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Do Temperature Thresholds Threaten American Farmland?

Emanuele Massetti and Robert Mendelsohn

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Summary

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Keywords: Agriculture, Climate Change, Weather, Crop Yields, Ricardian, Threshold

JEL Classification: Q1, Q5

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Emanuele Massetti* and Robert Mendelsohn**

August 7th, 2017

Abstract

Estimated Ricardian models have been criticized because they rely on mean temperatures and do not explicitly include extreme temperatures. This paper uses a cross sectional approach to compare a standard quadratic Ricardian model of mean temperature with a fully flexible daily temperature bin model of farmland values in the Eastern United States. The flexible bin model leads to smaller damages from warming than the quadratic mean specification, but the difference is not statistically significant. Although weather panel studies find high temperature events lead to large annual damage, high temperature events have no harmful effect on farmland values. The results are robust to alternative model specifications and data sets.

Keywords: agriculture, climate change, weather, crop yields, Ricardian, threshold.

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1 Introduction

Several studies suggest there is a temperature "threshold" effect on agricultural productivity. Schlenker, Hanemann, and Fisher (2006) use a Ricardian analysis with a measure of extreme temperature to show that temperatures above 34°C cause farmland values to fall precipitously. Schlenker and Roberts (2009) use a panel weather approach to show that annual yields of corn, soybeans and cotton fall sharply when temperatures exceed 29°C, 30°C and 32°C respectively. These papers imply that a Ricardian model of mean temperatures would underestimate the threat from climate change because such a model does not explicitly include the effect of extreme temperatures.

This paper uses farmland values in the Eastern United States to test the hypothesis that high extreme temperatures would harm farmland values. The paper compares the results of a Ricardian model using a quadratic representation of mean growing season temperature with a temperature bin model that explicitly accounts for the full distribution of temperatures at each site. The hypothesis is that farms exposed to high extreme temperatures would have markedly lower farmland value. A model that explicitly accounted for hot extreme temperatures would lead to larger impacts from warming. The paper tests whether the impacts of the bin model are greater than the impacts of the model based on mean temperature. The paper also tests whether the warmest temperature bins exhibit evidence of a threshold.

We perform a number of robustness checks. We present our main results using climate data from the North America Regional Reanalysis (NARR) (Mesinger et al. 2006) but we also test our main results using climate data from Schlenker and Roberts (2009). We also estimate a two-season model that separates April-May-June temperatures from July-August-September temperatures. The results are robust to alternative data sets and model specifications.

The temperature bin model suggests a noisy hill-shaped relationship between temperature and farmland values. The quadratic model predicts warming is strictly harmful in the Eastern US. When warming scenarios are tested against these two functional forms, the quadratic mean specification predicts larger welfare losses than the flexible bin model, although the difference is not statistically significant. There is no additional harm associated with including the full distribution of temperatures in the Ricardian model.

The flexible functional form does not reveal a high temperature threshold. Land values have a hill-shaped relationship with temperature. However, very cold temperatures have no effect in the bin model. One possible explanation of this result is subsidized crop insurance. Another possibility is a mistaken assumption in the literature that growing seasons are fixed. Farmers in cold places tend to plant later than farmers in warmer locations. The coldest temperatures in the data set appear to be in April and apply to farms in the north that are fallow, which explains why they have no effect. A third possibility is that farmers facing extreme temperatures have adapted, and rely on livestock in places where crops would be vulnerable.

The next section of the paper reviews the methodology to measure climate effects. Section 3 examines the climate data in more detail. Section 4 displays the results. The paper concludes with a discussion of the limitations of the research, the main conclusions, and the policy implications.

2 Methodology

We build on previous Ricardian studies and regress the log of land value per hectare at time *t* for county *i* ($V_{i,t}$) on climate and control variables (Mendelsohn, Nordhaus, and Shaw 1994, Massetti and Mendelsohn 2011a). We specifically follow the Schlenker, Hanemann, and Fisher (2006) model and use a second order polynomial (quadratic) model of temperature and precipitation during the growing season:

$$V_{i,t} = \alpha + \beta_1 T_i + \beta_2 T_i^2 + \gamma_1 P_i + \gamma_2 P_i^2 + \boldsymbol{\eta} X_{i,t} + \boldsymbol{\theta} Z_i + \psi_s + \epsilon_{i,t} \,. \qquad (1)$$

Where T_i and P_i are mean temperature and precipitations from April to September, between 1979 and 2007, a period that spans our Census data. X is a set of socio-economic variables that vary over time, including time fixed effects, Z is a set of county geographic and soil characteristics that are fixed over time, ψ_s is a state fixed effect, and ε is assumed to be a random component. α, β, γ, η, and θ are estimated coefficients. We use a logarithmic transformation of land values as the dependent variable because they are log-normally distributed and because it is sensible that variables have a proportional rather than a linear effect (Schlenker, Hanemann and Fisher, 2006). By including state-fixed effects we are controlling for within-state unobservables such as state level policies and factors that affect land values and may be correlated with climate (Deschenes and Greenstone 2007). By including time fixed effects we exploit the panel variation of average aggregate land values to control for macroeconomic trends and changes in national policies that may be correlated with local unobserved characteristics.

We contrast this traditional Ricardian model with a flexible functional form model using the entire temperature distribution (Schlenker and Roberts 2009). The temperature relationship is estimated using a series of bins which are 3°C wide:

$$V_{i,t} = \alpha + \sum_{j=1.}^{J} \beta_j TB_{i,j} + \gamma_1 P_i + \gamma_2 P_i^2 + \boldsymbol{\eta} X_{i,t} + \boldsymbol{\theta} Z_i + \psi_s + \epsilon_{i,t} \,. \qquad (2)$$

Where $TB_{i,j}$ is the number of days in each temperature bin *j* in the growing season between 1979 and 2007. Otherwise, (2) is identical to (1).

