. (1997), and Dai et al. (1999) present a more thorough picture of the differential changes in the maximum and minimum temperatures as well as the potential mechanism of a falling DTR trend around the globe. Most agree that cloud covers and water evaporation are among the most important factors causing the observed differential changes in temperatures and resultant DTR trends. Karl et al. (1993) determined the global rate of change to be around -1.4°C per 100 years, roughly the increase of the mean temperature. Meanwhile Easterling et al. suggested a significantly lower estimate at $-.84^{\circ}\text{C}/100$ years. Further, Vose et al. (2005) provide an update of their earlier estimate in Easterling et al. (1997), which show that the falling DTR trend for the globe was stalled from 1979-2004. Lauritsen et

al. (2012) claim that the decreasing trend in DTR was still observed in the US during this period, though it was statistically insignificant.

This study attempts to fill in the gap that exists between what we may have observed globally, and what may exhibit locally. Firstly, to which extent does a global trend in DTR as suggested in earlier studies, and especially latter by Vose et al. (2005), influence national aggregate and local trends? What is the spatial pattern of a falling DTR trend in the US at a higher spatial scale up to a county and sub-county level? Which season is experiencing the largest change in DTR? Is the falling trend statistically significant? Is there any temporal variation in DTR observations?

I focus on a non-parametric approach which allows for examining the pattern of the dataset and determining the rate of change without making restrictive assumptions on the property of time series observations. Whether temperature series following an unit-root or a stationary process is still an active research area. As a side note, unit-root tests overwhelmingly rejected non-stationarity in most PRISM grids covering the conterminous US, the data used in this study.

Several major conclusions were drawn. First, there is evidence that DTR has been falling in the conterminous US since the 1950s. While short-term fluctuations up to a decade may exist, the overall decreasing trend has not been reversed (Figure 1). This is in sharp contrast with Vose et al. (2005) that the global DTR may have reversed since the last three decades. Second, spatial variations in DTR have been widening, with a few regions observed an increasing trend, while others saw little to no change, and many experienced a negative trend. Importantly, even if the overall trend in DTR (whether globally or nationally) may show little changes, strong and consistent trends in subregions can still be identified from analyzing fine-scale data. Third, the warming trend in the mean temperature in the US is significantly similar to the global trend. The mean temperature trend has been rising since the early 20th century, with a possible cooling period between 1960-1980, primarily in the eastern US. Over the past several decades, the mean temperature has rose significantly and it is still rising today. The National Oceanic and Atmospheric Administration (NOAA) confirmed that the US has warmed at a faster rate than the global rate¹.

Examining recent data through 2012, the observed temperature pattern is consistent with Karl et al.'s (1984) earlier estimates that a decreasing DTR is most apparent in summers, and in the eastern US, supposedly primarily agricultural regions. The mean temperature was observed as decreasing in the southeast. Yet, little change was observed in the central US, also in agreement with Karl et al., and Portmann et al. (2009). There were significant seasonal variations from summers to winters. Cooling effects come primarily from cooler summers. In contrast, the western US appears to experience warming in all seasons.

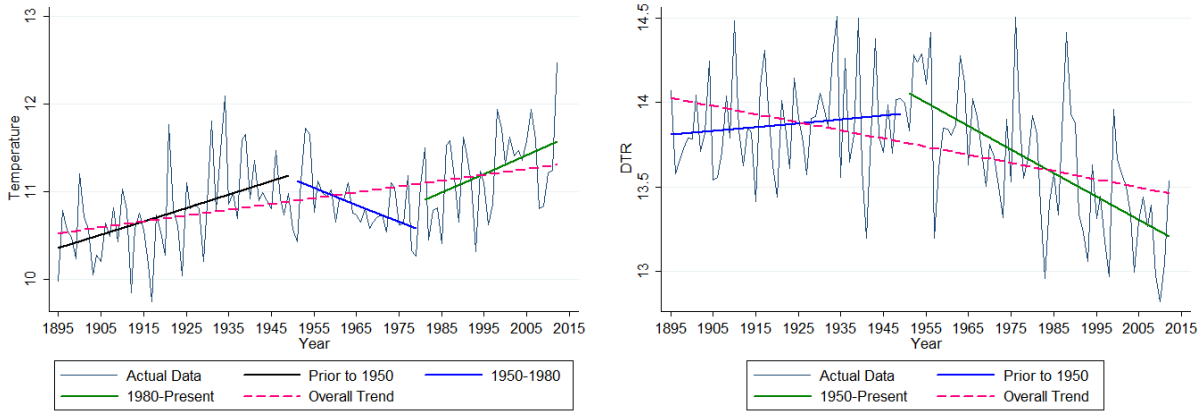
It is tempting to try to explain why this finding (the continuation of a statistically significant and decreasing DTR trend in the US) is different from Lauritsen et al. (2012) (which claims a decreasing DTR trend but statistically insignificant), and to a broader

¹<http://www.epa.gov/climatechange/science/indicators/weather-climate/temperature.html>

extent, Vose et al. (2005) (a falling DTR trend has been reversed to increasing globally since 1979). The first possible reason is that too few observations (25 years between 79-2004) led to a low power of trend tests. As shown in Figure 1, a few outlying observations around 1980 may bias the trend toward zero for the later years. Second, spatial variations have increased, causing coarse-scale aggregations to cancel out opposing trends, resulting in trendlessness. In fact, consistent trends can still be identified, and may have become stronger over time, from analyzing fine-scale data.

The causes or attributes of the observed spatial and temporal patterns of temperatures in the US are beyond the scope of this study. Neither could the patterns identified be exclusively linked to climate change nor the PRISM dataset appropriate for identifying climate change signal without adjustments. The effects of human-induced activities such as urbanization and urban heat islands, changes in vegetation cover, and irrigation may have played a role in the observed falling DTR as suggested by Karl et al. (1993).

Figure 1. Trends in Mean Temperature and DTR from 118-year PRISM Dataset



Note: Mean temperature (left) and DTR (right) values were averaged over the sampled grids selected from PRISM dataset covering the conterminous US. The straight lines help visualize the pattern of changes over time. Since DTR is bounded below by zero, the trend lines should not be used for inference beyond the observed period.

2 Dataset Description

The primary dataset is monthly climatic data produced by the PRISM group, which offers the best spatial and temporal coverage for the US, for the period of 1895 to 2012². The data is gridded at a 2.5-arcminute resolution (approximately 4km near the Earth’s equator). Variables of interest are the monthly maximum and minimum temperature. Mean temperature or the average surface temperature is derived as the average of the maximum and minimum temperature. Diurnal temperature range is the difference between maximum and minimum temperature. Yearly average and seasonal average for summer and

²<http://prism.oregonstate.edu/>

winter growing seasons are calculated as a simple mean for all 12 months, May to October for summer (6 months), and November to April of the year after for winter (6 months). These definitions of the seasons are rather arbitrary as the starting and concluding time for each growing season varies in different regions. Sensitivity checks including relaxing the starting and finishing months do not show any substantial change from the pattern presented hereafter.

The secondary data, county-level climate from 1940 to 2006 provided by the USDA Forest Service, is also available at monthly intervals³. This dataset is interpolated from the PRISM fine-scale grids up to a county level by firstly integrating the 2.5-arcminute resolution to a 5-arcminute scale, from which a weighted mean was generated for each county.

Sampling Procedure

Since the PRISM data for the conterminous US consists of 621*1,405 rows by columns, totalling 872,505 grids, among which there are 491,631 grids lying within the landmass with valid measures, and each grid has 118*12 = 1,416 monthly observations, it is unwise to analyze each and every grids. Furthermore, since PRISM grids were interpolated from a limited number of weather stations, adjacent grids likely yield similar values and patterns of fluctuations. As a result, it is sufficient to sample only a portion of the data that fully represents the spatial coverage over the country. I restrict the number of grids in the sample to be analyzed by about 1/100 of the complete dataset.

To better explain this scheme, the PRISM dataset is gridded at 621*1,405 rows by columns, each separated by $1/24 = 0.04166666667$ degree, starting from the southwesterly corner at `xllcorner = -125.020833333333` and `yllcorner = 24.062500000000`. Grids were sampled at a regular interval, starting with the first row, then the 11th row, then 21st, etc, and finished with the 621st row. Therefore, 62 rows were selected from the master dataset consisting of 621 rows. The same procedure was applied to the column selection. The first column, then the 11th column, 21st, etc, was selected, and finished with the 1,401st column. The total number of grids sampled from the dataset is $62*140=8,680$ grids. However, only grids with valid data (i.e. those lying within the landmass, not in the ocean or lakes) will be useful. Eventually, a subset of 4,856 valid grids was created. While this number may seem substantially smaller than to the total number of valid grids (491,631), it is still the finest resolution ever studied for trends in the US.

For county data, all 3,108 conterminous counties were used. County sizes were used as weights in calculating the mean and variance of the regional temperature series. Due to a higher density of smaller counties east of the 100th meridian (2,510 counties, covering roughly the same area as 598 counties in the west), national trends calculated by averaging over county data must be adjusted for county sizes.

³<http://www.fs.usda.gov/rds/archive/data/open/RDS-2010-0010/RDS-2010-0010.aspx>

3 Methods

3.1 Trend Test of Mean Temperature and DTR Series

The Mann-Kendall trend test is utilized to determine a monotonic trend in a time series. The purpose is to check if there is a tendency of increasing or decreasing in the data out of random year-to-year fluctuations. The test is based on the ranking between the observations over time.

The advantage of Mann-Kendall test is that it does not make restrictive assumptions on the distribution of the observations, except serial correlations. The Mann-Kendall test only makes use of the ranking between observations, not the absolute changes. As a result, the test is robust to outliers, such as weather shocks that may be encountered in most temperature series. Even a single shock may cause a significant bias in regression analyses. However, the absolute magnitude of shocks is irrelevant to the calculation of the Kendall τ statistics.

Because temperatures (whether annual or seasonal average) may carry significant autoregressive components together with random variations, I implement Yue et al. (2002) corrections by firstly removing the persistence in each series by an AR(1) process, then trend tests were conducted on the corrected series.

I follow Helsel and Frans (2006)'s formulation. Suppose M_i is the measured temperature at time i , $i = 1, \dots, T$, the series M likely has an increasing trend if pairs of $\{M_i > M_j$ if $i > j\}$ is observed more frequently than pairs of $\{M_i < M_j$ if $i > j\}$, and conversely, a decreasing trend. The series is trendless if the number of increasing pairs is about the same as that of decreasing pairs.

The Kendall's statistic is defined as:

$$S = \sum_{i>j} \text{sign}(M_i - M_j)$$

where

$$\text{sign}(x) = \begin{cases} 1, & x > 0 \\ 0, & \text{if } x = 0 \\ -1, & x < 0 \end{cases}$$

In short,

$$S = P - N$$

where P and N is the numbers of concordant and discordant pairs, corresponding to $\{M_i > M_j$ if $i > j\}$ and $\{M_i < M_j$ if $i > j\}$. The size of the S statistic indicates the level of correlation between series M and time trend t . If the series is completely random then we should expect to see P and N in similar number, and the S statistic is close to zero. If

P and N takes significantly different values then S is significantly larger or smaller than zero, and a trend is expected.

Since each series has T observations, there are $\frac{T(T-1)}{2}$ pairs to be drawn from. S takes on values between $-\frac{T(T-1)}{2}$ and $\frac{T(T-1)}{2}$, corresponding to an all-increasing to an all-decreasing trend series. The Kendall's τ correlation coefficient is therefore derived as:

$$\tau = \frac{S}{\frac{T(T-1)}{2}}$$

which will take on values between $[-1, 1]$.

For a large sample, the significance test for trends using either S or τ can be done by a normal approximation:

$$Z = \frac{|S| - 1}{\sigma_S}$$

with

$$\sigma_S = \sqrt{\frac{T(T-1)(2T+5)}{18}}$$

Since temperature measures are highly correlated over time, the Mann-Kendall test may inflate the test statistic and fail to reject the null of trendlessness too often. Removing the AR(1) component from each series will reduce the persistence, but at a loss of power:

$$\tilde{M}_i = M_i - rM_{i-1}$$

with r is the autocorrelation coefficient of the M series.

This is done by extracting temperature residuals from the regression of M_i on M_{i-1} . Note that the majority of temperature series are stationary, as suggested by Augmented Dickey-Fuller and KPSS tests for unit-root processes.

3.2 Rate of Change

The median rate of change is calculated using the Theil-Sen method:

$$g = \text{Median}\left\{\frac{M_i - M_j}{i - j}\right\}$$

for $i > j$.

The formula provides a rough estimate of the rate of change without possible influence from outlying observations as suffered in regression analyses. The Theil-Sen slope is not a test, however. The trends identified in Figures 2-7 and rate of change in Figure 8 should be interpreted in relation with one another.

4 Results

4.1 Trend Tests using Individual Series

4.1.1 Annual Temperature and DTR

Trend tests using county data and county data adjusted for serial correlations are shown in Figures 2 and 3. Figures 4 and 5 are trend tests using PRISM sampled grids. All tests were conducted at the 95 percent confidence level against the null hypothesis of no trend. After adjustments for serial correlations all tests appear to be less powerful as expected.

The mean temperature pattern is more spatially coherent, with most warming observed in the arid climate and northern US. While the DTR picture is less coherent, an overwhelming number of grids has a falling trend across the US. Still, sparsely located pockets of increasing DTR grids observed in southeastern and northwestern US require explanations whether the phenomena is due to urbanization or other processes.

Figure 2. Trend in Mean Temperature (left) and DTR (right), County Data.

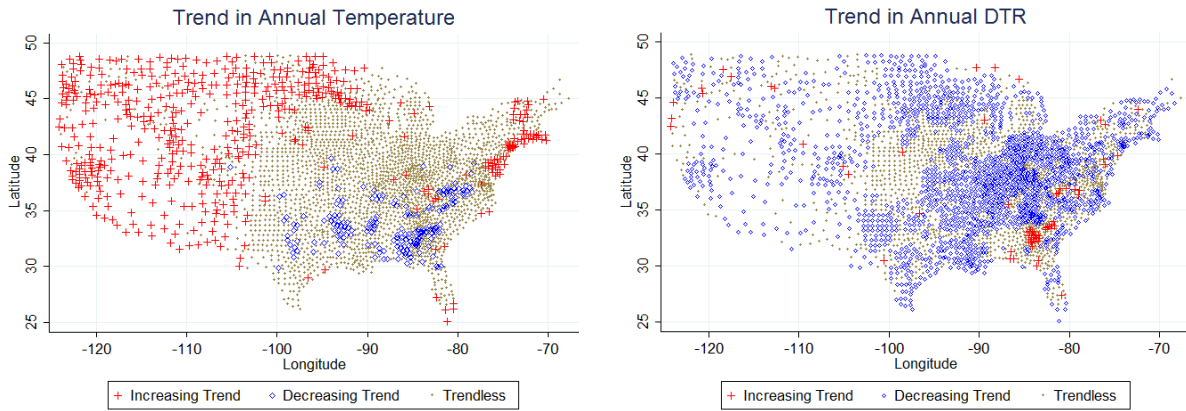


Figure 3. Trend in Mean Temperature and DTR, County Data, Corrected for Autocorrelation.

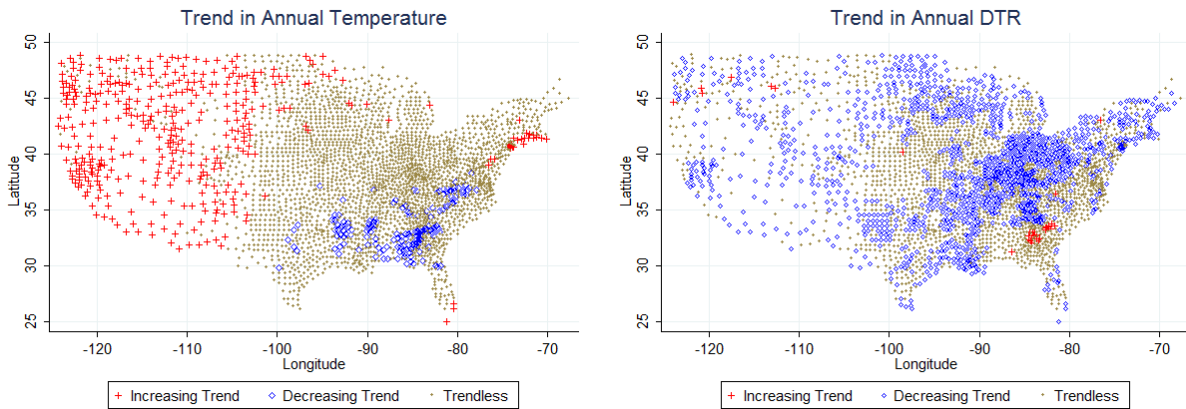


Figure 4. Trend in Mean Temperature and DTR, sampled PRISM grids

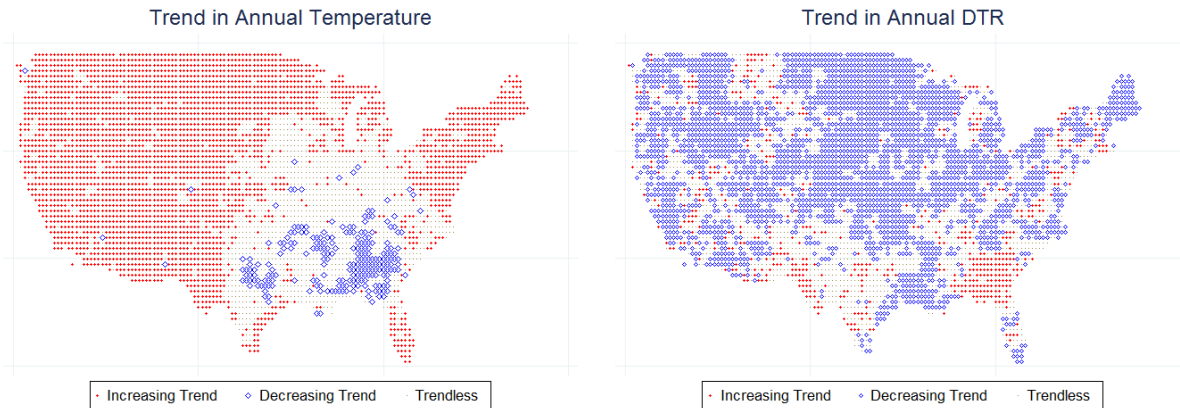
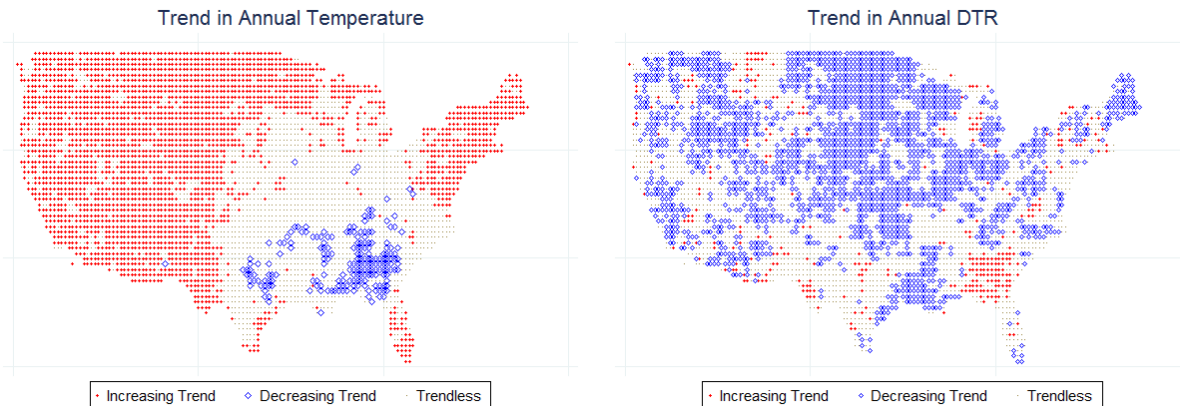


Figure 5. Trend in Mean Temperature and DTR, sampled PRISM grids, Corrected for Autoregression.



4.1.2 Seasonal Trends

Seasonal trends for two growing seasons in summers and winters are shown in Figures 6 and 7. Distinct seasonal patterns in both mean temperature and DTR are visible: the western US appears to have seen warming consistently, while the eastern US pattern varies between seasons. The mean temperature appears to have fallen in southeastern US in summers. Meanwhile, the north-central US may have experienced warming in the winters. The rest was trendless with intersperse pockets of opposing trends. The DTR pattern was clearer. DTR was seen falling almost everywhere in summers. Winter pattern was less clear. Southeastern US was the exception, where an increasing DTR was observed in winters. Central US saw very little change in all seasons, which could be evidence to corroborate the “warming hole” proposed by Pan et al. (2004). These distinct seasonal and annual patterns suggest that aggregations may be problematic for identifying changes in temperatures due to heterogeneous spatial and temporal variations.

Figure 6. Trends in Summer

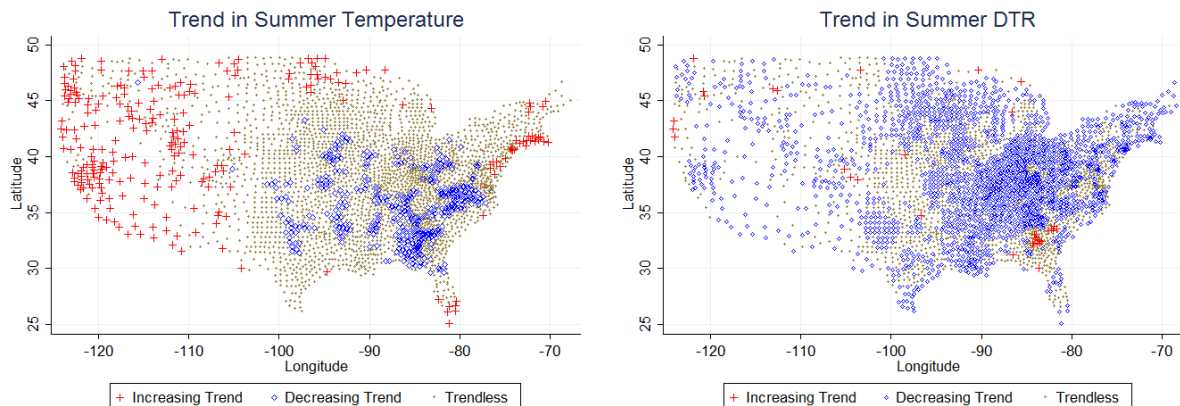
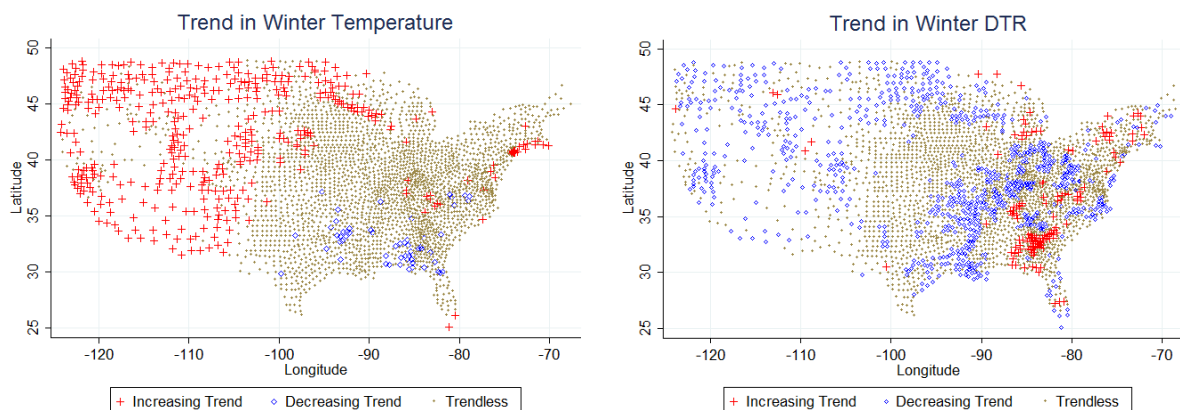


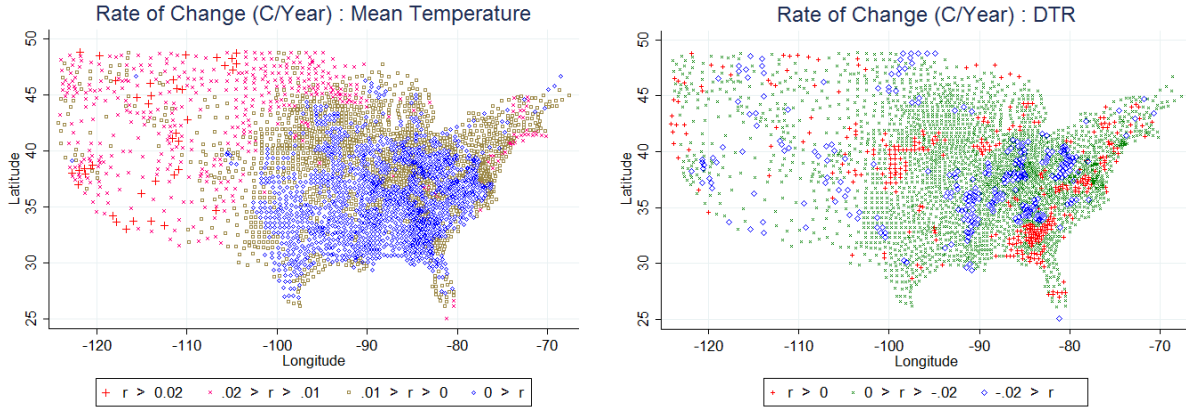
Figure 7. Trends in Winter



4.1.3 Rate of Changes

The median rate of change, in degree Celsius per year, is shown in Figure 8. It is not surprise to see the largest positive change in mean temperature in the western US and north-central Plain, at a rate up to .02 C/year over the last 60 years. Cooling effects were dominant in the southeast, with little change was seen in the northeast along the Canada-US border. An increasing DTR was most evident in the southeast, and in some sparsely located counties along the west coast and in central Plain. A decreasing DTR at the highest rates less than -.02 C/year was seen near the Corn Belt. The remaining counties were also seeing a falling DTR trend, though at a lower rate. Note that Theil-Sen slope is not a test, so not all calculated rates of change were statistically significant. Figure 8 should be interpreted in relation with Figures 2-5 if trends were both visible and statistically significant.

Figure 8. Median Rate of Change, Annual Data



4.2 Trends in Regional Mean Temperature and DTR

Figures 9-13 show the temporal patterns of the mean temperature and DTR for two segregated regions, the east and the west of the 100th meridian, and the aggregate US. To project regional trends from county observations, a smoothing procedure using local regressions was first applied to each county temperature series, then the regional mean temperature T_m and standard deviation sd_m was spatially averaged from the smoothed values T_i in each county. The weight is proportional to the county size $area_i$.

$$T_m = \frac{\sum_i T_i * area_i}{\sum_i area_i}$$

and

$$sd_m = \sqrt{\frac{\sum_i (T_i - T_m)^2 * area_i}{\sum_i area_i}}$$

for $i = 1, \dots, N$ counties.

The calculation of the regional DTR trends and standard deviations follows the same procedure.

4.2.1 Annual Temperature and DTR

All figures show rising mean temperature trends, though patterns may be different between the arid and humid climates. The national trend is consistent with the pattern displayed in Figure 1, of a short cooling period, occurred mostly in the eastern US, in between 1950-80. The cooling effect was not seen in the western US. From 1980, temperature started to rise all over the country. Particularly, spatial variations, as indicated by the standard deviations, have been falling consistently over time.

A falling DTR trend was evident in all seasons, whether at the national or regional levels. However, the variations in DTR were perplexing and require further analysis. These series saw a short period of narrowing variations for roughly a decade in between 1965-1975, after which DTR variations have been widening significantly until today.

Figure 9. Country Aggregate

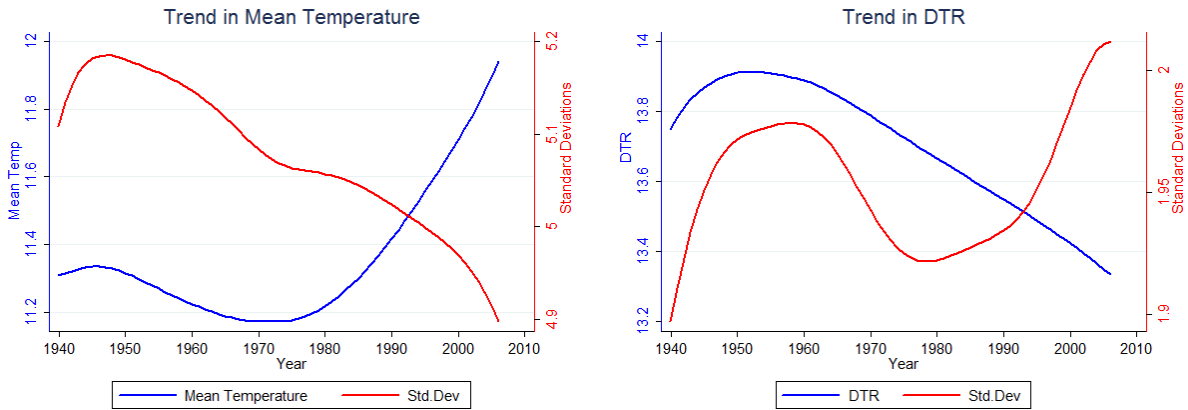


Figure 10. West of 100th Meridian

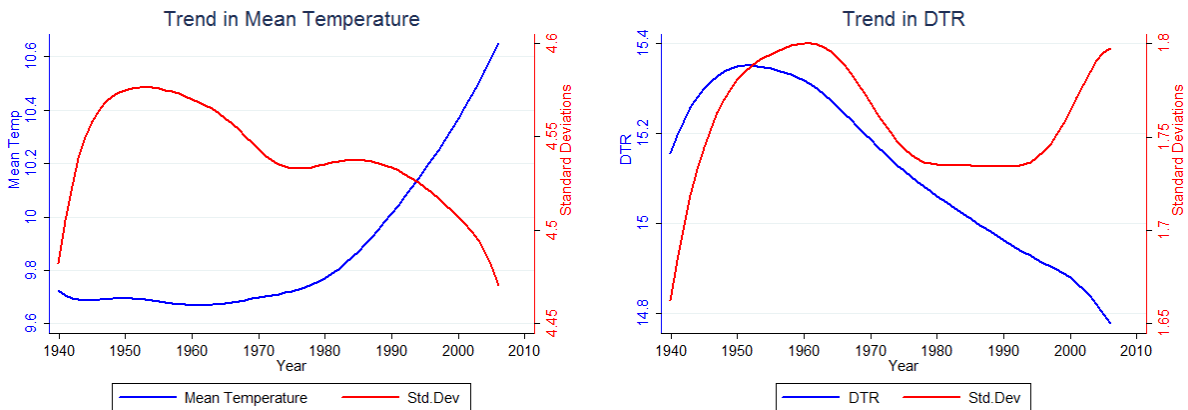
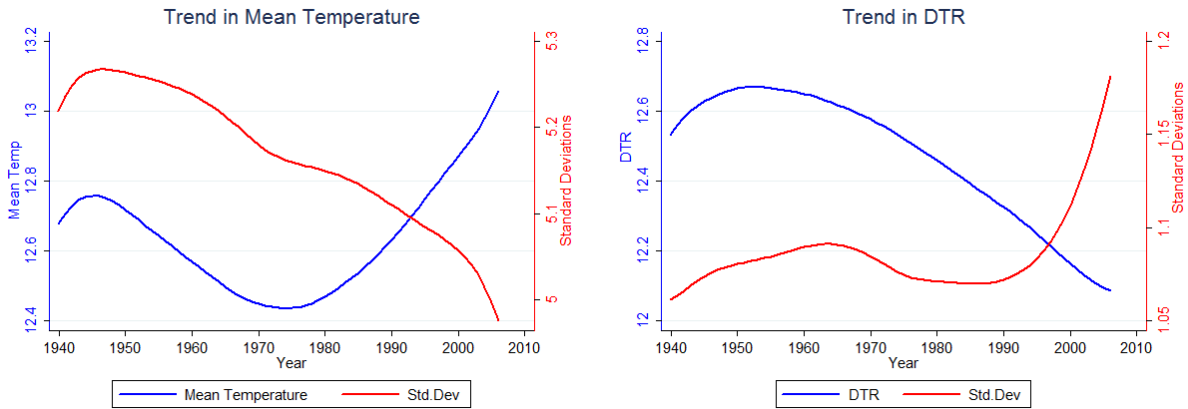


Figure 11. East of 100th Meridian



4.2.2 Seasonal Trends

Again, trends in mean temperatures in the left of Figures 12-13 were consistent with more warming in winters, at a rate up to almost one degree Celsius since the warming trend has set in in early 1970s, compared to almost half of a degree Celsius observed in summers. Additionally, the standard deviations decreased in all seasons, suggesting a convergent tendency of the mean temperature trends between regions. DTR patterns were opposite of the changes in mean temperatures. Since 1950s, summers have seen a higher level of reductions at about -0.8 degree Celsius, compared to just less than a half of a degree Celsius in winters. Spatial variations have increased in all seasons, after the perplexing period in between 1965-75.

