Climate Change, Crop Yields, and Implications for Food Supply in Africa

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MADS - October 14, 2008

Links to Papers

- Nonlinear relationship between weather and crop yields:
  - Regression estimates and climate impacts in the US [link]
  - Paper outlining fine-scaled weather data for the US [link]
- Food Security in Africa
  - Prioritizing Climate Change Adaptation Needs for Food Security in 2030 [link]
- Cross-sectional analysis of farmland values in the US using temperature extremes: [link]
- Difference to previous studies and why our results differ:
  - Storage and price effects in a profit regression [link]
  - Irrigation subsidies in a hedonic model [link]

Outline

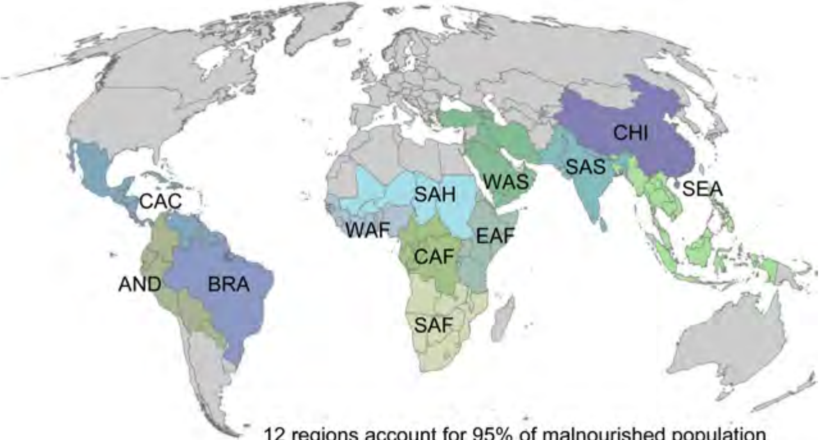
Background - Agriculture and Climate Change

- Mounting evidence that climate is changing
  - Emerging consenus that temperature will increase
- Several studies focus on agricultural sector
  - Climate / weather directly impacts agricultural production
  - Green revolution drastically increased yields