We also uses a two season model (April-May-June and July-August-September) to test whether temperature has the same effect in the spring and summer (Massetti, Mendelsohn, and Chonabayashi 2016) with the flexible functional form.

We estimate (1) and (2) using a weighted pooled OLS with data from six Census years (1987, 1992, 1997, 2002, 2007, and 2012). We weight each observation using the inverse of farmland in each county (Deschênes and Greenstone 2007). As county-level unobserved characteristics are likely correlated over neighboring counties and beyond the state boundaries, throughout the paper we present standard errors corrected for spatial correlation over a maximum range of 500 km. We also control for within county serial correlation over a maximum of two preceding Census years (10 years).[1]

The coefficients β_j in model (2) estimate the semi-elasticity of land values to the substitution of one day of temperature at the temperature level in bin *j*. The 18-20 °C temperature bin, which captures the mean temperature of the growing season in the sample is assumed to be the reference bin. We then estimate the relative coefficient for each other observed bin. For example, if the coefficient for the bin between 27-29 °C in the daily regression is equal to 0.01, it suggests that substituting a day at 19 °C with a day at 28 °C reduces land values by 1%.

The advantage of using bins is that one can observe the consequence of either extremely cold or extremely warm temperatures without any restriction on the functional form. The most extreme

[1] We use the Conley (1999) panel data equivalent algorithm developed by Solomon Hsiang and available at http://www.solomonhsiang.com/computing/stata-code. The covariance matrix estimator is obtained using the inverse distance weighted average of spatial autocovariances that fall within a uniform kernel with a cutoff point set at 500 km.

temperature bins, however, are limited by the observations. Throughout the paper we use the rule that each bin must have at least 1% of the total temperature observations, with each observation weighted using the average amount of farmland over the study period. The first and the last temperature bins are open-ended and include all temperature observations at the tail of the distribution.

We simulate non-marginal impacts of warming on land values using uniform warming scenarios from +1 °C to + 5 °C with respect to the temperature climatologies used to estimate the model. For the temperature bins model we extrapolate the effect of warming beyond the hottest bin using a linear trend fitted between the omitted bin and the hottest bin. We follow Duan et al. (1983) to re-transform log land values in land values per hectare with and without temperature variation and we calculate the impact of warming on land values per hectare in each county in our sample.[2] Finally, we estimate aggregate welfare losses by summing over all hectares in the county and over all counties. We use the bootstrap standard deviation of welfare losses to derive the 95% confidence intervals for the non-marginal impacts.[3] Standard bootstrap methods are based on the assumption that data is identically and independently distributed (iid) but our data is likely to be both spatially and serially correlated. We deal with the problem of serial correlation by using a panel block bootstrap with 1,000 repetitions: we resample over each county and obtain all the time observations for the chosen county (Cameron and Trivedi 2005, p. 358). We also test a spatial panel block bootstrap in which the observations are clustered over space before being clustered over time. Specifically, we select *c* counties as cluster cores by sampling with replacement from the full set of counties. For each cluster core we select the $m-1$ geographically closest counties to form a sample of size $c \times m$, which is approximately equal to the total number of counties.[4] This method permits tracking spatial correlation across state borders. Then we select all the time periods for all the selected counties to form the bootstrap panel. The panel block bootstrap corresponds to the special case of $m = 1$.

[2] In particular, under the assumption that observations are i.i.d. the predicted value of land per hectare in each county is $\hat{y}_i = exp\left(x_i'\widehat{\boldsymbol{\beta}}\right)N^{-1}\sum_{i=1}^{N} exp(\hat{u}_i)$.

[3] Confidence intervals built using the percentile method are almost identical and are not reported.

[4] We use $c \times m = 2{,}400$. After adding all the observations over time for each county we have a panel with 14,400 observations, which is very close to 14,460, the size of the full panel.

3 Data

We begin the analysis with results from the North American Regional Reanalysis (NARR) climate data set,[5] a high-resolution extension of the NOAA National Centers for Environmental Prediction (NCEP) Global Reanalysis (Mesinger et al. 2006). However, we subsequently present results from other climate data as robustness check. We use 2 meter air temperature data, the standard weather measurement in the literature. Data is available at 3 hour time steps from 1979 to 2014 over a 0.3 x 0.3 degrees grid, about 32 x 32 km at 40° of latitude north. NARR uses observations from weather stations, satellites and other measurement instruments. Observations are used to initialize weather forecast models that generate a larger set of variables using the initial constraints and the laws of physics.

We start from grid level raw 3-hour data and we compute average daily (24-hour) temperatures. We then count the number of days in each temperature bin of width 3°C from April 1st to September 30th in each year from 1979 to 2007. We determine the bins at county level by averaging all the bins from all the climate model grid cells that fall within a county. For the few counties that do not have any grid cell falling within their borders we interpolate bins from the four closest grid cells, with weights inversely proportional to distance. We finally calculate the 1979-2007 climatologies, from the first year in which NARR data is available to the last year of the panel, by averaging over all years. We proceed analogously for rainfall.

We also replicate the results using daily and monthly temperature bins using the data set used by Schlenker and Roberts (2009) (SR).[6] The SR dataset has a high-resolution daily minimum and maximum temperature over the entire US (approximately 5 x 5 km at 40° of latitude north). We calculate daily mean temperatures by averaging daily minimum and maximum temperature. Monthly average temperatures are calculated as the average of the daily mean temperatures. We calculate temperature bins at county level using the same method used for NARR data.