Figure 12. Summer, all conterminous counties

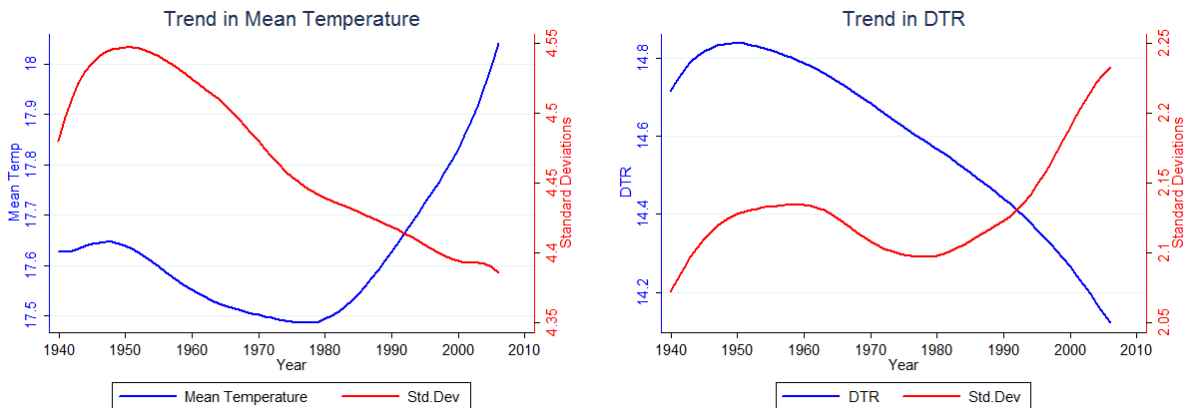
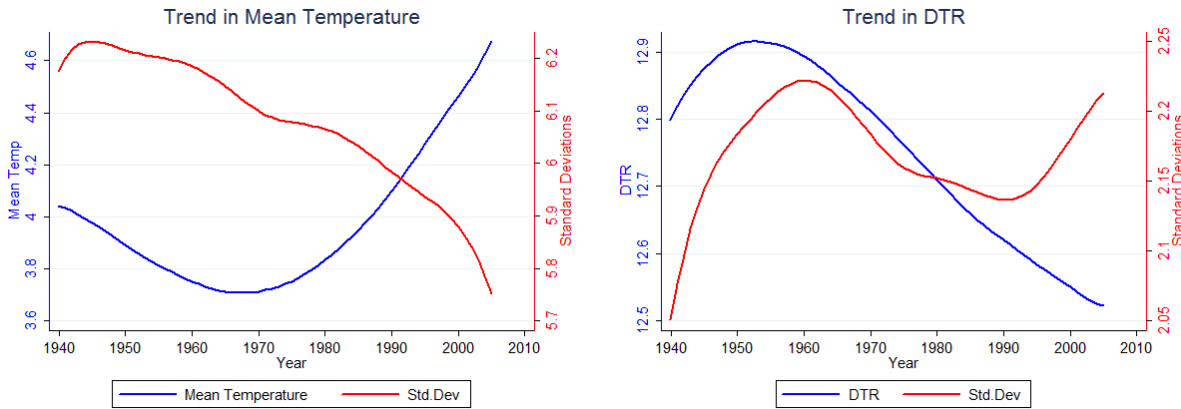


Figure 13. Winter, all conterminous counties



5 Remarks

There are two distinct patterns in the distribution of observed temperatures. For the national mean temperature, the increasing trend is more consistent with the global tendency in observing a short downward trend from 1950-1970, then increasing at a faster rate through today. As indicated in Figures 2-5, the trends of the mean temperature in most eastern counties are statistically insignificant. This is not because there has been no warming. The problem is that there was a significant cooling period lasting over two decades within the temperature series, monotonic trend tests may not be able to reveal any deterministic trend. Considering solely the last three decades, warming signals are unambiguous. The warming trend is more consistent in the dry climate west of the 100th meridian. Spatial variations were seen narrowing down except during an initial period in 1940s, suggesting a converging trend of increasing temperatures across regions, with a higher rate of warming observed in colder climates or at higher latitudes. In contrast, DTR has been falling since 1950 in most places in the US, and the trend has not been reversed. Most regions have observed widening spatial variations in DTR lately, indicating the existence of heterogeneous trends, both increasing and decreasing, and trends of significantly different rates of change.

Essay 2

Were there Modern-Day Dust Bowls? Evidence Suggests that Recent Extreme Droughts Contributed to Cropland Conversion in the United States

Abstract

Climate and weather extremes have always been a critical problem for the sustainability of US agriculture. In this study, I focus on the single most destructive event - extreme droughts. I present the first evidence of the effect of severe drought condition on farmland loss trend in the US in late twentieth century. By incorporating extreme drought into the total factor productivity, I model the cropland conversion as a consequence of weather shocks that produced permanent damages to the productive capacity of the soil, such as losses of the topsoil from extreme drought events like the Dust Bowl. The result indicates that extreme droughts and uncertainty regarding their long lasting effect on soil productivity discourage sustainable agricultural use and accelerate irreversible conversion out of agricultural production. This result also highlights a major threat to US agriculture arising from climate change that may introduce significant agricultural regions to extreme dry condition. The threat could be worse if future yield growth cannot keep up with observed historical pattern. Irrigated farms in the Western US appear to be less affected by droughts than rainfed agriculture east of the 100th meridian. In addition, I suggest a potential mechanism in which Ricardian approach to estimating the impact of climate change, by assuming full adaptation, may have underreported actual damages from the extremes. I also consider a fat-tail climate change scenario that disproportionately increases the frequency or intensity of extreme drought events could be particularly damaging to the US agricultural landscape.

Key words: Extreme drought, climate change impact, Ricardian hedonic regression, dynamic discrete choice modelling

1 Introduction

Following a period of severe decline in rainfall, and baked under the Sun, the topsoil, the most productive soil, became loosely bound to the ground and was blown away in a series

of dust storms that blanketed the ground and hundreds of millions of acres of cropped land in the Great Plains covering parts of Oklahoma, Kansas, Texas, Colorado and New Mexico. Two and a half million people were forced to leave homes and seek refuge in neighboring states. Perhaps, the Dust Bowl is the most memorable, and inarguably, the worst natural disaster in the United States. A combination of human-made unsustainable farming practice and naturally occurring extreme drought conditions resulted in the virtual total destruction of the ecological and agricultural landscape over the Great Plains.

During a period of increasingly high crop demand, coupled with favorable rainfalls, millions of people flocked to the Great Plains under a false “rain follows the plows” pretense that the temporary increase in rainfalls was indicator of a permanent shift to favorable climate conditions, creating a false sense of coming prosperity. The prosperous time was quickly over, however, once limited rainfalls coupled with strong winds characteristic of the flat Plains set in, exposing the peak period of the agricultural influx to only short-term economic gains resultant of a disregard for environmental constraints and careful long-term planning. In 1935 alone, over 850 million tons of topsoil, an equivalence of at least five inches of topsoil in over 10 million acres of affected lands, was blown away, leaving behind bare soil depleted of necessary nutrients for cropping. Several studies, including Lockeretz (1978) and Hornbeck (2009) suggest the long-term consequences, including immediate destruction of the local economies, extended well beyond on the Plains states. Wind erosion and the loss of soil organic matters can lessen crop productivity for many years after a drought (Whitmore, 2000).

The late twentieth century saw similar events to that of the Dust Bowl era. Although recent drought events bear little semblance with the Dust Bowl, economic impact, according to Ross and Lott (2003), were equally destructive. During 1980-2003, extreme droughts accounted for only 17 percent of the number of extreme weather events, yet caused more damages than any other natural disasters, and the cumulated damages were nearly a half of the total damages from all natural disasters combined (Appendix 1). The drought in early 1980 and 1988 resulted in almost a hundred billion dollars in combined damages (including long-term cost) and thousands of deaths (including indirect deaths attributable to drought and heat wave). In fact, the 1988 drought remains the single costliest natural disaster in the US history. The agricultural industry, as the largest user of water in the US, is without doubt the most vulnerable sector affected by droughts.

Historically, estimating the impact of weather extremes, such as severe droughts, is difficult and remains poorly understood in almost every regard. For agriculture, in general, and cropland production in particular, the task is even more challenging. First, extremes, by definition, were rare, and the extent of damages was hard to measure accurately. In the worst-case scenario, the immediate impact could be the destruction of a local (or greater) economy, or at minimum, imposes significant financial cost in terms of lost revenue from crop failure, livestock losses, and massively increased expenses to agricultural productions. While immediate damages to infrastructure or crops could be tallied relatively easily, the long-term impact of drought remains difficult to quantify. In fact, the long-lasting impact of droughts or extreme weathers could be significantly more destructive. Permanent soil degradation following extreme drought events could force farmers to permanently abandon

cropping. A recent study by Biggelaar et al. (2004) shows evidence of a significant soil erosion impact on global agricultural productivity. Although short-term remedies such as crop insurance could help farm owners cope with unexpected weather extremes, the long-term impact is still significant and must be studied carefully.

Admittedly, there is a significant gap in the understanding between the impact of climate change and that of climate and weather extremes. While these may seem like two distinct subjects, it is difficult to separate one from the other. Climate change, often poorly understood as gradual changes of temperatures and precipitations, can induce disproportionate increases at the extreme ends, such as greater extreme precipitations simultaneous to an increase in extreme droughts, or a higher number of extreme heating days and fewer cold spells (Field et al., 2012). However, extreme event occurrence could be driven purely by natural variabilities, not necessarily linked to anthropogenic forcings. Extreme weathers are not necessarily an indicator of climate change as it is impossible to link any specific extreme event to an underlying changing climate. A balanced view on the impact of climate change should take into account a possibility that these two effects, gradual shifts in the average and the extremes, are simultaneously present and perhaps more likely in the future.

To measure agricultural impacts, empirical literature often relies on a crucial assumption regarding forward-looking behavior and the long-term impact of climate change. In essence, the assumption is that long-term climate conditions tend to be favorable and will positively effect profits much more than short-term losses induced by a year or two of extreme weathers. Short term events are not believed to leave any long-lasting impact or influence future economic returns. The traditional Ricardian approach offered by Mendelsohn, Nordhaus, and Shaw (1994), and later adopted by Schlenker, Hanemann, and Fisher (2005) utilize the past climate to predict current farmland values. This assumption is admissible, but with caution. In the absence of climate and weather extremes, this method can be used to estimate farmland value at the *long-term land-use equilibrium*, which reflects the highest-value use if the land market operates properly.

However, the assumption that the Ricardian approach relies on may not fare well in the presence of extreme events such as the Dust Bowl, which caused permanent soil damages to the affected land. The Ricardian approach assumes that climate normals such as the average temperature or precipitation capitalize on the farmland value and the optimal land-use choice via effects on agricultural production. However, climate and weather extremes, understood as abnormal events, are not evaluated in a “normal” climate. A single extreme event, even if it is a temporary phenomenon, could shift the established land-use equilibrium if land owners heavily weigh short-term economic damages over possible long-term gains. In such a situation, using the Ricardian approach to estimate farmland value and optimal land-use choice may be incorrect. That is, farmland values or the optimal land-use choice reflects the effect of the short-term extreme weather event rather than the established long-term climate.

Certainly, it is difficult to imagine how one temporary weather excursion may force land conversions en masse. However, if damage to soils reaches the extent as that of the Dust Bowl, there is a reason to suspect that even short-term weather shocks could be

a significant cause of cropland losses. While studies employing the Ricardian approach may safely ignore any uncertainty associated with projected long-term benefit of climate change, they also ignore possible damages from extreme conditions in the short term¹. This study attempts to fill in this gap: How do short-term weather and climate shocks affect cropland production, and land-use conversions? And what is the prospect of the agricultural landscape if climate change results in many more damaging extremes in the future?

The ultimate concern is that even though an increase in precipitation in North America is projected in all global warming scenarios, there is also an increase in the likelihood of droughts, including extreme drought conditions (Dai et al., 2004, 2011a,b). This is especially problematic for studies using mean shifts in climatic normals to project the long-term climate change impact. Restricting climate change to gradual changes does not account for a possible scenario, one that has just only recently gained attention, that droughts may become prevalent in as soon as the 2030s, especially for most of the western US (Dai, 2011a, and Seager et al., 2007).

To answer these questions, this study seeks to address two outstanding issues overlooked by the Ricardian approach up to this point: using a climate or weather extreme indicator that is truly representative of extreme events, one that is not captured by a normal climatic index; and a way to model the long-lasting impact of extreme events. I present strong evidence of the influence of severe droughts, notwithstanding other factors including productivity growth and urbanization processes, on cropland loss to developed land. The cornerstone of this result is a structural model of land-use transition which allows for modeling the long-lasting impact of extreme droughts on cropland productivity, the uncertainty associated with future productivity growth, and the irreversibility of the conversion decision.

2 Evidence of the Impact of Recent Extreme Droughts on Agricultural Productivity

I examine the total factor productivity (TFP) in agriculture for possible fingerprint of the extreme events, and its importance for future farming. While existing studies including Schlenker and Roberts (2006) and Le (2010) show the impact of temperature fluctuation on crop yields, also known as land productivity or production per acre, the yield measures may be biased. Farmers often respond to adverse weathers by adding more variable inputs. This will affect reported yields. Furthermore, crop rotations and temporary abandonment

¹Schlenker, Hanemann, and Fisher (2006) predict a negative impact of Harmful Degree Days (GDD34), Degree Days measured at a temperature above 34 degree Celsius, on farmland value. This may be considered as an indicator of extreme heating in a static sense. However, extreme weathers can also be defined based on a probabilistic approach, i.e. what is statistically abnormal. Under the second definition, there is no fixed threshold for determining whether a weather record could be classified as an extreme. For example, 34 degree Celsius may be considered as extreme for higher latitude states, but normal for the lower latitude states like Arizona or Texas. This paper adopts the second definition of extremity.

of planted acreage is also a problem. It is reflected as an upward bias in the reported per-acre production or yields. This issue is explained extensively in Le (2010). Improvements in input quality may also affect reported crop yields. TFP, as an output-per-unit of (combined) inputs measurement, is less prone to bias suffered by yield reports. I found possible evidence of the influence of extreme drought conditions on TFP fluctuations measured at a state level during 1948-2000 period in Figure 1. Details of these variables are provided in the Data Description section.

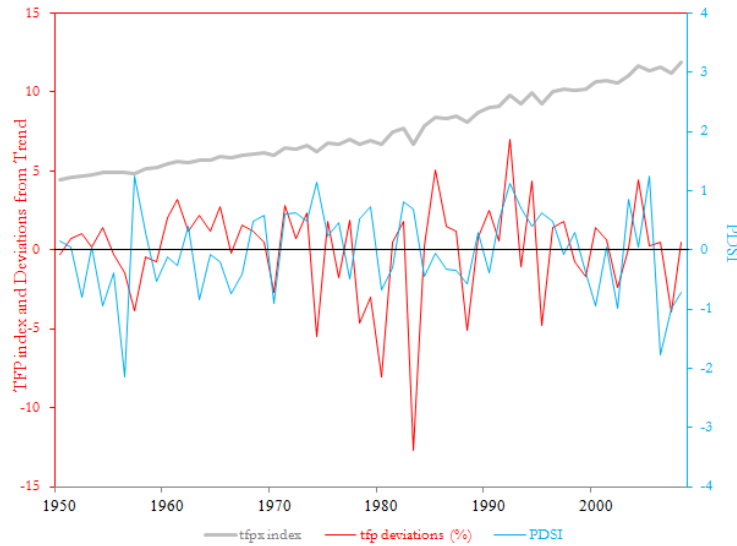
First, despite large year to year fluctuations, annual productivity growth has been averaged over 1.8 percent during 1950-2008. In fact, TFP growth is the single most important factor behind agricultural output growth in the US. Aggregate input use has been decreasing at a rate of -0.11 percent per year for the US during this time (James et al., 2009). This means that the US' agricultural prospect rests squarely on productivity improvement to drive long-term output growth (Fuglie et al., 2007). Second, even with clear evidence of a consistently rising TFP, individual state trends vary, and have slowed down since the late 90s. In addition, structural breaks were reported in various studies (James et al., 2009 and Alston et al., 2010). No consensus was reached, however, if a yield plateau could occur in the coming decades (Reilly et al., 1998 and Meredith, 2000). The implication is that if cropland loss accelerates in the future, improvement in other factors such as higher quality inputs (e.g. fertilizer, skilled labor, and machineries) must be realized in order to offset loss of cropland acreage.

The large deviations in TFP could be attributable to weather shocks, policy change, or measurement errors (Fuglie et al., 2007). Visual examination of the graphs suggests a high possibility of an influence of the mega-drought events on agricultural productivity shocks. While this relationship may appear easy to comprehend, the long-term impact of the extreme drought condition is not evident. Restricting to aggregate data, it is possible to wrongly hypothesize that a short-term setback could be offset by future growth, given a pervasive long-term TFP growing trend. This might be true for the economy as a whole, but not for individual farms whose productive property was permanently damaged after extreme events such as the Dust Bowl (Morehart et al., 1999). While storage and price effects could have buffered the large-scale impact of the droughts (Whittaker, 1990, and Fisher et al., 2007), self-insured policies do not work for individuals, as the long-term costs are expected to increase for affected farms.

3 Potential Impact of Extreme Droughts on Cropland Conversion and Implication

Given that extreme droughts may have produced recognizable shocks on agricultural productivity, the question is whether those shocks were either strong enough or lasted long enough to shift the contemporaneous land use equilibrium. In other words, did the recent Dust Bowl droughts share blames for the farmland loss tendency in the US, and if yes, to what extent? Careful examination of the determinants of farmland economic returns yields a notable fact. Agricultural output price have been lagging behind input

Figure 1: **TFP Fluctuations with Observed PDSI index.** TFP deviation from time trend (tfp deviations, in percent) is calculated as the residuals from the observed TFP (tfpx_index, a normalized TFP index scaled up by 10, based on 1996 data in Alabama) after filtering out time trend using Hodrick-Prescott estimator for time series data decomposition.

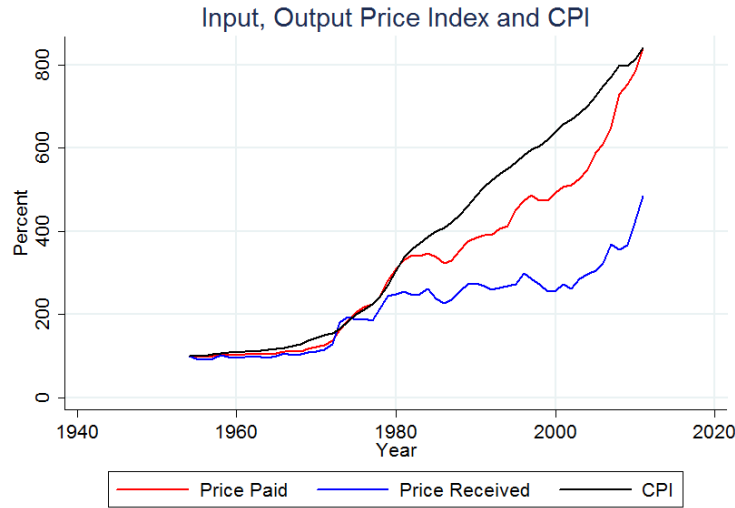


costs over an extended period of time. The input prices keep rising steadily in consistence with the general price index. Therefore, increasing economic returns to farming have more to do with rising productivity to maintain their economic competitiveness against competing uses.

This raises a critical question regarding the role of productivity growth and the future of US agricultural farmland. What if we were to reach yield plateau in the near future? Historical evidence illustrates a consistent yield growth trend over the last four decades, since the Green Revolution, which is a major factor contributing to agricultural output growth. A question looms, however, over whether the yield trend is stationary, or if structural breaks might occur in coming decades. A possible scenario, perhaps a “doomsday” one to be exact, is that yield growth halts while a fat-tail climate change scenario materializes². Yields may level out in combination with increasingly large uncertainty over

²The idea of fat-tail vs thin-tail uncertainty originally refers to the probability of low frequency and high impact events (Weitzman, 2009). Later, Pindyck (2011) describes the concept in more technical expression that uncertainty of the fat tail distribution declines to zero slower than an exponential power. In thin tails such as the normal distribution, the extremes’ probability declines to zero at an exponential power. Graphically, the thin-tail distribution is exponentially bounded. In contrast, for an unbounded fat-tail distribution the moment generation function is infinite. In the demonstration figure, we present

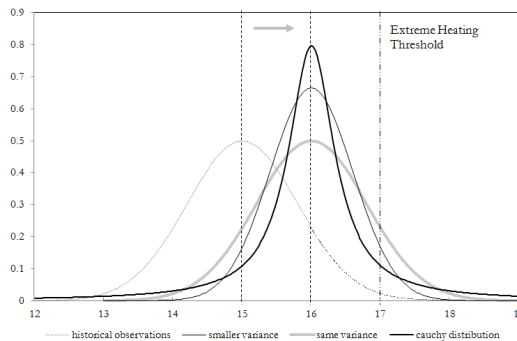
Figure 2: **Agricultural Price Trend.**



the frequency and severity of harmful weather extremes. What prospect will exist for the farming economy, and thus, cropland future? Will there be further cropland losses coming resulting from this scenario?

In summary, the debate about the impact of climate change has received increasingly more attention since seminal works by Mendelsohn, Nordhaus, and Shaw (1994) and later by Schlenker, Hanemann, and Fisher (2005), that forward-looking behavior offers a way to model the impact of climate change using Ricardian farmland value framework. Rational decision makers, by locking into long-term optimal use, can absorb any short-term cost

three possible climate change scenarios. All scenarios expect the same change in the mean temperature but come with different variance. This figure shows that even a thin-tail same-variance climate change scenario is subject to a disproportionate increase in heating condition. If the uncertainty is indeed a fat-tail one, the prospect of both more frequent and more severe extreme heating events will be even more threatening.



exuded by extreme weathers. As a result, a few degrees increase in temperature and enhanced precipitation by the end of 21st century may look promising to future farming. Yet, this study suggests that short-term extreme events could cause significant damages and accelerate private farmland conversion, based on an analysis of field-level land-use observations. This reinforces our belief that even if climate change brings a vast swath of territory to warmer and more favorable conditions for agriculture, the likelihood of more frequent and intense extreme events could outweigh any potential gain.

This paper proceeds with a short introduction on a conventional production approach to modeling farmland profit and a framework for discrete choice of land-use change. The model is then extended to incorporate uncertainties in a dynamic setting, followed by the result and implications. Interested readers may find a rigorous discussion of the estimation procedure in the Technical Appendix.

4 Modeling the Impact of Extreme Droughts on Cropland Conversion

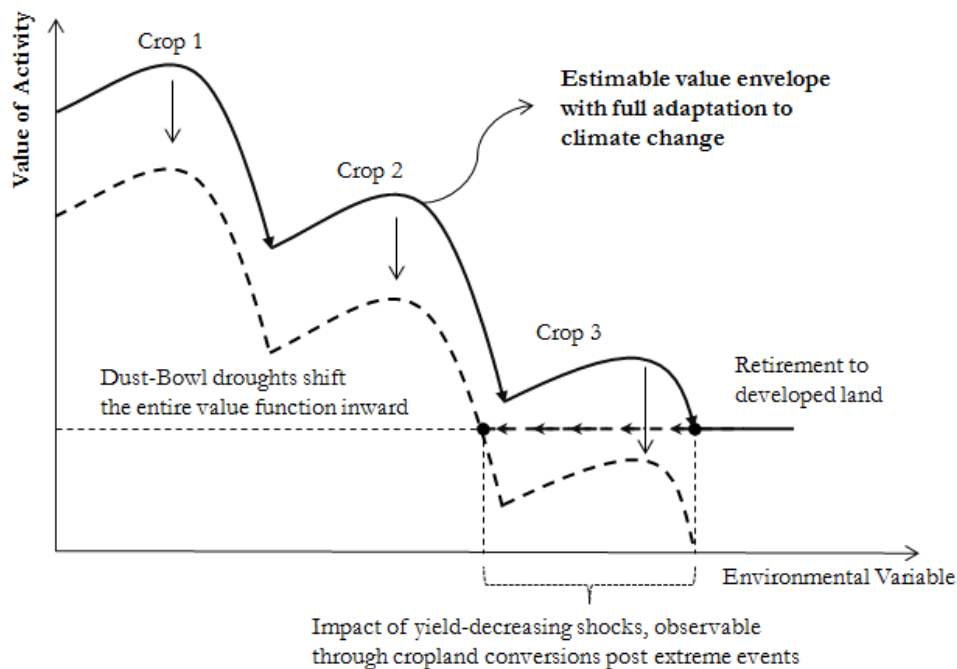
The land-use model such as Chomitz and Gray (1996), understood as a static equilibrium model, is a useful tool for modeling the optimal land-use choice based on the comparison of financial returns between alternative uses, and has been used in a number of studies such as Nelson and Hellerstein (1997) and Deininger and Minten (2002). These static models, in essence, share the same hedonic approach, which determines the influence of time-invariant characteristics on land value, thus the optimal land-use choice. However, to explain the land-use dynamic, one has to identify shock(s) that shift the land-use equilibrium, and integrates it into the common land-rent framework. Fixed effects cannot explain how a dynamic system transits from one state to another. Also, year-to-year weather fluctuations as well as temporary price shocks are not expected to shift the optimal long-term land-use equilibrium.

In fact, we observe land-use changes in a far shorter time scale than reasonably expected to shift the long-term land-use equilibrium (as a possible result of climate change). The urbanization process is most likely the predominant driver of farmland losses. Secondary factors include things such as agricultural input or output price shocks, or adverse weathers. Climate change, if understood as a gradual change in temperature or precipitation level, has not generated identifiable signals on land-use change, considering the prolonged time horizon needed to yield a recognizable signal of climate change. In particular, I focus on the short-term weather shocks such as the Dust Bowl drought that permanently shift the value function of cropland. To illustrate this concept, I employ the same intuition used by Mendelsohn, Nordhaus, and Shaw (1994).

Suppose that farmland value is a function, linear or nonlinear, of a single environmental variable such as the mean temperature or precipitation. The Ricardian model of climate change impact maps out the boundary of the farmland value function on the environmental variable, as illustrated in Figure 3. In a dual-use system, the best lands will be used for crops. Farmlands with economic returns less than developed land rents will be converted

to urban use and earn urban land's rent, independent of the environmental variable. Assuming that farmers automatically adapt to changing conditions, then crop choice is implicit, based on the highest economic return. The hedonic approach to farmland value is presented as the solid line, for three crops at three different temperature ranges, and then retirement to developed land.

Figure 3: **Impact of Climate Change vs Climate and Weather Extremes on Farmland Value.**



The Mendelsohn, Nordhaus, and Shaw (1994)'s framework is useful for projecting climate change impact if full adaptation is allowed. That is to say, climate change only induces movement along the value function, including possible impacts of changes in climate and weather extremes. In fact, their study restricts climate change to gradual changes in temperature and precipitation. Though latter work incorporates climate variance and diurnal temperature (Mendelsohn and Dinar, 2003), it still does not account for extremes. If extremes are not fully adaptable, which should be expected, the Ricardian approach will likely overestimate the benefit of adaptation.

Graphically, the Ricardian approach, understood as an equilibrium response approach, assumes that any potential climate change impact is restricted to a change in equilibrium or movement along the value envelope curve. This assumption is acceptable if farmers are allowed sufficient time to adapt to the new climate. Adjustments could be capital build-ups, irrigation improvements, advancement in farming skills, crop choices etc. However, transient climate change is intentionally ignored in this framework. If transients are not

adaptable, or at least not costless, then the equilibrium response model may produce a set of parameters which best fit the new local condition independent of any transient process.

There are two possible explanations for an understatement of the impact of climate change using the Ricardian approach. Firstly, farmers are slow to adjust in equilibrium responses, even if adjustment is possible. Kelly et al. (2005) predicts that adjustment cost accounts for 1.4 percent of annual land rents. Adjustment costs could come from being unable to change input mix quickly enough, especially as it relates to an increase in capital stock in order to mediate the impact of adverse weather fluctuations or gradual climate change. The second reason, which is interest to us, is farmers' inability to adjust. This is more likely the case with most weather extremes. Regardless of preparation, damage is likely unavoidable.

