Social Cost of Carbon: Agricultural Sector

Wolfram Schlenker

Columbia University and NBER

National Academy of Sciences
November 13, 2015

Outline

1. Recent Evidence that Can be Used in IAMs
2. Improvements for Damage Functions
   - Adapting to Changes in Mean Climate
   - Adapting to Changes in Climate Variability
   - Damages: Non-market Values
3. Aggregate vs Disaggregate Damage Functions
4. Reliability of Potential Improvements
5. Improvements for Damages over Time

Outline

1. Recent Evidence that Can be Used in IAMs
2. Improvements for Damage Functions
   - Adapting to Changes in Mean Climate
   - Adapting to Changes in Climate Variability
   - Damages: Non-market Values
3. Aggregate vs Disaggregate Damage Functions
4. Reliability of Potential Improvements
5. Improvements for Damages over Time

What Have We Learned Recently?

- IAMs do not utilize latest studies (usually use studies from 1990s)

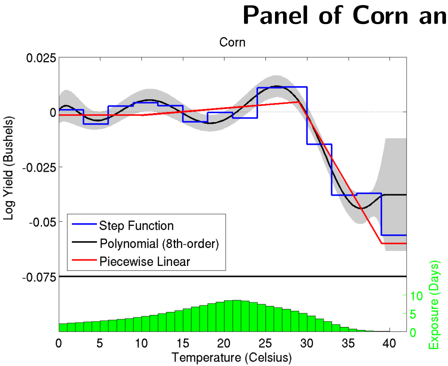
1. Statistical models
    - Data availability: new fine-scaled weather and yield data
    - Daily data available on temperature maxima, minima, etc
    - Crucial for nonlinear models
        - Averaging over space and/or time can "hide" nonlinearities
        - Key finding that extremes (especially temperature extremes matter most)
    - Uncertainty about predicted climate change
        - Need to look at range of possible outcomes, not just average outcome

2. Agronomic models
    - Agricultural Intercomparison and Improvement Project (AG-MIIP)
    - Similar to Coupled Model Intercomparison Project (CMIP5)
        - Use comparable set of input parameters
        - Comparison of model output

Link between Weather and US Yields

- Four commodity crops account for 75% of calories consumed by humans
  - Maize (corn), wheat, rice and soybeans
  - United States produces 23% of those calories
  - Global market share of US corn $> 40\%$
- Statistical analysis
  - Panel of county-level yields in Eastern United States
  - Corn and Soybeans (two biggest staple commodities in US)
  - Fine-scale weather (daily temperature / precip on 2.5mile grid)
  - Years: 1950-2005
- Model accounts for
  - Amount of time spent in each 1°C interval
  - Quadratic in total precipitation
  - State-specific quadratic time trends
  - County fixed effects

Results: Effect of Temperature on Yields



Source: Schlenker & Roberts (2009)

Temperature versus Precipitation

Few Selected Other Studies

- Corn Yields in Africa ▸ Slides
- Rice Yields in Asia ▸ Slides
- Wheat Trials in Kansas ▸ Slides

Outline

1 Recent Evidence that Can be Used in IAMs

2 Improvements for Damage Functions
- Adapting to Changes in Mean Climate
- Adapting to Changes in Climate Variability
- Damages: Non-market Values

3 Aggregate vs Disaggregate Damage Functions

4 Reliability of Potential Improvements

5 Improvements for Damages over Time

Outline

1. Recent Evidence that Can be Used in IAMs
2. Improvements for Damage Functions
   - Adapting to Changes in Mean Climate
   - Adapting to Changes in Climate Variability
   - Damages: Non-market Values
3. Aggregate vs Disaggregate Damage Functions
4. Reliability of Potential Improvements
5. Improvements for Damages over Time