  - 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

Background - Agricultural Production

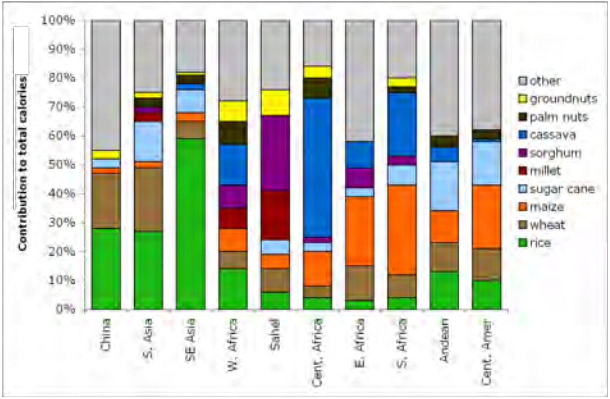
Defining Production Regions



12 regions account for 95% of malnourished population

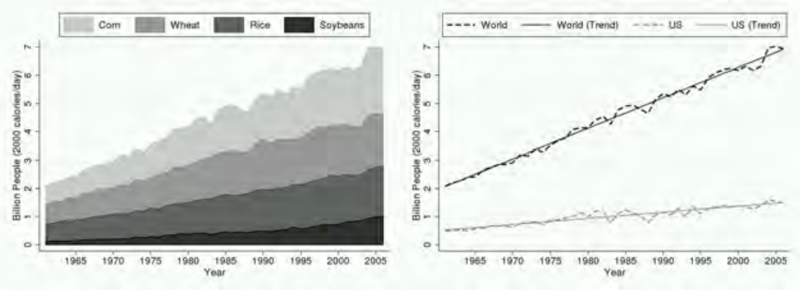
Background - Agricultural Production

Consumption by Region



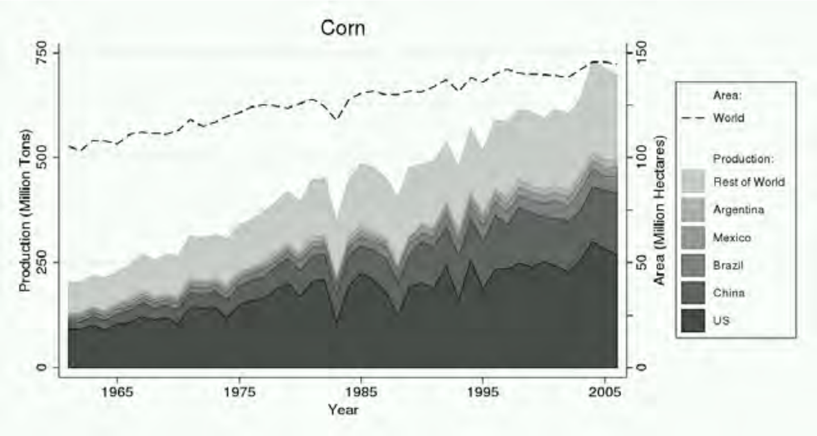
Background - Agricultural Production

Caloric Production (Corn, Rice, Soybeans, and Wheat)



Background - Agricultural Production

Five Largest Producers



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

The Importance of Extreme Temperatures

- Nonlinear relationship between yields and temperature in US
  - Yields increasing in temperature until upper threshold
    - 29°C for corn, 30°C for soybeans, 32°C for soybeans
  - Yields decreasing in temperature above threshold
- Extreme heat measured by degree days 30°C
  - Degrees above 30C, e.g., 34C is 4 degree days 30C
- Degree days model
  - Superior out-of-sample forecast for crops in Africa and US
  - US: similar relationship in cross section and time series

Implication for Climate Change

- Both panel and cross-section give similar results in US
  - 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

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)

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

- Chebyshev polynomials (mth-order)

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

- Piecewise Linear

Data Sources

- Crop Yields
- Africa: country-level yields from FAO (1961-2006)
  - Crops: maize, wheat, sorghum, groundnuts, millet, cassava, rice
  - Working on sub-country level yields
- US: county level yields from NASS (1950-2005)
  - Crops: corn, soybeans, and cotton
  - 2275 counties in the eastern US with corn yields

Fine-scaled Weather Data Set: US

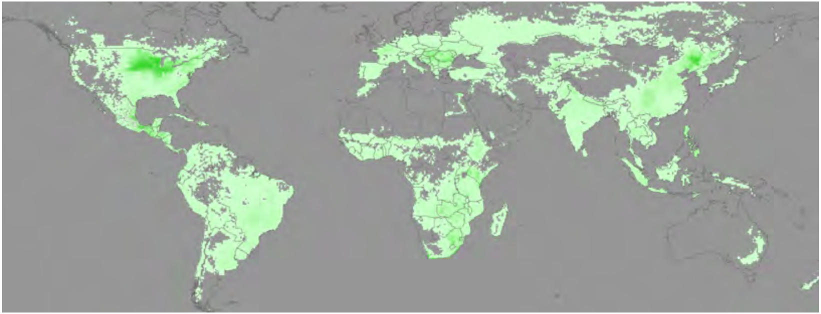
- Daily minimum / maximum temperature and precipitation
  - 2.5x2.5 mile grid for entire US
  - Constructed from individual weather stations
  - PRISM interpolation procedure
- Time temperatures are in each 1°C interval
  - Sinusoidal curve between minimum and maximum temp.
  - Sum over days in growing 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

Weather Data Set: Africa

- CRU (Climate Research Unit - East Anglia University)
  - monthly minimum and maximum temperature
    - (v2.10: 1901-2002, v3.0: 1901-2006)
  - construct degree days using Thom's formula
- NCC (Institute of Industrial Science, University of Tokyo)
  - 4 observations per day (1949-2000)
    - midnight, 6am, noon, 6pm
  - Get daily minimum and maximum temperature
  - Degree days based on daily sinusoidal interpolation
- Sum daily values over growing season