I hypothesize that extreme drought events shift the entire value function or the production possibility frontier of the affected cropland inward, when graphed, as exemplified by the loss of topsoil, or damages to farming infrastructure. The new value function is the dotted line, below the original value function after an extreme event. However, we are not interested in estimating the value function, per se. We seek to find how the value function shifts in response to shocks such as Dust Bowl-type droughts. And the consequence of such a shift may result in some farmland conversions.

Analytically, hedonic regression models, relying on a cross-sectional method, estimates farmland value based on *historically established* climate, assuming that long-term equilibrium of land-use choice has been established. With this implicit assumption removed, I model the transition of land-use equilibrium caused by *recent* shocks, such as extreme weather events, that caused significant and irreparable damages to the productive capacity of the land. Then, lands with low economic returns (Crop 3) would likely be converted following extreme events. A unique feature of the National Resource Inventory (NRI)'s repeated field-level survey, before and after land conversion, allows controlling for fields' fixed effects and disentangling the influence of extreme events from other shocks. Understandably, information about private land value is severely limited, as it is extremely difficult to monitor private land market transactions. However, we can identify the conversions from NRI database, which aids in determining the effect of external shocks including Dust Bowl-type droughts on marginal lands.

Without uncertainty regarding future economic returns, the optimal land use choice should reflect the highest net present value, thus a simple cost-benefit analysis is sufficient in most situations. However, if the impact of extreme shocks is uncertain (which is inarguably certain!), the decision to permanently convert a piece of land must take into account the option value of remaining in cropland production. Irreversibility of land use conversion places an additional value on top of the expected discounted value from agricultural production. The existence of option value adds substantial complication to the optimization problem. Chomitz and Gray (1996), and many subsequent studies, failed to take uncertainty and the irreversibility effect into account, resulting in overestimation of negative consequences of shocks. In this study, I propose a dynamic discrete choice framework that incorporates both the uncertainty of the impact of extreme droughts and

future productivity growth³.

4.1 Derivation of the Agricultural Profit Function

For lands in agricultural production, the farm owners' decision is to maximize profit, the difference between total revenue and total cost. Realistically, price is the forward price of commodity-crop on each piece of land. Since farm owners' input decision is made simultaneously with crop choice, we cannot use farm's reported cost of inputs or revenue as exogenous determinants of profit. Farm owners are faced with exogenous price P for farm output, where there are K inputs each with unit cost ω_i :

$$\pi = TR - TC = P * Q(x_1, \dots, x_K) - \sum_i \omega_i x_i \quad (1)$$

I adopt a conventional Cobb-Douglas production function:

$$Q(x_1, \dots, x_K) = A \prod_i x_i^{\beta_i} \quad (2)$$

For $i = \overline{1, K}$, and A is the Total Factor Productivity (TFP).

Due to the existence of fixed climatic inputs such as temperature or Growing Degree Days and precipitation, we should expect a decreasing return to scale with respect to the variable inputs, meaning that when all variable inputs like fertilizer or labor double, output increases at a rate less than double.

Indirect Profit Function

Start with a standard profit maximization problem:

$$\max_i = A \prod_i x_i^{\beta_i} * P - \sum_i \omega_i x_i \quad (3)$$

Since there is no information about type of crops or input cost at the plot level, we have to estimate an indirect profit function based on exogenous input and output prices. The indirect profit function associated with exogenous output and input price is:

$$\pi(P, \omega) = (1 - \sum_i \beta_i)(PA)^{\frac{1}{1-\sum_i \beta_i}} \left[\prod_i \omega_i^{-\beta_i} \right]^{\frac{1}{1-\sum_i \beta_i}} \quad (4)$$

For proof of a simple model with two inputs, see Beattie, Taylor, and Watts (2009).

³As a side note, this model is likely to underestimate the economic impact of extreme droughts. Farmlands with greater adaptive capacity (such as those currently in Crop 1 and 2) will remain utilized as cropland, but become less valuable. Thus, caution is advised when interpreting the result. Future attempt may help determine the exact location of the value function following extreme events.

Extreme Droughts' Impact as a Productivity Shifter

The strategy is to decompose the exogenous total factor productivity (A) into two components: a pure time-dependent productivity growth component that represents exogenous technological progress, and another to capture time-dependent location-specific random shocks, which is most obviously extreme weathers such as severe droughts. This formulation is extremely important for several reasons. The Cobb-Douglas production function allows for some level of substitutability between inputs. Farm owners predicting a higher cost of certain inputs can always substitute those inputs with other cheaper inputs. However, weather extremes, by nature, are unprecedented and unpredictable. Therefore, substitutability or adaptability is limited, if not impossible, and damage to agricultural production is unavoidable. Incorporating weather extremes in the exogenous component as a productivity shifter of the agricultural profit function eliminates the capability for adaptation, since it shifts the whole production function up or down with an unknown magnitude, depending on the severity of the extreme condition. In other words, one cannot substitute weather extremes with by adding more variable inputs.

Following Carlino and Voith (1992), I assume the total factor productivity of each farm plot has the following exponential specification:

$$A_{ft} = A_0 TFP_{ft}^{\alpha_0} e^{\alpha_1 PDSI_t + \alpha_2 PDSI_t * FE} \quad (5)$$

A_0 is a positive constant,

$PDSI$ is the Palmer Drought Severity Index, a measure of extreme drought condition.

TFP_{ft} is the time-dependent field-level *productivity index*, measuring technological progress, and exogenous to farm operators. Field-level TFP_{ft} is not observed directly and must be extrapolated from deflating the reported annual state-level productivity index by soil quality classification.

The second term $e^{\alpha_1 PDSI_t + \alpha_2 PDSI_t * FE}$ is a scale parameter that represents the effect of extreme drought conditions on productivity. This formula assumes that extreme droughts enter the productivity component exponentially, thus damage rises exponentially as the severity of droughts increases (as opposed to a linear relationship, wherein damage rises at a constant rate with drought severity). The exponential term separates the impact of extreme droughts into two components: impact of pure drought shock - captured by the $PDSI$ index (which centers zero for normal weather conditions) - and interaction with field-level fixed effects. The interaction term $PDSI * FE$ captures the differential impact of extreme droughts at different climates, which may be related to past experience or the capability of farmers to adapt to extreme events. Detailed explanations of these variables are given in the Data Description section.

By this setup, if extreme droughts did not affect agricultural productivity then we would expect α_1 and α_2 to be insignificant or close to zero. If droughts adversely affect crops then we would expect to see that α_1 is significant and positive. For normal or near normal conditions ($-2 < PDSI < 2$), the impact of drought is expected to be minimal. However, for severe droughts ($PDSI < -3$), and extreme droughts ($PDSI < -4$, very

rarely observed), the impact will be significant. $PDSI > 2$ indicates wetter than normal conditions, which are supposedly good for crops.

Note that the formulation of the dynamic optimization problem will take care of the long-lasting impact of an extreme event, so the current period profit function does not include an explanatory variable representing the impact of past extreme events. Details are discussed in the dynamic programming section.

Using the indirect profit function, with the total factor productivity substituted from (5), and for simplicity, the time index suppressed:

$$\begin{aligned} \pi(P, \omega, TFP_f, PDSI, FE) \\ = (1 - \sum_i \beta_i) P^{\frac{1}{1 - \sum_i \beta_i}} (A_0 TFP_f^{\alpha_0} e^{\alpha_1 PDSI + \alpha_2 PDSI * FE})^{\frac{1}{1 - \sum_i \beta_i}} \left[\prod_i \omega_i^{-\beta_i} \beta_i^{\beta_i} \right]^{\frac{1}{1 - \sum_i \beta_i}} \end{aligned} \quad (6)$$

Taking natural logarithm of both sides gives:

$$\begin{aligned} \ln \pi = \ln(1 - \sum_i \beta_i) + \frac{1}{1 - \sum_i \beta_i} \ln P + \frac{1}{1 - \sum_i \beta_i} (\ln A_0 + \alpha_0 \ln TFP_f + \alpha_1 PDSI + \alpha_2 PDSI * FE) \\ + \frac{1}{1 - \sum_i \beta_i} (-\sum_i \beta_i \ln \omega_i + \sum_i \beta_i \ln \beta_i) \end{aligned} \quad (7)$$

Collect the terms and parameters to get an estimable function of current-period agricultural profit based on observable prices, climatic variables, field-level TFP_f , and weather extremes:

$$\begin{aligned} \ln \pi(P, \omega, TFP_f, PDSI, FE) = \\ \gamma_0 + \gamma_1 \ln P + \sum_i \gamma_{2i} \ln \omega_i + \gamma_3 \ln TFP_f + \gamma_4 PDSI + \gamma_5 PDSI * FE \end{aligned} \quad (8)$$

where

$$\begin{aligned} \gamma_0 &= \ln(1 - \sum_i \beta_i) + \frac{1}{1 - \sum_i \beta_i} (\ln A_0 + \sum_i \beta_i \ln \beta_i) \\ \gamma_1 &= \frac{1}{1 - \sum_i \beta_i} & \gamma_{2i} &= \frac{-\beta_i}{1 - \sum_i \beta_i} & \gamma_3 &= \frac{\alpha_0}{1 - \sum_i \beta_i} \\ \gamma_4 &= \frac{\alpha_1}{1 - \sum_i \beta_i} & \gamma_5 &= \frac{\alpha_2}{1 - \sum_i \beta_i} \end{aligned}$$

4.2 Discrete Choice Model of Cropland Conversion without Uncertainty

I restrict the conversion problem to two broad land-use choices: remaining in cropland production or conversion to developed use. Further, I simplify the model in which economic returns to developed land only depend on population density and per-capita income, the two most important determinants of urban land's rent. Cropland profit is affected by a host of factors including weather extremes, farm productivity, climate, and price of input and output.

Farm owner has to make a decision i , $i = 1$ or $i = 0$, for converting the land to developed land (d) or remaining in cropland production (c), based on an unobserved comparison of latent profit functions:

$$i = \begin{cases} 1 & \text{if } \pi_d^* > \pi_c^* \\ 0 & \text{otherwise} \end{cases} \quad (9)$$

where π_d^* and π_c^* is the unobserved discounted stream of rents from developed land and cropland.

The profit function consists of two components: an observable part that could be modeled explicitly π_d, π_c and an unobservable residual $\varepsilon_d, \varepsilon_c$ that follows extreme values distribution.

$$\pi_d^* = \pi_d + \varepsilon_d$$

$$\pi_c^* = \pi_c + \varepsilon_c$$

The observable part of the profit function of developed land is modeled as:

$$\pi_d = A_d PopDens^{\alpha_{d1}} PerCapInc^{\alpha_{d2}}$$

$PopDens$ and $PerCapInc$ is the population density and per-capita income at county level where the farm plot is located,

A_d is a positive constant,

π_c , the observable part of agricultural profit, follows (6),

and ε_d and ε_c is the unobservable residual of the profit function, supposedly following GEV type I.

Note that this formulation of the payoff functions assumes that developed land's rent is unrelated to drought shocks. Fixed effects such as climatic conditions or locations may affect urban land's rent via the shift parameter A_d , which is not of interest.

Farm owners are supposed behaving rationally by comparing and making the choice yielding the highest net present value. To simplify the model, assume that conversion cost is minimal compared to long-term economic benefit. Also, land market can reach an

equilibrium in a timely manner so as long as farm owners can identify a better payoff, a decision could be taken and carried out within a five-year interval.

Then, this formulation allows us to utilize the McFadden’s approach to model the conversion using a conditional logistic regression framework,

$$P(i = j|X_c, X_d) = \frac{e^{\alpha_j x_j}}{\sum_i e^{\alpha_i x_i}} \quad (10)$$

where $j = 1$ or $j = 0$ for converted to developed land or remained in cropland, X_c and X_d is the vector of explanatory variables of the cropland and developed land profit function. α_i is the vector of coefficients associated with each profit function.

Since land-use transitions are modeled as a consequence of shocks introduced to the economy, all explanatory variables such as *TFP*, *PDSI*, input and output prices, population density and per-capita income are time-variant. Time-invariant factors such as climatic variables, soil quality or other regional-level fixed effects are not expected to drive short-term land-use choice and thus drop out of the regression model. Fixed effects can be included as interaction terms with a time-variant determinant like *PDSI*.

The result of the static-shock model without uncertainty is presented in Table 2, and serves as a diagnostic counterpart for the structural model to follow.

Understandably, this static-shock model does not address two important issues: (1) uncertainties over the long-lasting impact of extreme droughts on productivity, and (2) uncertainties over future *TFP* growth. The static shock model automatically assumes that extreme droughts permanently shift the value envelope function with a known magnitude in the future. It is not the case. The long-term impact of drought on the farm economy is hardly known with any certainties. Furthermore, as discussed in the introduction, by adjusting *TFP* growth, we can predict how farm owners may behave if the threat of yield plateau is real. Lastly, without considering uncertainties, the static-shock model may overestimate the damages of shocks by ignoring the irreversibility and option value associated with of irreversible land-use choice. The following section presents a framework which allows for modeling simultaneous uncertainties regarding future yield growth and extreme droughts.

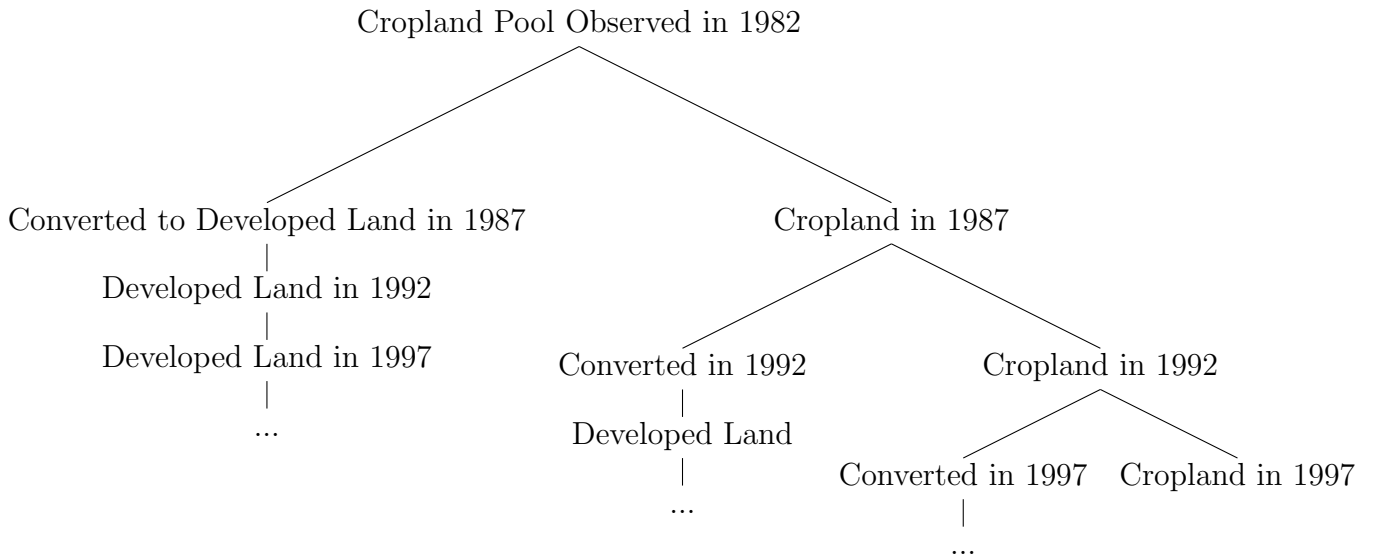
It is worthwhile to point out a distinct feature between this study in contrast to agricultural land value studies such as Plantinga and Miller (2011). The former relies on a structural model of land-use choice, while the latter, following Capozza and Helsley (1990), derive a closed-form expression of land price, then an optimal stopping rule can be established. The latter approach is only feasible if land market is present, so land price and conversion information could be obtained. Evidently, this is not the case for most private land conversions.

4.3 Structural Model of Cropland Conversion with Uncertain Weather Shocks and Productivity Growth

To lay groundwork for a dynamic model, I introduce several notations and assumptions following Rust (1987)'s canonical work on the bus engine replacement problem. The cropland conversion dynamic can be framed in the following decision tree.

Starting with the cropland pool during the initial NRI 1977-1982 survey period, those cropland plots were subject to exogenous shocks and underwent the first conversion decision cycle prior to the second NRI survey period. Lands remaining in cropland were subject to shocks again prior to the third NRI survey period, and so on. At any given time, farm owners have to weigh the decision on whether to keep a piece of land in crop production or convert it to developed use. Once converted, developed land cannot be reconverted to cropland, recalling that developed land's economic return is certain and independent from other farmland profit's determinants such as weather shocks or productivity growth. Weather shocks such as extreme droughts put downward pressure on agricultural productivity, as well as uncertain long-lasting impact on future productivity. These negative impacts of weather shocks were countered by productivity growth that continued into the future.

Figure 4: **Cropland Conversion under Uncertainty.**



Note that the NRI survey only reports conversion by an entire plot. This eliminates the possibility that uncertainty and information about the evolution of shocks can be learned through piecemeal conversions. To further simplify the dynamic problem, we also ignore the possibility of acquiring further information in the future. Specifically, I adopt

an open-loop information structure in which the uncertainty structure is fully exposed before the decision to convert a piece of land is made.

Formally, at time t , an economic agent must choose a series of a binary choice i which maximizes the current discounted net present value of an infinite stream of future income:

$$V(X_{i,t}, i, \varepsilon_{i,t}) = \sum_{t=0}^{\infty} \beta^t \pi_t^*(X_t, \varepsilon_t) \quad (11)$$

where β is the discount factor, $0 \leq \beta \leq 1$

X_t and ε_t is the vector of the state variables, or shocks observed between two survey periods, and the residual profit,

π_t^* is the unobserved profit function at period t .

Then, the cropland conversion problem can be considered as a controlled stochastic process, $\{i, X_t\}$, for $t = 1 \rightarrow \infty$, for controlled decision i whether to remain in cropland production ($i = 0$) or convert to developed land ($i = 1$), and the vector of stochastic state variable X_t . To simplify, assuming that the evolution of the exogenous shocks is a Markovian process, meaning that the future value of the state variable only depends on its preceding realized value and choice i , $X_{t+1} = f(X_t, i_t)$. That is, a state variable follows the transition rule conditional on the course of action taken in the current period.

This is particularly important because a choice in the current period can have an impact on future choice and exposure to exogenous shocks. As in the case of converting out of cropland, a current choice will eliminate future choice since conversion is irreversible. Furthermore, once a farm plot has been converted to developed land, all future agricultural productivity improvement is irrelevant to that plot's economic return. The transition rule has to be modeled in a way such that the payoff from developed land is independent from rising agricultural productivity growth.

Next, we can frame the land-use conversion problem in a recursive form using Bellman's principle of optimality:

$$V(X_{i,t}, i, \varepsilon_t) = \max_{i,t} \left\{ \pi_t^*(X_t, \varepsilon_t) + \beta E[V(X_{t+1}, \varepsilon_{t+1} | X_t, \varepsilon_t)] \right\} \quad (12)$$

Due to the recursive nature of the integrated value function, the optimization routine only requires solving the optimal decision for one future period, assuming that future utility function already takes into account the optimal choice faced by the agent in the current period. Coupled with assumptions on the distribution of the residual terms and the transition of the shocks, the problem can be significantly reduced and solved numerically.

Assumption 1: Additive Separability of the Profit Function

The profit function is additively separable by two components, the observable part as a function of the observed state variables X_t and the unobservable part ε_t :

$$\pi_t^*(X_t, i, \theta, \varepsilon_t) = \pi(X, i, \theta) + \varepsilon_t$$

θ is an unknown vector of structural parameters. The economic agents observe both components of the profit function. However, only observable components such as prices, productivity, and weather shocks are available to researchers. This assumption is necessary because without adding the unobservable part, all economic agents with the same observable attributes are expected to behave in an exact fashion. Observed land-use conversion pattern is apparently very heterogeneous over both spatial and temporal dimension, not strictly tied to any observed shock.

Assumption 2: Conditional Independence of the Transition of the State Variables

Let $X_t = \{P_t, \omega_t, TFP_t, PDSI_t, FE, PopDens_t, PerCapInc_t\}$ be the vector of the observable state variables at time t , corresponding to output price P_t , input price ω_t , farm productivity TFP_t , extreme drought index $PDSI_t$, fixed effects FE and two urban land rents determinants: population density $PopDens_t$ and per-capita income $PerCapInc_t$.

Let $p(X_{t+1}, \varepsilon_{t+1}|X_t, \varepsilon_t, i_t, \theta)$ be the conditional transition probability of the state variables at period $t + 1$, conditional on choice i_t and other state variables at time t :

$$p(X_{t+1}, \varepsilon_{t+1}|X_t, \varepsilon_t, i_t, \theta) = q(\varepsilon_{t+1}|X_{t+1}, \theta_2)p(X_{t+1}|X_t, \varepsilon_t, i_t, \theta_3)$$

In words, X_{t+1} is a sufficient statistics of ε_{t+1} and the probability density of X_{t+1} is independent of ε_t . ε_t is noise of the observed state variable X_t process. Arguably, this assumption is a strong, yet not an unrealistic one, should the observable part of the utility function be modeled sufficiently close.

With these two assumptions in mind, the value function can be written as:

$$V(X_{i,t}, i, \varepsilon_t) = \max_{i,t} \left\{ \pi_t(X_t, i, \theta) + \varepsilon_t(i) + \beta E[V(X_{t+1}, \varepsilon_{t+1}|X_t, \varepsilon_t, i_t)] \right\} \quad (13)$$

Denote EV the expected value function from the Bellman's equation:

$$EV(X_t, \varepsilon_t) = E[V(X_{t+1}, \varepsilon_{t+1}|X_t, \varepsilon_t, i_t)]$$

Since the state variable X_t and ε_t is continuous:

$$EV(X_t, \varepsilon_t) = \int_{X_{t+1}} \int_{\varepsilon_{t+1}} V(X_{t+1}, \varepsilon_{t+1}) p(dX_{t+1}, d\varepsilon_{t+1}|X_t, \varepsilon_t, i_t, \theta) \quad (14)$$

where $p(dX_{t+1}, d\varepsilon_{t+1}|X_t, \varepsilon_t, i_t, \theta)$ is the joint transition probability of the state variables in a controlled stochastic process.

With conditional independence, the expected value function specified above can be written as:

$$EV(X_t, \varepsilon_t) = \int_{X_{t+1}} \int_{\varepsilon_{t+1}} V(X_{t+1}, \varepsilon_{t+1}) dq(\varepsilon_{t+1}|X_{t+1}, \theta_2) dp(dX_{t+1}|X_t, i_t, \theta_3) \quad (15)$$

Which is equivalent to:

$$EV(X_t, \varepsilon_t) = \int_{X_{t+1}} \left[\int_{\varepsilon_{t+1}} V(X_{t+1}, \varepsilon_{t+1}) dq(\varepsilon_{t+1}|X_{t+1}, \theta_2) \right] dp(dX_{t+1}|X_t, i_t, \theta_3) \quad (16)$$

Assumption 3: Distribution of the Unobserved Profit Residuals

We also need a standard assumption about the distribution of the profit residuals. The conditional distribution of the unobserved part ε_t is multivariate *iid* extreme value distributed, GEV Type I or Gumbel distribution.

Then, by integrating out ε_{t+1} , the component in square brackets in (16) reduces to a very convenient form without the unobserved profit residual ε_t (proof in Appendix 8):

$$\left[\int_{\varepsilon_{t+1}} V(X_{t+1}, \varepsilon_{t+1}) dq(\varepsilon_{t+1}|X_{t+1}, \theta_2) \right] = \log \left\{ \sum_i \exp[\pi(X_{t+1}, i, \theta_2) + \beta EV(X_{t+1})] \right\} \quad (17)$$

Then substitute (17) into (16) to yield the recursive form of the value function without the unobservable profit residual ε_t :

$$EV(X_t, \varepsilon_t) = \int_{X_{t+1}} \log \left\{ \sum_i \exp[\pi(X_{t+1}, i, \theta_2) + \beta EV(X_{t+1})] \right\} dp(X_{t+1}|X_t, i_t, \theta_3) \quad (18)$$

Equation (18) is a contraction mapping of the integrated value function $EV(X_t)$ into itself:

$$EV(X) = T[EV(X)] \quad (19)$$

A unique fixed point EV_0 of this mapping can be approximated in the observable state space X_t .

Next, we can connect the conditional probability of choice j to the social surplus function using the Williams-Daly-Zachary theorem:

$$\begin{aligned} \frac{\partial}{\partial \pi_j} \log \left\{ \sum_i \exp[\pi(X_{t+1}, i, \theta_2) + \beta EV(X_{t+1})] \right\} &= \frac{\exp[\pi(X_{t+1}, j, \theta_2) + \beta EV(X_{t+1})]}{\sum_i \exp[\pi(X_{t+1}, i, \theta_2) + \beta EV(X_{t+1})]} \\ &= P\{i = j | X_t, \theta_2\} \end{aligned} \tag{20}$$

Then the likelihood function can be formulated as:

$$\mathcal{L}(X_t, i_t, \theta_2) = \prod_{i_t} P\{i = j | X_t, \theta_2\} \tag{21}$$

Note that the structural parameters of θ_2 are estimated while θ_3 , the parameters of the transition of the exogenous state variables, are assumed or estimated separately from the dataset.

4.4 Estimation Procedure

The estimation of the structural parameters, θ_2 , involves the approximation of the fixed point in (18) in the inner loop for each set of starting value of θ_2 . Then with the approximated fixed point, maximize the conditional choice probability in (21) in the outer loop with respect to θ_2 until convergence is achieved. Evidently, the nested fixed point algorithm proposed by Rust (1987) is very computationally intensive. I utilize Aguirregabiria and Mira (2002)'s Nested Pseudo Likelihood estimator in the probability space to achieve substantial reduction in the computation time. The full procedure is described in the Technical Appendix.

5 Data Description

5.1 National Farmland Survey Data

The main dataset is a multi-source, balanced longitudinal survey conducted by the National Resources Inventory (NRI). I use the 1997 database release cycle, which incorporates four 5-year surveys ending in 1982, 1987, 1992 and 1997. The 1997 release is the longest panel record currently obtainable. The survey covers 48 conterminous states. The subjects are non-federal soil, water and related resources which could be used to determine farm-level characteristics and land use trend every five years between each cycle release. A full set of land use type and related characteristics specific to each plot was obtained in every survey and tracked over the full four survey periods. Since the NRI survey is a statistical database, and not a spatial database, this restricts the type of modeling technique used.

NRI Land Cover/Land-Use Classification and Derivation of Cropland Conversion

The classification used by NRI data as single-use, single-cropping for each unit (plot) of land, regardless of size, allows us to identify the choice of land-use made by farm owners at the end of each survey period. There are up to 64 specific land-use types. The land-use types were then grouped into 12 major broad land covers including (1) cultivated cropland, (2) non-cultivated cropland, (3) pastureland, (4) rangeland, (5) forest land, (6) other rural land, (7) urban and built-up land, (8) rural transportation land, (9) small water areas, (10) census water, (11) federal land, and (12) conservation reserve program (CRP) land.

I further simplify the choice of land uses to binary uses, either keeping the land in agricultural production or converting it to urban/developed use, to fit our discrete choice framework. Intra-crop rotation is not qualified as a land use change. Similarly, conversion from one agricultural use to another such as from cultivated to non-cultivated land also does not qualify as a permanent conversion or a loss to the cropland pool. Thus, abandonment of cropland to idle land does not qualify for re-categorization. The reason for this rather restrictive definition of conversion is that temporary conversion, especially for completely reversible conversion between agricultural lands, may not reflect a long-term decision. In fact, reversible conversion may not be a problem to be concerned with as far as sustainability goes. Short-term or temporary change in land-use types may reflect short-term factors such as rising price of a certain crop, or adverse weather causes farmers to abandon harvests. However, long-term or permanent conversions such as conversions to built-up or developed land are assumed to be a consequence of more dramatic events that may change the ground conditions forever.

Most importantly, this classification helps avoid false conversion reporting and allows for focus on the most central question: Did extreme droughts contribute to permanent cropland loss? Taking option value into account, conversion or temporary abandonment of agricultural land does not result in a loss of an option to re-use the land for crops, should favorable conditions arise in the future. Obviously, this definition of land-use change underestimates the impact of short-term drought shocks, if damages were not acute enough to force farm owners to abandon farming permanently. To rephrase our objective, this study focuses on permanent conversions that resulted from dramatic events that caused permanent damages to the ecosystem. For some regions where active farmland tracking program exists, such as in California, temporary land-use conversion is much more prevalent than permanent farmland loss. Using this definition of cropland conversion, the actual amount of permanent loss may be significantly less than the official statistics state, which categorizes converting to temporary idling land as conversions.

Furthermore, I only consider cultivated and non-cultivated lands as potential croplands for conversion in this study. There are several practical reasons for this limited set of choices. First, non-intensive agricultural use such as pasture and range-land have non-market value including offsite amenities such as runoff prevention and retained soil nutrients, which are hard to measure. For CRP enrolled lands, there was little likelihood that owners were optimizing long-term benefits by making a short-term decision, given

Table 1: **Historical Cropland Conversion Patterns (Full NRI Sample).**

		1982		1987		1992		1997	
	Broad	Freq.	Percent	Freq.	Percent	Freq.	Percent	Freq.	Percent
Cultivated Cropland	1	234,444	17.83	222,846	16.95	201,114	15.3	190,399	14.48
Noncultivated Cropland	2	32,741	2.49	31,695	2.41	32,958	2.51	33,257	2.53
Pasture	3	92,620	7.04	87,265	6.64	82,646	6.29	73,455	5.59
Rangeland	4	130,268	9.91	126,446	9.62	122,891	9.35	120,245	9.15
Forest	5	252,931	19.24	248,231	18.88	240,791	18.31	229,555	17.46
Other Rural Land	6	84,289	6.41	85,223	6.48	86,532	6.58	87,784	6.68
Urban and Built-up	7	72,097	5.48	87,606	6.66	105,676	8.04	136,325	10.37
Rural Transportation	8	133,916	10.19	134,213	10.21	134,819	10.25	135,946	10.34
Small Water	9	58,588	4.46	59,607	4.53	61,310	4.66	62,874	4.78
Census land	10	38,197	2.91	38,728	2.95	38,686	2.94	38,760	2.95
Federal Water	11	184,635	14.04	185,318	14.1	187,518	14.26	187,710	14.28
CRP land	12			7,548	0.57	19,785	1.5	18,416	1.4
Total		1,314,726	100						

the fact that short-term profit was not affected by temporary weather shocks. In other categories such as forest land or other rural land, rural transportation, small water areas, or census lands, it is even more unlikely that extreme droughts could affect the economic uses in any understandable way, or quantified the way, like it could be with cultivated or non-cultivated lands. As a result, the number of plots was limited to 204,859 plots, for a total of 819,436 observations throughout four survey periods. These observations were used to derive three transitions between four survey periods for each farm plot, generating 602,073 distinct land-use transitions, from cropland to cropland and from cropland to developed land. Once a plot is converted to developed land, it remains classified as developed land and can no longer be considered for re-conversion in the following period.

