Estimating the Effect of Climate Change on Crop Yields and Farmland Values: The Importance of Extreme Temperatures

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Links to Papers

- Papers used in this talk

- Nonlinear relationship between weather and crop yields:
  - Regression estimates and climate impacts [link]
  - Paper outlining fine-scaled weather data [link]

- Cross-sectional analysis of farmland values:
  - Hedonic regression using degree days [link]

- Why other studies find different results:
  - Storage and price effects in a profit regression [link]
    - Deschenes and Greenstone (2007)
  - Irrigation subsidies in a hedonic model [link]
    - Mendelsohn, Nordhaus and Shaw (1994)

Outline

Outline

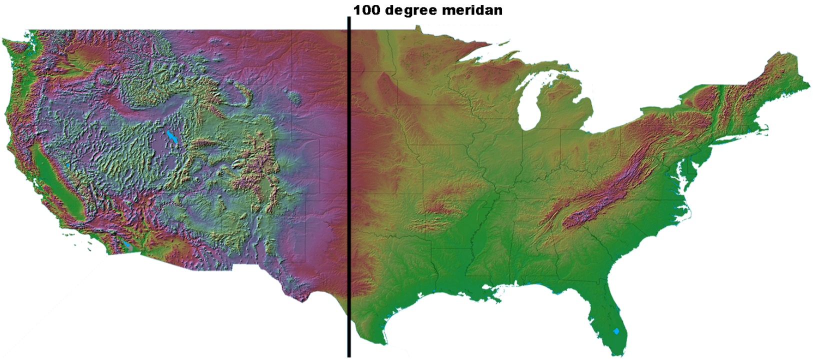
Background - Agriculture and Climate Change

- Mounting evidence that climate is changing
- Several studies focus on agricultural sector
  - Climate / weather directly impacts agricultural production
  - Agriculture - large share of GDP in developing countries
  - Agriculture - small share of GDP in the US, but
    - US produces 40% of all corn in the world
      (38% of all soybeans, 20% of all cotton)
    - Impacts in the US will influence world supply and prices
    - Discussion whether US will be net beneficiary or net loser
- We focus on US agriculture

Setting the Stage

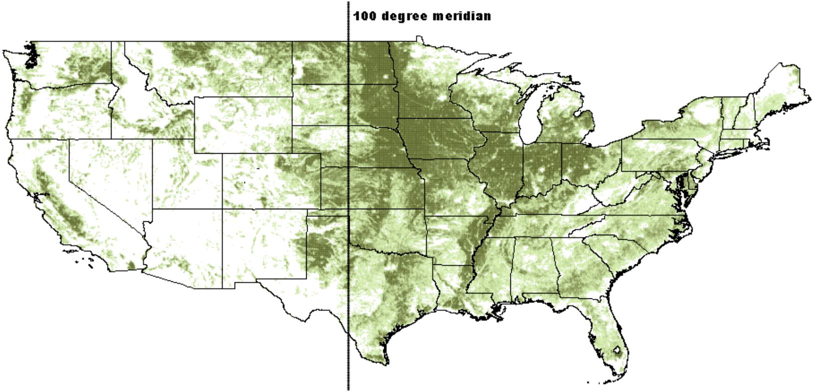
Background - Agriculture in the US

Elevation Map



Background - Agriculture in the US

Agricultural Area (2.5x2.5mile grids)



The Importance of Extreme Temperatures

- Nonlinear relationship between yields and temperature
  - Yields increasing in temperature until upper threshold
    - 29°C for corn, 30°C for soybeans, and 32°C for cotton
  - Yields decreasing in temperature above threshold
  - Slope of decline much steeper than slope of incline
- Extreme heat measured by degree days 30°C
  - Degrees above 30C, e.g., 34C is 4 degree days 30C
- Degree days 30°C
  - Explain 45% of variation in aggregate corn yields
  - Similar relationship in cross section and time series
  - Similar relationship in cross section of farmland values

Implication for Climate Change

- Both panel and cross-section give similar results
  - If extreme temperatures are included in regression equation
  - Difficulty to adapt to extreme temperatures
- Different results in previous studies
  - Not driven by different sources of identification
    - Cross section versus panel
  - But by how temperatures are modeled
    - Average temperature versus degree days
- Large predicted damages
  - Extreme temperatures become more frequent

Outline

Literature Review

- Early studies of agricultural productivity
  - Ronald Fisher: "Studies in Crop Variation I-VI"
  - Developed Maximum Likelihood Estimator
- More recent studies of agricultural productivity
  - Crop simulation models
    - Daily temperature and precipitation values
    - Too many parameters to estimate (calibrated instead)
    - Other inputs are held constant
  - Reduced-form studies
    - Large geographic extend (entire US)
    - Average weather variables (spatial or temporal)

Cross Section versus Panel

- Cross-section analysis of farmland values
  - Value of land if put to best use
  - Climate varies across space (south is hotter)
  - Pro: measures how farmers adapt to various climates
  - Con: omitted variables problem
- Panel of yields or profits
  - Link year-to-year fluctuations in weather to profits/yield
  - Pro: panel allows for use of fixed effects
  - mitigates omitted variables problem
  - Con: Short-run response different from long-run response
  - difference between weather and climate

Model Specification

Log yields y_{it} are additively influenced by temperature h

$$y_{it} = \int_{\underline{h}}^{\overline{h}} g(h)\phi_{it}(h)dh + \mathbf{z}_{it}\delta + c_i + \epsilon_{it}$$

where

- y_{it}: log yield in county i in year t
- h: heat / temperature
- $g()$: growth as a function of heat
- ϕ_{it}: time crop is exposed to heat t in county i in year t
- $\mathbf{z}_{it}$: other controls (precipitation, quadratic time trend by state)
- c_i: county fixed effect
- ϵ_{it}: error (we adjust for spatial correlation)

Model Specification

- Let $\Phi_{it}(h)$ be the total time temperatures are below h
- Dummy-variable approach (discretize integral)