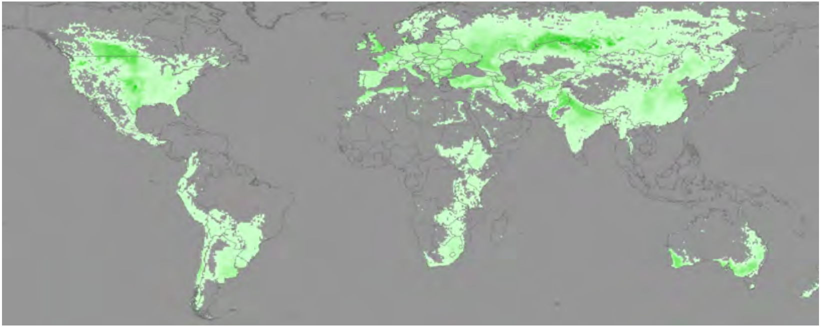
Weather Data Set: Africa

Maize growing areas (0.5 degree latitude/longitude grid)



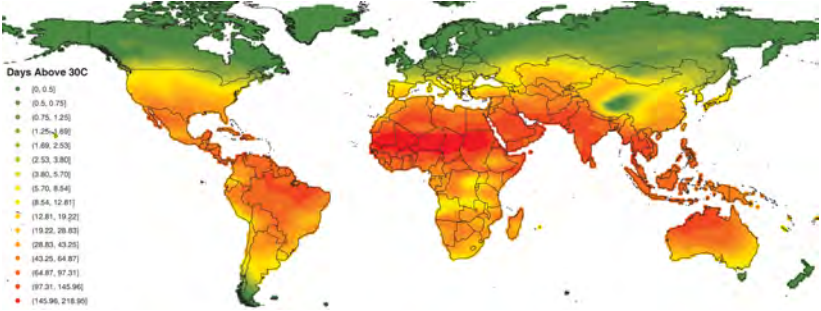
Weather Data Set: Africa

Wheat growing areas (0.5 degree latitude/longitude grid)



Weather Data Set: Africa

Extreme Heat - Individual Weather Stations

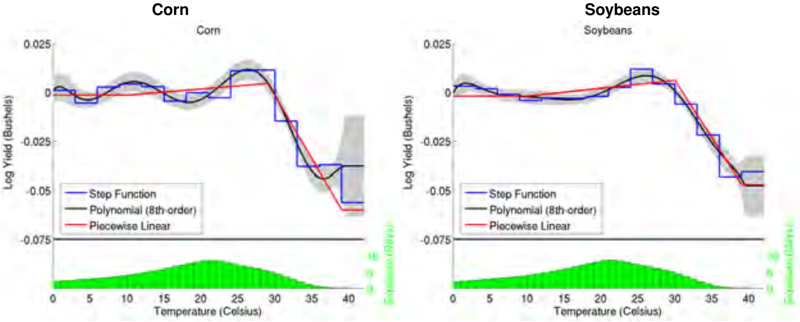


Outline

Link between Temperature and Yields

Panel of Corn and Soybean Yields

point estimates (solid lines), 95% confidence band (shaded area)

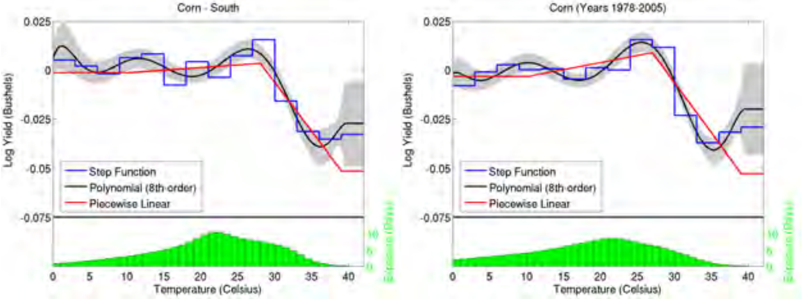


Link between Temperature and Yields

Panel of Corn and Soybean Yields

point estimates (solid lines), 95% confidence band (shaded area)