Adversely, due to confidentiality requirements, field-level spatial information is only known up to county level. Geospatial data such as longitude and latitude location is not available. As a result, I address possible spatial correlation between observations by clustering NRI sampling polygons, assuming that farm plots are homogeneous within each sampling polygon. The final sample size, after excluding 70 fields without associated sampling polygon identifiers, stands at 602,003 individual land-use transitions. Derived conversion statistics and patterns are reported in Appendix 2 and 4.

5.2 Agricultural Productivity

I employ the reported TFP time series at state level, available on an annual basis. This is a broad measure of the productivity of the entire agricultural sector, not restricted to crops alone. Succinctly, TFP measures output per unit of all inputs combined. Technical innovation, more efficient organization, better input quality, as well as random weather shocks contribute to TFP growth and deviations from the observed trend. The measurement of TFP is complex, as it must adjust for changing input and output quality, and the simultaneous altering of the relative price of inputs may change input mixes, and facilitate

the development of substitutes. Fortunately, the USDA's ERS provides a comprehensive panel of state-level TFP index, which could be used to extrapolate farm-level TFP by adjusting for land quality classifications.

Since TFP is unobservable at the individual farm level, it is assumed that the state-level productivity growth rate applies to all individual farms within each state, scaled by the land quality classification:

$$TFP_{field} = \frac{TFP_{state}}{LCC}$$

where LCC is the land cover classification, or land quality, a measure of suitability of a plot for cropping, reported by the NRI survey. LCC is assigned as a numerical number from 1 to 7, reflecting respectively the highest to lowest land quality⁴.

5.3 Input and Output Price

Output Price

Since there is no information about the type of crops or inputs or their prices, I must calculate a generalized output price from the USDA's price bulletins. To elaborate, I calculate farm output price as the weighted average of prices of all major crops in each state. Each state carries its own weight assignment, based on acreage or total production of each crop. Crop price series were published by the USDA's Price Paid and Received Program and available at annual and monthly intervals.

Using the generalized output price has an advantage as it assumes that farm owners automatically choose crops that yield the average payoff. The profit function, by using the generalized price, is not crop-dependent. As long as croplands remain in agricultural production, they will remain at the same generalized state price, regardless of what crop is grown. This is in line with our statement that intra-crop rotation is not a problem.

Input Price

I focus on two major components of inputs: labor and material input. Thus, agricultural wages and fertilizer (ammonium nitrate) price were picked as the representative for all inputs. I scanned and digitized hardcopies of monthly and yearly price summary reports from ERS, for the years preceding each NRI survey. Except for wage reports, which are prevalent at state level, other input price series were collected by major production regions. States without price statistics are assumed to have the same price as adjacent states. A few missing wage values are assumed using linear growth interpolation of the wage series.

⁴In fact, LCC is related to soil properties, which does not change over time. Thus, TFP_{state} can be used in the place of TFP_{field} , because LCC , as a fixed effect, drops out of the estimation.

Regions by State Abbreviations

Fertilizer Regions	Production Regions
East South Central (1): AL, KY, LA, MS, TN Mountain (2): CO, MT, NM, WY North Central (3): IL, IN, IA, MA, MN, MO, OH, WI Northeast (4): CT, DE, ME, MD, MA, NH, NJ, NY, PA, RI, VT, WV Northern Plains (5): KS, NE, ND, SD	Appalachian (1): KY, VA, NC, WV, TN Corn Belt (2): IL, IN, IA, MO, OH Delta States (3): AR, MS, LA Lake States (4): MI, MN, WI
Northwest (6): ID, OR, WA	Mountain (5): AZ, NV, CO, NM, ID, UT, MT, WY Northeast (6): CT, DE, ME, MD, MA, NH, NJ, NY, PA, RI, VT
South Central (7): AR, OK, TX Southeast (8): FL, GA, NC, SC, VA Southwest (9): AZ, CA, NV, UT	Northern Plains (7): KS, NE, SD, ND Pacific (8): CA, OR, WA Southeast (9): AL, FL, GA, SC Southern Plains (10): OK, TX

5.4 Palmer Drought Severity Index

Palmer Drought Severity Index (PDSI) is the most widely used, well calibrated indicator of drought severity in the US. The dataset is produced by Dai, Trenberth and Qian (2010), and contains monthly PDSI values for the globe at a 2.5-degree resolution from the years 1870 to 2002. Data grids were extracted and interpolated by inverse distance weighting to all counties in the conterminous US. I use the average value of the PDSI index in the five years prior to each NRI release cycle.

The PDSI index is a long-term drought indicator used to measure water balance of the soil. This index provides a more precise indicator of extreme drought conditions than a conventional definition of rainfall shortage. The PDSI index is calculated as deviations from the normal condition, based on a probabilistic approach rather than deviations from a predefined threshold. Conventional rainfall measurement only addresses water supply, but fails to account for water demand including evapotranspiration, recharges, and runoffs. The PDSI takes a negative value for water shortage or dry conditions, and positive value for water surplus or wet conditions. A PDSI between -2 and 2 indicates a normal condition from a mildly drought to a slightly wet condition. Values between -3 and -2 reflect moderate droughts, and values between -4 and -3 reflect severe droughts. Very rarely was PDSI observed with values less than -4, which falls into the extreme drought category. For comparison, an annual PDSI value of less than -2.5 was observed for six consecutive Dust-Bowl years (Gutzler and Robbins, 2010). Statistics and patterns of droughts are described in Appendix 2 and 3.

5.5 Auxiliary Data

The per-capita income, population density, and climatic variables such as mean temperature, precipitation, Growing Degree Days (GDD, calculated from 8-32 degree Celsius

temperature bin), and Harmful Degree Days (degree days over 34 degree Celsius) are obtained from various sources, including the Agricultural Census. Population density and per capita income is extracted from file CA1-3 from the Bureau of Economic Analysis. Growing Degree Days, Harmful Degree Days, and precipitation level is the 30-year average prior to the conversion report.

6 Empirical Results

6.1 Benchmark Model with Static Shocks and No Uncertainty

I start with the benchmark model, where shocks are deterministic, implying that there is no uncertainty regarding the evolution of the state variables such as all prices, extreme drought conditions and their long-term impact, agricultural productivity, and other determinants of urban land rents. An implicit assumption is that drought shocks permanently shift the TFP down with a known magnitude. In this simplified setting, there is no option value associated with the irreversibility of cropland conversions. Croplands would be converted instantly to urban lands if the discounted urban rents were greater than farming profits. Fields within the same county were subject to the same exogenous shocks such as input and output price at the state or production region level, extreme drought index up to county level, productivity shocks deflated to farm level, and urban pressure through rising population density and per-capita income at county level. A set of interactions with fixed effects such as mean temperature (or Growing Degree Days), extreme heating condition (Harmful Degree Days), and average precipitation could be included to measure how drought impact varies in different climates.

Table 2 shows the result of logistic regression where the dependent variable is the logarithm of the odds ratio of conversion status. Once converted to developed land, a plot will remain in developed use and is no longer available for future conversion. Thus, only plots that could be converted at the beginning of each NRI survey release were considered in the analysis. Effectively, it is a pooled regression of the conversion status on all shocks that happened prior to the conversion decision. Table 2 is restricted to the region east of the 100th meridian, where agriculture is primarily rainfed. Estimates for the Western US and the entire country are presented and discussed in the Sensitivity Analysis.

In the most basic model (Model 1), shocks were limited to droughts, an interaction term with the annual Growing Degree Days (closely related to average daily temperature) and productivity shock among other determinants. Plot size may influence the conversion decision, as pointed out by Libecap and Hansen (2001), stating that smaller farms were subject to more intensive use with less preservative measures, and therefore more prone to Dust Bowl-type events. I adjust for size heterogeneity by weighing the regression with the square root of the farm acreage in Model 2. The idea behind this weighting scheme is that for a larger plot to be converted, the influence of shocks must be significantly stronger

than in the case where all plots are treated as homogeneous, implying that a larger plot must be assigned a larger weight than a smaller plot. The root of acreage indicates the distance from the boundary of the farm polygon to its centroid increasing at the rate of the square root the area, assuming impact decreases linearly with distance.

In Model 3, I extend the controls to a complete set of fixed effects of several climatic variables thought to substantially affect to crops. They are (1) Precipitation and (2) Harmful Growing Degree Days (degree days over 34 Celsius degrees). I also control for a set of year's fixed effects in Model 4, and year and production region's fixed effects in Model 5. In the most general setting, I include a full set of state-by-year fixed effects. This most comprehensive specification is presented in Model 6.

What do the signs and magnitude of the estimated coefficients illustrate?

First, the sign of the extreme drought coefficient and the interaction terms explains the negative impact of drought shock on cropland conversion, and is consistent with the basic model without fixed effects to the most comprehensive model (Model 1-5). Since PDSI is centered at zero with negative values for drought condition, the lower the value of PDSI (thus more severe drought), the more likely a land plot is to be converted.

Second, the interaction terms have an interesting interpretation: a positive interaction term with GDD, closely related to daily mean temperature and more relevant to crop growth, indicates that given the same magnitude of drought shock, then the higher the mean temperature, the less the impact of drought on cropland conversions. This implies that a warmer climate region adapts better to sudden drought shock than cold climate regions do. However, a negative interaction term with extreme heating conditions (GDD34) indicates that drought is always more harmful when it comes with more extreme heating. This result is consistent with a nonlinear impact of temperature on crops and land value as suggested in early work by Schlenker, Hanemann, and Fisher (2005, 2006): a higher mean temperature is initially beneficial as it implies a longer growing season, but if the increase is too excessive then a harmful consequence is expected.

Such distinct reactions to drought shocks may be indicative of physical difference at the field level, either in the infrastructure to cope with the onset of extreme droughts, or because of past experience or expectation about future impact. Yet, adaptation is limited. Extreme droughts coupled with extreme heating temperature are always harmful for the farm economy, which is not surprising. The physio-ecological mechanism of the impact of extreme droughts on land productivity - as well their long-lasting impact - is beyond the scope of this paper.

When the regression is weighted by the root of plot size, the estimated coefficients change slightly. However, PDSI coefficient decreases minimally from -0.6473 to -0.6743, while the interaction term increases slightly. The odds ratio, measured at the mean of the climatic variable where $GDD = 2129$, is $e^{(-0.6743+2129*0.0001113)*PDSI} = e^{-0.4373*PDSI}$. Compared to the same ratio when assuming all plots are homogeneous, $e^{(-0.6473+2129*0.0001078)*PDSI} = e^{-.4178*PDSI}$. If drought is severe, $PDSI < -3$, then the odds ratio of observing a conversion is $e^{-0.4373*-3} = 3.71$ using the plot size-weighted regression, and slightly higher than

Table 2: **Static Shock Models.** Dependent Variable - Conversion Status: (1) for converted to developed land and (0) for remained in cropland

Coefficients	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
PDSI	-0.6473 ⁽³⁾	-0.6743 ⁽³⁾	-1.0483 ⁽³⁾	-1.1862 ⁽³⁾	-0.8811 ⁽³⁾	0.2025 ^(.)
PDSI*GDD	1.078e-4 ⁽³⁾	1.113e-4 ⁽³⁾	1.645e-4 ⁽³⁾	1.85e-4 ⁽³⁾	1.055e-4 ⁽³⁾	0.515e-4 ^(.)
log(TFP)	-1.3804 ⁽³⁾	-1.0396 ⁽²⁾	0.2584 ^(.)	1.0203 ⁽²⁾	1.8260 ⁽³⁾	0.6144 ^(.)
log(Price)	0.3602 ⁽³⁾	0.4162 ⁽³⁾	0.4011 ⁽³⁾	0.7510 ⁽³⁾	0.3230 ⁽³⁾	0.0556 ^(.)
log(Wage)	-0.5618 ⁽¹⁾	-0.3615 ^(.)	0.3296 ^(.)	0.7713 ⁽²⁾	-1.5911 ⁽³⁾	-1.1100 ⁽³⁾
log(Fertilizer)	2.7314 ⁽³⁾	2.8297 ⁽³⁾	1.2608 ⁽²⁾	-0.3239 ^(.)	-1.6181 ⁽³⁾	-2.1711 ⁽³⁾
log(Population Density)	8.9196 ⁽³⁾	9.7510 ⁽³⁾	9.5906 ⁽³⁾	9.5055 ⁽³⁾	8.7536 ⁽³⁾	8.5263 ⁽³⁾
log(Per Capita Income)	-0.9268 ⁽³⁾	-0.4474 ⁽¹⁾	-0.1402 ^(.)	1.3086 ⁽³⁾	0.7129 ⁽²⁾	0.5143 ^(.)
Constant	-3.3499 ⁽³⁾	-6.1636 ⁽³⁾	-4.6945 ⁽³⁾	-5.1951 ⁽³⁾	-4.0943 ⁽³⁾	-3.8461 ⁽³⁾
Additional Controls						
PDSI*GDD34			-0.0927 ⁽³⁾	-0.0886 ⁽³⁾	-0.0252 ^(.)	-0.0921 ⁽³⁾
PDSI*Precipitation			5.464e-3 ⁽³⁾	5.022e-3 ⁽³⁾	4.577e-3 ⁽³⁾	-1.425e-3 ^(.)
Fixed Effects						
1987-1992				-0.0684 ^(.)	0.0048 ^(.)	
1992-1997				0.4998 ⁽³⁾	0.4306 ⁽³⁾	
Production Region	No	No	No	No	Yes	No
State and Year Fixed Effects	No	No	No	No	No	Yes
Number of Observations	476,606					

Note:

Model 1: Interacting PDSI with GDD only, no other fixed effects

Model 2: Weighted regression, with weight is the root of the inverted farm size

Model 3: With the full set of interaction terms including precipitation and Harmful Degree Days

Model 4: Additional year's fixed effects with base period in 1992-1997 survey

Model 5: Both year's and production region's fixed effects

Model 6: A complete set of state-by-year fixed effects is included

Each model is reported with clustered standard errors identified by 7,525 NRI sampling polygons.

(1), (2), (3), and (.) denotes statistically significant at 10, 5 and 1 percent level, and statistically insignificant, respectively.

No spatial standard errors can be implemented with the NRI dataset.

The data is restricted to the East of the 100th meridian, the boundary between the arid West and the humid East, where the agriculture is dominantly rainfed.

Estimates from a complete dataset of all counties are presented in Appendix 7.

$e^{-0.4178 \times -3} = 3.50$ using the homogeneous size regression. For $PDSI < -4$, the ratio is 5.75 versus 5.32. Thus, in all cases, when not account for size effect on conversion, the impact of drought on cropland conversions is likely underestimated. And the more severe the drought, the greater the downward bias of the unweighed regression is.

In the most comprehensive model a full set of state-by-year fixed effects is included (Model 6), the effect of drought shocks is still present via the negative interaction coefficient with extreme heating conditions (GDD34).

Among other combinations of the explanatory variables, the significant and positive output price coefficient in the first five models is inconsistent with expectation, forcing some clarification. It is expected that a higher output price raises farm profit, thus helps keep farmland in farming. Similarly, a higher input price lowers farm profit, and contributes to farmland conversion. Therefore, we should expect a negative coefficient of output price and positive coefficient of input price. As for TFP coefficient, a negative sign as illustrated in Model 1 and 2 would indicate that rising agricultural productivity reduces farmland the conversion problem as expected. The coefficient is insignificant, however, in Model 3 and 6, and positive in Model 4 and 5. One possible reason, as mentioned earlier, is that drought shocks may influence prices in the short term, causing irregularities in the direction of impact. More likely explanation is that price is measured at the state level (the generalized output price and wage), and at the production region level (fertilizer price). Given that there were only minimal price variations from state to state and year to year, the estimation could be over or underestimated, especially when a set of state and year fixed effect is included. Population density is estimated to influence urban land rent consistently and as expected: a higher population density will push the demand side for land and cause more farmland conversions, while per-capita income is not.

Most importantly, the sign of the PDSI index is always consistent and significant across all models. These results are suggestive that the impact of severe droughts on cropland conversions is consistent and independent of the choice of covariates and specifications. Is extreme drought correlated with any unobservable that influences conversions? Extreme droughts and heating may happen at the same time and strengthen the combined impact. However, it is doubtful that any other event occurred that could cause permanent damage to soil or other productive capital. Since the PDSI coefficient calculation has already accounted for the impact of extreme heating condition into account via the evapotranspiration component, adding an extra variable representing time-variant extreme heating condition will only cause colinearity in the model.

Figure 5 shows the bootstrap estimates for the basic model (Model 1) including the $PDSI$, the interaction term, $PDSI * GDD$, from 3,000 random draws of 50,000 observations. There is a valid concern that the reported result was driven by outlying observations. Estimates from subsets of the data indicates that the $PDSI$ and the interaction coefficient $PDSI * GDD$ are always negative and positive, respectively, and the distribution of the estimated coefficients suggests that the harmful impact of extreme drought on cropland conversion is unambiguous. The possibility of higher TFP growth offsetting drought impact and damages is exhibited in the productivity surface $A_f = A_0 TFP^{\alpha_0} e^{\alpha_1 PDSI + \alpha_2 PDSI * GDD}$ at mean $GDD = 2129$ in Figure 6. Evidently, for

limited droughts $PDSI > -2$, it is possible that dramatic TFP growth can offset the negative impact of droughts. However, for severe or extreme droughts ($PDSI$ closes to -4), the impact is too harmful - remember that drought impact grows at an exponential rate - that the total factor productivity is close to zero. Based on this diagnostic result, I present a more elaborate structural estimation dealing with uncertainty in the following section.

Figure 5: **Bootstrap Estimates with 3,000 Draws and 50,000 Observations.**

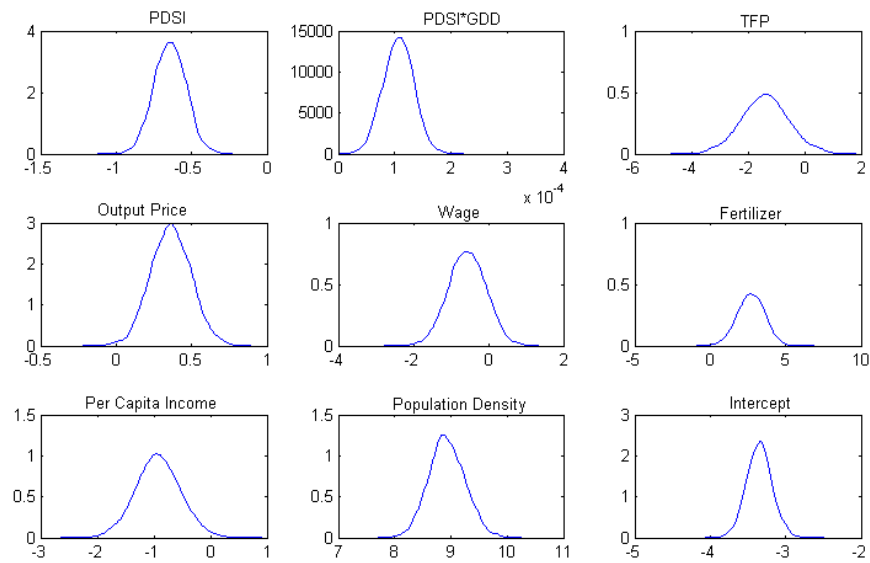
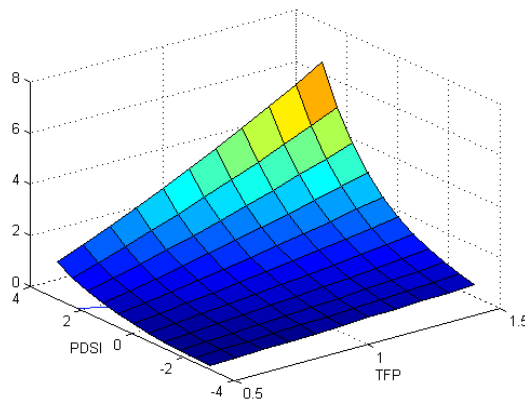


Figure 6: **Productivity Surface - Static Shock (Model 1).**



6.2 Structural Model with Uncertain Impact of Extreme Droughts and TFP Growth

I focus on the specification used in Model 1 of Table 2 in the previous section which projects the conversion problem on eight exogenous shocks including: $PDSI$ and $PDSI * GDD$, TFP , Price, Wage, Fertilizer Price, Population Density and Per Capita Income. This choice reflects the constraint facing the computation in discrete-choice dynamic programming. A major deviation from the static shock model is that extreme drought produces uncertain long-lasting impacts on soil productivity. In addition, TFP growth can be uncertain. Since cropland conversion is irreversible, I examine how decision-making under uncertainty diverges from a static model with certainty.

A couple of notes before discussing the result: first, the structural models are estimated from the discretized state space instead of exact data points, thus each estimate may be different, and in some cases, significantly vary from the static shock model. However, what we are looking for is how the dynamic system may behave differently when uncertainty is incorporated. Second, the structure of the uncertainty has to be specified in advance. Please refer to the Technical Appendix and Appendix 6 for more details.

The results are illustrated in Table 3-5. In Table 3 and 4, uncertainty is restricted to only one exogenous shock at a time: TFP growth or drought shock, respectively. In Table 5, simultaneous uncertainty in TFP growth and drought shock is considered.

Each column in Table 3 corresponds to a different assumption of the evolution of shock: yield growth is uniformly distributed (A1.1), higher probability of higher yield (A1.2), higher probability of lower yield (A1.3), and yield growth is almost certain, with some small probability of getting either higher or lower (A1.4).

Table 4 displays the result for: the long-lasting impact of drought is uniformly distributed (A2.1), higher probability of less damaging impact (A2.2), higher probability of more damaging impact (A2.3), and drought impact almost certain, with some small probability of becoming more or less damaging (A2.4).

And Table 5: both TFP growth and drought impact is uniformly distributed (B.1), higher probability of less TFP growth and more damaging impact (B.2 or worst-case scenario), and higher probability of TFP growth and less damaging impact (B.3 or best-case scenario).

These results confirm that drought impact is significantly negative in all models and all specifications. All other coefficients are also as expected: TFP growth is always positive for farming, and acts to dampen the negative impact of drought shocks; urban land rent's determinants are positive, indicating the demand-pull's side of the land-use equilibrium. This is true with the exception of the output price and wage coefficient which yield similar signs as the static model, possibly due to lack of variations in the dataset. Most importantly, the estimated productivity surfaces provide insight in to how uncertainty changes the behavior of the structural model.

Table 3: **Stochastic Productivity Growth.** Dependent Variable - Conversion Status: (1) for converted to developed land and (0) for remained in cropland.

Model	A.1.1	A.1.2	A.1.3	A.1.4
PDSI	-4757	-4674	-4781	-4722
(t-stat)	(27.57)	(27.49)	(27.51)	(27.79)
PDSI*GDD	8.01e-05	7.68e-05	8.33e-05	7.76e-05
	(13.69)	(13.31)	(14.17)	(13.43)
log(TFP)	-2.169	-0.97	-0.5853	-0.3995
	(10.2)	(13.3)	(5.828)	(11.32)
log(Price)	.5963	.5931	.6	.5759
	(15.46)	(15.69)	(15.42)	(15.12)
log(Wage)	-3.824	-3.762	-3.818	-3.792
	(13.81)	(13.72)	(13.74)	(13.82)
log(Fertilizer)	8.342	8.314	8.276	8.112
	(36.16)	(36.75)	(35.61)	(35.77)
log(PopDens)	3.545	3.469	3.55	3.447
	(21.88)	(22.12)	(21.68)	(21.86)
log(PerCapInc)	0.7126	0.7202	0.6046	0.7197
	(2.694)	(2.798)	(2.275)	(2.848)
Constant	-2.651	-2.643	-2.924	-2.834
	(53.65)	(59.98)	(76.17)	(74.63)

Table 4: **Stochastic Drought Impact.** Dependent Variable - Conversion Status: (1) for converted to developed land and (0) for remained in cropland.

Model	A.2.1	A.2.2	A.2.3	A.2.4
PDSI	-4778	-146	-2782	-0911
(t-stat)	(27.52)	(28.38)	(24.25)	(26.02)
PDSI*GDD	8.04e-05	2.17e-05	6.04e-05	1.87e-05
	(13.70)	(12.59)	(15.37)	(14.98)
log(TFP)	-2.171	-2.253	-1.999	-2.146
	(10.17)	(10.65)	(9.28)	(10.03)
log(Price)	.6021	.6057	.557	.5686
	(15.38)	(16.02)	(14.44)	(15.54)
log(Wage)	-3.857	-3.782	-3.901	-3.818
	(13.85)	(13.72)	(14.01)	(13.91)
log(Fertilizer)	8.419	8.504	7.858	8.007
	(35.76)	(36.85)	(34.17)	(35.57)
log(PopDens)	3.596	3.549	3.632	3.581
	(21.79)	(21.94)	(21.92)	(22.15)
log(PerCapInc)	.7223	.716	.7493	.733
	(2.70)	(2.68)	(2.80)	(2.73)
Constant	-2.686	-2.795	-2.961	-2.894
	(65.06)	(71.32)	(74.24)	(74.95)

Table 5: **Simultaneous Stochastic TFP Growth and Drought Impact.** Dependent Variable - Conversion Status: (1) for converted to developed land and (0) for remained in cropland.

Model	B.1	B.2	B.3
PDSI	-4783	-2782	-1443
(t-stat)	(27.55)	(24.22)	(28.24)
PDSI*GDD	8.07e-05	6.25e-05	2.11e-05
	(13.74)	(15.89)	(12.30)
log(TFP)	-2.167	-.4577	-.9701
	(10.18)	(4.53)	(13.44)
log(Price)	.5982	.5591	.6005
	(15.43)	(14.48)	(16.33)
log(Wage)	-3.834	-3.862	-3.702
	(13.82)	(13.87)	(13.59)
log(Fertilizer)	8.365	7.742	8.422
	(35.88)	(33.76)	(37.46)
log(PopDens)	3.564	3.599	3.463
	(21.90)	(21.79)	(22.28)
log(PerCapInc)	0.7156	0.6131	0.7118
	(2.69)	(2.29)	(2.74)
Constant	-2.504	-3.047	-2.602
	(48.84)	(78.61)	(59.05)

In Figure 7, the TFP shock is most damaging when it is uniformly distributed - implying that the farm owners do not have any information or knowledge regarding the future evolution of productivity shocks. This is evidenced by the spike of the productivity surface at higher value of *PDSI* (wetter is good for crops) and TFP in Model A1.1. Adverse productivity shocks could produce significant impact on farmland profit through productivity, thus necessitating conversion decision. The possible value of the productivity surface spreads over a wide range, indicating high uncertainty about the future. Comparing Model A1.2 (higher growth more likely) and A1.3 (lower growth more likely), it is clear that if shocks increase future TFP, then farm profit is higher in A1.2 than in A1.3. However, the variations in both A1.2 and A1.3 is significantly less than in A1.1 since there is less uncertainty present. Most visibly, when TFP shocks have limited uncertainty structure in A1.4, the productivity surface is even flatter. The same phenomenon is observed in Figure 8 with only stochastic drought impact.

The most interesting result is Figure 9, when simultaneous stochastic TFP and drought shocks are considered. When both shocks are uniformly distributed, the productivity surface is most volatile as was expected. When uncertainty is restricted to “worst-case scenario” (B.2), a higher probability of more damaging impact and lower TFP growth, and “best-case scenario” (B.3), a higher probability of less damaging impact and higher TFP growth, both have less variation in the productivity surface. However, the steepness of the surface along the drought impact axis is most telling: to maintain the same productivity

level, a higher TFP growth is needed to compensate for the damage of drought impact - as illustrated by the contour line at the base of each graph B.2 and B.3.

These graphs suggest an interesting theory that if uncertainty structures of the long-lasting impact of droughts and TFP growth both support a greater future farming profit, then recent drought shocks are less substantive. The contour line is relatively flat along the drought indicator index, PDSI axis (B3). In this case, farm owners might want to keep farms in production even if a drought shock could cause significant damage in the short term. Alternatively, if uncertainty structures indicate a more severe long-lasting drought impact and lower TFP growth, the contour line is substantially steeper (B2). Then, TFP has to increase at a faster rate to offset damage caused by extreme droughts. If yield plateau is real, the threat of mass cropland loss could materialize.

Figure 7: **Stochastic TFP Growth.**

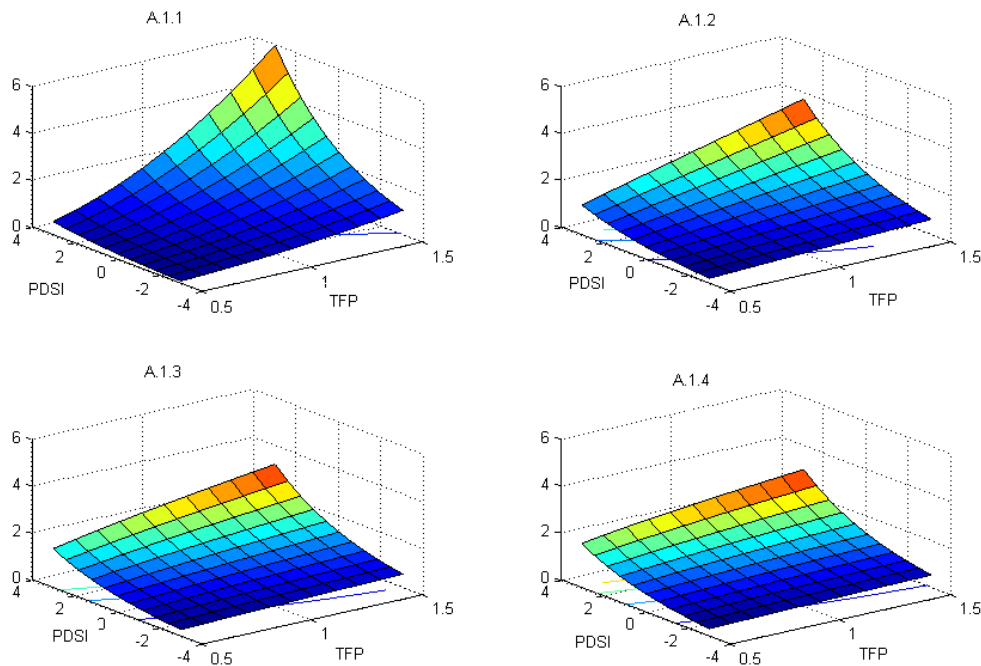


Figure 8: Stochastic Drought Impact.