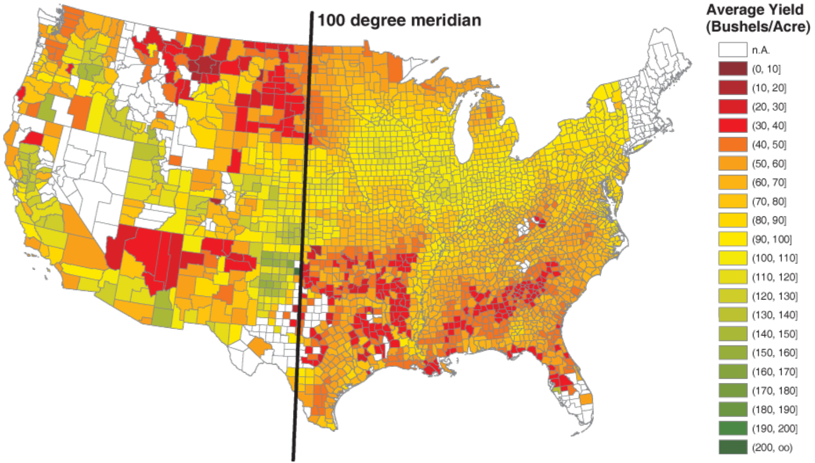
$$y_{it} = \sum_{j=0,3,6,9,\ldots}^{39} \gamma_j \underbrace{[\Phi_{it}(h+3) - \Phi_{it}(h)]}_{x_{it,j}} + \mathbf{z}_{it}\delta + c_i + \epsilon_{it}$$

- Chebyshev polynomials (mth-order)

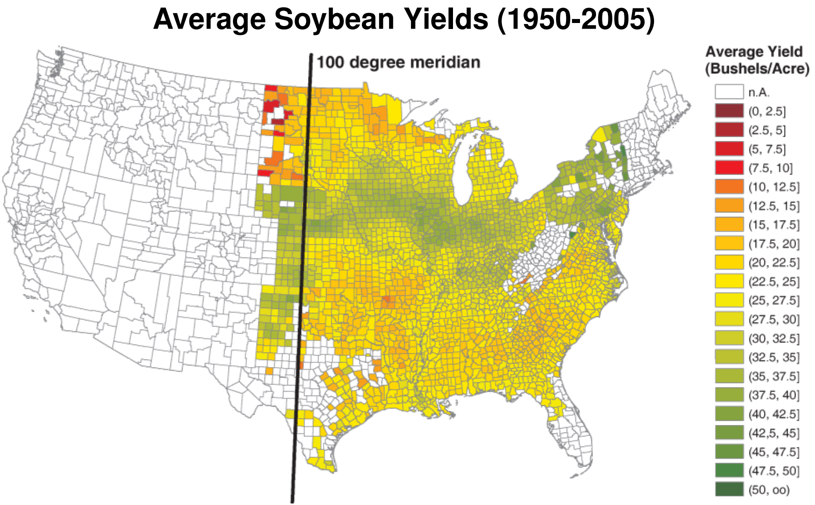
$$\begin{aligned} y_{it} &= \sum_{h=-1}^{39} \sum_{j=1}^{m} \gamma_j T_j(h+0.5)\left[\Phi_{it}(h+1) - \Phi_{it}(h)\right] + \mathbf{z}_{it}\delta + c_i + \epsilon_{it} \\ &= \sum_{j=1}^{m} \gamma_j \underbrace{\sum_{h=-1}^{39} T_j(h+0.5)\left[\Phi_{it}(h+1) - \Phi_{it}(h)\right]}_{x_{it,j}} + \mathbf{z}_{it}\delta + c_i + \epsilon_{it} \end{aligned}$$

Descriptive Statistics - Dependent Variables

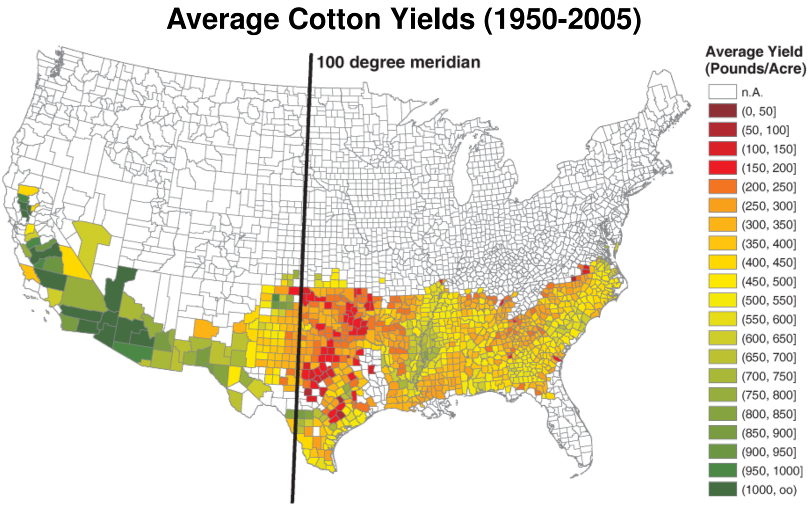
Average Corn Yields (1950-2005)