We use the balanced panel of agricultural data built by Massetti and Mendelsohn (2011a, 2011b) and updated by Massetti, Mendelsohn, and Chonabayashi (2016) using US Agricultural Census data for 1982, 1987, 1992, 1997, 2002 and 2007. We use the following time varying socio-economic variables: income

[5] See http://nomads.ncdc.noaa.gov/docs/ncdc-narrdsi-6175-final.pdf for further information. NCEP Reanalysis data provided by the NOAA/OAR/ESRL PSD, Boulder, Colorado, USA, from their Web site at http://www.esrl.noaa.gov/psd/.

[6] See the Appendix of Massetti, Mendelsohn, and Chonabayashi (2016) for a thorough comparison of these and other climate datasets.

per capita, population density, population density squared, residential house price index. We also control for a set of geographic, time invariant characteristics at counties centroids: latitude, elevation, and distance from major metropolitan areas. We use USGS data to estimate the average annual surface and ground water use per hectare of farmland during 1982-2007. Finally, we control for some important soil characteristics: salinity, percentage of soil subject to flooding, percentage of land with low drainage, soil erodibility, average slope length factor, percentage of sand and of clay, minimum available water capacity, and permeability. In our main specification we use soil characteristics data from the USDA National Resources Inventory (NRI) (Nusser and Goebel 1997) and we test our main results by using soil data from the Harmonized World Soil Database (HWSD).[7]

We include 2,410 counties out of the 2,471 counties east of the 100th meridian. The few counties left outside of the analysis are predominantly metropolitan counties for which some data is missing. We cover more than 99% of agricultural land east of the 100th meridian. Further details on the data used and summary statistics for all the variables used in this study are available in the Appendix.

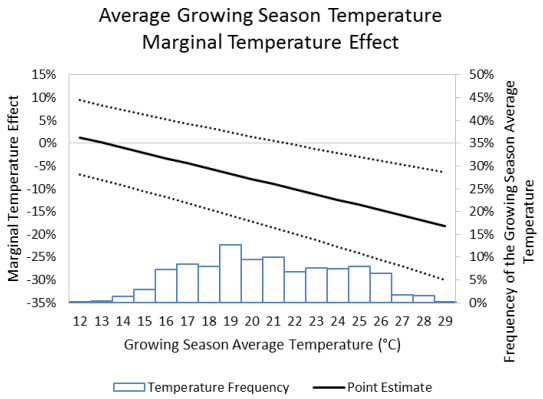
4 Results

Figure 1 shows the results of the quadratic model of mean growing season temperature. The results suggest that warmer temperatures over the growing season greater than 12 °C are harmful in the east of the US. The marginal effects of warmer temperatures are increasingly harmful, reducing farmland value.

We then introduce the bin model using the complete distribution of daily temperatures. The results in Figure **2** use the number of days in each temperature bin. The reference bin of 18-20 °C bin reflects the mean daily temperature in this sample. Both the coefficient and the 95% confidence interval are shown. According to the bin model, the optimal temperature range during the growing season lies between 12-21 °C. Temperatures above 21 °C are harmful as are temperatures of 6-12 °C. The daily results suggest that temperature has a hill-shaped effect on farmland values, suggesting that farmland value is vulnerable to hot temperatures but especially to cool temperatures.

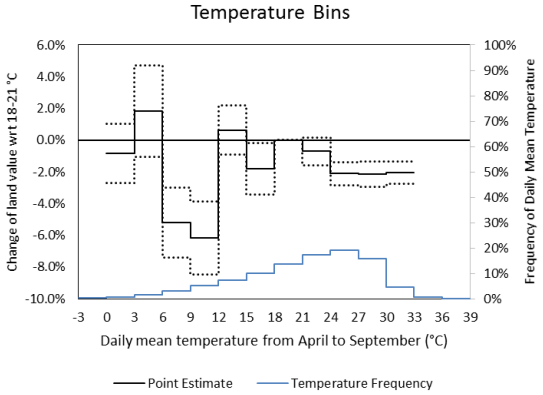
[7] FAO/IIASA/ISRIC/ISS-CAS/JRC (2008). Harmonized World Soil Database (version 1.0). Rome, Italy and Laxenburg, Austria: FAO and IIASA.

There are big differences between Figure 1 and Figure **2**. The mean temperature during the growing season has a different impact on farmland value compared to the distribution of temperatures within the growing season. A warmer mean temperature is harmful in this data set whereas the number of days at a specific temperature within a growing season have a hill-shaped impact on farmland value. The bin data capture both the effect of the mean temperature as well as temperature variance (weather deviations). The more days that are either cold or hot versus close to the mean temperature, the lower the farm value.



Note: Marginal impact of warming using a quadratic specification of average temperature between April and September. 95% confidence interval marked with dotted lines and calculated correcting standard errors for spatial correlation.

Figure 1. The marginal effect of temperature in the model with average temperature.



Note: The vertical axis measures the percentage change of land values that results from substituting a 24-hour period with temperatures of 18-21 °C versus a 24-hour period with temperatures in each other bin. Throughout the paper we use standard errors corrected for spatial correlation using a 500 km Bartlett kernel and accounting for serial correlation with 2 period time lags. First and last bins have at least 1% of daily mean temperature observations. The bottom of each figure depicts the distribution of mean daily and monthly temperature.

Figure 2**. Percentage change in land value.**

Interestingly, very cold temperatures below 6 °C have no significant effect. This may be due to the assumption in this literature that the growing season is the same for farms in both cold and warm climates. The coldest temperatures happen in April in the colder climates of the sample. Many farmers in these colder climates have not yet planted and so these coldest temperatures have no effect. We show later in the results that this neutral effect of low temperatures is specific to the north. An alternative explanation of the neutral effect of cold temperatures may be due to grazing land and not cropland as also discussed later in the results.