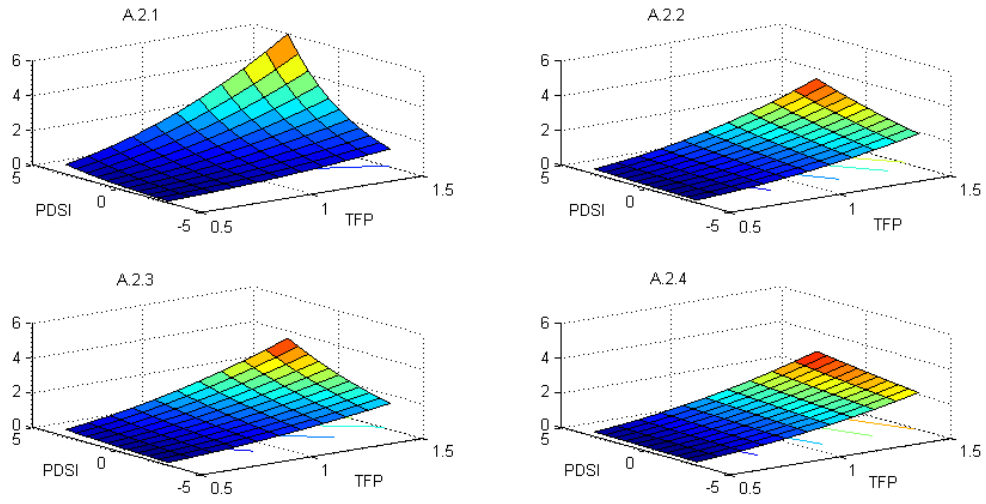
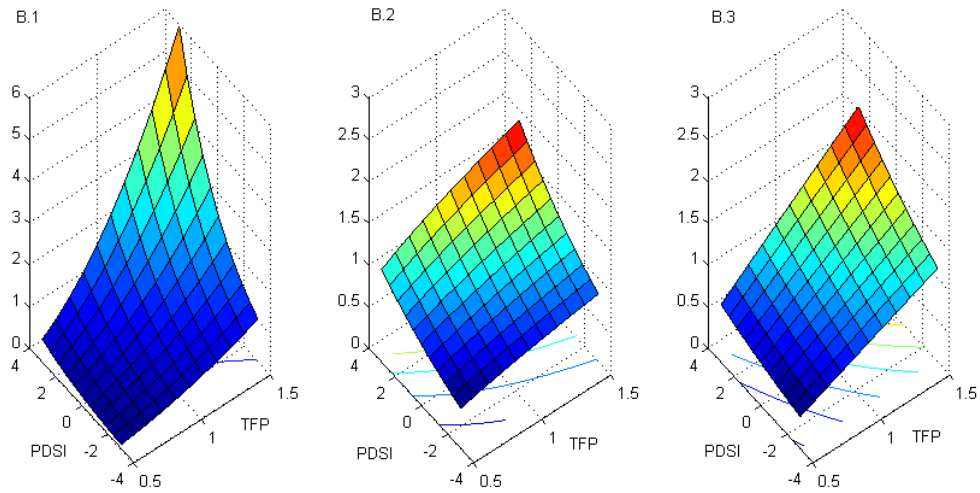


Figure 9: Simultaneous Stochastic TFP and Drought Impact.



7 Sensitivity and Robust Checks

I implement a series of robust checks to make sure that these results are (1) robust to choice of variables (2) robust to geographical areas (3) insensitive to endogenous price effects of shocks. Details are reported in Appendix 7.

First, various specifications of the profit function are estimated with different combinations of explanatory variables to test the stability of the estimated coefficients. I separate the sample into different conversion periods of 82-87, 87-92 and 92-97. For each period, a separate set of estimates is presented. If drought impact is consistently estimated throughout each individual sample, then it is a strong indicator that the effect is indeed present and not confounded with other location fixed effects.

In the second scheme, a model for each geographical region is estimated separately: the East (Table 2), the West of the 100th meridian and combined data. Then, central Plains states from -90 to -110 degree longitude are separated from the dataset. This region has observed a surprisingly low rate of conversion (less than 3 percent the total available cropland plots in each county during any two consecutive survey periods, as shown in the conversion pattern in Appendix 4). Next, the sample is stratified by urban and non-urban counties. Urban counties are defined as having more than 400 people per square mile or 147 people per square kilometer.

In the third sensitivity check, as mentioned in Fox et al. (2011), droughts tend to have a larger effect on farm-gate prices of locally consumed produces such as corn or hay than exported produces such as wheat or cotton. These temporary price shocks could help farmers recoup losses of harvests and partially reduce drought damages. I split the dataset by states of major producers of major crops including corn, wheat, cotton, hay, soybean, sorghum and oats as defined in Appendix 5. I then apply an individual crop price series, which is assumed to be highly correlated with drought shocks for locally consumed crops, in each region of major crop producers. This scheme can mitigate some of the simultaneity problem associated with using output price as an explanatory variable.

The result is unambiguously consistent across most models and specifications. It is surprising that drought is significantly less sensitive in almost all models of cropland conversions to the West of 100th meridian. This is perhaps an indication that irrigated farms are better managed and less prone to short-term shocks than naturally rainfed croplands. Rather, it could be that the drought index is irrelevant for irrigated farm's production and profitability. Central Plains states appear to be less prone to drought shocks than those on the East coast. Drought impact on urban counties is significantly less than on non-urban counties, presumably due to higher demand for urban land, thus remaining croplands in urban areas are either better protected or have higher profitability. In all specifications, effect of extreme drought is always enhanced by extreme heating condition, as evidenced by the coefficient of interaction between drought and Harmful Degree Days (PDSI*GDD34) being negative and significant: the higher the number of Harmful Degree Days, the higher the probability of conversion is. Furthermore, restricting to the East of the 100th meridian, drought is less harmful in wetter climate (higher average precipitation) as indicated by a positive and significant PDSI*PRECIPITATION

coefficient. This may be an indication of the soil's ability to retain moisture or other physical difference on the ground which supports crops when unexpected drought events occur.

Effects of price shock appear to be insignificant for three major crops including corn for grain, soybean, winter wheat, but exhibit an intriguing sign for cotton. Most importantly, none shows that price effect could help offset profit loss due to drought shocks. As mentioned earlier, for the economy as a whole, aggregate impact could be offset by rising prices. Yet, individual producers suffering from weather shocks may not necessarily benefit if their harvests were destroyed and productive capacity diminished in the long term. In other words, price effect appears to be a non-issue.

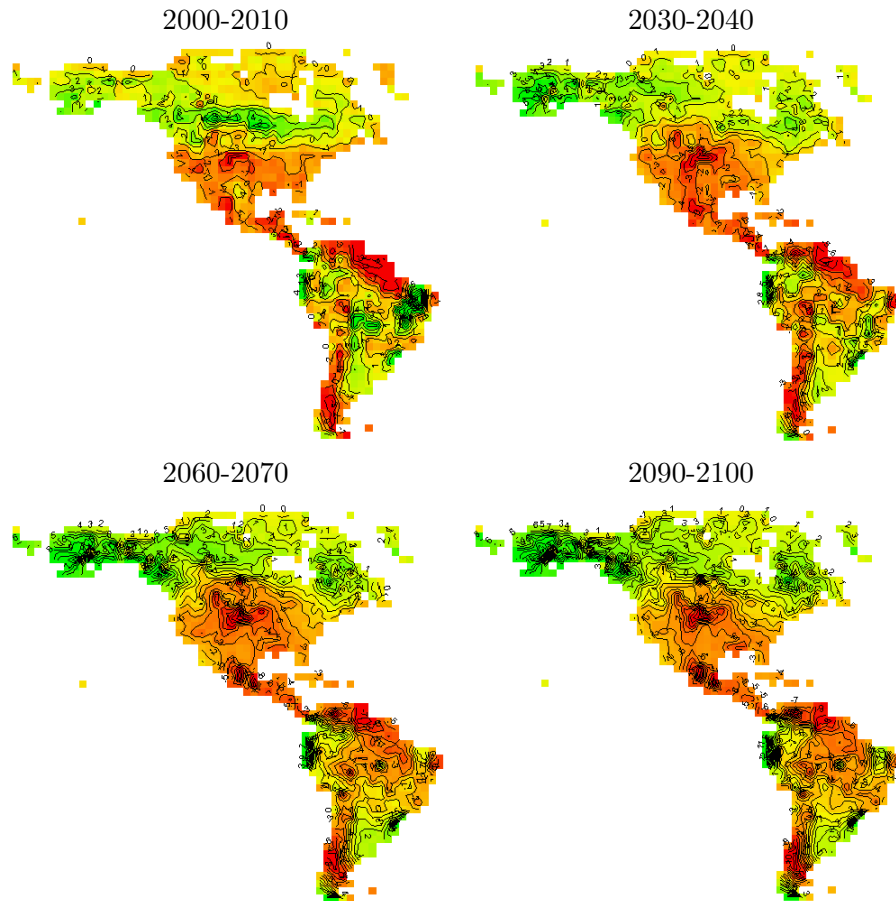
8 Potential Impact of Future Droughts with Climate Change

Under a moderate emission scenario (B1 and A1B), global mean temperature will have increased by approximately 2 and 3 degree Celsius by 2100, respectively, according to the latest Intergovernmental Panel on Climate Change (IPCC)'s AR4. Higher global temperature increases more evaporation in almost every area around the globe. Drought conditions, viewed as abnormal deviations from normal water balance, are influenced by both water demand (evaporation) and supply (precipitation), could yield a very different pattern of change than the increase in precipitation alone. A shift toward heavier precipitation accompanied by less frequent rains could also have an adverse impact on runoffs and lower soil moisture. As a result, even with increased rainfalls, the actually usable amount of water could be reduced. Under all scenarios considered, the US may expect consistently more severe droughts even with projected higher precipitation, as illustrated by the PDSI index in Figure 10.

Impacts likely vary between regions, but even within the same region, impacts between crops are likely different. Shifts toward increased precipitation in the winter and less in the summer will adversely affect summer crops. Local conditions also dictate how and whether water constraints can be addressed. For much of the Western US where agriculture is reliant on irrigated water, impact could be less dramatic. Impact on rainfed agriculture is naturally more severe. Better agricultural management may help reduce water use, but would not eliminate the threat. Using predicted total precipitation to project the impact of climate change will likely underreport the negative impact of this shifting precipitation pattern. As a side note, several earlier studies, such as Mendelsohn, Nordhaus, and Shaw (1994) and Deschenes and Greenstone (2007), suggest a potential beneficial impact of climate change. Those estimates are likely inflated due to this precipitation effect alone.

Figure 10: Drought Projection under IPCC's A1B until 2100

Mean annual, self-calibrated PDSI using Penman-Monteith method at a 2.5-degree resolution in 21st century. Yellow and orange colors indicate a drier-than-normal condition, and blue color indicates a wetter-than-normal condition. PDSI value can be read off the contour line. Data is generated using 22-model ensemble-mean of surface air temperature, precipitation, humidity, net radiation and wind speed from 20th century and SRES A1B simulations, and used in IPCC's AR4. The data is produced by Dai (2011a) and available at <http://www.cgd.ucar.edu/cas/catalog/clipind/pdsi.html>.



9 Concluding Remarks

This result indicates that natural disasters such as extreme drought events generate identifiable signal on farmland use and farmland conversion. Extreme droughts damage soil, lower productivity, reduce farming profits and accelerate permanent farmland conversion to urban use. Facing highly anticipated drought condition in the coming decades, the prospect of the future agricultural landscape in the US rests largely on the capability to spur higher agricultural productivity to compensate for possible damage from severe droughts. The threat of a yield plateau could have a dramatic effect on the agricultural sector.

Under the most benign climate change scenario, the Earth would have warmed by 2 degrees Celsius by the end of 21st century. That is an equivalence of a few hundredths of a degree per year. Given that minimal increase, the economic system will hardly feel or respond to such a small change. Conventional wisdom of climate change has been particularly reluctant on taking mitigating measures, citing the lack of dramatic damages from climate change. In a few studies, even a positive effect of climate change on US agriculture is reported. I maintain that while the Ricardian approach is a strong tool for projecting climate change impact on agriculture, it is insufficient. Removing the most important assumption - climate change is completely adaptable, which is arguably unrealistic at best - the impact could be more damaging than some studies have reported. The difference arises from how extreme events are modeled. If complete adaptation to extreme events is not possible, then the loss of croplands due to short-term weather shocks is not accounted for using the traditional Ricardian approach. Understandably, extreme events are neither predictable nor adaptable, nor can their impact be mitigated easily. This conclusion is also consistent with Schneider et al. (2000) and Kelly et al. (2005), among others regarding the limitation of the Ricardian approach. However, in this study, an impact is identified through empirical estimation of observed data rather than by simulation models.

Methodologically, focusing on the drawbacks of the Ricardian approach, I present a innovative method of incorporating climate and weather extremes into the conventional production approach, therefore surmising that the impact of such events can be estimated indirectly through cropland conversions. I do not attempt to estimate the cost of extreme events or potential cost of cropland conversions. Implicitly, the cost of climate and weather extremes could encompass permanent losses of productive croplands, not restricted to immediate losses of harvests.

A retrospective review indicates that the original Ricardian approach, and a recent study using repeated cross-sectional data by Massetti and Mendelsohn (2011), were aware of the impact of climate extremes on farmland values and that the estimates may be downward biased. Those estimated coefficients are highly unstable since unpredictable short-term events could largely influence farmland values. By using plot-level data, I am able to identify the irreversible impact of climate and weather extremes on land-use change. This impact is missing or unidentifiable from studies using county-level data. Furthermore, this result suggests that all studies using aggregate data will necessarily

suffer from aggregation bias, and in particular, downward bias of the climate coefficient, resulting in lesser predicted damages or even beneficial impacts from potential climate change.

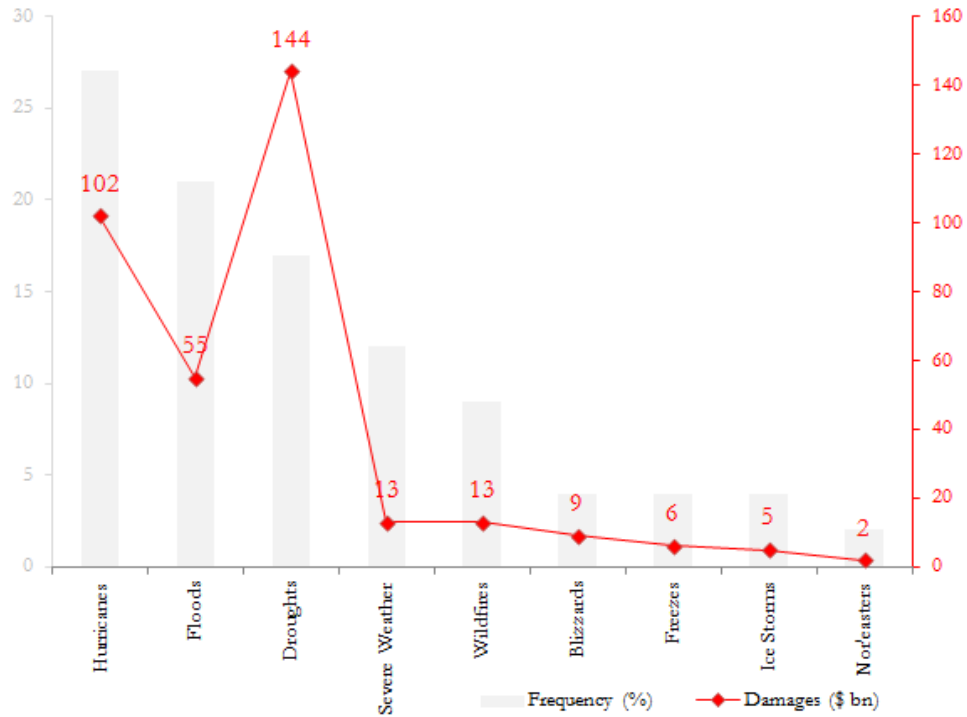
In summary, transient climate change effects are not evident in the Ricardian hedonic regression of farmland value, which is understood as an equilibrium response model with a complete adaptation assumption. Problematic use of climate change indicators such as predicted total precipitation and average temperature may over-smooth the value function and inflate potential benefits from seemingly modest changes in precipitation or temperature. Broadly speaking, the impact of climate change and weather extremes should be investigated in tandem. Climate change is often assumed as a mean shift in temperature and precipitation, with little consideration given to extra moments such as variance or diurnal range. This is insufficient, regardless of specifications or functional forms the impact is modeled. Without considering the extreme conditions that are most damaging to agriculture, the impact of climate change could be underestimated. However, not all climate and weather extremes should be considered as a result of anthropogenic GHG emissions and much scientific evidence is needed to firmly connect the two.

Appendices

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Appendix 1. Frequency and Cumulative Damages of Weather Disasters in 1980-2003.



Note: Damages are in billions of dollars, normalized to 2002 dollars. Only events which damage more than US\$1 billion are reported. Source: Ross and Lott (2003).

Appendix 2. Summary Statistics: (Mean)(Min)(Max)(Std.Dev.)

Variables	1982	1987	1992	1997
Plot Size (Acres)	(16.61)(1)(495)(12.31)			
Variables				
PDSI	(.62)(-1.40)(2.40)(.62)	(1.11)(-1.05)(4.50)(.94)	(.63)(-3.13)(3.09)(.72)	(1.39)(-2.02)(4.96)(.93)
TFP (normalized in 1996)	(.74)(.41)(1.25)(.14)	(.83)(.49)(1.44)(.16)	(.93)(.55)(1.56)(.20)	(1.01)(.59)(1.61)(.21)
Generalized Price (\$/unit)	(12.30)(2.74)(51.86)(8.06)	(14.22)(3.44)(59.21)(9.98)	(21.85)(4.31)(76.73)(14.92)	(24.88)(6.18)(85.61)(16.02)
Wage (\$/hour)	(3.48)(3.19)(4.27)(.20)	(4.24)(3.93)(5.21)(.26)	(5.02)(4.36)(6.02)(.33)	(5.97)(5.07)(7.33)(.55)
Fertilizer Price (\$/ton)	(145)(136)(171.75)(9.6)	(169.45)(155)(220)(18.98)	(186)(169.5)(237)(18.91)	(211)(192.5)(261)(18.22)
Population Density	(34.37)(-1)(1328)(82.73)	(35.70)(-1)(1249)(85.04)	(37.25)(-1)(1216)(88.56)	(39.69)(-1)(1247)(93.20)
Per Capita Income	(8205)(3317)(17531)(1656)	(11468)(4291)(26727)(2378)	(14842)(5532)(34822)(3068)	(18522)(7780)(45920)(3767)
Number of Plots in Cropland	204,859	200,792	196,418	189,963
Number of Plots Converted	0	4,067	8,441	14,896
GDD8-32	(2750)(750)(5575)(933)	(2734)(732)(5589)(925)	(2741)(726)(5632)(927)	(2732)(719)(5672)(928)
GDD34	(7.43)(0)(275)(15.32)	(6.52)(0)(275)(14.58)	(6.56)(0)(271)(14.15)	(6.39)(0)(284)(14.35)
PRECIPITATION	(90.47)(6.51)(194.13)(34.97)	(91.90)(7.49)(190)(34.76)	(92.21)(7.96)(181.47)(35.24)	(94.04)(8.06)(184.39)(35.63)
Crop price series (by state)				
Corn (\$/bu)	(2.79)(2.31)(3.44)(.23)	(2.55)(2.17)(3.15)(.24)	(2.52)(2.10)(3.03)(.23)	(2.90)(2.38)(3.44)(.27)
Wheat (\$/bu)	(3.55)(3)(4.03)(.20)	(3.06)(2.75)(3.71)(.18)	(3.30)(3.06)(3.84)(.18)	(3.71)(3.26)(4.58)(.26)
Cotton (\$/lb)	(.63)(.49)(.71)(.05)	(.59)(.52)(.70)(.05)	(.61)(.54)(.75)(.06)	(.67)(.62)(.78)(.04)
Soybean (\$/bu)	(6.41)(6.02)(6.68)(.18)	(5.99)(5.60)(6.57)(.22)	(5.99)(5.53)(6.42)(.22)	(6.49)(6.20)(6.74)(.16)
Sorghum (\$/cwt)	(4.22)(3.52)(5.72)(.49)	(4.01)(3.37)(5.34)(.48)	(4.06)(3.34)(5.37)(.50)	(4.47)(3.67)(5.01)(.29)
Hay (\$/ton)	(61.18)(45.56)(82.97)(10.33)	(67.40)(39.98)(100.89)(13.91)	(76.42)(51.47)(111.27)(15.49)	(83.18)(49.44)(118.94)(19.44)
Oats (\$/bu)	(1.75)(1.32)(2.55)(.24)	(1.64)(1.34)(2.27)(.19)	(1.70)(1.23)(2.10)(.17)	(1.80)(1.34)(2.30)(.22)
Total Number of Plots	204,859	204,859	204,859	204,859

Note:

GDD is calculated by BE method from daily minimum and maximum temperature.

Precipitation is the county average during the growing season from April to September (cm).

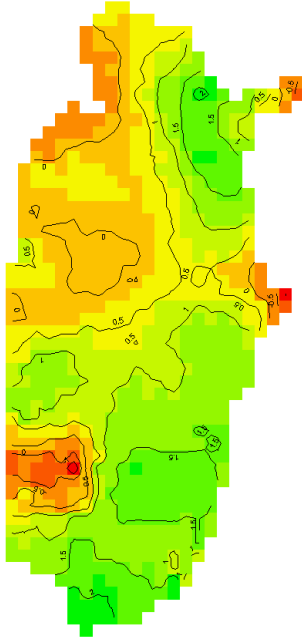
Climate variable is 30-year average prior to the conversion report (i.e. 1953-1982 for conversions reported in 1982 and so on).

Population density is people/square mile, and income per capita is \$1000/person.

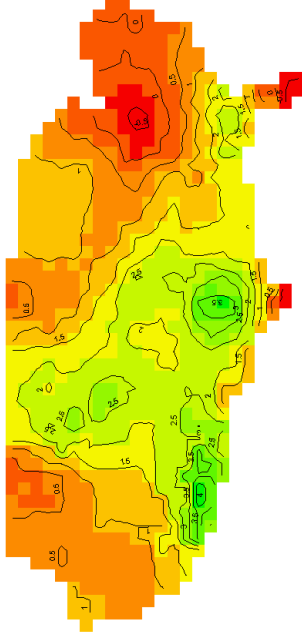
TFP is a normalized index, with the base year set equal to 1 in 1996 in Alabama.

Appendix 3. PDSI Records during 1978-1997

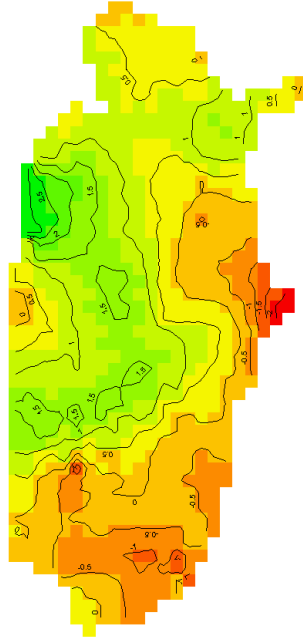
1978-1982



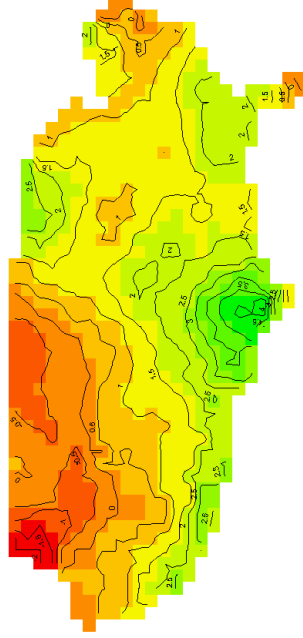
1983-1987



1988-1992



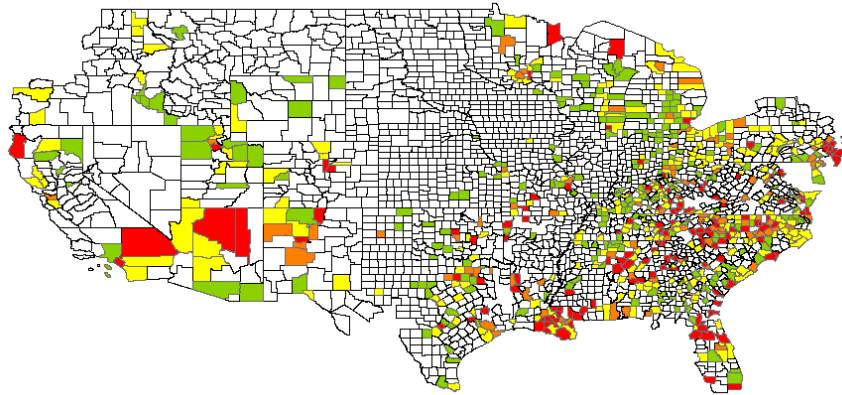
1993-1997



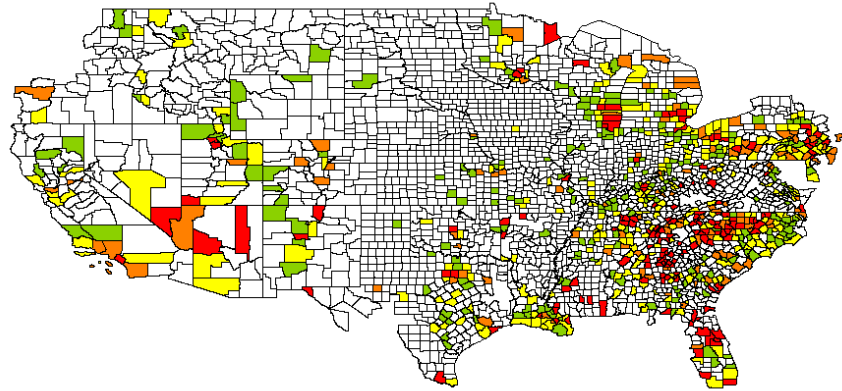
PDSI Records: The numbers are five-year average, for the period 1978-1982, 1983-1987, 1988-1992, and 1993-1997. County values are raster interpolated by inverse distance from 6 nearest grids on Albers projection, producing a rather smooth value transition from one location to another. Contour lines separate regions with different ranges of drought severity index. Green color denotes wetter than normal condition, while red color denotes drier than normal condition. Color intensity indicates the level of drought/wet condition. It is evident that drought condition could emerge anywhere, whether the lower or higher latitude. This is an important characteristic of the drought anomaly index as a deviation from normal condition. Using average precipitation to measure impact of weather shocks would have confounded with other climate or location's fixed effects.

Appendix 4. Conversion Patterns

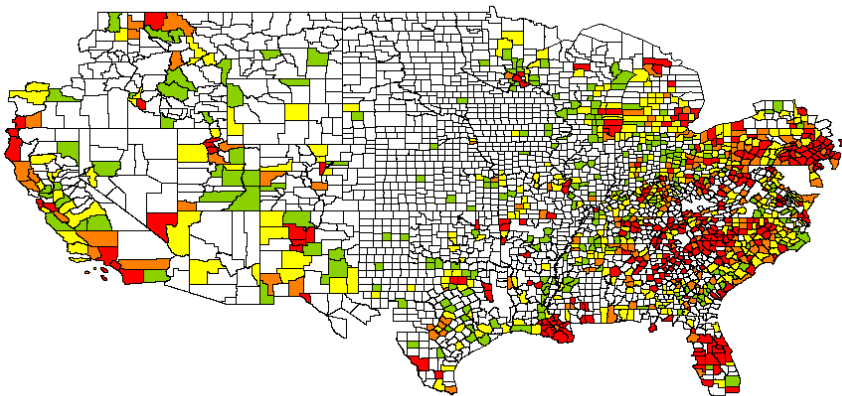
1982-1987



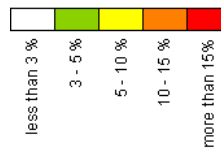
1987-1992



1992-1997



Conversion Ratio

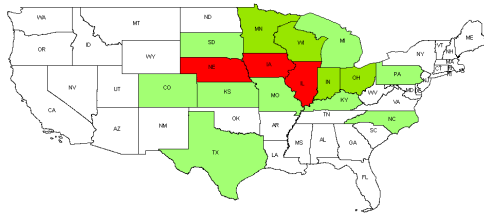


Appendix 5. Major Producing States

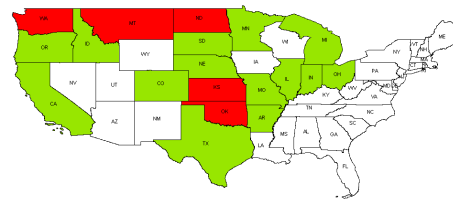
Major producing states of seven high-value crops with plain color denotes states whose value accounts for less than one percent total production value, light green and dark green denotes between 3-5 percent and 5-10 percent of the total production value. Red states are most major producing states.

It appears that corn is primarily produced in the Corn Belt, with some limited production in Texas. Temperate crop like cotton (upland) is grown mostly in the lower latitude including California, Arizona, Texas, and Mississippi. Hay crops are most prevalent almost everywhere as expected. Hays are primarily used for local consumption (forage).

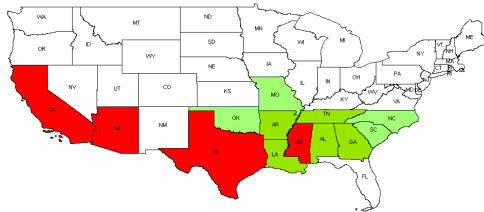
Corn



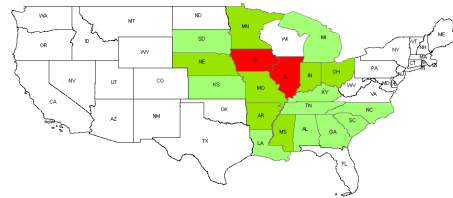
Wheat



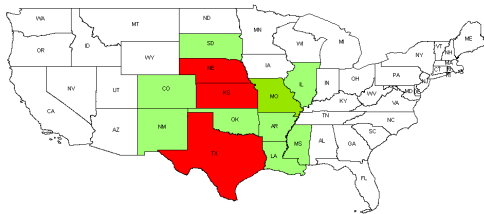
Cotton



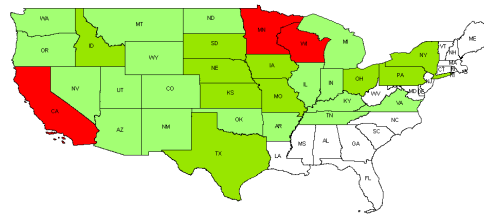
Soybean



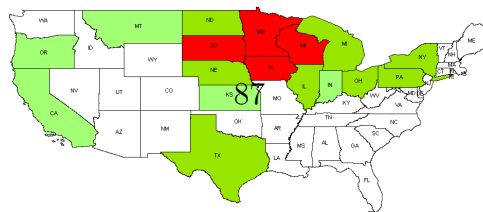
Sorghum



Hay



Oats



Technical Appendix

Aguirregabiria and Mira (2002)'s Nested Pseudo Likelihood (NPL) Estimator of the Discrete Choice Dynamic Programming Problem

In this section I briefly describe the NPL approach and its application to the structural model encountered in this paper. Essentially, this is an efficient method to transform the calculation of the fixed point of the integrated value function in the parameter space to a fixed point in probability space. I present the main structural equation and how uncertainty and irreversibility of an environmental process could be translated into a pure technical term. The majority of the proof is not included to maintain readability to nontechnical readers.