Descriptive Statistics - Dependent Variables

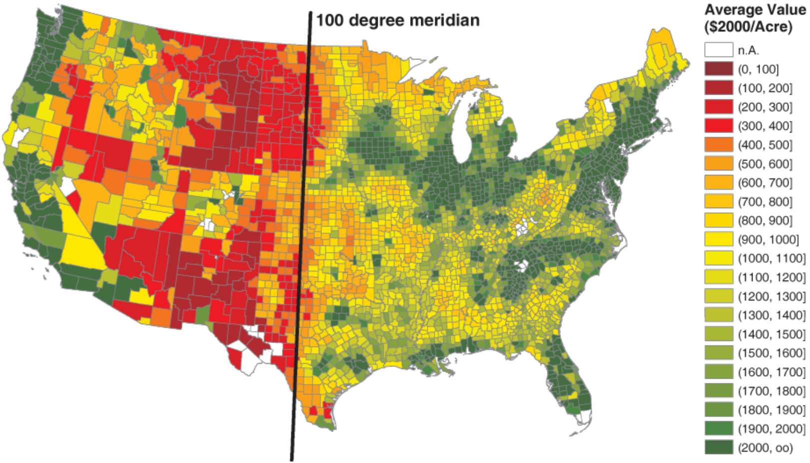


Descriptive Statistics - Dependent Variables



Descriptive Statistics - Dependent Variables

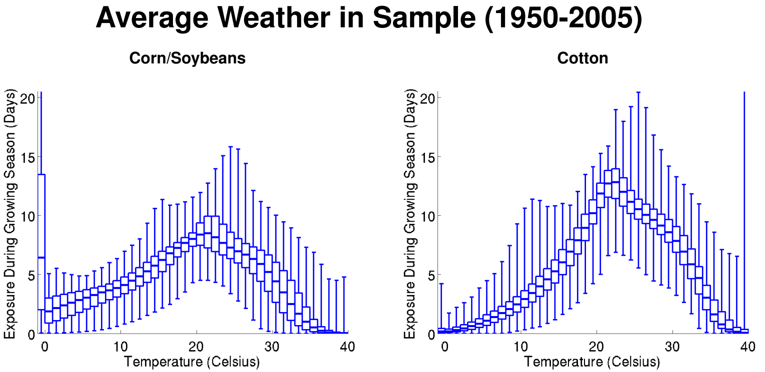
Average Farmland Values (1982, 1987, 1992, 1997)



Fine-scaled Weather Data Set

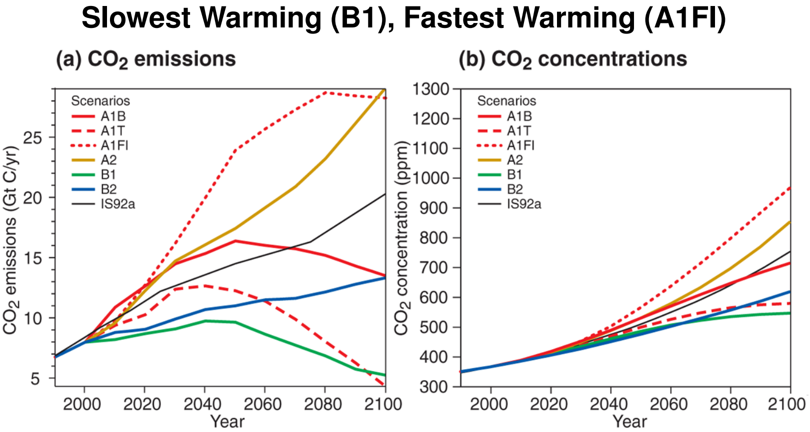
- Daily minimum / maximum temperature and precipitation
  - 2.5x2.5 mile grid for entire US
  - Constructed from individual weather stations
  - PRISM interpolation procedure
- Time temperatures are in each 1°C interval
  - Sinusoidal curve between minimum and maximum temp.
  - Sum over days in growing season
    - March-August for corn and soybeans
    - April-October for cotton
- Weather in county
  - Satellite scan of agricultural area
  - Weighted average of all 2.5x2.5 mile grids in county

Descriptive Statistics - Weather



Notes: Graphs display the amount of time a crop is exposed to each 1°C interval during the growing season. The lowest interval has no lower bound and includes the time temperatures fall below 0°C . The topmost interval has no upper bound and includes the time temperatures are above 39°C. For each interval, the range between minimum and maximum among counties is shown by whiskers, the 25%-75% percentile range is outlined by a box, and the median is added as a solid bold line.

IPCC Emission Scenarios

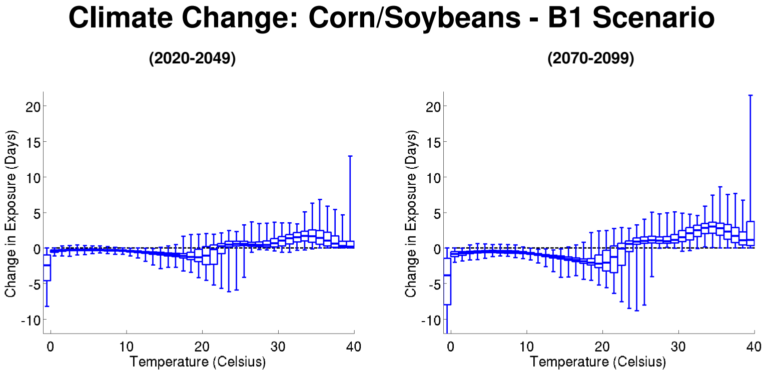


Climate Change Predictions

- Hadley HCM3 model (216 grid points covering the US)
  - Change in climatic variables (2020-2049) and (2070-2099) compared to (1960-1989)
  - Absolute change in minimum and maximum temperature
  - Relative change in precipitation

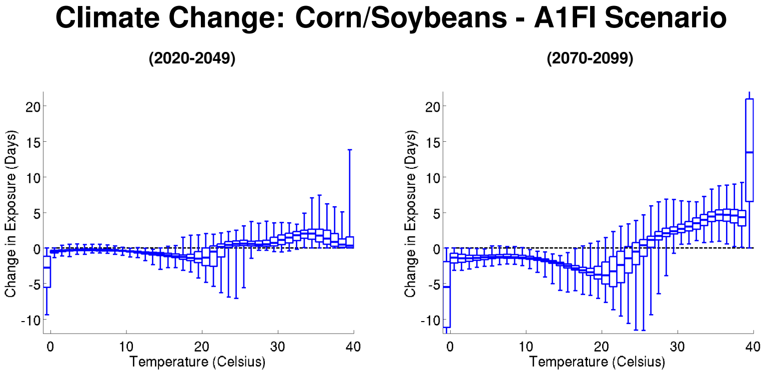
- Distance-weighted change at each 2.5x2.5mile grid
  - Using four surrounding Hadley grids
  - Add predicted temperature change to historic baseline
    - Mean shift with constant variance
  - Multiply historic precipitation with predicted change
    - Variance increase if predicted change >1

Descriptive Statistics - Climate Change



Notes: Graphs display the predicted *change* in the amount of time a crop is exposed to each 1°C interval during the growing season. The lowest interval has no lower bound and includes the time temperatures fall below 0°C. The topmost interval has no upper bound and includes the time temperatures are above 39°C. For each interval, the range between minimum and maximum among counties is shown by whiskers, the 25%-75% percentile range is outlined by a box, and the median is added as a solid bold line.