Adapting Crops to a Warmer Climate

- Panel models may over or understate long-term impacts
  - Depends which set of adaptation strategies are larger
  - Short-term adaptation cost not captured in yield regression
- Recent evidence suggests that adaptation is difficult
  - Comparable results in panel and cross-section of farmland values
  - Comparable results in panel and when looking at trends (Burke and Emerick, 2013)
  - Comparable sensitivities in different climatic zones
  - Newer varieties seem more, not less sensitive to extreme heat
- More likely outcome
  - Shift where crops are grown
  - Change in comparative advantage (Costinot, Donaldson & Smith, 2014)
- Challenge
  - Soils not as good in higher latitudes
    - Last glacial expansion scraped off good top soil
  - Non-uniform warming (higher latitudes warm more)
  - Sunlight restrictions

Outline

1. Recent Evidence that Can be Used in IAMs
2. Improvements for Damage Functions
   - Adapting to Changes in Mean Climate
   - Adapting to Changes in Climate Variability
   - Damages: Non-market Values
3. Aggregate vs Disaggregate Damage Functions
4. Reliability of Potential Improvements
5. Improvements for Damages over Time

Adapting to An Increase in Variability

- Yield-weather function
  - Higher concavity at higher temperatures
  - Increase in mean temperature will increase production variability
    - Even if weather variability does not change
- Seems "relatively" easy to adapt to
  - Most crops are storable
  - Higher variability can be smoothed by higher storage
  - Higher average food prices (cover storage cost), but decreased variability

  Details
- Challenge
  - Export restrictions / government interventions
    - Disincentive to store

Outline

1. Recent Evidence that Can be Used in IAMs
2. Improvements for Damage Functions
   - Adapting to Changes in Mean Climate
   - Adapting to Changes in Climate Variability
   - Damages: Non-market Values
3. Aggregate vs Disaggregate Damage Functions
4. Reliability of Potential Improvements
5. Improvements for Damages over Time

Spillovers from Agriculture

- Agriculture is a major contributor to water / air pollution
  - Non-point sources are not regulated as stringently

- Some spillovers have not been studied much
  - Hotter climate can lead to more pests
  - Increased pesticide use (large and significant in agriculture: Eyal Frank)
  - Spillover for human health

- Pollutants (especially ozone) impact yields and livestock
  - Hotter temperatures can lead to more ozone
    - Crucial ingredient when VOCs and NOx combine to ozone

Outline

1. Recent Evidence that Can be Used in IAMs
2. Improvements for Damage Functions
   - Adapting to Changes in Mean Climate
   - Adapting to Changes in Climate Variability
   - Damages: Non-market Values
3. Aggregate vs Disaggregate Damage Functions
4. Reliability of Potential Improvements
5. Improvements for Damages over Time

Effect of Production Changes on Prices

- Disaggregate studies crucial to identify non-linearities
  - Check for adaptation by how response changes with climate
- Aggregate studies crucial for price feedbacks. My personal view
  - US farmers are likely benefiting from climate change
  - US is big player
    - Produces 23% of basic calories - corn, wheat, rice and soybeans
  - Significant drop in production (yields)
    - Price increase more than offsets this
    - Climate change "accomplishes" what supply restrictions tried to do
  - Consumers are hurt through higher food prices
- Effect on US depends on what happens to rest of the world
  - Price levels determined by aggregate supply / demand
  - Not uncommon to have large production shortfalls on one farmers
    - Crop insurance (free, i.e., fully subsidized) for yield drops below 50%
  - Individual shocks average out around globe
    - In the last 50 years: aggregate caloric shock $\pm 5.7\%$
- Demand and supply must be highly inelastic

IV to Identify Demand and Supply

- Roberts & Schlenker (2013)
  - Instrument: Yield Shock (deviations from trend)
  - Identification of Demand
    - Current yield shock shifts supply-curve
    - Used since P.G. Wright introduced IV (1928)
  - Identification of Supply
    - Past yield shocks shift expected price
    - Instrument futures price in supply equation
    - New extension: Previous estimates find inelastic supply, yet simulations use positive elasticity.
- Significant supply and demand elasticity
  - Demand: -0.05 / Supply 0.11
  - But where is new supply coming from?
    - Area-expansion can lead to deforestation (high source of CO_2 emissions)
    - Recent working papers on depforestation in Brazil
- Recent observed climate trends already have effect on food prices Slides