Note that there is no indication of a sudden drop-off in farmland values as temperatures rise to their highest observed level in the data set. There appears to be no threshold effect. Even if yields dramatically fall in years with high temperatures (Schlenker and Roberts 2009), farmland values do not exhibit a dramatic downturn in counties with extreme temperatures. It could be that these low return years happen infrequently enough that they do not affect farmland value. It is also possible that crop insurance eliminates their impact on net revenue.

One practical disadvantage of the bin models is that the effect of extreme bins cannot be measured if they have few observations. In Figure **2**, for example, the warmest bin shown contains all temperatures above 30°C. The effects of temperature in the 30-33°C bin cannot be distinguished from the effects of temperature in the 33-36°C bin because there are not enough observations to estimate the effect of this last bin. Using a linear trend from the omitted 18-20 °C bin to the last estimated bin to predict the impact of the next missing bin is one way to estimate impacts. Alternatively, one could use the effect of all the observations above 30°C. A similar procedure can be instituted for the cold side.

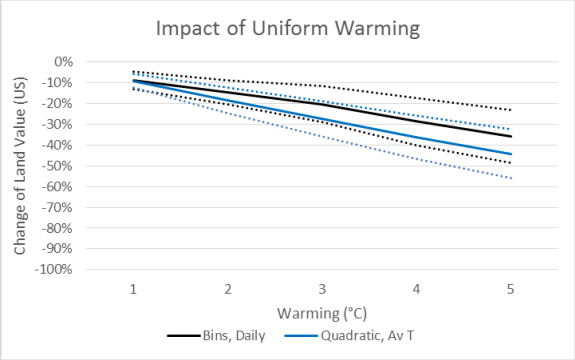
Errore. L'origine riferimento non è stata trovata. displays the impact of large uniform changes in temperature using both the traditional and bin models. In both the mean growing season model and the temperature bins models, the aggregate impact of higher temperatures on Eastern United States farms appears to be strictly harmful and linear. The average temperature model predicts slightly larger impacts than the bin model. Including the full distribution of temperatures leads to smaller damage estimates. The difference however, is not quite significant at the 5% level.

There are several possible explanations for the smaller effects predicted by the bin model. The bin model predicts that warming of cold temperatures is beneficial whereas the mean temperature model treats this effect as harmful. The bin model also predicts that high temperatures have a milder effect than the mean temperature model. As the daily temperature distributions at almost all sites are skewed

to the cold side (Massetti, Mendelsohn and Chonabayashi, 2016), it is likely that the cold side differences are more important than the hot side differences.

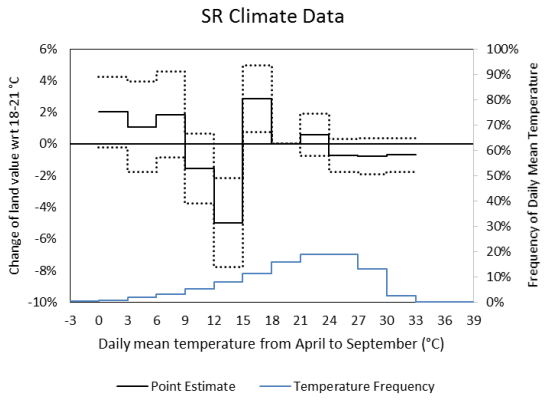
Errore. L'origine riferimento non è stata trovata. displays the confidence intervals obtained using the standard deviation of impacts estimated using 1,000 panel block bootstrap samples. We also calculate spatial block panel bootstrap confidence intervals but we do not report them to keep the figure readable. The spatial block confidence intervals are larger than those obtained using the panel block bootstrap and are quite robust to alternative choices of cluster size. With 80 clusters of 30 counties each and 1,000 bootstrap samples all the impact estimates remain significantly negative throughout the range of temperature change. The model predictions remain within the 95% confidence intervals of each other.

The next robustness test examines alternative climate data (Figure 4). The SR results are very similar to the NARR results. There are damages associated with both cool and warm temperatures and no obvious drop off at high temperatures. The daily temperatures suggest a stronger effect from cool temperatures relative to warm temperatures.



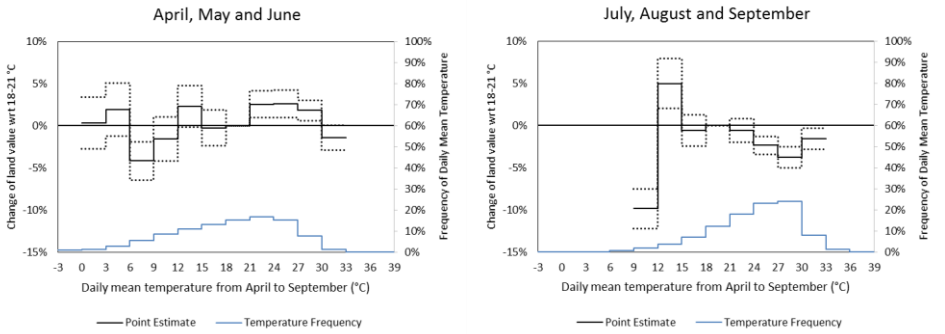
Note: The vertical axis measures the percentage change of total land values that results from a non-marginal change of temperature of 1 to 5 °C using daily and monthly temperature bins. Impacts are linearly interpolated between the unit temperature intervals. The impact estimated using a quadratic functional form of April-September mean temperature is added for comparison. 95% confidence intervals obtained estimating the standard deviation of impact estimates from 1,000 panel block bootstrap samples are reported as dotted lines. The effect of the high temperatures is extrapolated beyond the last bin using a linear trend from the 18-21 °C bin to the last bin.