Descriptive Statistics - Climate Change



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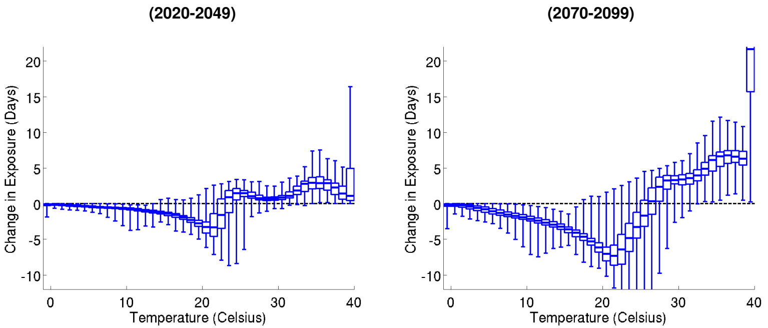
Descriptive Statistics - Climate Change

Climate Change: Cotton - A1FI Scenario



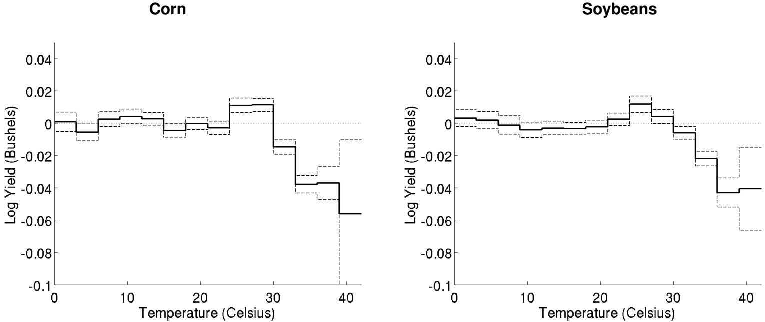
Notes: Graphs display the predicted *change* in the amount of time a crop is exposed to each 1°C interval during the growing season. The lowest interval has no lower bound and includes the time temperatures fall below 0°C . The topmost interval has no upper bound and includes the time temperatures are above 39°C. For each interval, the range between minimum and maximum among counties is shown by whiskers, the 25%-75% percentile range is outlined by a box, and the median is added as a solid bold line.

Outline

Link between Temperature and Yields

Panel of Corn and Soybean Yields

3°C dummy variables (solid line), 95% confidence band (dashed line)



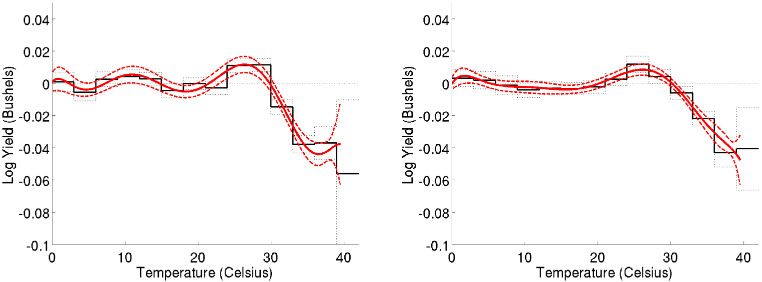
Notes: Graphs show the impact of a given temperature for one day of the growing season on yearly log yields. Curves are centered so the exposure-weighted impact is zero.

Link between Temperature and Yields

Panel of Corn and Soybeans Yields

3°C dummy variables (black line), 8th order Chebyshev polynomial (red line)

Corn **Soybeans**

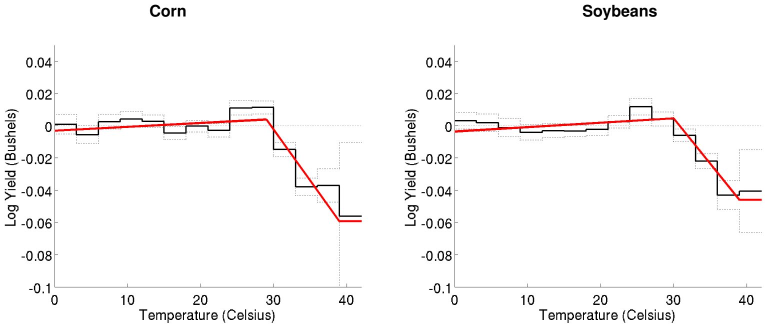


Notes: Graphs show the impact of a given temperature for one day of the growing season on yearly log yields. Curves are centered so the exposure-weighted impact is zero.

Link between Temperature and Yields

Panel of Corn and Soybeans Yields

3°C dummy variables (black line), piecewise-linear (red line)

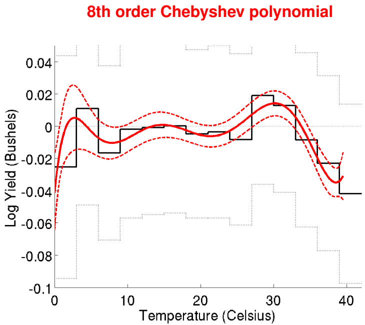


Notes: Graphs show the impact of a given temperature for one day of the growing season on yearly log yields. Curves are centered so the exposure-weighted impact is zero. The lower bounds for the piecewise linear function were fixed at 0°C, but the optimal breakpoint was estimated.