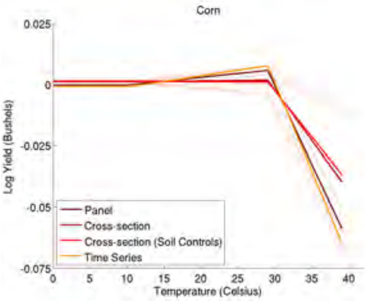
Corn **Soybeans**

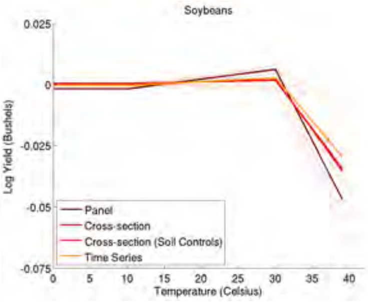


Link between Temperature and Yields

Varous Sources of Identification

point estimates (solid lines) for piecewise linear model





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

Comparison of Temperature Variables

- 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
- 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

Comparison of Temperature Variables

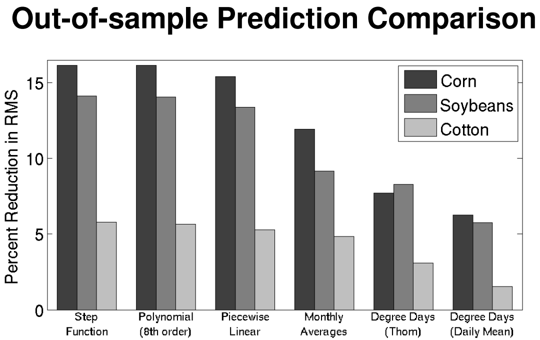


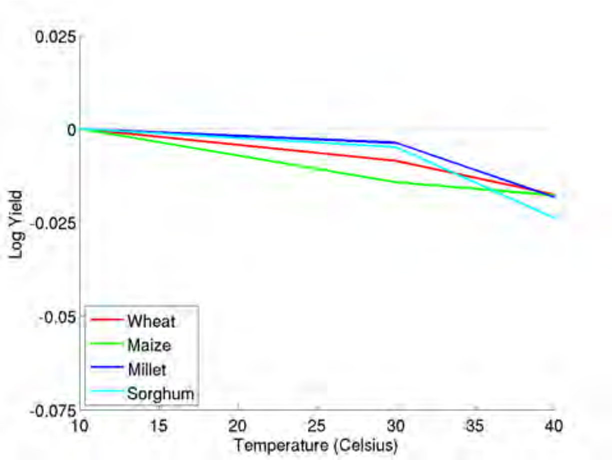
Figure compares various temperature specifications for corn, soybeans, and cotton according to the root mean squared out-of sample prediction error.

Comparison of Temperature Variables (NCC)

	In-sample R2				Out-of-sample RMS			
Crop	**(1)**	**(2)**	**(3)**	**(4)**	**(1)**	**(2)**	**(3)**	**(4)**
Wheat	0.6957	0.6965	0.6970	0.7083	0.6501	0.7859	0.2971	0.6520
Maize	0.5884	0.5897	0.5901	0.5926	1.1022	0.8574	0.5844	1.3730
Millet	0.6895	0.7255	0.6980	0.7043	1.1569	9.2676	0.2216	1.1802
Sorghum	0.6272	0.6328	0.6359	0.6394	0.9796	1.4200	0.2451	0.4536
Cassava	0.5336	0.5435	0.5407	0.5597	0.6965	5.3160	0.5913	1.8681
Groundnuts	0.3957	0.4010	0.3991	0.4044	1.1930	0.6919	0.4783	2.1060
Rice	0.6229	0.6231	0.6269	0.6300	0.5395	1.0393	0.5532	1.5734

Notes: Table reports R-square and root mean squared prediction error for various models: **(1)** uses average temperature and precipitation; **(2)** uses a quadrtaic in temperature and precipitation; **(3)** uses degree days 10-30C and degree days 30C; **(4)** uses 5C intervals from 10C to 45C and a quadratic in precipitation.