Figure 3. Impact of uniform warming from April to September.



Note: The vertical axis measures the percentage change of land values that results from substituting a 24-hour period with temperatures of 18-21 °C versus a 24-hour period with temperatures in each other bin. The bottom of each figure depicts the distribution of mean daily and monthly temperature for each climate data set.

Figure 4. Impact of alternative climate data.



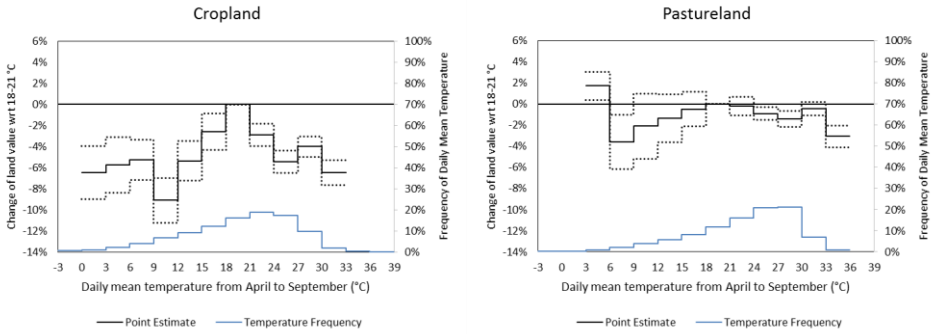
Note: The vertical axis measures the percentage change of land values that results from substituting a 24-hour period with temperatures of 18-21 °C versus a 24-hour period with temperatures in each other bin. The bottom of each figure depicts the distribution of mean daily and monthly temperature in each part of the growing season.

Figure 5. Impacts with two seasons.

The next test explores the consequence of dividing the growing season in two halves and comparing the effects in spring versus summer (Figure 5). The effects of temperature are significantly different in the two seasons. Cool daily temperatures (6-9 °C) in the first half of the growing season and cool daily temperatures (9-12 °C) in the second half of the growing season (though rare) are especially harmful. This is suggestive of a threshold effect on the cool side of the temperature distribution (though this effect is above freezing). Daily temperatures from 21-30 °C are beneficial in the first half of the growing season and only begin to become harmful over 30 °C. But in the second half of the season, daily temperatures over 24 °C are strictly harmful. It is not clear why farmland value is more sensitive to warm temperatures in the second half of the season compared to the first. But again there is no evidence of a warm threshold effect.

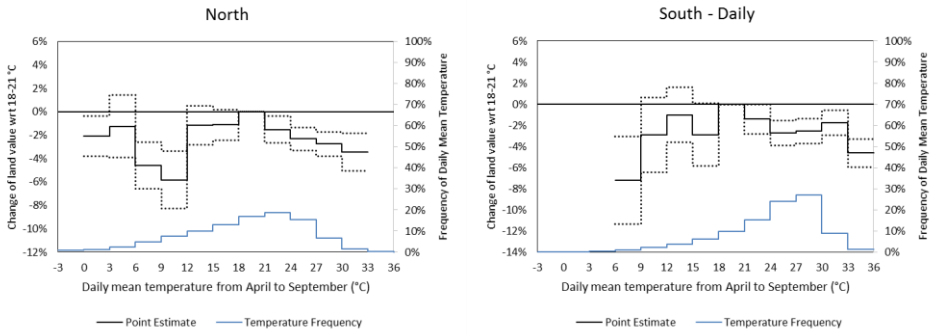
We also conduct an experiment comparing grazing land and cropland (Figure 6). One drawback of American Agriculture Census data is that these two types of farmland are combined at the county level into a single measure of farmland value. We divide them by splitting the sample into counties with predominantly cropland (more than 2/3 of agricultural land is cropland) versus mixed cropland and pastureland and predominantly pastureland counties. The farmland value-temperature response of cropland and grazing land are different. Cropland is more sensitive to both cooler and warmer temperatures than grazing land. When cropland is isolated from grazing land, it is also possible to see harmful effects at temperatures below 6 °C. The value of grazing land is not sensitive to temperatures below 6 °C as many animals are protected by shelters on cold days.

The next test we make is to see whether Southern versus Northern counties have different temperature sensitivity (Figure 7). The frequency of daily temperatures clearly reveals that the North is much colder than the South. Looking at the Southern and Northern farmland temperature results reveals that they are not statistically different and both follow a hill-shaped pattern with respect to temperatures above 6 °C. However, the neutral effect of temperatures below 6 °C is peculiar to the North.



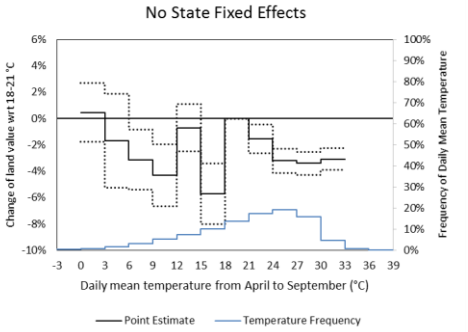
Note: The vertical axis measures the percentage change of land values that results from substituting a 24-hour period with temperatures of 18-21 °C versus a 24-hour period with temperatures in each other bin. The bottom of each figure depicts the distribution of mean daily and monthly temperature in the two sub-samples. We have 892 predominantly cropland counties and 1,451 mixed and predominantly pastureland counties.

Figure 6. Impacts of daily and monthly temperature on cropland and pastureland.