To rephrase the problem, farm owners face a binary choice at the beginning of each period whether to keep the land in crop production, or to convert the land to developed use (urban land). We know that fixed effects like climatic variables do not affect the conversion decision. Rather, farm owners, under the threat of short-term exogenous shocks, have to weigh the costs and benefits of continuing to use the land for agricultural production. If shocks are deterministic (implying that the transition of the exogenous state variables are known with certainty), then the conversion problem can be solved in a single-period conditional logistic regression model. However, if one or more exogenous shocks carry uncertain impact, then the decision to convert a farm plot has to take into account the irreversibility of farmland conversion. Starting from the Bellman's equation:

$$V(X_{i,t}, i, \varepsilon_{i,t}) = \max_{i,t} \left\{ \pi_t(X_t, i, \theta) + \varepsilon_t(i) + \beta E[V(X_{t+1}, \varepsilon_{t+1} | X_t, \varepsilon_t, i_t)] \right\} \quad (22)$$

for the vector of state variables $X_{i,t}$, binary choice i , and the profit residual $\varepsilon_{i,t}$.

The expected value function, expressed in conditional probability, is:

$$EV = E \left[\max_i (EV(X, i) + \varepsilon_i) \right] = \sum_i P(i|X) \left[EV(X, i) + \varepsilon(i|X) \right] \quad (23)$$

with $\varepsilon(i|X) = \epsilon - \ln[P(i|X)]$, and $\epsilon = \lim_{n \rightarrow \infty} \left[\sum_{k=1}^n \frac{1}{k} - \ln(n) \right] = .5772$ or the *Euler* constant.

Aguirregabiria and Mira (2002) show that this expected value function is equivalent to:

$$EV = \sum_i P(i|X) \left[\pi_{x,i} + \beta \sum_x f(X_{t+1}|X_t, i) EV(X) + \varepsilon(i|X) \right] \quad (24)$$

where $f(X_{t+1}|X_t, i)$ is the transition matrix of the state variable at period $t + 1$ conditional on past value X_t and choice i taken in the previous period.

Rewrite equation (24) in matrix format:

$$EV = \sum_i P(i|X) * [\pi(X, i) + \beta F(i)EV + \varepsilon(i|X)] \quad (25)$$

Where $*$ is the Hadamard product of two matrices, or element-by-element multiplication.

Rearrange the terms to get a closed form solution of the expected value function in the probability space:

$$EV = \left[I_K - \beta \sum_i P(i|X) * F(i) \right]^{-1} \sum_i P(i|X) * \left[\pi(X, i) + \varepsilon(i|X) \right] \quad (26)$$

Then the conditional value function, conditional on choice i , is:

$$V(i) = \pi(i) + \beta F(i) EV \quad (27)$$

Substitute EV from (26):

$$V(i) = \pi(i) + \beta F(i) \left[I_K - \beta \sum_i P(i|X) * F(i) \right]^{-1} \sum_i P(i|X) * \left[\pi(X, i) + \varepsilon(i|X) \right] \quad (28)$$

By adding another simplified assumption that the payoff function is multiplicatively separable in the coefficients, meaning that:

$$\pi(X, i) = z(X) * \theta + \varepsilon_i \quad (29)$$

Check that the Cobb-Douglas profit function in logarithm form can meet this definition of multiplicative separability.

Then equation (28) can be expressed as:

$$V(i) = [z(i) + \beta F(i) W_z(X, P)] \theta + \beta F(i) W_z(P) \quad (30)$$

where

$$W_z(X, P) = \left[I_K - \beta \sum_i P(i|X) * F(i) \right]^{-1} \sum_i P(i|X) * z(X) \quad (31)$$

and

$$W_z(P) = \left[I_K - \beta \sum_i P(i|X) * F(i) \right]^{-1} \sum_i P(i|X) * \varepsilon(i|X) \quad (32)$$

Then denotes $\tilde{z} = [z(i) + \beta F(i) W_z(X, P)]$ and $\tilde{\varepsilon} = \beta F(i) W_z(P)$, which is a function of the conditional probability P , the value function can be written in an abstract form as:

$$V(i) = \tilde{z}_i \theta + \tilde{\varepsilon}_i \quad (33)$$

then the conditional probability of choice i can be derived in the probability space as:

$$P(i|X) = \frac{e^{\tilde{z}_i \theta + \tilde{\varepsilon}_i}}{\sum_j e^{\tilde{z}_j \theta + \tilde{\varepsilon}_j}} \quad (34)$$

Since both \tilde{z} and $\tilde{\varepsilon}$ are a function of the conditional choice probability P , the above equation is indeed a mapping in the probability space, thus a fixed point exists and is the unique solution to the contraction mapping. Therefore, the conditional choice approach works in two steps: in the inner loop the conditional choice model estimates the set of the structural parameters from

a trial value of the conditional probability, while in the outer loop a fixed point algorithm is used to find the fixed point in the probability space. β , the discount rate, is not estimated and assumed a value of .95 in all models. A complete dataset and the Gauss code used in this paper are available upon request.

Appendix 6

Assumptions on the Transition of Shocks, Uncertainty and Irreversibility

Unlike the static shock model, in a dynamic model with uncertainty, the evolution of the shocks must be specified. A standard approach would be an empirical estimation and inference based on historical patterns. However, I adopted a new approach in which the transition is subjective, based on various assumptions regarding the future productivity growth and the long lasting impact of extreme droughts. The reason is that shocks such as extreme droughts are unpredictable, and impacts are uncertain. Had the impact of extreme events been known with certainty, the model would have been reduced to a static shock model as estimated in the Table 2. TFP or yield growth may assume parametric transition rule such as an AR1 process, estimated from historical data. However, those estimates are largely arbitrary and not quite good predictors of future yield growth, as suggested by many studies.

I make three assumptions with regard to the transition of the shocks. The first two are in line with the objective of this study - to determine the impact of extreme droughts and productivity growth on cropland loss, while the third one is fairly standard for dynamic discrete choice modeling.

- (1) The uncertainty is limited to either the evolution of productivity growth, and the long-lasting impact of extreme drought events, or both.
- (2) Other exogenous shocks such as price of input and output, and urban rent's determinants are deterministic.
- (3) The structure of uncertainty is stationary, implying that there is a finite support for the discretized values of the state variable vector. Furthermore, the distribution of uncertainty is known in advance, and there is no learning through piecemeal conversion.

Restriction of the uncertainty structure is consistent with exploratory analysis shown in Figure 2 that price shocks are unlikely to last long. Favorable price shocks after catastrophic events may help offset losses for a buffer period until supply is secured. There is not large uncertainty with regard to urban land rent determinants, such as sudden changes in the population or income, as expected. What remains is the two major determinants of long-term productivity growth - the exogenous technological growth, and the damage from extreme events on soil productivity.

The assumption about the uncertainty and irreversibility of cropland conversion is specified on the discretized state space of the observed variables⁵. For those shocks with deterministic transitions, the transition matrix is just an identity matrix, which maps the current state to the future state with the exact value as the current value. For example, price is discretized in two states, high and low. Then a deterministic shock would imply that a low price state would transit to a low price state with a probability of one, and to a high state with a probability of zero, in the future. Then the transition matrix for deterministic shocks is formulated as:

⁵Since all the state variables are continuous in nature, they have to be discretized. The choice of the maximum number of grids is limited by the maximum matrix size a computer can handle - in this case about 4,000 - for a 32-bit operating system. As a result, for the 8 state variables used in the structural model (PDSI, PDSI*GDD, log(TFP), log(Price), log(Wage), log(Fertilizer), log(PopDens) and log(PerCapInc), I restrict the number of grids as (4,4,4,2,2,2,2,2) for a total of 2,048 discrete states for each choice, and 4,096 states for a binary discrete choice model.

$$P(\text{Price}_{t+1}|\text{Price}_t, i) = \begin{bmatrix} P_{LL} & P_{LH} \\ P_{HL} & P_{HH} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \quad (35)$$

For uncertain shocks, the cross transition could practically take on any positive value. For example, for a 4-state transition matrix, between Low (L), Quartile 1 (Q1), Quartile 2 (Q2), and High values (H):

$$P(\text{PDSI}_{t+1}|\text{PDSI}_t, i) = \begin{bmatrix} P_{LL} & P_{LQ1} & P_{LQ2} & P_{LH} \\ P_{Q1L} & P_{Q1Q1} & P_{Q1Q2} & P_{Q1H} \\ P_{Q2L} & P_{Q2Q1} & P_{Q2Q2} & P_{Q2H} \\ P_{HL} & P_{HQ1} & P_{HQ2} & P_{HH} \end{bmatrix} \quad (36)$$

with all value $P_{I,J}$ non-negative, as the row sum is one.

How to incorporate irreversibility?

Once a plot has been converted, it no longer benefits from better growing condition such as more favorable yield growth. In other words, the potential profit from agricultural productivity growth is zero, once the land has been converted to developed use. Translate this into the transition of the productivity growth, conditional on past choice is developed land⁶:

$$P(\text{TFP}_{t+1}|\text{TFP}_t, i = \text{develop}) = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \end{bmatrix} \quad (37)$$

This means that for developed land, any uncertainty with regard to productivity growth vanishes. And there is no gain for developed land from increasing future productivity since productivity shock no longer works in favor of developed land. The choice of the constraint is to determine the state for which developed land could obtain the lowest value if it could still be converted back to cropland.

For droughts' impact⁷:

$$P(\text{PDSI}_{t+1}|\text{PDSI}_t, i = \text{develop}) = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \quad (38)$$

⁶To be accurate, we should work with $P(\log\text{TFP}_{t+1}|\log\text{TFP}_t, i = \text{develop})$, which is not the same as $P(\text{TFP}_{t+1}|\text{TFP}_t, i = \text{develop})$ since transforming a variable to log form will shift the probability mass around. For example, if TFP is uniformly distributed then $\log(\text{TFP})$ has exponential distribution. To make the matter easier to handle, I assume the transition of the logarithm of TFP instead of the original TFP index.

⁷To remind readers about the meaning of PDSI's measurement: [-2,2] is for mild drought to mild wet, and the lower end is for more severe drought, while the higher end for wetter condition, supposedly good for crops. Value between [-2,2] reflects neutral to mild condition, which does not yield significant impact either way - good or bad.

or

$$P(PDSI_{t+1}|PDSI_t, i = develop) = \begin{bmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \quad (39)$$

The results are not significantly different whether the choice of either the lower or upper-midsection so only one result is reported.

Perhaps to be realistic, we also need to make a simplifying assumption that weather extremes do not cause price to shoot up in the long term. There may be short-term impacts, however. One possible reason is that price is the expected or forward price, committed before the choice of land use was made. While the realized price may be affected by weather extremes, it's only a short-lived event and will not have an impact on the long term benefit of agricultural production.

Then the transition matrix is derived as the Kronecker's product of all transition matrices of each state variable:

$$F(X_{t+1}|X_t, i)_{2048} =$$

$$[PDSI]_4 \otimes [PDSI * GDD]_4 \otimes [TFP]_4 \otimes [Price]_2 \otimes [Wage]_2 \otimes [Fertilizer]_2 \otimes [PopDens]_2 \otimes [IncCap]_2 \quad (40)$$

I experiment different uncertainty structures of the long lasting impact of extreme droughts and the prospect of productivity growth. Other state variables are assumed deterministic transitions. The combinations of the uncertainty structure result in the following models:

A. One uncertainty at a time

A1. Drought shock is deterministic, while TFP growth is uncertain

This uncertainty structure implies that:

$$P(PDSI_{t+1}|PDSI_t, i) = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (41)$$

Meaning that there is no uncertainty over PDSI shock for cropland return, and that the current state of each discretized value maps into the exact value with a probability of one.

Model A.1.1: Farm owners assume TFP growth is completely random, with a uniform distribution over the discretized state space:

$$P(TFP_{t+1}|TFP_t, i) = \begin{bmatrix} .25 & .25 & .25 & .25 \\ .25 & .25 & .25 & .25 \\ .25 & .25 & .25 & .25 \\ .25 & .25 & .25 & .25 \end{bmatrix} \quad (42)$$

Model A.1.2: Farm owners assume higher TFP growth in the future, with a higher chance that TFP would be larger than the current value:

$$P(TFP_{t+1}|TFP_t, i) = \begin{bmatrix} .25 & .75 & 0 & 0 \\ 0 & .25 & .75 & 0 \\ 0 & 0 & .25 & .75 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (43)$$

Model A.1.3: Farm owners assume lower TFP growth in the future, with a higher chance that TFP would be smaller than the current value:

$$P(TFP_{t+1}|TFP_t, i) = \begin{bmatrix} 1 & 0 & 0 & 0 \\ .75 & .25 & 0 & 0 \\ 0 & .75 & .25 & 0 \\ 0 & 0 & .75 & .25 \end{bmatrix} \quad (44)$$

Model A.1.4: TFP growth is uncertain, with a higher chance that the future TFP growth is the same as the current period, while there is a small chance of either a higher or lower value:

$$P(TFP_{t+1}|TFP_t, i) = \begin{bmatrix} .8 & .2 & 0 & 0 \\ .1 & .8 & .1 & 0 \\ 0 & .1 & .8 & .1 \\ 0 & 0 & .2 & .8 \end{bmatrix} \quad (45)$$

A2. Drought shock's impact is uncertain, while TFP growth is deterministic
This uncertainty structure implies that:

$$P(TFP_{t+1}|TFP_t, i) = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (46)$$

and

Model A2.1: Impact of drought is uniformly randomly distributed:

$$P(PDSI_{t+1}|PDSI_t, i) = \begin{bmatrix} .25 & .25 & .25 & .25 \\ .25 & .25 & .25 & .25 \\ .25 & .25 & .25 & .25 \\ .25 & .25 & .25 & .25 \end{bmatrix} \quad (47)$$

Model A2.2: Drought impact is less severe in the future:

$$P(PDSI_{t+1}|PDSI_t, i) = \begin{bmatrix} .25 & .75 & 0 & 0 \\ 0 & .25 & .75 & 0 \\ 0 & 0 & .25 & .75 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (48)$$

Model A2.3: Drought impact is more severe with a higher probability of damages in the future:

$$P(PDSI_{t+1}|PDSI_t, i) = \begin{bmatrix} 1 & 0 & 0 & 0 \\ .75 & .25 & 0 & 0 \\ 0 & .75 & .25 & 0 \\ 0 & 0 & .75 & .25 \end{bmatrix} \quad (49)$$

Model A2.4: Uncertain impact:

$$P(PDSI_{t+1}|PDSI_t, i) = \begin{bmatrix} .8 & .2 & 0 & 0 \\ .1 & .8 & .1 & 0 \\ 0 & .1 & .8 & .1 \\ 0 & 0 & .2 & .8 \end{bmatrix} \quad (50)$$

B. Both uncertainties at the same time, drought shocks and TFP growth

Model B.1: Both uncertainties are uniformly randomly distributed:

$$P(PDSI_{t+1}|PDSI_t, i) = P(TFP_{t+1}|TFP_t, i) = \begin{bmatrix} .25 & .25 & .25 & .25 \\ .25 & .25 & .25 & .25 \\ .25 & .25 & .25 & .25 \\ .25 & .25 & .25 & .25 \end{bmatrix} \quad (51)$$

Model B.2: *Worst-case scenario* with more severe drought impact and less TFP growth:

$$P(PDSI_{t+1}|PDSI_t, i) = P(TFP_{t+1}|TFP_t, i) = \begin{bmatrix} 1 & 0 & 0 & 0 \\ .75 & .25 & 0 & 0 \\ 0 & .75 & .25 & 0 \\ 0 & 0 & .75 & .25 \end{bmatrix} \quad (52)$$

Model B.3: *Best-case scenario* with less severe drought and higher productivity growth:

$$P(PDSI_{t+1}|PDSI_t, i) = P(TFP_{t+1}|TFP_t, i) = \begin{bmatrix} .25 & .75 & 0 & 0 \\ 0 & .25 & .75 & 0 \\ 0 & 0 & .25 & .75 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (53)$$

Appendix 7. Sensitivity Analysis

Different subset of variables

East of 100th Meridian

Variables	1982-1987	p-value	1987-1992	p-value	1992-1997	p-value
PDSI	-1.9626	0	-1.5869	0	-0.2948	0.016
PDSI*GDD8_32	0.0003	0	0.0000	0.81	0.0001	0.098
PDSI*GDD34	-0.0577	0.081	0.0268	0.624	-0.1744	0
PDSI*PRECIPITATION	0.0076	0	0.0131	0	0.0030	0.011
TFP	2.2215	0.025	0.6925	0.327	-4.2576	0
PRICE	2.5929	0	0.1165	0.568	-0.3515	0.308
WAGE	-1.5455	0.155	3.9852	0	-2.2579	0
FERTILIZER	1.2628	0.142	-5.3141	0.004	-15.5549	0
PER CAP INCOME	2.1619	0	3.6190	0	-1.0785	0.047
POP DENSITY	7.8594	0	9.8619	0	9.9207	0
INTERCEPT	-5.7111	0	-5.7962	0	-1.1571	0
Number of Observations	162,541		158,959		155,106	

West of 100th Meridian

Variables	1982-1987	p-value	1987-1992	p-value	1992-1997	p-value
PDSI	1.0007	0.001	1.8018	0	-0.0652	0.785
PDSI*GDD8_32	0.0003	0.04	-0.0010	0.004	0.0004	0
PDSI*GDD34	-0.1030	0.016	0.2538	0.047	-0.1236	0
PDSI*PRECIPITATION	-0.0207	0.001	-0.0097	0.289	-0.0111	0.009
TFP	6.4847	0.048	5.6462	0.011	4.1947	0.076
PRICE	1.7548	0.011	0.3447	0.681	0.3049	0.719
WAGE	4.4796	0.216	-14.7028	0.002	-4.3157	0.014
FERTILIZER	4.2587	0.001	-11.9987	0.023	-30.3175	0
PER CAP INCOME	1.3251	0.036	0.9330	0.269	4.3656	0
POP DENSITY	6.3005	0	7.9876	0	7.0154	0
INTERCEPT	-9.6152	0	-3.1804	0.001	-2.9451	0
Number of Observations	42,292		41,810		41,295	

Estimates by geographic area

Variables	Full Sample	p-value	Western US	p-value	Central Plains	p-value
PDSI	-0.4498	0	0.0810	0.563	-0.4036	0.001
PDSI*GDD8_32	0.0000473	0.237	0.0004	0	0.0001	0.238
PDSI*GDD34	-0.0310	0.145	-0.0955	0	-0.0524	0.03
PDSI*PRECIPITATION	0.0043	0	-0.0160	0	0.0043	0.004
TFP	-0.4320	0.353	-0.6227	0.618	-3.2344	0
PRICE	0.5004	0	0.8196	0	0.1165	0.419
WAGE	-0.7178	0.027	-4.0646	0	-1.9872	0
FERTILIZER	1.9916	0	-0.2269	0.779	0.7989	0.552
PER CAP INCOME	0.9308	0	2.0484	0	0.0063	0.985
POP DENSITY	8.6054	0	8.3561	0	9.8495	0
INTERCEPT	-5.1766	0	-5.4618	0	-4.8784	0
Number of Observations	602,003		125,397		334,316	

Urban vs Non-urban Counties (urban if population density > 147 people/square mile), East of 100th Meridian only.

Variables	Urban	p-value	Non-urban	p-value
PDSI	-0.7156	0.008	-1.1417	0
PDSI*GDD8_32	0.000184	0.004	0.0001	0
PDSI*GDD34	-0.0766	0.042	-0.0728	0
PDSI*PRECIPITATION	0.0019	0.491	0.0080	0
TFP	0.0404	0.971	0.4039	0.417
PRICE	-0.0666	0.686	0.4104	0
WAGE	1.1899	0.165	-0.3010	0.373
FERTILIZER	1.1118	0.225	0.96230	0.085
PER CAP INCOME	-1.9102	0.002	0.3207	0.197
POP DENSITY	3.5673	0	9.2006	0
INTERCEPT	-2.5488	0	-4.9482	0
Number of Observations	27,860		448,746	

Separating potential price effect using individual crop price.

Variables	Corn	p-value	Wheat	p-value	Cotton	p-value
PDSI	-1.0042	0	-0.1476	0.195	-0.166	0.321
PDSI*GDD8_32	-0.0005	0.097	-0.0001	0.191	-0.0001	0.195
PDSI*GDD34	-0.1747	0.224	-0.0104	0.681	0.024	0.145
PDSI*PRECIPITATION	0.0206	0.001	0.0064	0	0.003	0.001
TFP	-1.7288	0.089	-4.3951	0	-2.346	0.153
PRICE	0.9797	0.239	0.3129	0.236	2.133	0
WAGE	-1.3376	0.057	-2.3437	0	-1.470	0.011
FERTILIZER	-3.4100	0.24	1.0610	0.425	0.762	0.389
PER CAP INCOME	0.9009	0.267	0.7551	0.071	1.403	0.01
POP DENSITY	13.2884	0	9.7903	0	6.802	0
INTERCEPT	-3.9731	0	-5.1057	0	-4.669	0
Number of Observations	226,757		249,981		100,981	

Separating potential price effect using individual crop price. The most important crops are corn for grain, cotton, soybeans and winter wheat. Sorghum, oats and hay contributed little to overall production value, though widely observed.

Variables	Soybean	p-value	Sorghum	p-value	Hay	p-value	Oats	p-value
PDSI	-0.7074	0	-1.1004	0	-0.2004	0.005	-0.8336	0
PDSI*GDD8_32	-0.0007	0.032	0.0001	0.38	-0.0001	0.117	-0.0001	0.288
PDSI*GDD34	-0.1533	0.152	0.0517	0.065	0.0050	0.805	-0.0136	0.616
PDSI*PRECIPITATION	0.0234	0	0.0056	0.002	0.0042	0	0.0099	0
TFP	-1.1284	0.209	-4.0670	0.01	-2.9986	0	-3.9525	0
PRICE	0.2437	0.724	0.8269	0.088	0.2781	0.032	1.3616	0.003
WAGE	-0.8375	0.157	-2.5235	0	-0.4012	0.247	0.0720	0.843
FERTILIZER	0.0129	0.994	0.0109	0.995	1.5369	0.001	0.6018	0.494
PER CAP INCOME	1.1142	0.078	0.9313	0.102	0.8891	0	0.4843	0.151
POP DENSITY	12.1718	0	8.5956	0	8.9294	0	9.7181	0
INTERCEPT	-4.7376	0	-4.3882	0	-4.9560	0	-4.5020	0
Number of Observations	252,415		124,620		545,607		331,733	

Appendix 8.

If $\varepsilon = (\varepsilon_1, \dots, \varepsilon_J)$ are multivariate *iid* extreme value random variables, then $\max_i \{\varepsilon_i\}$ is *max-stable*, meaning that $\max_i \{\varepsilon_i\}$ is also extreme value distributed.

Normalize the scale of the distribution by $\sigma = 1$, then $P(\varepsilon \leq x) = e^{-e^{-x}}$, thus

$$P(u_d + \varepsilon_d \leq x) = P(\varepsilon_d \leq x - u_d) = e^{-e^{-(x-u_d)}}$$

Then, for the multivariate *iid* extreme value distribution $P(\varepsilon|x, \theta) = \prod_i e^{-e^{-\varepsilon}}$

$$\begin{aligned} P[\max_i (u_i + \varepsilon_i) \leq x] &= P[u_1 + \varepsilon_1 \leq x] * \dots * P[u_J + \varepsilon_J \leq x] \\ &= P[\varepsilon_1 \leq x - u_1] * \dots * P[\varepsilon_J \leq x - u_J] \\ &= \prod_i e^{-e^{-(x-u_i)}} \\ &= e^{-\sum_i e^{-(x-u_i)}} \\ &= e^{-\log[\sum_i e^{-(x-u_i)}]} \\ &= e^{-e^{-x} \sum_i e^{u_i}} \\ &= e^{-e^{-x} \log(\sum_i e^{u_i})} \\ &= e^{-e^{-x} \log(\sum_i e^{u_i})} \end{aligned}$$

which is the probability distribution of an extreme value random variable with the same scale of 1 and location $\log(\sum_i e^{u_i})$.

Hence, the expected value of the distribution of the maximum is:

$$E[\max_i (u_i + \varepsilon_i)] = \log(\sum_i e^{u_i})$$

Essay 3

Impact of Extreme Heating Condition on Farmland Conversion in California

Abstract

This paper presents a method of estimating the impact of extreme heating conditions on prime farmland conversion using a spatial database constructed from publicly available GISs. Particularly, I construct a 25-year climate extreme surface, using real time observations from the weather station network in California, and investigate the number of extreme heating days - days with recorded temperature reaching 90 degrees Fahrenheit, believed to adversely affect both crops and farmland values. The result confirms that farmland conversion is affected by extreme heating conditions, and while the effect is minimal, it is present and remains highly significant across a number of specifications. Farmland conversion is non-linearly affected: a mild increase in the number of heating days may be good for crops, raise farmland value, and help keep farmland in agricultural production, but an excessive increase is harmful and will accelerate farmland conversion. This result suggests that California's agricultural lands face additional pressure from a predicted disproportionate increase in climate change-induced temperature extremes.

Key words: Extreme heating condition, climate change impact, spatial regression

1 Introduction

There is a growing consensus that climate change¹ will bring harmful consequences. The impacts of climate change have already occurred and will likely worsen in the future. According to IPCC WGII Fourth Assessment Report (WGII-AR4), Chapter 14, "North America has experienced substantial social, cultural, economic and ecological disruption from recent climate related extremes, especially storms, heatwaves, and wildfires." The report also states "North American people, economies and ecosystems tend to be much more sensitive to extremes than to average conditions. Incomplete understanding of the relationship between changes on the average climate and extremes limits our ability to connect future impacts and the options for adaptation."

¹Climate change is defined as a long-term trend in weather fluctuations, versus short-term deviation of weather variables from average daily values. IPCC WGII emphasizes that "detection of climate change is the process of demonstrating that an observed change is significantly different (in a statistical sense) from what can be explained by natural variability."

There has been much research available on the possible impacts of climate change to economies, public health, urban growth, and the environment. The challenge when studying climate change impacts, however, is that modeling the impacts of extreme events is much more difficult than the impact of shifting in average conditions (WGII, Chapter 5). In the agricultural industry, there is no universal agreement or understanding of how crops respond in various conditions, although it is generally understood that the increasing frequency of extreme events may lower crop yields - beyond only marginal gains - resultant of longer growing seasons and increased precipitation. It is important to note that there is still uncertainty about the true and quantified impact on agricultural production. North American agriculture, especially in mid and high latitude regions, may benefit from moderate increases in local temperatures, but extensive warming would be harmful (with medium to low confidence, WGII, chapter 5), and lower latitude regions such as California would likely suffer.

In this study I attempt to identify the impact of climate extremes, particularly the number of extreme heating days, on farmland conversion in California. I use comprehensive state-wide farmland tracking data from 1984 to 2006 to map out the location of conversions in each county, then model the conversion using a set of explanatory variables representing the extremes, while controlling for other potential factors such as climate normals, soil, and other socio-economic characteristics.

1.1 Review of Climate Change Impact and Farmland Conversion

Although there have been many studies on the conversion of agricultural land to urban usage (often known as land-use change or urbanization model²), limited efforts have been expended on studying the impacts of climate change on land conversion.

Studying the impacts of climate change on land conversion presents multiple challenges. First, climate change occurs over a long time horizon, so to reliably study the impacts of climate change there must be accurate and concise time series data. Second, there are many factors that lead to farmland conversion, the most often cited being urban-driven factors such as rapid population growth, increasing income, and expansion of urban infrastructure, although many studies model these factors as the exclusive causes of urbanization.

²I distinguish the term “urbanization” in general literature from “farmland conversion” or “farmland loss” used in this study since the former specifically refers to the conversion of agricultural land to urban usage, but the latter does not hold the same reciprocal meaning. This view is also reflected in California Department of Conservation’s Farmland Monitoring and Management Program (FMMP) report that farmland loss is not due to urbanization alone (FMMP 2002-2004 report, page 2). FMMP classifies farmlands into 8 categories (see appendix), and in this paper I look at the conversion away from prime farmland to any other usage, urban or non-urban. Attention is paid to the conversion of prime farmland, the most productive land, for the economic reason that climate change and agricultural production are interdependent. Inclusion of unproductive land would divert attention from the impacts on agricultural production. Although climate change may affect land conversion in many different facets, non-agricultural conversion has more to do with urban-driven factors than agricultural production.

Another reason as often perceived in public opinions, is that climate change happens gradually rather than suddenly, thus adaptive capability can be introduced on time, to withstand the possible impacts from global warming. This is not the case, however. Climate change, defined as the long-term trend in average climatic conditions such as temperature and precipitation, with increasing fluctuations in climate and extreme events have the most serious of consequences, and short-term adjustment may not be feasible, or the adaptive capability to extreme events is “uneven and not adequate” (IPCC, WGII).

In most climate change impact studies, temperature and precipitation are used as indicators and are the most easily observed variables. Mean temperature and seasonal temperature cycle, over relatively large spatial areas, illustrate clearest signals of changes in an climate (WGII, Chapter 1). However, this comes with a cost: the effects of extreme events are not able to be determined at a local level. This would result in significant underestimation of the effect of climate change, since the extreme events have more significant impacts than the projected gradual changes. Climate models using mean temperature and precipitation often aggregate data over a large spatial and extended temporal scale, and are therefore unable to estimate the effect of localized events such as heavy precipitation or local droughts. Using only the trend in mean variables to predict the impacts of climate change is not enough to capture the full variations, and leads to questionable results in many existing models. Without accounting for climate extremes, the impacts would be vastly underestimated. While anticipated changes are often well expected, extreme events are often unexpected and thus cannot be prepared for.

The next section will briefly review two relevant branches of literature in climate change impacts on US agriculture, and California specifically, and land-use change models.

1.2 Climate Change Impact on California Agriculture

Most studies seem to agree that future agriculture in California will be adversely affected by climate change, although the US as a whole may yield different results. Schlenker, Hanemann, and Fisher (2005) maintain that there is a significant relationship between precipitation, temperature measured at selected months for primarily non-irrigated farmland in the US, and farmland values. Further work by Schlenker, Hanemann, and Fisher (2006), with a spatial model using a more sophisticated modeling of climate variables such as degree days and precipitation over growing season, also confirms the effect of harmful high temperature or precipitation. That is, a reasonable amount of precipitation and degree days positively affect farm values, but too excessive amounts will be harmful. Extreme temperature (Degree Days over 34°C) can yield negative and significant effects. Schlenker, Hanemann, and Fisher (2007), applying the water availability model to California (access to irrigation water), also predict damages from climate change resulting from a potentially large increase in growing-season temperatures and less water for irrigation.