Link between Temperature and Yields

Panel of Cotton Yields

3°C dummy variables (black line)



Notes: Graphs show the impact of a given temperature for one day of the growing season on yearly log yields. Curves are centered so the exposure-weighted impact is zero. The lower bounds for the piecewise linear function were fixed at 0°C, but the optimal breakpoint was estimated.

Other Regression Results

- Precipitation variable
  - Significant inverted U-shape for corn and soybeans
  - Optimum: 25 inches for corn / 27.2 inches for soybeans
  - Not significant for cotton (highly irrigated)
- Quadratic time trend by state
  - Almost threefold increase in average yields 1950-2005
- Summary statistics
  - Corn: R-squared of 0.77 using 105,981 observations
  - Soybeans: R-squared of 0.63 using 82,385 observations
  - Cotton: R-squared of 0.37 using 31,540 observations
  - Weather explains roughly one third of variance

The Importance of Extreme Temperatures

- Model comparison tests
  - Horse race: which specification does best?
  - Estimate model using 85% of data
  - Predict observations for remaining 15% of data
  - Check how close predictions are to actual outcomes

- New model gives best forecasts
  - Nonlinear effects of temperatures
  - Extreme temperatures drive down yields significantly

Out-of-Sample Prediction Test: Corn

Comparison of models explaining corn yields

	RMS	GW	MGN
Dummy Variables	0.2179		
Chebyshev Polynomials	0.2179	0.5028	0.03
Piecewise Linear	0.2199	0.9858	8.60
Monthly Averages	0.2289	0.7113	13.33
Degree Days 8-32°C, >34°C (Thom)	0.2398	0.9935	28.81
Degree Days 8-32°C (Daily Mean)	0.2436	0.9763	30.76
County-Fixed Effects (No Weather)	0.2598		

Notes: Table compares various temperature specifications for corn, soybeans, and cotton according to three out-of-sample criteria: (i) **RMS** is the root mean squared out-of sample prediction error; (ii) **GW** gives the Granger weight on the dummy variable regression of the optimal convex combination between the dummy variables regression and the model listed in the row; (iii) **MGN** is the normally distributed Morgan-Newbold-Granger statistic of equal forecasting accuracy. Each model is estimated using the same 85% of the data (randomly selected) and yields are forecasted out-of-sample for the omitted 15%.

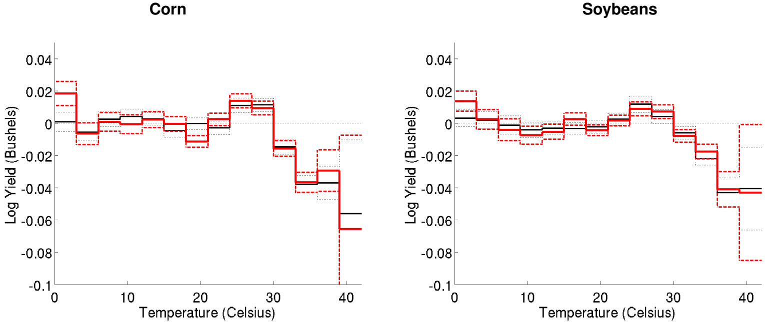
The Importance of Extreme Temperatures

- Assessment of extreme heat by futures market
  - New information about expected yields will move prices
  - Weekly corn futures returns 1950-2006
  - Extreme temperatures move prices up significantly
  - No significant relationship with average temperature
- Next steps
  - Check various sources of identification
  - How robust are results?

Various Sources of Identification

Results without County Fixed Effects

3° C dummy variables (black line), 3° C dummy variables without county fixed effects (red line)

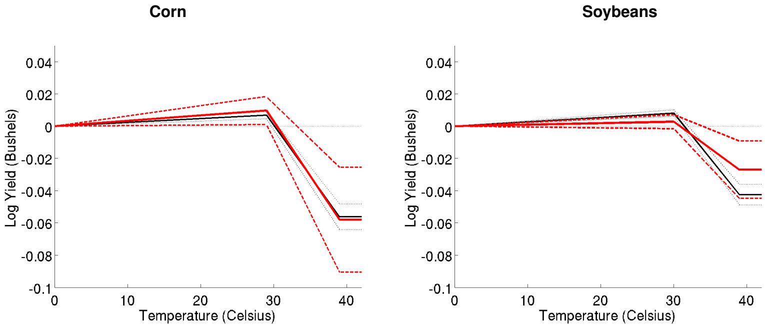


Notes: Graphs show the impact of a given temperature for one day of the growing season on yearly log yields. Curves are centered so the exposure-weighted impact is zero.

Various Sources of Identification

Results using Time Series (56 observations)

piecewise linear using panel (black line), piecewise linear using 56 yearly aggregates (red line)

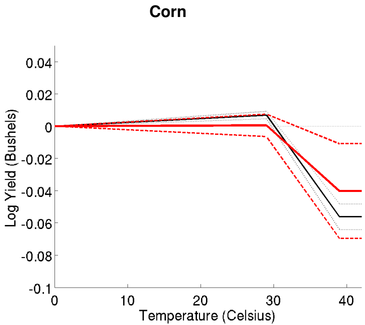


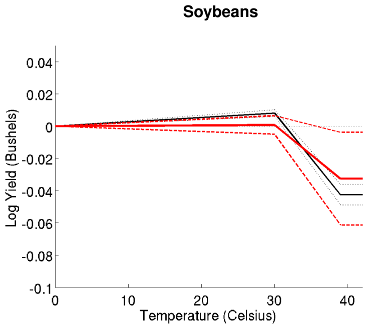
Notes: Graphs show the impact of a given temperature for one day of the growing season on yearly log yields. We use a piecewise linear function as there are only 56 observations in the time series which makes estimation of the dummy-variable model undesirable due to a lack of degrees of freedom.