Outline

1. Recent Evidence that Can be Used in IAMs
2. Improvements for Damage Functions
   - Adapting to Changes in Mean Climate
   - Adapting to Changes in Climate Variability
   - Damages: Non-market Values
3. Aggregate vs Disaggregate Damage Functions
4. Reliability of Potential Improvements
5. Improvements for Damages over Time

What Model Should you Believe?

- Crucial importance of out-of-sample forecasts
- Recent forecasting exercise for wheat (Asseng et al, NCC 2014)
  - Researcher were given data at beginning and throughout growing season
    - 29 crop models / 1 statistical model
  - Asked to predict wheat yield at various stages
    - Subsequently compared to actual / measured yields
- Model mean performs better than any single model
  - Most crop models perform less well for very high temperatures
  - Simple statistical model performed very well!
  - Money ball: Parsimonious models can be very good predictors
- Average predicted reduction in yields
  - 6% for 1°C increase in temperature
- Recent predictive power of statical model

Outline

1. Recent Evidence that Can be Used in IAMs
2. Improvements for Damage Functions
   - Adapting to Changes in Mean Climate
   - Adapting to Changes in Climate Variability
   - Damages: Non-market Values
3. Aggregate vs Disaggregate Damage Functions
4. Reliability of Potential Improvements
5. Improvements for Damages over Time

Big Uncertainty: Exogenous Growth

- Agricultural output directly depends on weather / climate
  - Most of human history, largest share of population worked in agriculture
  - Climate fluctuations correlated with rise/demise of empires
    - Last 2500 years in Europe (Büntgen et al., 2011)
    - Roman empire, period of enlightenment, etc
- Agricultural (green) revolution
  - Before World War II
    - Increase in production through increase in growing area
    - Yields (output per area) rather constant
  - After World War II
    - Increase in production mostly through higher yields
    - Growing area increased moderately
- So far we model impacts *on top of trend*
  - Statistical models do not predict yields compared to today
    - If yield trends go up 100%
    - Climate change lowers yields by 40%
    - Yields are still 60% higher than today
  - Very difficult to model trend (not just agriculture)

Outline

6. Water versus Temperature
7. Yields in Africa
8. Rice Yields in Asia
9. Kansas Wheat Trials
10. Cross-Section in US Farmland Values
11. Adaptation to Production Variability
12. Observed Climate Change and Global Production Trends
13. Statistical Model: Recent Performance

Agronomic Evidence on Mechanism

- Biophysical evidence
  - Lobell, Hammer, McLean, Messina, Roberts, Schlenker (2013)
    - APSIM: biophysical model of crop growth
    - Includes water balance, etc
- Mechanism behind EDD (extreme heat)
  - Impacts water stress in two ways
    - Reducing soil water (evaporation)
    - Increased demand for soil water to sustain carbon uptake
  - Precipitation only impacts soil moisture
- Drought is a relative concept
  - Water requirements depend on temperature

Outline

6 Water versus Temperature

7 Yields in Africa

8 Rice Yields in Asia

9 Kansas Wheat Trials

10 Cross-Section in US Farmland Values

11 Adaptation to Production Variability

12 Observed Climate Change and Global Production Trends

13 Statistical Model: Recent Performance

Statistical Study in Africa

- Lobell, Bänzinger, Magorokosho, and Vivek (Nature Climate Change, 2011)
- Unique data set of field trials
  - 123 research stations
    - CIMMYT
  - Testing for drought conditions
- Matched with closest weather station
  - Better than gridded weather data
  - Authors split season into three phases (separate coefficients)
- Major results
  - Find nonlinearity effect of temperature on yield
  - Stronger under drought conditions