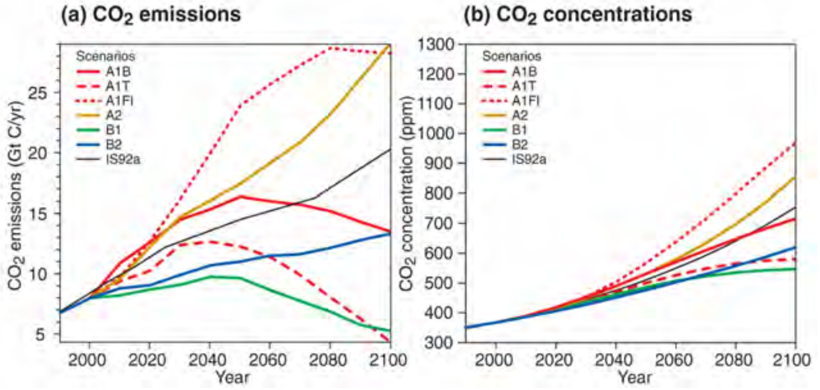
Link between Temperature and Yields



Outline

IPCC Emission Scenarios

Slowest Warming (B1), Fastest Warming (A1FI)



Climate Change Predictions - Africa

- A1b scenario for 16 climate models in Africa
  - Change in climatic variables (2046-2065) compared to (1961-2000)
- B1, B2, A2, A1FI scenario for Hadley model in US
  - Change in climatic variables (2020-2049) and (2070-2099) compared to (1961-1990)

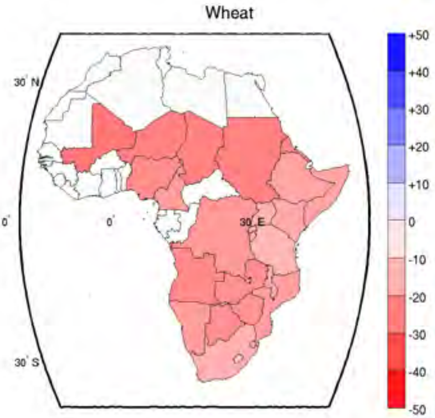
- Distance-weighted change at each NCC/CRU grid
  - Absolute change in minimum and maximum temperature
  - Using four surrounding climate model grids
  - Add predicted temperature change to historic baseline
    - Mean shift with constant variance
  - Multiply historic precipitation with predicted relative change
    - Variance increase if predicted change >1

Predicted Changes in Crop Yields

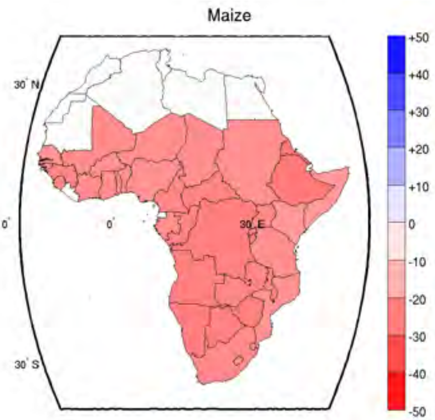
Crop	**(1)**	**(2)**
Wheat	-17.38	-8.93
Maize	-22.74	-24.00
Millet	-24.57	-50.27
Sorghum	-29.24	-46.23

Notes: Table reports predicted changes in crop yields 2046-2065: **(1)** uses coefficients estimated using a panel for Africa; **(2)** uses coefficients from US - maize