Various Sources of Identification

Results using Cross Section

piecewise linear using panel (black line), piecewise linear using average yield in county (red line)



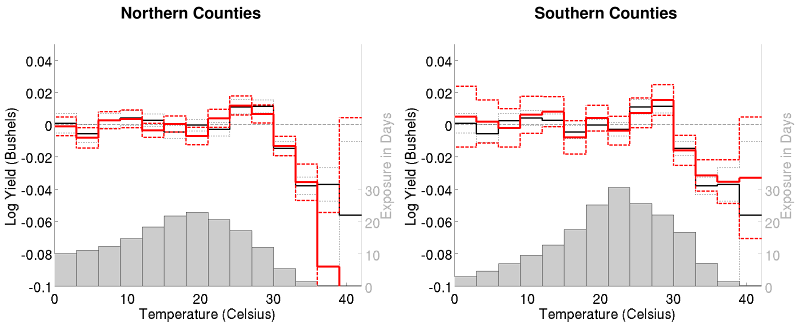


Notes: Graphs show the impact of a given temperature for one day of the growing season on yearly log yields. We use a piecewise linear function as there are only 56 observations in the time series which makes estimation of the dummy-variable model undesirable due to a lack of degrees of freedom.

Adaptation and Technology Progress

Corn: Limited Adaptation in Warmer Climates

full sample (black lines), subset of counties (red lines)

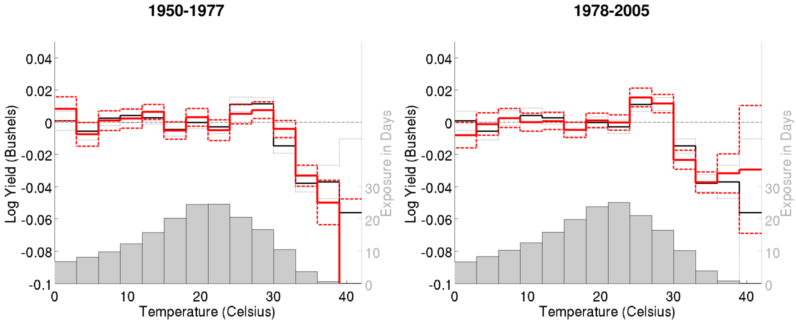


Notes: Graphs show the impact of a given temperature for one day of the growing season on yearly log yields. Curves are centered so the exposure-weighted impact is zero.

Adaptation and Technology Progress

Corn: Limited Progress in Heat Tolerance

full sample (black lines), subset of years (red lines)

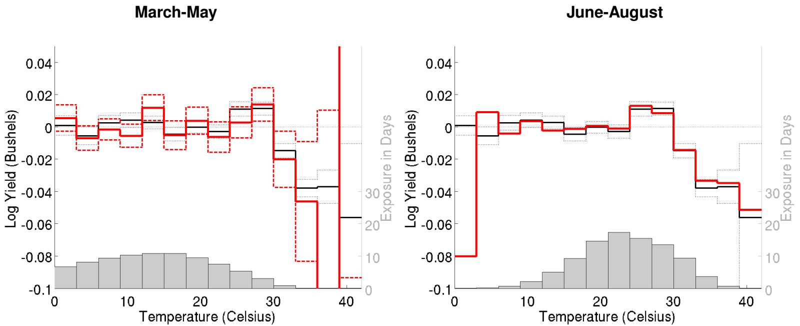


Notes: Graphs show the impact of a given temperature for one day of the growing season on yearly log yields. Curves are centered so the exposure-weighted impact is zero.

Additive Effects of Heat

Corn: Temperature Effects are Additive

full sample (black lines), 3-month subset (red lines)



Notes: Graphs show the impact of a given temperature for one day of the growing season on yearly log yields. Curves are centered so the exposure-weighted impact is zero.

Robustness

- Nonlinear effects of temperatures
  - Yields increasing in temperature until upper threshold
    - 29°C for corn, 30°C for soybeans, and 32°C for cotton
  - Yields decreasing in temperature above threshold
  - Slope of decline much steeper than slope of incline
- Comparable results from
  - Panel of yields
  - Time series of aggregate (national yields)
  - Cross section of average yields in a county
  - Futures market returns
  - Various subsets (geographic / temporal)

Outline

Impact on Crop Yields

- Predicted damages large and significant
  - Driving Force: extreme heat predicted to increase
    - Especially by end of century
  - Extreme temperature are highly damaging to crop

- Caveats
  - Does not allow for CO_2 fertilization
  - Keeps crops, growing area, and planting dates fixed
    - Will present sensitivity checks below

Changes in Crop Yields (Percent)

Medium Term (2020-2049)

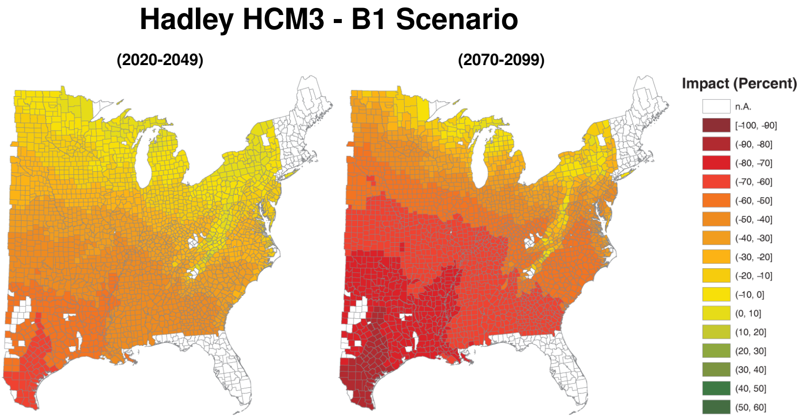
Variable	Area-weighted Impact	(t-val)	Impact by County Mean	Min	Max	Std
Corn						
HCM3 - B1	-22.34	(21.03)	-28.32	-63.67	11.70	17.78
HCM3 - B2	-23.02	(22.70)	-29.43	-70.01	11.08	17.09
HCM3 - A2	-27.62	(23.29)	-32.55	-68.99	14.39	17.09
HCM3 - A1FI	-28.54	(21.14)	-32.26	-68.95	11.55	17.19
Soybeans						
HCM3 - B1	-18.62	(21.10)	-19.39	-62.24	16.49	17.10
HCM3 - B2	-19.50	(22.37)	-20.24	-67.21	17.49	16.55
HCM3 - A2	-23.11	(23.43)	-23.02	-67.71	20.08	16.78
HCM3 - A1FI	-23.04	(21.76)	-22.72	-67.82	16.61	17.11
Cotton						
HCM3 - B1	-21.71	(6.58)	-15.39	-47.37	21.82	14.53
HCM3 - B2	-20.98	(5.30)	-14.54	-56.40	25.98	15.01
HCM3 - A2	-22.27	(5.81)	-15.41	-53.98	30.15	15.70
HCM3 - A1FI	-21.59	(5.53)	-14.67	-51.13	23.18	14.16