Outline

6. Water versus Temperature
7. Yields in Africa
8. Rice Yields in Asia
9. Kansas Wheat Trials
10. Cross-Section in US Farmland Values
11. Adaptation to Production Variability
12. Observed Climate Change and Global Production Trends
13. Statistical Model: Recent Performance

Rice Yields in Asia

- Welch, Vincent, Auffhammer, Moya, Dobermann & Dawe (PNAS, 2010)
- Rice field trials through South-eastern Asia
- Matched with weather station
  - Authors split season into three phases (separate coefficients)
- Major results
  - Effect varies by growing phase
  - Maximum and minimum temperatures have opposite effects
    - Higher maximum temperatures are beneficial
    - Lower minimum temperatures are harmful

Outline

6 Water versus Temperature

7 Yields in Africa

8 Rice Yields in Asia

9 Kansas Wheat Trials

10 Cross-Section in US Farmland Values

11 Adaptation to Production Variability

12 Observed Climate Change and Global Production Trends

13 Statistical Model: Recent Performance

Wheat in Kansas

- Tack, Barkley, and Nalley (PNAS, 2015)
- Unique data set of fiel trials
  - Kansas wheat variety field trials
    - 1985-2013
    - September - May growing season (split in fall, winter, spring)
- Matched with field-level weather data
  - Using full distribution between minimum and maximum temperature gives much better fit
- Major results
  - Biggest driver of yield losses: freezes and extreme heat
  - Climate change reduces freeze damage, increase damage from extreme heat
  - Newer varieties more sensitive to extreme heat than older varieties

Outline

6 Water versus Temperature

7 Yields in Africa

8 Rice Yields in Asia

9 Kansas Wheat Trials

10 Cross-Section in US Farmland Values

11 Adaptation to Production Variability

12 Observed Climate Change and Global Production Trends

13 Statistical Model: Recent Performance

Adaptation: Evidence from Cross-Section

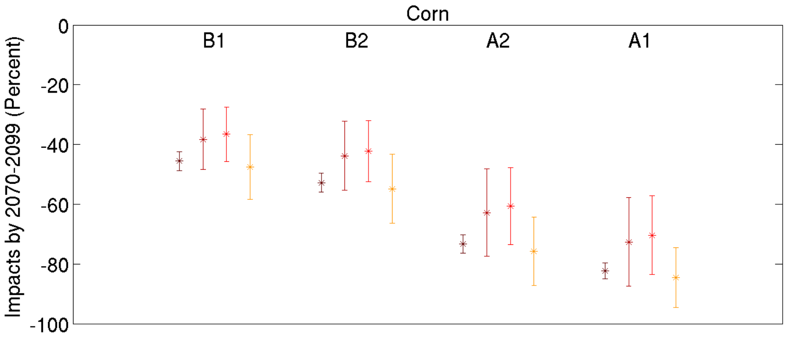
- Can crop switching save the day?
- Cross-sectional analysis of farmland values
  - Accounting for extreme heat
  - Limit to Eastern United States
  - Schlenker, Hanemann, and Fisher (2006)
- Similar results
  - Large negative effect of extreme heat
  - Robust to myriad of specification checks
    - Different census years
    - Permutations of other control variables