Note: The vertical axis measures the percentage change of land values that results from substituting a 24-hour period with temperatures of 18-21 °C versus a 24-hour period with temperatures in each other bin. The bottom of each figure depicts the distribution of mean daily and monthly temperature in the two sub-samples. We have 1,202 Northern counties and 1,141 Southern counties. The separation line is the 38th meridian.

Figure 7. Impact on Northern and Southern regions.



Note: The vertical axis measures the percentage change of land values that results from substituting a 24-hour period with temperatures of 18-21 °C versus a 24-hour period with temperatures in each other bin. The bottom of each figure depicts the distribution of mean daily and monthly temperature.

Figure 8. Without state fixed effects.

Another robustness test drops the state fixed effects (Figure 8). The daily effects for temperatures between 6-12 °C remain harmful as do the temperature effects above 21 °C. However, the daily temperatures effects between 12-18 °C become erratic. The monthly cool temperature become beneficial without state fixed effects but the effect of warm days remains harmful. Using state by year fixed effects leaves the estimates virtually unchanged. A final robustness test was to change the source of the soil data. This did not change the results at all.

We have not presented precipitation results as the focus of the paper is on temperature effects. Precipitation coefficients are always significant and we find a robust hill-shaped relationship between total precipitation during the growing season and farmland values. The optimal total amount of rainfall from April to September is equal to about 60 cm very close to the optimal average found by other studies (Schlenker, Hanemann, and Fisher 2006; Massetti, Mendelsohn, and Chonabayashi 2016). This optimal amount of rainfall is very robust across all the specifications used for the temperature variables. Different climate datasets do not imply significant differences in optimal rainfall.

5 Conclusion.

In this paper, we compare the results of a growing season mean temperature model with a flexible functional form daily temperature bin model. The test is done using the same growing season data on

the same sample of farms from the Eastern United States. The results suggest that farmland value reacts differently to the mean growing season temperature versus the distribution of temperatures within the growing season. Higher mean growing season temperatures appear to be harmful in this data set of eastern American farms. In contrast, farmland value has a hill-shaped relationship in the bin model with the full temperature distribution. The full distribution of temperature in the flexible functional form model suggests that farmland value is a little more sensitive to cooler temperatures than warmer temperatures.

Applying these models to uniform warming scenarios reveals that Eastern US farmland has damages that increase linearly with temperature at about 7% per °C. The mean growing season model predicts slightly higher damages than the flexible temperature bin model, although the difference is not significant at the 5% level.

It is useful to compare this temperature effect with the expected effect of carbon dioxide fertilization. If CO_2 levels double, laboratory tests suggest productivity increases on average about 30% whereas field experiments suggest gains of about 15% (Long et al. 2006, Leakey et al. 2009). Despite some uncertainty on the actual effect of carbon fertilization, there is growing evidence that it will likely compensate for a 2 °C temperature warming from today (Rosenzweig et al. 2014) and may even lead to higher farmland values in the Eastern United States.

A limitation of the analysis above is that it assumes prices remain constant. This would depend upon how global food supply changes relative to how global food demand changes. Higher prices would give farmers higher net revenues. This would encourage farmers to produce more. But higher prices would shift some of the welfare effect from farmers to consumers. Another important factor to keep in mind is that the climate sensitivity of the Western United States is different from the Eastern United States (citation). The results do not apply to the whole country.

The paper nonetheless raises a paradox. Why do farmland values remain relatively robust to high temperatures if yields are predicted to fall dramatically at high temperatures? One possibility is that the high temperatures are only rare weather events. The expected value of these events is modest despite the high damage when they occur. Another possibility is that farmers have learned to adapt to high temperatures with sparing use of crops that are likely to fail in high temperature locations. Finally, another possibility is that public crop insurance is compensating farmers whenever they have lower

yields from poor weather. So high and low temperatures would not affect farmland value even if they do affect annual yields.

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Appendix – Data

We have constructed a balanced panel with observations for 2,410 out of the 2,471 counties east of the 100th meridian, covering 99% of agricultural land, over the years 1982, 1987, 1992, 1997, 2002 and 2007. Units of measurement are in the metric system; economic variables are converted to constant 2005 United States Dollars ($) using the Implicit Price Deflators for Gross Domestic Product (Bureau of Economic Analysis Table 1.1.9). If not otherwise stated, variables measure data of interest in years 1982, 1987, 1992, 1997, 2002 and 2007.

Climate data

Temperature and precipitations – Temperature and precipitation data is obtained processing the North American Regional Reanalysis (NARR) dataset. Temperature at 2 meters above ground. Normals over the period 1979-2007. For further information on the NARR dataset see http://nomads.ncdc.noaa.gov/docs/ncdc-narrdsi-6175-final.pdf.

Agriculture data

Farmland value – Estimated value of land and buildings, USD per hectare of farmland. Data source is the Agricultural Census.

Farmland – Land in farms as in the Census of Agriculture from 1982 to 2007, hectares. The Census of Agriculture defines 'Land in farms' as agricultural land used for crops, pasture or grazing. It also includes woodland and wasteland not actually under cultivation or used for pasture or grazing, provided it was part of the farm operator's total operation. Large acreages of woodland or wasteland held for non-agricultural purposes were deleted from individual reports. Land in farms includes acres in the Conservation Reserve and Wetlands Reserve Programs. Land in farms is an operating unit concept and includes land owned and operated as well as land rented from others.