California agricultural landscapes are at risk to climate change impacts, which are further exacerbated by multiple vulnerabilities. Unlike the rest of the country, California agriculture is more dependent on irrigated water, and won't benefit from increased precipitation. Higher temperature, greater evaporation, and less precipitation would mean

increased demand for water from agriculture and urban uses. Furthermore, future water shortage is also expected due to rapid population growth, which is predicted to almost triple by the end of the century (Cavagnaro, Jackson, and Scow, 2006).

The most important result of the Schlenker, Hanemann, and Fisher (2005, 2007) studies is that farmland value is adversely affected by decreasing water availability or warming condition in California: Growing Degree Days is significant, but too much heat (quadratic Growing Degree Days), and extreme heat (temperature greater than 34°C) will harm the crops, thus decreasing farmland values. This immediately leads to the question about the extent to which farmland conversion is affected by changing climate conditions. As we assume farm owners maximize economic profit from the value of their land, adverse weather reduces farm productivity, thus adversely affecting the value of the land on which crops are grown. Therefore, it is expected that climate change would depreciate farmland values and accelerate the conversion to other usages, especially with the presence of increasing threats of urbanization.

I attempt to answer this question using a more comprehensive set of climate extreme variables in addition to the usual treatment of control variables, including all relevant soil and socio-economic characteristics. This paper specifically addresses the effects of climate extremes, particularly extreme heating days. This would be the first model to map farmland vulnerability to climate extreme events in California. This approach will extend the land-use change model with an added dimension to accommodate for the impact of climate change-induced extreme heating conditions. Another advantage is the application of Geographical Information System (GIS), which allows for the ability to track every piece of farmland converted between 1984 and 2006 in most counties in California, thus avoiding the issue of aggregation and possible aggregation bias in the result.

2 Modeling the Impact of Extreme Heating on Farmland Conversion

It is assumed that farmland owners maximize profit, either as a net discounted rent from future farming (or the Ricardian rent), or sell their land and convert it to another usage. This is the traditional approach to urbanization. Facing possible adverse climate change impacts that reduce future farming profits, an increase in farmland conversion is expected. Multiple factors should be noted. First, I assume that the conversion is based purely on economic decision. Farmlands that have been relegated for other usage will be excluded from the data. Unlike common land-use change models which requires the land to be converted to urban usage, in this model farmland can be converted to urban or other usage, or even left idling.

Second, is there any market mechanism which might benefit farm owners from harmful climate extreme events? If farm supply was disrupted by local climate events, but not replenished from other means, then price could be expected to increase. If price increases were to offset losses to damaged crops, then farm owners could actually benefit. In this scenario, there is a benefit in conversion from idle lands, or other land uses, reverting

to prime farmland use. However, it is reasonable to assume that such events, if they exist, would not be strong enough to interfere with the conversion trend since short-term gain would not outweigh the expected future cost of maintaining the farm. Similarly, if demand for crop increases, it is possible that idle land could revert to cultivated land status (FMMP 2002-2004 period reports irrigated acreage gains in Antelope Valley of Los Angeles County due to strong market demand of baby carrots and potatoes, although two thirds of those lands did not meet prime farmland criteria). This could partially offset the effects of short-term extreme events on conversion. The easiest way to consider this scenario is to assume the price as a constant, thus allowing no external market intervention. Existing studies, such as Deschenes and Greenstone (2007), also assign price as constant. Including a time fixed effects may also solve this problem.

Third, there is a legislative issue that may limit the option of farm owners from conversion. California initiated the 1965 Williamson Act in order to protect the state's farmland from conversion, by giving financial incentive to farm owners. Farm owners receive property tax credit by entering into a 10-year rolling contract with the government. Currently, up to a half of the state's farmland is under protection of the act. Only farms greater than 100 acres are eligible for this protection. Farm owners must pay a cancellation fee if they want to discontinue the program before contract is due. Thus, a downward bias of the impacts of climate change will be expected.

2.1 Data Sources and Processing

This section describes the construction of a spatial database and the necessary processes to generate a suitable dataset for analyzing farmland conversion. Most data used in this paper comes from public GIS databases, which often requires extensive processing prior to application. There are several occasions in which the use of GIS operations is explained in details, in order to provide insight into the raw data and data format used in spatial econometric modeling.

Data Sources and Description

Farmland data

The California Department of Conservation initiated the Farmland Mapping and Monitoring Program (FMMP) in response to "a critical need for assessing the location, quality, and quantity of agricultural lands and conversion of these lands over time. FMMP is a non-regulatory program and provides a consistent and impartial analysis of agricultural land use and land-use changes throughout California" (California Department of Conservation).

The first biennial report on farmland landscape was available in 1984. Since then there have been 10 published reports and 12 GIS databases made available to the public with the 2006 data is the final period of this study. Over time, there were more counties and land areas mapped and published, up from 38 counties in the 1984 report to 46 counties

in 2006. The database now maps nearly 96% of the state's privately held agricultural and urban land use, covering 47.9 million acres in 49 counties.

There are 8 types of important land use in the FMMP classification: prime farmland, farmland of statewide importance, unique farmland, farmland of local importance, grazing land, urban and built-up land, other land, and water (farmland list in appendix). The FMMP team uses remote sensing satellite images, aerial orthophotos, and soil survey data from the US Department of Agriculture in the classification process and verifies the information by ground survey, as well as inputs from other parties.

Climate data

Mean weather variables from the PRISM dataset (Parameter-elevation Regressions on Independent Slopes Model of the Oregon State University PRISM group) are utilized in this study. I use the 30-year average maximum, minimum, mean temperature, and precipitation for the period 1971-2000. PRISM data is available in grid cells at a resolution of 30 arcsecond (roughly 800mx800m). Within each cell it is assumed that weather variables are homogeneous.

Historical weather records

Another set of weather variables utilized real-time observations at the National Climatic Data Center (NCDC) weather station networks. I only extract observations from those stations having reports for the studied period from 1980 to 2006. There are data on daily maximum and minimum temperatures and precipitation. There were 628 stations listed as active during at least some of, or the full period under study. The station positions are matched onto state plane by longitude and latitude coordinate, from which weather data covering the state plane can be obtained by using interpolation methods.

Soil characteristics

Since the classification of the farmland was done on the USDA's SSURGO soil survey database, this paper will use the same dataset to make it consistent with the classification³. I use a set of variables representative of farmland quality, such as average water capacity, permeability, erodibility, percent clay, irrigation class, and depth to water table. Soil characteristics are assumed unchanged overtime.

Demographic and socio-economic data

To control for urban pressure which drives the conversion from the demand side, population density and median income are used. These come from US censuses in 1990 and 2000. The urban influence is weighted by distance from urban areas to the farm location.

³Soil Survey Geographic Database from the U.S. Department of Agriculture, Natural Resources Conservation Service. SSURGO version 2.1 (2006) is used.

Since there is no defined edge between urban-rural areas, many studies use the distance by centroid between the farm and the nearest census tract or the CBD in a monocentric urban growth model. The US census 2000 database provides a useful urban area designation⁴, which could be more informative than using census tract. Since the census is only available for two years, 1990 and 2000, to adjust the dynamics of population and income growth, adjustment must be made for the missing years. Naturally, it can be assumed that these variables increase by an exponential function $\rho_t = \rho_0 e^{rt}$. The rate of growth can be calculated from the difference between the two censuses, and remained constant for the whole period of study.

Data Processing

Since farmland polygons are not parceled, and most often comes with irregular shapes of various sizes, there need to standardize the unit of measure. I create a grid layer of .25x.25 arcmin (roughly 4x4 km), with the exact resolution as the climate data provided by PRISM climate group, on the state plane, which is to be used as the geo-referencing layer. The choice of cell size is made to facilitate computations, and at the same time preserves some local attributes. Too coarse a resolution would facilitate computation at a loss of local information, thus is prone to aggregation bias. This is particularly true when we have irregularly shaped, elongated, farm polygons spreading over a wide area, thus implying that different parts may have been exposed to different conditions (urban stress, soil, weather etc). Then I used this layer to join and clip with other data layers to extract all interested variables. The product will be a database with each cell associated with spatial references and attributes.

Extracting converted farmland polygons from state farmland layers

Each type of farmland is classified as farm polygon in FMMP data. To extract the converted area during each biennial report, I first perform an attribute query to select only prime farmland from each layer, then successively overlay the next period map on the previous period layer in order to detect where conversion has occurred. The dependent variable will be derived as the amount of prime farmland converted between two biennial reports in each cell (Figure 1 in appendix). The edge length (perimeter) will be calculated for each cell, since fragmented farms or farms in closer proximity to the edge are more prone to conversion than contiguous farms.

According to the FMMP report, the minimum mapping unit used in FMMP data is 10 acres. Farmland of smaller size was attached to adjacent land. The minimum unit of measurement within the GIS database is 0.3 acre. This has an implication on the number of the converted farmlands found. Due to mapping inconsistency, or human errors, there are occasions when the polygons or lines do not perfectly line up. The result is that some

⁴Urban areas are designated as places where core census block groups or blocks that have a population density of at least 1,000 people per square mile (386 per square kilometer) and surrounding census blocks that have an overall density of at least 500 people per square mile (193 per square kilometer).

areas that were incorrectly determined to have undergone conversion, as well as some converted areas appearing small compared to the minimum unit of measurement of 0.3 acre. Therefore, areas containing mapping errors are excluded from the analysis. Extra caution is taken with regard to farmland conversion due to administrative issues. Due to the reclassification of farmland in some areas, farmland loss due to reclassification is not used in the analysis. Farmland loss due to government plans is also excluded. Reports on big conversions were often available at county level and published by FMMP. These plots were removed from the data.

Deriving climate extreme surface - choice of interpolation methods

This section will explain the weather interpolation method from weather station dataset. This is a crucial part of predicting the effects of climate change and weather extremes, especially since extreme events are rare. Generalization and interpolation must therefore be very cautiously implemented. I focus on the use of extreme temperature, rather, temperature believed as harmful to crops. According to agronomic literature, this threshold is set at 90°F for maximum temperature. The number of days with recorded maximum temperature above 90°F, at every location, were interpolated from a series of nearby stations.

Since the records of extreme events are a set of point estimates at weather station locations, in order to estimate the impacts on a farm location far away from the observatories, we must interpolate the value of extremes to different places (on a surface). Several interpolation methods are used. Examples include inverse distance weighting (IDW), nearest neighbors, spline, and Kriging. The results of Schenker, Hanemann, and Fisher (2006), and Deschenes and Greenstone (2007) illustrate how different interpolation methods can yield hugely different consequences. One method utilizes regression model to predict the number of degree days by monthly temperature in growing seasons, while the other averages observations from weather stations in the same county. Using the mean temperature or precipitation often results in underestimation of the impacts since it tends to produce an overly smooth value, and suppresses fluctuations at the extremes. In this paper, I have attempted to use several interpolation methods, including IDW and Kriging. IDW assumes that the effects decrease by a linear function of the distance, while Kriging can accommodate for spatial dependence in the observations in which nearby stations tend to report more similar values than distant ones.

Kriging is a geostatistical method, and is unlike deterministic approaches such as IDW. The problem with a deterministic approach is that interpolated value is purely a function of distance between locations. Kriging takes into account the spatial autocorrelation between observations, here is the locations of weather stations and observed temperature. The difference is evident when the observations are not randomly distributed. Examination of Figure 2 illustrates how stations with high and low records cluster at different places: high number of days above 90°F is concentrated in Southern California, as well as the desert and central valley areas; in areas with very low records, clusters are noted

in coastal and Northern areas. A test for spatial dependence⁵ rejects the spatial independence of these observations. Averaging the records over space will result in underestimating the high temperatures and overestimating the low temperatures. Kriging method will help resolve this issue, by giving less statistical weight to un-clustered weather stations.

Structure of Farmland Conversion Spatial Database

In Figure 3, the georeferencing layer is generated at 4x4km resolution (the bottom layer), and used to clip other layers of explanatory variables such as the extreme surface layer (2nd from bottom layer), climate variables including the average maximum, minimum temperature, and precipitation for the period 1971-2000 (3), soil attributes (4), socio-economic and demographics (5), and prime farmland layer on top (6). Only those polygons whose prime farmlands present are extracted. In each polygon, a portion of acreage converted is calculated and used as the dependent variable for the spatial regression.

Data Summary

Farmland conversion

The conversion of agricultural lands poses a serious threat to California agriculture. The FMMP reported a consistent trend of increasing urbanization and movement of agricultural land to other uses in most counties in California during the past two decades. According to the last report, during 2002-2004, there was a loss of 170,982 acres of farmland of all types, among which the highest quality farmland (prime farmland) accounted for 46% of the total. To put the acreage loss in to perspective, prime farmland loss from 2002-2004 was 78,575 acres, which was a staggering increase from 47,172 acres in 2000-2002. Figure 4 illustrates that the trend of prime farmland conversion is particularly damaging in the past decade, accounting for almost half of all farmland conversion across all types, in almost all periods except 2000-2002. Total prime farmland loss during the period of study was 461,272 acres, approximately 9 percent of total prime farmland stock available by the end of 2004 (5,076,207 acres).

Urbanization is not the only cause of conversion, however, as nearly 40% of all con-

⁵Moran's I statistics of spatial autocorrelation reports a z score of 16.62, which surely rejects the null hypothesis of independence at 99% significance level. Even if we allow for spatial effects to fall more quickly by using IDW squared, a Moran's I value of 2.77 is enough to show that the values are spatially correlated. The use of mean variations in Deschenes and Greenstone (2007) only works if stations are uniformly distributed on the state plane, which is not the case. Imagine two stations, both were located in close proximity to one another, used to interpolate a county-wide average temperature. They would likely give large errors, since these nearby stations likely reported similar temperature, yet these values were only valid for the immediate region surrounding these stations. Replicated study by Costello, Deschenes, and Kolstad (2009) use of IDW instead of simple averaging appears to have addressed to concerns about weather variables, but results in an opposite conclusion that climate change does not have a negative impact on California agriculture. The original study by Deschenes and Greenstone (2007), page 377, states that "The most striking finding is that California will be significantly harmed by climate change. Its loss in agricultural profits is approximately \$750 million, and this is nearly 15 percent of total California agricultural profits"!

Table 1: **Data Summary.** (For PRISM data, temperature is in hundredths of a degree Celsius, precipitation in hundredths of a millimeter; interpolated precipitation is in inches.)

Description	Source	Mean	Std. Dev.	Min	Max
Climate Data					
30-year Average Max Temperature	PRISM	2372.78	287.46	1351	3165
30-year Average Min Temperature	PRISM	854.34	254.51	-196	1482
30-year Mean Temperature	Average of max and min temp.	1613.56	260.34	676.5	2293.5
30-year Mean Precipitation	PRISM	41213.75	22925.66	7108	186940
<i>Interpolated Data</i>					
25-year Average Number of Days Above 90F (IDW)	Interpolated from NCDC observations	70.04	32.61	4.46	191.55
25-year Average Number of Days Above 90F (Kriging)	Interpolated	114.09	24.94	52.74	190.11
25-year Average Precipitation (IDW)	Interpolated	14.00	6.89	1.74	49.17
25-year Average Precipitation (Kriging)	Interpolated	14.38	6.84	2.43	50.25
Soil Data					
Average Water Capacity (AWC)	SSURGO	.1314	.0431	0	.4652
Saturated Hydraulic Conductivity (Ksat)	SSURGO	16.62	14.84	1.21	96.68
Percent Clay	SSURGO	23.56	8.98	.78	51.3
K-factor, whole soil	SSURGO	.2906	.0878	0	.49
Depth to Water Table	SSURGO	190.24	28.92	0	201.00
Irrigation Class	SSURGO	2.26	.85	1	7
Socio-economic data					
Median Family Income, IDW (US dollar, 1999)	US Census 2000, SF3, entry P077001	45340.37	10672.72	27331.87	90768
Population Density, IDW (people per square km)	US Census 2000, SF3, entry P003001	3631.01	1186.47	555.32	31956.36

versions out of agricultural land were to other uses. There are also other conversion types that occur from productive farmland to idling land, non-irrigated cropping, wildlife areas, low density residential uses, mining, or confined animal agriculture facilities. This demonstrates that the dynamics of farmland conversion in California are more complex than urbanization alone (FMMP report 2002-2004). As a consequence, any study modeling farmland conversion must consider factors above and beyond urban forces.

Explanatory variables

There are some anomalies worth mentioning in the values of soil characteristics regarding average water capacity: K-factor and depth to water table, that is, the reported values are zeros. They aren't necessarily missing or incorrect values, strictly speaking. Since the values are either weighted average or the dominant condition at each cell level, it is possible to render such values. However, the impact of such anomaly is minimal. There are only 30 cells with reported zero value of AWC, 7 cells of depth to water table and 37 cells of K-factor less than .02 (the minimum value reported by SSURGO), representing less than 1% of the total number of cells. Models tested with and without such cells did not reveal any significant change at all.

The largest missing cells come from irrigation class, which only have values for 3064 cells. However, excluding the irrigation class does not change the result, especially with regards to the significance of the climate indicators.

The difference when separating maximum and minimum temperature, opposed to only

Table 2: Correlation between Climate and Extreme Indicators.

	T_{max}	T_{min}	T_{mean}	90°F (IDW)	90°F (Kriging)
Max Temperature, 30-year Average	1				
Min Temperature, 30-year Average	.8454	1			
Mean Temperature, 30-year Average	.9653	.9555	1		
Number of Days above 90F, IDW	.8288	.6474	.7740	1	
Number of Days above 90F, Kriging	.8134	.6901	.7864	.9294	1

using the mean temperature, is significant. Figure 5 illustrates the distribution of these three climate normals at 4220 cells. It is evident that averaging between the extremes suppresses the variations, thus resulting in a loss of information. This would later prove to be important in models using maximum and minimum temperature versus models using mean temperature alone.

It is also interesting to see how using extreme conditions (i.e. number of days above 90°F) will better keep the variation, opposed to separating maximum and minimum temperature. Table 2 illustrates the correlation coefficients of these variables. Although the correlation is high, it is not as high as the correlation between maximum and minimum temperature. It is clear that maximum and minimum temperature tends to exhibit homogeneous correlation (i.e. Southern part is, on average, warmer than other areas). Yet, the pattern of extreme heating days is quite different from the average condition, and when examining the correlation between number of extreme days with maximum and minimum temperature, .83 and .65, the correlation between maximum and minimum temperature is even higher at .85. A changing pattern of extreme heating days may yield additional impacts, which is not captured by other temperature measures, on farmland values and conversions.

In the analytical part, I will use several combinations of climate indicators, using mean temperature and precipitation, separating out maximum and minimum temperature from the mean, using the number of extreme heating days, and I will validate the result with Schlenker, Hanemann, and Fisher (2006)'s data using the Growing Degree Days unit.

2.2 Econometric Model

I adopt a reduced-form approach to land-use conversion as in Chomitz and Gray (1996), which models the conversion at each cell as a function of biophysical and socioeconomic characteristics:

$$Y_i = \beta_0 + X_i\beta + Z_i\gamma + \varepsilon_i \tag{1}$$

where i is the index for each cell

Y is the amount of prime farmland converted in each cell between two report periods.

Since land conversions are one-way, from farmland to urban land, the amount of land converted in each cell is limited to between zero and $4 \times 4 = 16 \text{ km}^2$, or normalized to between $[0, 1]$.

X is the vector of climate normals and extremes

Z is the vector of control variables including soil and socio-economic characteristics.

The underlying assumption is that a land-use conversion will be made if urban rents exceed farming profits. Farmland rent is assumed a function of farm attributes, such as the proximity to city, the location's average per capita income, population density, soil quality, climate, and a variable representing the extreme heating condition.

To control for the non-linear effects of climate and extremes, I use the squared maximum temperature, squared precipitation and squared maximum number of days above 90°F. I use three different combinations of climate indicators, by using mean temperature and precipitation only, separating maximum and minimum temperature from the mean, then another specification using the number of days above 90°F.

There is an issue of spatial dependency between observations, as said in the first law of geography, that near-things are more related than distant units, therefore spatial autocorrelation must be accounted for. For instance, a farm owner may be affected by his neighbor's conversion decision, or the process of clipping and extracting converted areas may inadvertently create nearby observations that share attributes.

I adopt a spatial errors model:

$$Y_i = \beta_0 + X_i\beta + Z_i\gamma + \varepsilon_i \quad (2)$$

$$\varepsilon_i = \rho W\varepsilon + \nu_i$$

where W is the spatial weighing matrix, σ and ρ are the spatial autocorrelation coefficients. The presence of spatial dependence violates the condition that the error terms are uncorrelated, thus ordinary least square regression on spatial data is still unbiased, but inefficient (Elhorst, 2003).

I present models estimated with robust standard errors, with county fixed effects to control for county difference, then a model with spatial errors using popular treatment to cross-sectional spatial dependence such as Conley's GMM approach (1999) and Elhorst's MLE estimator (2003). Tests for spatial autocorrelation using robust standard errors demonstrate that there is a significant spatial dependence between the residuals, necessitating the spatial approach. I use two weighting schemes, which allows for the spatial spillover effects to extend from .1 degree in distance (approx. 10km) to .5 degree (approx. 50 km). Extending the distance can correct for spatial influence, but there is a tradeoff, as spatial standard errors will be significantly higher, thus lowering statistical significance for the interested variables.

The result is presented for the period 2002-2006 farmland reports. Similar results were obtained for several other periods.

3 Results and Interpretation

The results are reported in Tables 4, 5 and 6 for three different combinations of climate variables: maximum and minimum temperature, extreme heating conditions, and mean temperature. Robust standard errors without spatial dependence are presented in column 1. Columns 2 and 3 are modeled with spatial standard errors using inverse distance weighting schemes at two different cutoff ranges. Column 4 is modeled with robust standard errors, and county fixed effects included. The dependent variable is the difference in prime farmland acreage in each cell from 2004-2006 and 2000-2002 reports, so effectively it is the negative amount of converted acreage.

The first column in all three tables illustrates that all climate variables are highly significant and with the expected sign: 30-year average maximum temperature and minimum temperature have positive effects on the *negative* farmland loss, or an increase in these variables will counter farmland loss. Yet, the squared maximum temperature is negative, meaning it will accelerate farmland loss. The same holds for precipitation. This result is exactly as expected for the impact of climate condition on farm production: an increase in average temperature means prolonged growing seasons, thus increasing farm values and helping to keep farms in agricultural production. Table 1 displays the average maximum and minimum temperature as 23.7 and 8.5 degree Celsius, well below the threshold for which crops may be harmed. The squared terms each have a negative sign, demonstrating that excessive increase in temperature and precipitation is harmful and will accelerate conversion.

Table 6 yields the same conclusion as using maximum and minimum temperature separately: an increase in mean condition can help reduce farm conversion, yet to a certain extent the negative coefficient of the squared term will shadow the benefit of change in mean condition and harmful feedback will occur. What makes Table 4 and Table 6 different is the magnitude of the coefficients. Separating maximum and minimum temperature, both impacts are higher than averaging: for maximum temperature coefficient at 2202, 30% higher compared to 1566 using mean temperature, and for the squared term -0.50 vs. -0.48⁶. Coefficients using the number of days above 90°F are not directly comparable with temperature.

The result estimated from the number of days above 90°F (Table 5) is interesting: a small increase in the number of days above 90°F will be beneficial, but a significant increase in the number of these days will be harmful.

With regard to the soil coefficients, higher water capacity and higher permeability (K-saturation) are both positive, as expected: a farm with higher AWC can better support crop growth, thus higher farm values and less conversion. Higher permeability means that farms are less prone to heavy precipitation events. Clay presence is positive and significant. A higher clay content in soil implies a greater capability for water retention, opposed to having more sand, which does not retain water well. Irrigation capability class is the suitability of farmland for most kinds of field crops. Higher values indicate greater limitations and narrower choices for practical usage, thus less convertibility. So a positive

⁶Note that temperature is measured in hundredths of a degree Celsius.

and highly significant coefficient for irrigation class is well expected. Two soil variables with negative estimates are K-factor, and depth to water table. K-factor indicates the susceptibility of a soil to sheet and rill erosion by water, where a higher value of K-factor implies more erodible soils. So the results for K-factor and water table depth are both intuitive. However, the depth to water table variable is not significant in all models.

For other control variables, the perimeter is negative and significant in all models, as expected. This comes from the fact that conversion often took place near the edge rather than deep inside farm polygons. Further, farmlands more fragmented or close to the edge are more likely influenced by urban factors, planning, or other factors than contiguous farms.

Median family income is highly significant and also intuitive. Higher income indicates more pressure due to urban demand, either through higher demand for land or through implicitly driving up land price, thus inducing conversion. The population density coefficient is unexpectedly positive, however insignificant in all models.

Column 2 and 3 are modeled with spatial correlation in error terms. Moran's test of spatial correlation in the error terms report a value of 14.65, indicating the need to correct for spatial autocorrelation. Spatial standard errors are higher than those from least squared estimation, thus many explanatory variables will become less or insignificant. Increasing the cutoff ranges will also increase the spatial standard errors. Most variables remain significant with cutoff range of .1 degree (about 10 km, compared to the cell size of 4x4 km, so it spreads over the length of 3 cells from an observation's centroid). At cutoff range of .5 degree, only maximum temperature and its squared term is significant. Perhaps the most interesting finding is that the number of days above 90°F remains significant, while using mean temperature is not after all.

Column 4 is modeled with county fixed effects. There are reasons to think that county differences may be an input to permitting conversion such as difference in policy, existing farmland supply, or any unobserved county difference. The result is still very indicative that maximum temperature and maximum temperature squared are significant with expected signs, same as the squared number of extreme heating days. Using mean temperature will not allow for detection of any effect of temperature changes on conversion. Soil and other socio-economic variables are still significant, as expected, with the exception of precipitation and K-factor now insignificant in all models.

To validate this result, instead of using maximum temperature or extreme heating days, I use a more agrarian approach, degree days, to see how the conversion may be affected. Growing degree days is defined as the sum of degrees above a lower baseline and below an upper threshold during the growing season. With the lower bound set at 8°C and upper bound at 32°C, a day can contribute a maximum of up to 24 degree days unit. Healthy crop growth needs a certain amount of degree days, yet too many degree days may mean too warm conditions and is therefore harmful. For temperature above 34°C, the effect is always harmful. Harmful degree days is the total number of degrees for any day which maximum temperature passes the 34°C threshold.

I replace my proposed climate variables with the Schlenker, Hanemann, and Fisher (2006) data on precipitation, squared precipitation, degree days, squared degree days and

Table 3: **Precipitation, Degree Days and Harmful Degree Days in California - County Average, 50 Counties.**

Variable	Mean	Std. Dev.	Min	Max
Precipitation (cm)	68.0088	4.8512	62.1884	87.1772
Degree Days (8 – 32°C)	2738.44	170.45	2421.77	3072.05
Harmful Degree Days (34°C)	2.3594	.2863	1.8008	2.9927

the square root of harmful degree days, at every cell for each county using county fips code. The validation result is shown in Table 7. It is interesting that the result corresponds perfectly with other models, and remains significant across all three specification checks. Since normal degree days has been shown to be positively related to farmland value, it will therefore help keep farms from converting. Furthermore, too many degree days and harmful degree days (34°C) is indeed a contributing factor to farmland conversion, as suggested by negative coefficients of squared degree days and square-root of harmful degree days. Precipitation follows the same pattern. Note that the sign of population density is counterintuitive in the first two columns (robust standard errors and cutoff range of .1 degree), but no longer an issue at the cutoff range of .5 degree. At cutoff range of .5 degree, the result still holds for degree days and squared degree days. One reason to suspect that harmful degree days is not significant is that there are very few observations and little variations in this variable.

These results confirm the proposition that maximum temperature or extreme heating days adversely affects land use and accelerates farmland conversion. Although the models only explain a fraction of conversion pattern (R-square is low, about 6% for models without fixed effects or roughly 25% for models with fixed effects), the most important conclusion is that the effect is present and significant.

4 Concluding Remarks

This paper presents a new approach in studying the impact of extreme heating conditions on farmland conversion in California. This approach has been proved to better predict the potential impact of climate change: using the number of days above 90°F or separating maximum and minimum temperature from average temperature, both are better predictors of the negative impact of excessive heating on farmland conversion. This conclusion is also consistent with the result obtained in the second essay that extreme condition can be used to estimate the effect of transient climate change. Whether it is extreme heating or an extreme drought, all are shown to have similar harmful effects on farmland profitability and farmland conversion. This effect could become more damaging if future climate change introduces more regions to extreme conditions.

Appendix

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FMMP Farmland Classification

- **Prime Farmland** has the best combination of physical and chemical features able to sustain long-term agricultural production. This land has the soil quality, growing season, and moisture supply needed to produce sustained high yields. Land must have been used for irrigated agricultural production at some time during the four years prior to the mapping date.
- **Farmland of Statewide Importance** is similar to Prime Farmland but with minor shortcomings, such as greater slopes or less ability to store soil moisture. Land must have been used for irrigated agricultural production at some time during the four years prior to the mapping date.
- **Unique Farmland** consists of lesser quality soils used for the production of the state's leading agricultural crops. This land is usually irrigated, but may include non irrigated orchards or vineyards as found in some climatic zones in California. Land must have been cropped at some time during the four years prior to the mapping date.
- **Farmland of Local Importance** is land of importance to the local agricultural economy as determined by each county's board of supervisors and a local advisory committee.
- **Grazing Land** is land on which the existing vegetation is suited to the grazing of livestock. This category was developed in cooperation with the California Cattlemen's Association, University of California Cooperative Extension, and other groups interested in the extent of grazing activities.
- **Urban and Built-up Land** is occupied by structures with a building density of at least 1 unit to 1.5 acres, or approximately 6 structures to a 10-acre parcel. Common examples include residential, industrial, commercial, institutional facilities, cemeteries, airports, golf courses, sanitary landfills, sewage treatment, and water control structures.

- **Other Land** is land not included in any other mapping category. Common examples include low density rural developments; vegetative and riparian areas not suitable for livestock grazing; confined animal agriculture facilities; strip mines, borrow pits; and water bodies smaller than 40 acres. Vacant and nonagricultural land surrounded on all sides by urban development and greater than 40 acres is mapped as Other Land.
- **Water** - perennial water bodies with an extent of at least 40 acres.