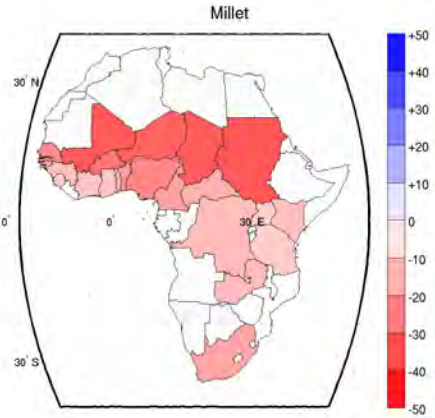
Predicted Changes in Crop Yields



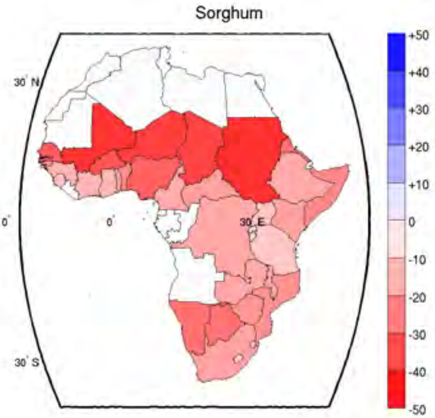
Predicted Changes in Crop Yields



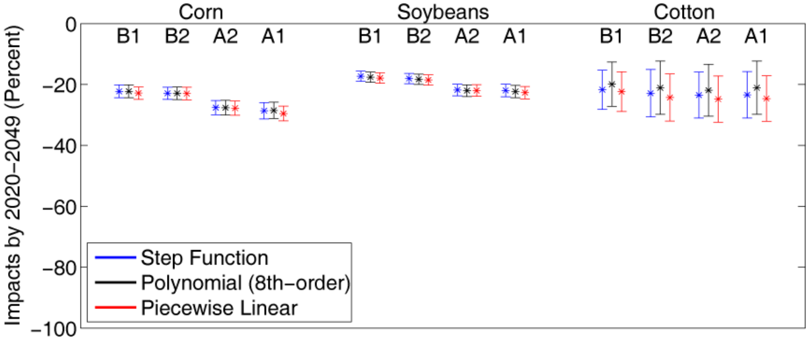
Predicted Changes in Crop Yields



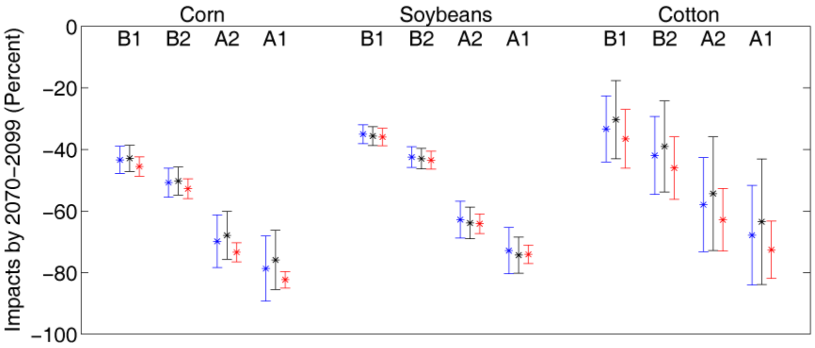
Predicted Changes in Crop Yields



Predicted Changes in Crop Yields



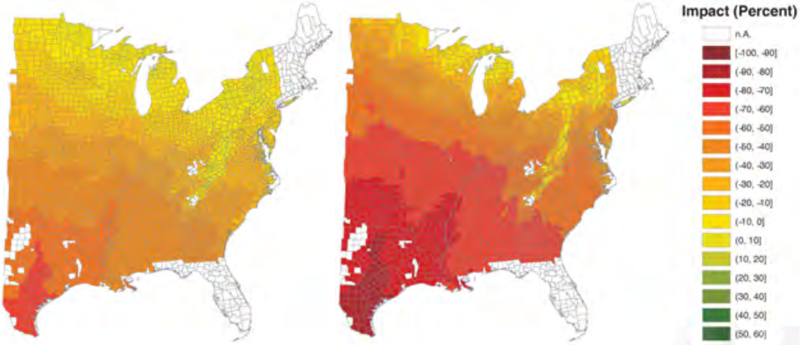
Predicted Changes in Crop Yields



Predicted Changes in Crop Yields

Hadley HCM3 - B1 Scenario

(2020-2049) (2070-2099)



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
  - 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

- Significant damages from global warming even in medium-term
- Limited potential for adaptation
  - Cross-section of yields has same shape as time-series
  - Comparable results for Africa and the US
  - 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