Surface or ground water withdrawals – Thousands of liters per day, per hectare, of surface or ground water for irrigation purposes. The 'Estimated use of water in the United States', published every five years by the United States Geological Survey, supplies data on water use at county level starting from 1985. We divided the amount of water used at county level for years 1985, 1990, 1995, 2000, 2005 by the amount of farmland in that county in census years 1987, 1992, 1997, 2002 and 2007, respectively,

and we computed the time average of surface water use per hectare of land. We used this variable as a proxy for surface and ground water availability at county level for all time observations of our panel.

Socio-economic data

Income per capita – Per capita personal income, measured in thousands of $; Bureau of Economic Analysis, Regional Economic Accounts, table CA1-3.

Population density – Population from the Bureau of Economic Analysis, Regional Economic Accounts, table CA1-3, measured in hundred persons per squared kilometer. Area estimated from current division of counties boundaries.

Value of owner occupied homes – Median value of owner occupied homes, measured in thousands of $. We use data on the median value of owner occupied homes (SF3 H085) at county level from the 2000 United States Census. Data for other years is obtained using the Home Price Index (HPI) for metropolitan areas or at state level estimated by the Office of Federal Housing Enterprise Oversight (OFHEO). The HPI measures the movement of single-family house prices. It is a repeat-sales index that measures average price changes in repeat sales or refinancing on the same properties (www.fhfa.gov/webfiles/896/hpi_tech.pdf). The HPI was adjusted to reflect inflation using the Implicit Price Deflator of GDP.

Geographic data

Latitude – Latitude of county's centroid, measured in decimal degrees.

Elevation – Elevation of county's centroid, measured in thousands of meters.

Distance from cities – Distance between county's centroid and metropolitan areas with more than 200,000 inhabitants in 2000, measured in kilometers.

Soil characteristics – NRI dataset

Soil data is from the National Resources Inventory (NRI), developed by the United States Department of Agriculture, years 1992 and 1997 (Nusser and Goebel 1997; NRI 2000). The NRI is a longitudinal sample survey of natural resource conditions and trends on non-Federal land in the United States based upon scientific statistical principles and procedures. It is conducted by the U.S. Department of Agriculture's Natural Resources Conservation Service (NRCS). We consider soil samples classified as: cultivated

cropland, noncultivated cropland, pastureland and rangeland. We calculate a sample area weighted average of soil characteristics from all samples that fall within a county. In some cases we reclassify qualitative soil characteristics into numeric indicators, as detailed below.

Salinity – Percentage of agricultural land that has salinity–sodium problems.

Flooding – Percentage of agricultural land occasionally or frequently prone to flooding.

Wet factor – Percentage of agricultural land that has very low drainage (poor and very poor).

k factor – Average soil erodibility factor. It is the average soil loss, measured in tons/hectare. The k factor is a measure of the susceptibility of soil particles to detachment and transport by rainfall and runoff.

Slope length – Average slope length factor, measured in meters. Slope length is the distance from the point of origin of overland flow to the point where either the slope gradient decreases enough that deposition begins, or the runoff water enters a well-defined channel that may be part of a drainage network or a constructed channel. For the NRI, length of slope is taken through the sample point.

Sand – Percentage of agricultural land classified as sand or coarse- textured soils.

Clay – Percentage of agricultural land that is classified as clay.

Moisture level – Minimum value for the range of available water capacity for the soil layer or horizon. Available water capacity is the volume of water retained in 1 cm3 of whole soil between 1/3-bar and 15-bar tension. It is reported as cm of water per centimeters of soil.

Permeability – The minimum value for the range in permeability rate for the soil layer or horizon, expressed as centimeters/hour.

Appendix – Summary Statistics

Temperature Bin	NARR	SR	ERA-INTERIM
< 0	0.46%	0.44%	0.43%
0 - 2	0.69%	0.82%	0.77%
3 - 5	1.54%	1.82%	1.67%
6 - 8	3.05%	3.23%	2.98%
9 - 11	5.24%	5.25%	4.91%
12 - 14	7.31%	7.86%	7.39%
15 - 17	10.05%	11.34%	10.60%
18 - 20	13.80%	15.74%	15.20%
21 - 23	17.32%	18.97%	19.59%
24 - 26	19.25%	18.76%	20.35%
27 - 29	15.86%	13.13%	12.78%
30 - 32	4.72%	2.57%	3.16%
33 - 35	0.69%	0.06%	0.17%
≥ 36	0.01%	0.00%	0.00%

Notes. Each observation weighted by the average amount of farmland over the study period.

Table A-1. Frequency of bins of average temperature over different time periods.

Variable	Mean	Std. Dev.	Min	Max
Farmland Value ($/ha)	1692	1160	209	38564
Farmland ('000 ha)	85129	71729	390	880615
Cropland ('000 ha)	52747	50070	0	434214
Percentage of Farmland used for Crops (%)	62.0%	23.8%	0.0%	98.7%
Latitude (Degrees)	38.2	5.2	26.1	48.8
Elevation (m)	289	175	1	1221
Distance from Metropolitan Areas (Km)	172	109	0	664
Surface Water Withdrawals ('000 lt/day/ha)	0.14	0.75	0.00	16.16
Ground Water Withdrawals ('000 lt/day/ha)	0.33	1.09	0.00	11.75
Total Rainfall from April to September (cm)	55.4	9.9	23.9	92.9

Notes. Observations weighted by the average amount of farmland over the study period, except for Farmland and Cropland.