Changes in Crop Yields (Percent)

Long Term (2070-2099)

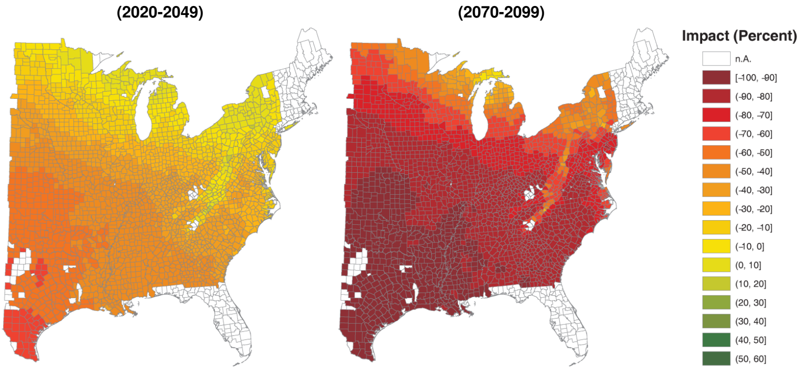
	Area-weighted		Impact by County			
Variable	Impact	(t-val)	Mean	Min	Max	Std
Corn						
HCM3 - B1	-43.16	(19.50)	-45.70	-83.76	18.11	18.18
HCM3 - B2	-50.66	(21.24)	-53.51	-90.03	18.16	18.08
HCM3 - A2	-69.71	(16.07)	-71.07	-96.34	4.27	16.33
HCM3 - A1FI	-78.59	(14.75)	-79.83	-98.45	-7.70	14.35
Soybeans						
HCM3 - B1	-36.10	(22.94)	-34.27	-82.53	25.01	19.61
HCM3 - B2	-43.73	(25.04)	-42.15	-87.53	26.09	20.42
HCM3 - A2	-63.72	(20.87)	-61.33	-94.56	19.72	19.54
HCM3 - A1FI	-73.64	(19.53)	-71.36	-96.79	11.87	17.32
Cotton						
HCM3 - B1	-31.08	(5.59)	-22.37	-66.83	31.24	18.20
HCM3 - B2	-40.42	(6.21)	-31.45	-73.82	32.48	18.60
HCM3 - A2	-56.99	(7.10)	-49.26	-86.22	42.03	18.93
HCM3 - A1FI	-67.18	(7.97)	-58.79	-91.95	50.78	19.43

Geographic Distribution of Impacts on Corn



Geographic Distribution of Impacts on Corn

Hadley HCM3 - A1FI Scenario



Impact on Crop Yields

- Examining adaptation possibilities
- Limited effect of shift in planting dates
  - Corn: Shift planting dates one month forward (Feb-July)
  - Damages (A1FI - long term) decrease from 79% to 64%
    - Less extreme heat in February than August
    - But: Also less solar radiation
- Limited potential for adaptation within species
  - Comparable results for various subsets (north, south, etc)
  - Comparable results in time series and cross section

Changes in Crop Yields (Percent)

Various Sources of Identification: Long Term (2070-2099)

	B1	(t-val)	A1FI	(t-val)
Corn				
Piecewise-linear	-45.06	(27.18)	-81.87	(57.91)
Piecewise-linear (Time Series)	-45.85	(8.31)	-82.99	(16.27)
Piecewise-linear (Cross Section)	-37.88	(7.57)	-72.12	(9.83)
Piecewise-linear (Cross Section + Soil)	-37.61	(8.75)	-72.05	(12.40)
Soybeans				
Piecewise-linear	-37.33	(25.88)	-74.50	(48.52)
Piecewise-linear (Time Series)	-27.31	(5.75)	-59.18	(7.72)
Piecewise-linear (Cross Section)	-32.33	(4.99)	-65.38	(6.14)
Piecewise-linear (Cross Section + Soil)	-33.93	(7.31)	-68.18	(10.01)
Cotton				
Piecewise-linear	-35.37	(7.27)	-72.26	(14.71)
Piecewise-linear (Time Series)	-29.37	(2.32)	-65.67	(4.17)
Piecewise-linear (Cross Section)	-40.25	(2.01)	-71.75	(2.05)
Piecewise-linear (Cross Section + Soil)	-41.43	(2.00)	-72.90	(2.04)

Farmland Values

- Cross section analysis of farmland values
  - Value of land reflects profitability of land
  - Allows for adaptation (land is put to best use)
  - Compares values across climatic regions
- Schlenker, Hanemann and Fisher (2006)
  - Counties east of 100 degree meridian
  - Farmland values linked to degree days (8-32°C, 34°C)
  - Controls for income, population density, soil controls
  - Extreme heat (degree days 34°C) very damaging
- Omitted variable bias?
  - Robust to inclusion/exclusion of controls if model uses degree days!