Figure 1: **Extracting Converted Farm from GIS Layers.**

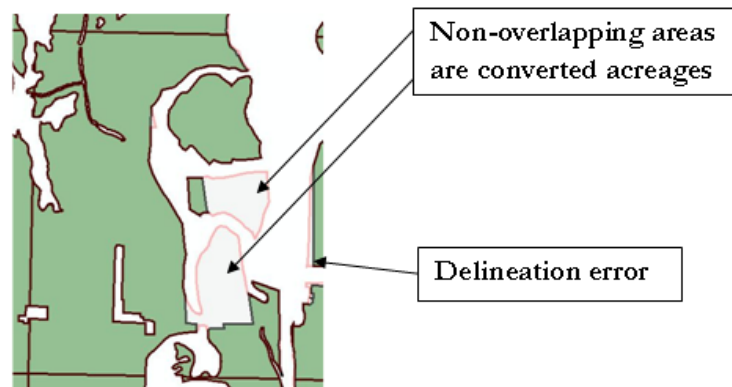


Figure 2: **Comparison between Interpolation Methods.** Figure in the left is created by inverse distance weighting, and in the right by spatial Kriging. Stars are the locations of weather stations, and size corresponds to the number of recorded extreme heating days. Note the distinct features observed around each station.

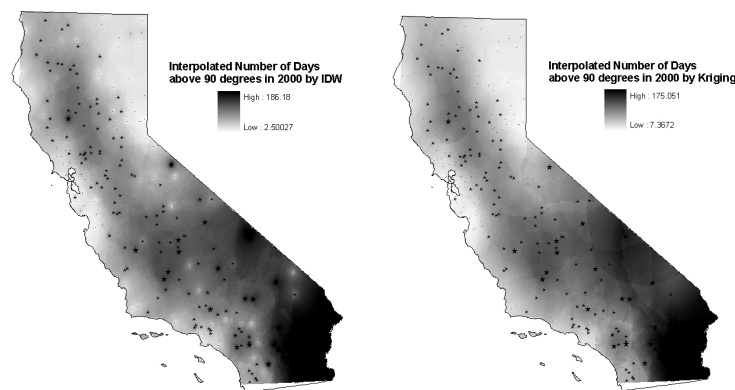


Figure 3: **Data Structure.**

The bottom lay was created corresponding to the PRISM dataset, at a 4-by-4 kilometer grid size. Then this layer was used as the geo-referencing layer to extract all relevant variables, from top down: farmland cover, socio-economic data, soil survey, 30-year climate, and extreme heating surface. The data is stored by cell, each with corresponding explanatory variables and spatial location.

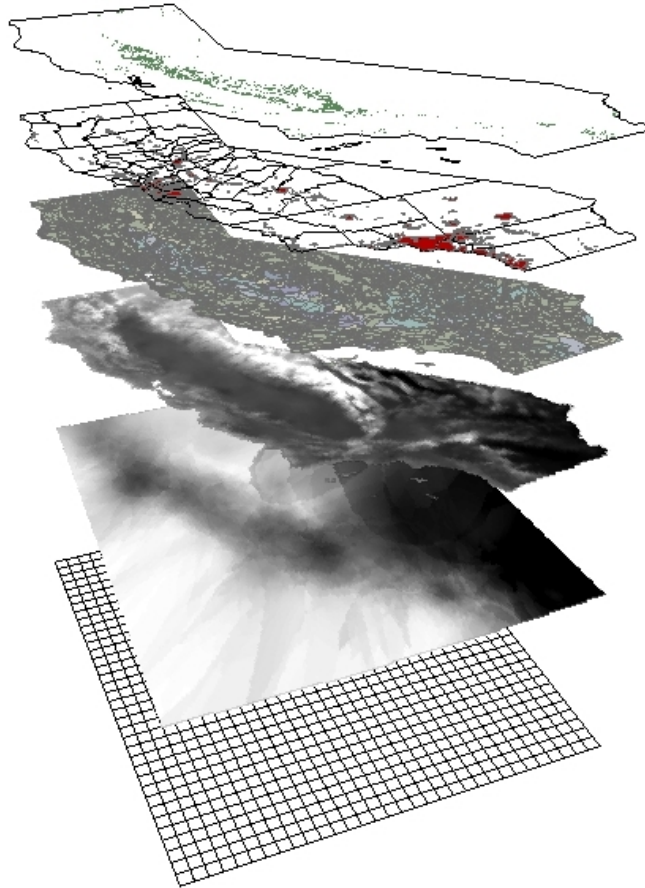


Figure 4: Farmland Conversion Trend by Type in California (acreares).

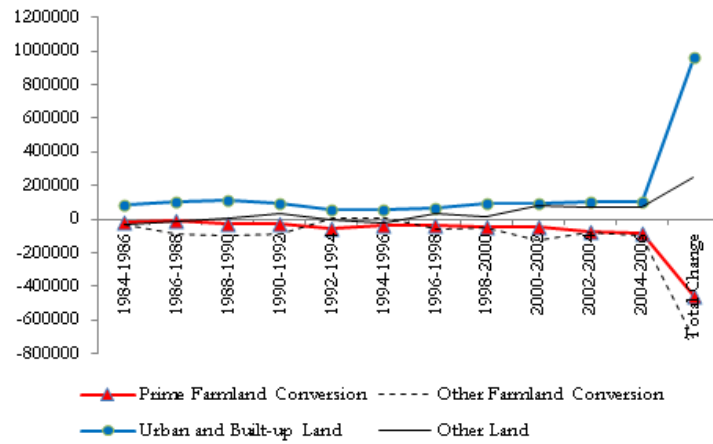


Figure 5: Distribution of Max, Min, and Average Temperature.

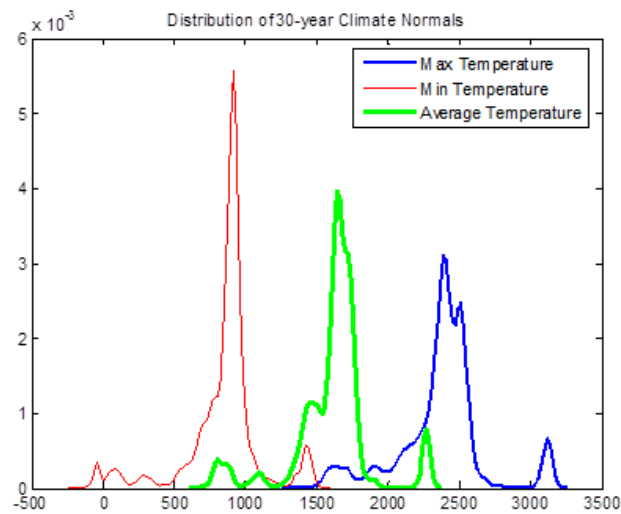


Table 4: Using 30-year average max, min temperature and precipitation including squared terms for 2002-2006 conversion, t-statistics in bracket. Baseline model is estimated with robust standard errors. Spatial model 1 and 2 is estimated with two different cutoff ranges at .1 and .5 degree. The last column is estimated with county fixed effects. ***, **, and * symbols denote coefficient significant at 1%, 5% and 10% significance level, respectively.

Variable	Baseline Col 1	Spatial Model 1 (cutoff =.1) Col 2	(2) (cutoff =.5) Col 3	Fixed Effects Col 4
Max Temperature	2202.01 (3.35)***	(2.40)**	(1.65)*	1582.31 (2.17)**
Max Temperature, squared	-.50 (-3.33)***	(-2.37)**	(-1.63)*	-.30 (-1.84)*
Min Temperature	243.06 (3.03)***	(2.19)**	(1.33)	137.39 (.99)
Precipitation	6.72 (1.96)**	(1.37)	(.85)	4.40 (1.22)
Precipitation, squared	-.0000486 (-2.40)**	(-1.68)*	(-1.04)	-.0000194 (-1.12)
Perimeter, 2002	-9.65 (-8.67)***	(-6.39)***	(-3.41)***	-10.39 (-9.33)***
Median Family Income, 2000	-10.02 (-5.23)***	(-3.67)***	(-2.33)**	-6.60 (-1.65)*
Population Density, 2000	8.52 (.75)	(.52)	(.33)	-20.83 (-1.11)
Water Capacity	3814582 (3.49)***	(2.50)**	(1.66)*	1727221 (2.08)**
K Saturation	11675.32 (3.46)***	(2.47)**	(1.84)*	10508.2 (3.29)***
Percent Clay	10623.35 (2.44)**	(1.73)*	(1.50)	11549.2 (2.23)**
K factor	-927405 (-1.97)**	(-1.44)	(-1.12)	-526346 (-1.30)
Irrigation Class	53252 (5.07)***	(3.71)***	(2.43)**	23969 (2.28)**
Water Depth	-1258.42 (-1.31)	(-1.34)	(-1.21)	-297.81 (-.41)
Constant	-2686994 (-3.21)***	(-2.32)**	(-1.61)	-2295537 (-2.52)**
F-stat	9.10			7.66
Spatial Autocorrelation (ρ)		.69 (32.28)***	.47 (7.67)***	

Table 5: Using 25-year average number of days above 90F, min temperature and precipitation including squared terms for 2002-2006 conversion, t-statistics in bracket.

Variable	Baseline Col 1	Spatial Model (1) (cutoff =.1) Col 2	(2) (cutoff =.5) Col 3	Fixed Effects Col 4
90F Days	7344.3 (3.50)***	(2.45)**	(1.59)	3007.2 (1.59)
90F Days, squared	-52.33 (-3.65)***	(-2.57)**	(-1.69)*	-20.80 (-1.79)*
Min Temperature	225.86 (2.55)**	(1.82)*	(1.10)	208.67 (1.24)
Precipitation	8.46 (2.45)**	(1.71)*	(1.05)	3.88 (1.01)
Precipitation, squared	-0.000582 (-2.77)***	(-1.94)*	(-1.19)	-0.000186 (-.99)
Perimeter, 2002	-9.33 (-8.39)***	(-6.18)***	(-3.37)***	-10.19 (-9.11)***
Median Family Income, 2000	-7.99 (-3.90)***	(-2.75)***	(-1.82)*	-6.94 (-1.71)*
Population Density, 2000	10.77 (.96)	(.66)	(.40)	-21.19 (-1.06)
Water Capacity	3789837 (3.56)***	(2.56)**	(1.69)*	1760094 (2.12)**
K Saturation	11436.6 (3.47)***	(2.49)**	(1.87)*	10394.8 (3.27)***
Percent Clay	10526.3 (2.46)**	(1.76)*	(1.59)	11779 (2.29)**
K factor	-866496 (-1.92)*	(-1.40)	(-1.09)	-467702 (-1.16)
Irrigation Class	49887 (5.00)***	(3.70)***	(2.48)**	23793.6 (2.24)**
Water Depth	-1317.30 (-1.38)	(-1.42)	(-1.29)	-244.75 (-.34)
Constant	-677112 (-2.11)**	(-1.63)*	(-1.18)	-383493.6 (-1.06)
F stat	8.99			7.56
Spatial Autocorrelation (ρ)			.45 (7.28)***	

Table 6: Using 30-year average temperature and precipitation for 2002-2006 conversion, t-statistics in bracket.

Variable	Baseline Col 1	Spatial Model (1) (cutoff =.1) Col 2	(2) (cutoff =.5) Col 3	Fixed Effects Col 4
Mean Temperature	1566.23 (3.13)***	(2.24)**	(1.54)	969.94 (1.60)
Mean Temperature, squared	-.48 (-2.89)***	(-2.06)**	(-1.40)	-.20 (-1.06)
Precipitation	8.26 (2.46)**	(1.72)*	(1.07)	4.99 (1.38)
Precipitation, squared	-0.000584 (-2.92)***	(-2.05)**	(-1.27)	-0.000237 (-1.37)
Perimeter, 2002	-9.55 (-8.60)***	(-6.33)***	(-3.40)***	-10.39 (-9.31)***
Median Family Income, 2000	-10.03 (-5.21)***	(-3.66)***	(-2.32)**	-6.50 (-1.63)*
Population Density, 2000	13.56 (1.18)	(.82)	(.51)	-19.02 (-1.02)
Water Capacity	3674447 (3.38)***	(2.43)**	(1.60)	1759850 (2.11)**
K Saturation	11330.9 (3.40)***	(2.43)**	(1.80)*	10323.3 (3.24)***
Percent Clay	10614.3 (2.44)**	(1.73)*	(1.49)	11515.8 (2.24)**
K factor	-880764 (-1.87)*	(-1.37)	(-1.05)	-517007 (-1.27)
Irrigation Class	53029 (5.09)***	(3.72)***	(2.43)**	24250 (2.30)**
Water Depth	-1295.26 (-1.35)	(-1.39)	(-1.26)	-269.30 (-.37)
Constant	-1415466 (-2.81)***	(-2.08)**	(-1.47)	-1171114 (-2.00)**
F stat	9.67			8.02
Spatial Autocorrelation(ρ)			.49 (7.96)***	

Table 7: **Validation with Schlenker, Hanemann, and Fisher (2006) climate data for 2002-2006 conversion.** Note that this data is county average, so no county fixed effects model could be estimated as the county-level data already capture all other county effects, if had, on conversion.

Variable	Baseline Col 1	Spatial Model (1) (cutoff =.1) Col 2	(2) (cutoff =.5) Col 3
Degree Days (8-32C)	17141 (3.60)***	(2.61)***	(1.74)*
Degree Days, squared	-3.17 (-3.61)***	(-2.62)***	(-1.76)*
Harmful Degree Days (34C), square root	-164748 (-2.44)**	(-1.86)*	(-1.16)
Precipitation	140167 (2.28)**	(1.68)*	(1.21)
Precipitation, squared	-876.78 (-2.09)**	(-1.55)	(-1.16)
Perimeter, 2002	-9.32 (-8.78)***	(-6.64)***	(-3.64)***
Median Family Income, 2000	-6.91 (-4.43)***	(-3.19)***	(-2.20)**
Population Density, 2000	31.82 (2.23)**	(1.71)*	(1.10)
Water Capacity	2908711 (3.12)***	(2.24)**	(1.48)
K Saturation	9562.9 (3.16)***	(2.26)**	(1.71)*
Percent Clay	13173 (2.85)***	(2.01)**	(1.68)*
K factor	-903759 (-2.17)**	(-1.59)	(-1.23)
Irrigation Class	54409 (4.64)***	(3.43)***	(2.16)**
Water Depth	-1431.4 (-1.48)	(-1.51)	(-1.34)
Constant	-2.82e+07 (-4.14)***	(-2.97)***	(-1.88)*
F stat	9.43		
Spatial Autocorrelation (ρ)			.48 (7.64)***

References

- Aguirregabiria, Victor, and Mira P. (2002), "Swapping the nested fixed point algorithm: a class of estimators for discrete Markov decision models," *Econometrica*, Vol. 70, pp. 1519-43
- Alston, Julian M., Bruce A. Babcock, and Philip G. Pardey (2010), "The Shifting Patterns of Agricultural Production and Productivity Worldwide," Midwest Agribusiness Trade Research and Information Center, Iowa State University, ISBN 978-0-9624121-8-9
- Beattie, Bruce R., Robert C. Taylor, and Myles J. Watts (2009), "The Economics of Production," Krieger Publishing Company, ISBN 978-1-57524-295-8
- Biggelaar, Christoffel den, Rattan Lal, Keith Wiebe, Hari Eswaran, Vince Breneman, and Paul Reich (2004), "The Global Impact of Soil Erosion on Productivity," *Advances in Agronomy*, Vol. 81, pp. 49-95
- Braganza, Karl, David J. Karoly, and J. M. Arblaster (2004), "Diurnal Temperature Range as an Index of Global Climate Change during the Twentieth Century", *Geophysical Research Letters*, Vol. 31, L13217
- Capozza, Dennis R. and Robert Helsley (1990), "The Stochastic City," *Journal of Urban Economics*, Vol. 28(2), pp. 295-306
- Carlino and Voith (1992), "Accounting for differences in aggregate state productivity," *Regional Science and Urban Economics*, Vol. 22, pp. 597-617
- Cavagnaro, Timothy, Louise Jackson, and Kate Scow (2006), "Climate Change: Challenges and Solutions for California Agricultural Landscapes", California Climate Change Center, CEC-500-2005-189-SF.
- Changnon, Stanley A. and Steven E. Hollinger (2003), "Problems in Estimating Impacts of Future Climate Change on Midwestern Corn Yields", *Climatic Change*, Kluwer Academic Publishers. Vol. 58, pp. 109-118
- Chomitz, Kenneth M. and David A. Gray (1996), "Roads, Land Use, and Deforestation A Spatial Model Applied to Belize." *The World Bank Economic Review*, Vol. 10 (3), pp. 487-512
- Conley, Timothy G. (1999), "GMM estimation with cross sectional dependence", *Journal of Econometrics*, Vol. 92, pp. 1-45
- Costello, Christopher J. , Olivier Deschenes, and Charles D. Kolstad (2009), "Economic

Impacts of Climate Changes on California Agriculture”, California Climate Change Center, University of California, Santa Barbara. CEC-500-2009-043-D.

Coulson, David P., and Linda A. Joyce (2010), “Historical Climate Data (1940-2006) for the Conterminous United States at the County Spatial Scale Based on PRISM Climatology”, U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station, Fort Collins, CO. <http://dx.doi.org/10.2737/RDS-2010-0010>

Dai, Aiguo (2011a), “Drought under Global Warming: a Review,” *Wiley Interdisciplinary Reviews: Climate Change*, Vol. 2, pp. 45-65

Dai, Aiguo (2011b), “Characteristics and Trends in Various Forms of the Palmer Drought Severity Index during 1900-2008,” *Journal of Geophysical Research*, Vol. 16, D12115, 2011

Dai, Aiguo, Kevin E. Trenberth, and Taotao Qian (2004), “A Global Dataset of Palmer Drought Severity Index for 1870-2002: Relationship with Soil Moisture and Effects of Surface Warming,” *Journal of Hydrometeorology*, Vol. 5, 2004

Dai, Aiguo, Kevin E. Trenberth, and Thomas R. Karl (1999), “Effects of Clouds, Soil Moisture, Precipitation, and Water Vapor on Diurnal Temperature Range”, *Journal of Climate*, Vol. 12, pp. 2451-2473, 1999

Deininger, Klaus, and Bart Minten (2002), “Determinants of Deforestation and the Economics of Protection: An Application to Mexico,” *American Journal of Agricultural Economics*, Vol. 84(4), pp. 943-960.

Deschenes, Olivier, and Michael Greenstone (2007), “The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather”, *American Economic Review*, Vol. 97(1), pp. 354-385

Dhakhwa, Gyanendra B., and Lee C. Campbell (1998), “Potential Effects of Differential Day-Night Warming in Global Climate Change on Crop Production”, *Climatic Change*, Kluwer Academic Publishers. Vol. 40, pp.647-667

Easterling, David R., Briony Horton, Phillip D. Jones, Thomas C. Peterson, Thomas R. Karl, David E. Parker, M. James Salinger, Vyacheslav Razuvayev, Neil Plummer, Paul Jamason, and Christopher K. Folland (1997), “Maximum and Minimum Temperature Trends for the Globe”, *Science*, Vol. 277, pp. 364-367, 1997

Elhorst, J. Paul (2001), “Panel Data Models Extended to Spatial Error Autocorrelation or Spatially Lagged Dependent Variable”, SOM-Theme C: Coordination and Growth in Economies.

Elhorst, J. Paul (2003), "Specification and Estimation of Spatial Panel Data Models", *International Regional Science Review* 2003, Vol. 26(3), pp. 244-268.

Farmland Monitoring and Management Program Reports from 1984-2004, California Department of Conservation, Division of Land Resource Protection.

Field, Christopher B. et al. (2012), "IPCC, 2012: Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation. A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change," Cambridge University Press, Cambridge, UK, and New York, NY, USA

Fisher, Anthony, Michael Hanemann, Michael Roberts, and Wolfram Schlenker (2007), "Potential Impacts of Climate Change on Crop Yields and Land Values in U.S. Agriculture: Negative, Significant, and Robust," <http://www.ucei.berkeley.edu/PDF/seminar050908.pdf>

Fox, Jonathan, Price V. Fishback, and Paul W. Rhode (2011), "The Effects of Weather Shocks on Crop Prices in Unfettered Markets: The United States Prior to the Farm Programs, 1985-1932," Chapter in NBER book: *The Economics of Climate Change: Adaptations Past and Present* (2011), Gary D. Libecap and Richard H. Steckel, editors, pp. 99-130

Fuglie, Keith O., James M. MacDonald, and Eldon Ball (2007), "Productivity Growth in U.S. Agriculture," *Economic Brief Number 9*, 2007, ERS, USDA

Gutzler, David S., and Tessia O. Robbins (2010), "Climate variability and projected change in the western United States: regional downscaling and drought statistics," *Climate Dynamics*, DOI 10.1007/s00382-010-0838-7, 2010

Helsel, Dennis R., and Lonna M. Frans (2006), "Regional Kendall Test for Trend", *Environmental Science and Technology*, Vol. 40(13), 2006

Hornbeck, Richard (2009), "The Enduring Impact of the American Dust Bowl: Short and Long-run Adjustment to Environmental Catastrophe," *American Economic Review*, Vol. 102(4), pp. 1477-1507

Intergovernmental Panel on Climate Change (2007), Working Group II Report on Impacts, Adaptation and Vulnerability.

James, Jennifer S., Julian M. Alston, Phillip G. Pardey, and Matthew A. Anderson (2009), "Structural Changes in U.S. Agricultural Production and Productivity," *Choices, The Magazine of Food, Farm and Resource Issues*, 4th Quarter 2009, 24(4)

James P. LeSage (1998), "Spatial Econometrics", University of Toledo, Department of Economics.

Karl, Thomas R., Philips D. Jones, Richard W. Knight, George Kukla, and Neil Plummer (1993), "Asymmetric Trends of Daily Maximum and Minimum Temperature", *Bulletin of the American Meteorological Society*, Vol. 74(6), 1993

Karl, Thomas R., George Kukla, and Joyce Gavin (1984), "Decreasing Diurnal Temperature Range in the United States and Canada from 1941 through 1980", *Journal of Climate and Applied Meteorology*, Vol. 23(11), 1984

Kelly, David L., Charles D. Kostad, and Glenn T. Mitchell (2005), "Adjustment Costs from Environmental Change," *Journal of Environmental Economics and Management*, Vol. 50, pp. 468-495

Knowles, N., M. D. Dettinger, and D. R. Cayan (2005), "Trends in Snowfall versus Rainfall in the Western United States", *Journal of Climate*, Vol. 19, pp. 4545-4559

Lauritsen, Ryan G., and Jeffrey C. Rogers (2012), "U.S. Diurnal Temperature Range Variability and Regional Causal Mechanism, 1901-2002", *Journal of Climate*, Vol. 25, pp. 7216-7231, 2012

Le, Phu V. (2010), "Climate Change Impacts on Crop Yields: Reexamine Evidence from Decreasing Diurnal Temperature Range", Paper presented at the European Association of Environmental and Resource Economists (EAERE) 2011, Rome, Italy, <http://www.webmeets.com/files/papers/EAERE/2011/628/JMP.pdf>

Libecap, Gary D. and Zeynep K. Hansen (2001), "US Land Policy, Property Rights, and The Dust Bowl of the 1930s," Fourth Toulouse Conference on Environment and Resource Economics-Property Rights, Institutions, and Management of Environmental and Natural Resources, Toulouse, France May 3-4, 2001

Loader, Clive (1999), "Local Regression and Likelihood", Springer-Verlag, ISBN 0-387-98775-4

Lobell, David B. (2007), "Changes in Diurnal Temperature Range and National Cereal Yields", *Agricultural and Forest Meteorology*, Vol. 145, pp. 229-238

Lobell, B. D. and G. P. Asner (2003), "Climate and Management Contributions to Recent Trends in U.S. Agricultural Yields", *Science*, Vol. 299, p. 1032

Lockeretz, William (1978), "The Lessons of the Dust Bowl", *American Scientist*, Vol. 66, pp. 560-569

Luc Anselin, Julie Le Gallo and Hubert Jayet, “The Econometrics of Panel Data”, Chapter 19 Spatial Panel Econometrics, pp. 625-660, Springer-Verlag Berlin Heidelberg 2008.

Masseti, Emanuele and Robert Mendelsohn (2011), “Estimating Ricardian Models with Panel Data,” NBER Working Paper No. 17101, <http://www.nber.org/papers/w17101>

Mastrandrea¹, Michael D., Claudia Tebaldi, Carolyn P. Snyder and Stephen H. Schneider (2009), “Current and Future Impacts of Extreme Events in California”, California Climate Change Center, CEC-500-2009-026-D.

Mendelsohn, Robert and Ariel Dinar (2003), “Climate, Water, and Agriculture,” *Land Economics*, Vol.79(3), pp. 328-341

Mendelsohn, Robert, William D. Nordhaus, and Daigee Shaw (1994), “The Impact of Global Warming on Agriculture: A Ricardian Analysis,” *American Economic Review*, Vol. 84(4), pp. 753-771

Meredith, William R., Jr. (2000), “Cotton Yield Progress - Why Has It Reached a Plateau?,” *Better Crops*, Vol. 84(4), pp. 6-9

Morehart, Mitchell, Noel Gollehon, Robert Dismukes, Vince Breneman, and Ralph Heimlich (1999), “An Economic Assessment of the 1999 Drought: Agricultural Impacts Are Severe Locally, but Limited Nationally,” An Economic Research Service Report, Agriculture Information Bulletin No. 755, September 1999, USDA

Nelson, Gerald C., and Daniel Hellerstein (1997), “Do Roads Cause Deforestation? Using Satellite Images in Econometric Analysis of Land Use,” *American Journal of Agricultural Economics*, Vol. 79(1), pp. 80-88

Newburn, David, Sarah Reed, Peter Berck, and Adina Merenlender (2005), “Economic and Land-use Change in Prioritizing Private Land Conversion”, *Conservation Biology*, Vol. 19(5), pp. 1411-1420

Pan, Zaitao, Raymond W. Arritt, Eugene S. Takle, William J. Gutowski Jr., Christopher J. Anderson, and Moti Segal (2004), “Altered Hydrologic Feedback in a Warming Climate Introduces a “Warming Hole””, *Geophysical Research Letters*, Vol. 31, L17109, 2004

Pindyck, Robert S. (2010), “Fat Tails, Thin Tails, and Climate Change Policy,” NBER Working Paper No. 16353, <http://www.nber.org/papers/w16353>

Portmann, Robert W., Susan Solomon, and Gabriele C. Hegerl (2009), “Spatial and

Seasonal Patterns in Climate Change, Temperatures, and Precipitation across the United States”, *Proceedings of the National Academy of Sciences*, USA, 10.1073/pnas.0808533106

Plantinga, Andrew J. and Douglas J. Miller (2001), “Agricultural Land Values and the Value of Rights to Future Land Development,” *Land Economics*, Vol. 77(1), pp. 56- 67

Price, David T., Daniel W. McKenney, Martin R. Siltanen, Pia Papadopol, Kevin Lawrence, Linda A. Joyce, and David P. Coulson (2011), “High Resolution Interpolation of Climate Scenario Change Factors for the Conterminous USA Derived from AR4 General Circulation Model Simulations”, USDA Forest Service, Rocky Mountain Research Station, Fort Collins, CO. <http://dx.doi.org/10.2737/RDS-2011-0023>

Reilly, John M., and Keith O. Fuglie (1998), “Future Yield Growth in Field Crops: What Evidence Exists?,” *Soil and Tillage Research*, Vol 47, pp.275-290

Rosenzweig, Cynthia, and Francesco N. Tubiello (1996), “Effects of Changes in Minimum and Maximum Temperature on Wheat Yields in the Central US - A Simulation Study”, *Agricultural and Forest Metereology*, Vol. 80, pp. 215-230

Ross, Tom and Neal Lott (2003), “A Climatology of 1980-2003 Extreme Weather and Climate Events,” National Climatic Data Center, Technical Report No. 2003-01

Rust, John (1987), “Optimal Replacement of GMC Bus Engines: An Empirical Model of Harold Zurcher,” *Econometrica*, Vol. 55(5) pp. 999-1033

Seager, Richard, Mingfang Ting, Isaac Held, Yochanan Kushnir, Jian Lu, Gabriel Vecchi, Huei-Ping Huang, Nili Harnik, Ants Leetmaa, Ngar-Cheung Lau, Cuihua Li, Jennifer Velez, and Naomi Naik (2007), “Model Projections of an Imminent Transition to a More Arid Climate in Southwestern North America,” *Science*, Vol. 316, 5/2007

Schlenker, Wolfram, Michael W. Hanemann, and Anthony C. Fisher (2005), “Will U.S. Agriculture Really Benefit from Global Warming? Accounting for Irrigation in the Hedonic Approach”, *American Economic Review*, Vol. 95(1), pp. 395-406.

Schlenker, Wolfram, Michael W. Hanemann, and Anthony C. Fisher (2006), “The Impact of Global Warming on U.S. Agriculture: An Econometric Analysis of Optimal Growing Conditions”, *The Review of Economics and Statistics*, Vol. 88(1): pp. 113-125

Schlenker, Wolfram, and Michael J. Roberts (2006), “Estimating the Impact of Climate Change on Crop Yields: The Importance of Non-Linear Temperature Effects,” *NBER Working Paper No. 13799*, <http://www.nber.org/papers/w13799>

Schlenker, Wolfram, W. Michael Hanemann, and Anthony C. Fisher (2007), “Water Avail-

ability, Degree Days, and the Potential Impact of Climate Change on Irrigated Agriculture in California.” *Climatic Change*, Vol. 81(1), pp. 19-38

Schneider, Stephen H., William E. Easterling, and Linda O. Mearns (2000), “Adaptation: Sensitivity to Natural Variability, Agent Assumptions and Dynamic Climate Changes,” *Climate Change*, Vol. 45, pp. 203-221

Yue, Sheng, Paul Pilon, Bob Phinney, and George Cavadias (2002), “The Influence of Autocorrelation on the Ability to Detect Trend in Hydrological Series”, *Hydrological Processes*, Vol. 16, pp. 1807-1829, 2002

United States Department of Agriculture (1997), “Usual Planting and Harvesting Dates for U.S. Field Crops”, *Agricultural Handbook Number 628*, NASS

Vose, Russell S., David R. Easterling, and Byron Gleason (2005), “Maximum and Minimum Temperature Trends for the Globe”, *Geophysical Research Letters*, Vol. 32, L23822, 2005

Weitzman, Martin L. (2009), “On Modelling and Interpreting the Economics of Catastrophic Climate Change,” *The Review of Economics and Statistics*, February 2009, 91(1): 1-19

Whitmore, Joan S. (2000), “Drought Management on Farmland”, Kluwer Academic Publishers, MA, USA

Whittaker, Gerald W. (1990), “Effects of the 1988 Drought on Farm Finances,” Agriculture Information Bulletin, Economic Research Service, Washington, DC.