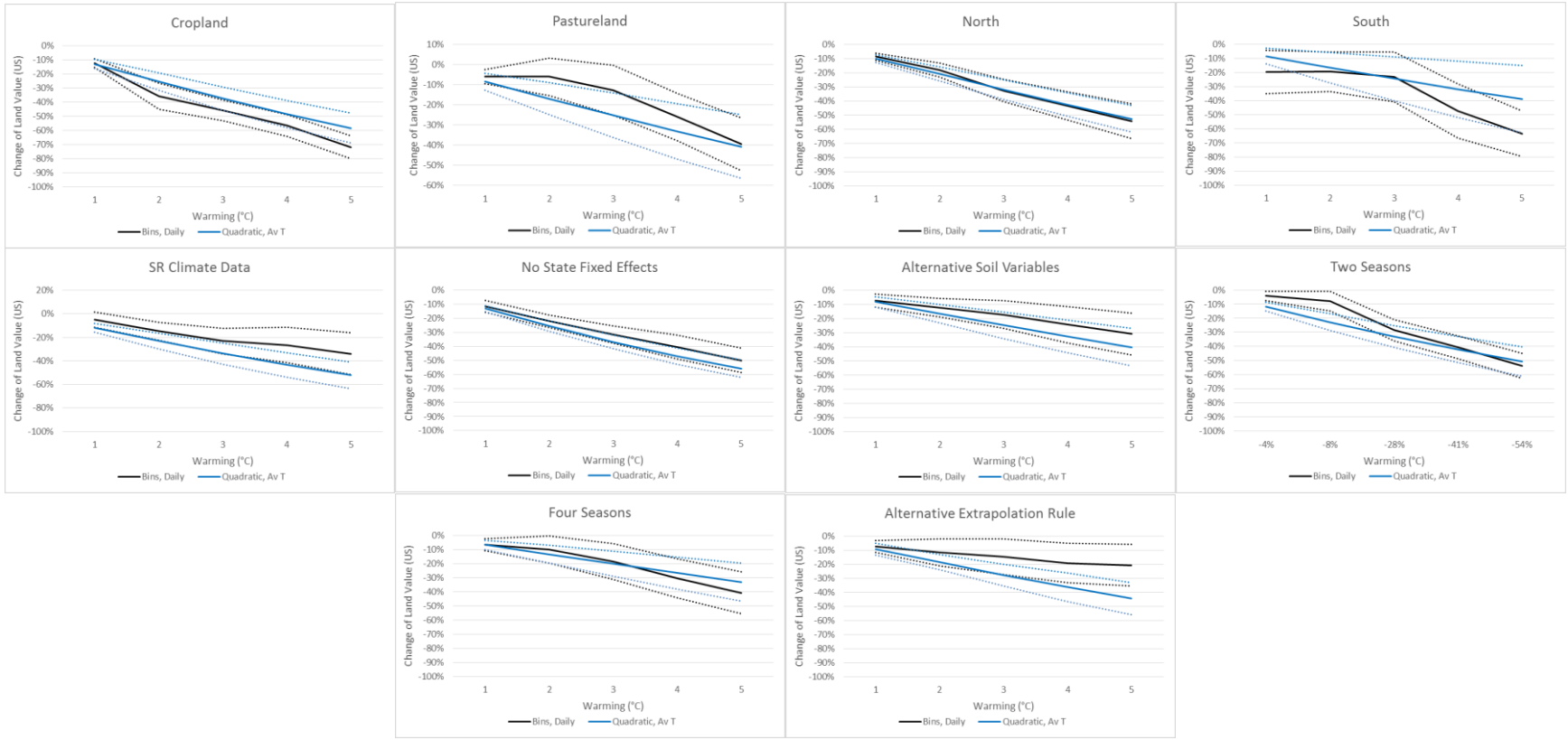
Table A-2. Frequency of bins of average temperature over different time periods.

Variable	Mean	Std. Dev.	Min	Max
Farmland with Salinity Problems (%)	11%	15%	0%	100%
Farmland Prone to Flooding (%)	9.1%	9.4%	0.0%	83%
Farmland with Low Drainage (%)	13%	20%	0%	100%
Average Soil Erodibility Factor (k-factor) (t/ha)	0.302	0.065	0.100	0.486
Slope Lenght (m)	147.0	88.0	0.6	792.6
Farmland Classified as Sand (%)	10%	21%	0%	100%
Farmland Classified as Clay (%)	7.8%	16%	0%	92%
Moisture Level (cm of water / cm of soil)	0.153	0.043	0.020	0.229
Permeability (cm of water / hour)	1.146	1.190	0.032	11.456

Notes. Observations weighted by the average amount of farmland over the study period.

Table A-3. Frequency of bins of average temperature over different time periods.

Appendix – Additional Robustness Tests



Notes: The vertical axis measures the percentage change of total land values that results from a non-marginal change of temperature of 1 to 5 °C using daily and monthly temperature bins. Impacts are linearly interpolated between the unit temperature intervals. The impact estimated using a quadratic functional form of April-September mean temperature is added for comparison. 95% confidence intervals obtained estimating the standard deviation of impact estimates from 1,000 panel block bootstrap samples are reported as dotted lines. Cropland: counties in which at least 2/3 of agricultural land is for crops. Pastureland: counties in which at most 2/3 of agricultural land is for crops. North: counties north of the 38th parallel. South: counties south of the 38th parallel. SR climate data: uses data from Schlenker and Roberts (2009). No State Fixed Effects: no state fixed effects. Alternative Soil Variables: uses the FAO Harmonized World Soil Database. Two Seasons: separate sets of variables for April, May and June from July, August and September. Four Seasons: uses different sets of variables for the four climatological seasons. Alternative Extrapolation Rule: the effect of the high temperatures is extrapolated beyond the last bin using a linear trend from the 18-21 °C bin to the last bin while in all previous panels and in Figure 3 we use a linear trend from the 18-21 °C bin to the last bin.

Figure A1. Impact of uniform warming from April to September under alternative datasets and rules.

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