Farmland Values versus Corn/Soybeans Yields

Long Term (2070-2099)

Variable	Area-weighted Impact	(t-val)	Impact by County Mean	Min	Max	Std
Farmland Values						
HCM3 - B1			-27.37	-78.77	44.15	22.58
HCM3 - B2			-31.61	-88.28	52.37	26.57
HCM3 - A2			-61.64	-94.72	27.87	20.25
HCM3 - A1FI			-68.54	-96.95	39.61	21.79
Corn						
HCM3 - B1	-43.16	(19.50)	-45.70	-83.76	18.11	18.18
HCM3 - B2	-50.66	(21.24)	-53.51	-90.03	18.16	18.08
HCM3 - A2	-69.71	(16.07)	-71.07	-96.34	4.27	16.33
HCM3 - A1FI	-78.59	(14.75)	-79.83	-98.45	-7.70	14.35
Soybeans						
HCM3 - B1	-36.10	(22.94)	-34.27	-82.53	25.01	19.61
HCM3 - B2	-43.73	(25.04)	-42.15	-87.53	26.09	20.42
HCM3 - A2	-63.72	(20.87)	-61.33	-94.56	19.72	19.54
HCM3 - A1FI	-73.64	(19.53)	-71.36	-96.79	11.87	17.32

Outline

Summary of Paper

- Paper pioneered the use of panel data
  - Authors focus predominantly on profits
  - One sensitivity check using corn and soybean yields
  - Find no significant relationship between weather and profit
  - Agriculture is predicted to benefit from warming
- Potential concerns
  - Profit uses sales in a given year
  - Omits storage / short-run price response
    - Assume weather is bad in a year
    - price increases and storage is depleted (as price is high)
    - sales will not necessarily decrease!
  - Yield regression does not account for extreme heat
  - Data quality issues

Do Yield Shocks Translate Into Sales?

	Storable Commodities		Non-storable Commodities	
	Corn	Soybeans	Strawberries	Oranges
Panel A: Average Price (Sum of Sales / Sum of Production)				
Average Price	2.05	6.23	1226	209
Panel B: Regression of Sales (per acre) on Yield (per acre)				
Yield	1.52	4.15	1229	212
	(28.94)	(24.95)	(12.09)	(27.79)
Observations	3714	3714	1427	251
County FE	Yes	Yes	Yes	Yes
State-by-year FE	Yes	Yes	Yes	Yes

Notes: Table lists average prices in the data in panel A and a regression of sales per acre on yield per acre in panel B (t-values are given in brackets). Note how the numbers in panels A and B differ for storable commodities as good (bad) yield shocks are counterbalanced by storage depletion (build-up) and hence bias the coefficient in panel B towards zero. All regressions use area-weights following DG's preferred specification. The yield data for corn and soybeans is taken from DG and merged with sales figures for these crops. Sales and yield figures for strawberries and oranges were extracted from Census micro-files.

Comparison of Yield Models

	Data from DG		Alternative Degree Days Variables		
	No weather	DG	Replication DG	SHF (2006)	SR
	(1)	(2)	(3)	(4)	(5)
Regression diagnostics					
R-square	0.8021	0.8270	0.8442	0.8447	0.8653
Variance explained by weather		12.6%	21.3%	21.5%	31.9%
Non-nested J-tests (model comparison tests)					
DG against other weather (t-value)			15.97	16.26	25.91
Other weather against DG (t-value)			1.85	1.80	1.52
Percent impact on yields under climate change					
Hadley II-IS92a scenario		-0.978	-11.5	-11.5	-13.2
(t-value)		(0.79)	(6.74)	(6.55)	(8.43)
Hadley III-B2 scenario			-44.5	-47.0	-67.0
(t-value)			(12.04)	(11.42)	(18.70)
Observations	6862	6862	6862	6862	6862
Soil controls	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Notes: Table compares various implementations of degree days and how well they explain corn yields. The first two columns replicate the results in DG using their data and code, while the last three columns merge in degree days measures used in various other papers: column (3) is our replication of the degree days measure in DG using our daily data, column (4) uses Thom's interpolation method using monthly data to derive degree days 8-32°C as well as degree days above 34°C, and column (5) uses daily minimum and maximum temperatures to derive degree days 8-29°C as well as degree days above 29°C.

Summary of Paper

- Paper pioneered hedonic analysis of farmland values
  - Link farmland values in the entire US to climate
  - Authors use two sets of weights
    - Cropland weights: large damages from global warming
    - Croprevenue weights: modest benefits from global warming

- Potential concerns
  - Access to highly subsidized irrigation water in the West
  - Subsidy higher than average farmland value in east
  - Subsidy capitalizes into farmland values
  - Regression equates higher temperature with subsidies!

- Test: Is East different from West
  - Chow test with p-value less than 0.0001
  - Focus on East only
    - Large damages under both set of weights

Outline

Conclusions

- Agricultural output directly linked to weather
  - Nonlinear relationship between weather and yields
  - Yields increasing in temperature until upper threshold
    - 29°C for corn, 30°C for soybeans, and 32°C for cotton
  - Yields decreasing in temperature above threshold
  - Slope of decline much steeper than slope of incline
    - Extreme temperatures have dominating effect
    - Accounting for extreme temperatures gives superior out-of-sample forecasts

- Comparable results using
  - Panel of yields
  - Time series of aggregate (national yields)
  - Cross section of average yields in a county
  - Futures market returns
  - Various subsets (geographic / temporal)
  - Cross section of average farmland value in a county

Conclusions - Impacts

- Large damages from global warming
  - Extreme temperatures become more frequent
  - Heat waves have strong negative effects
  - Yields by the end of the century are predicted to decrease
    - 31%-43% under slow-warming (B1) scenario
    - 67%-79% under fast-warming (A1FI) scenario
- Limited potential for adaptation
  - Cross-section of yields has same shape as time-series
  - Similar relationship for farmland values
    - wider set of adaptations
- Analysis first step
  - More structural model of crop choice, planting dates, etc
  - Need to account for extreme temperatures