Predicted Changes under Hadley III

Variable	2020–2049 Average (%) Mean	Min.	Max.	σ	2070–2099 Average (%) Mean	Min.	Max.	σ
Hadley HadCM3—Scenario B1								
Degree days (8–32°C)	−0.96	−26.83	24.33	12.11	−4.44	−41.73	49.83	20.13
Degree days (34°C)	−11.17	−33.66	2.75	4.82	−26.21	−59.01	−1.86	9.57
Precipitation	1.02	−19.51	13.26	4.99	1.11	−21.31	11.33	4.35
Total impact	−10.46	−58.58	28.02	16.21	−27.37	−78.77	44.15	22.58
Std. error, total impact	(2.89)	(4.85)	(4.51)		(4.90)	(4.83)	(8.93)	
Hadley HadCM3—Scenario B2								
Degree days (8–32°C)	−1.38	−31.50	30.37	14.02	−6.79	−45.71	60.91	22.40
Degree days (34°C)	−19.77	−42.84	−2.09	7.35	−29.79	−73.26	−8.20	12.73
Precipitation	−1.22	−30.61	13.42	5.44	0.18	−37.45	13.70	5.84
Total impact	−20.57	−67.67	34.41	18.66	−31.61	−88.28	52.37	26.57
Std. error, total impact	(3.44)	(4.75)	(5.70)		(5.17)	(3.66)	(11.20)	
Hadley HadCM3—Scenario A2								
Degree days (8–32°C)	−1.44	−30.12	30.11	14.19	−14.90	−52.76	80.70	26.54
Degree days (34°C)	−20.12	−49.19	−3.96	8.12	−56.53	−84.78	−23.59	10.85
Precipitation	−0.32	−28.56	8.94	3.83	−2.70	−41.48	15.83	7.62
Total impact	−20.21	−69.31	29.70	19.72	−61.64	−94.72	27.87	20.25
Std. error, total impact	(3.58)	(4.86)	(5.22)		(6.01)	(2.44)	(11.48)	
Hadley HadCM3—Scenario A1FI								
Degree days (8–32°C)	−0.54	−28.82	31.07	13.28	−23.29	−56.83	91.38	27.10
Degree days (34°C)	−24.99	−50.49	1.04	9.42	−63.16	−90.97	−20.08	13.39
Precipitation	−0.22	−15.15	13.28	4.39	−0.80	−41.66	18.74	9.20
Total impact	−24.50	−60.38	23.83	18.68	−68.54	−96.95	39.61	21.79
Std. error, total impact	(4.00)	(5.61)	(4.65)		(5.90)	(1.86)	(13.85)	

Source: Schlenker, Hanemann & Fisher (2006)

Predicted Changes under Hadley III - Yield Panel



Source: Schlenker, Hanemann & Fisher (2006) ▸ Back to Adaptation to Mean Change

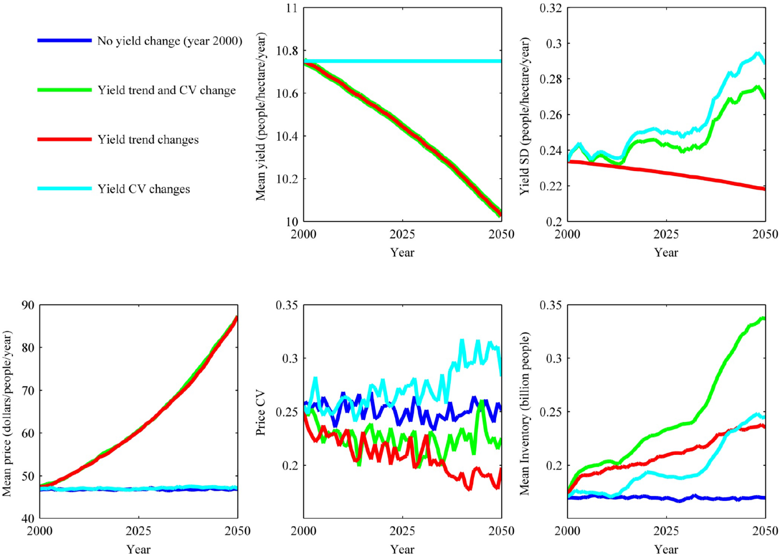
Outline

6. Water versus Temperature
7. Yields in Africa
8. Rice Yields in Asia
9. Kansas Wheat Trials
10. Cross-Section in US Farmland Values
11. Adaptation to Production Variability
12. Observed Climate Change and Global Production Trends
13. Statistical Model: Recent Performance

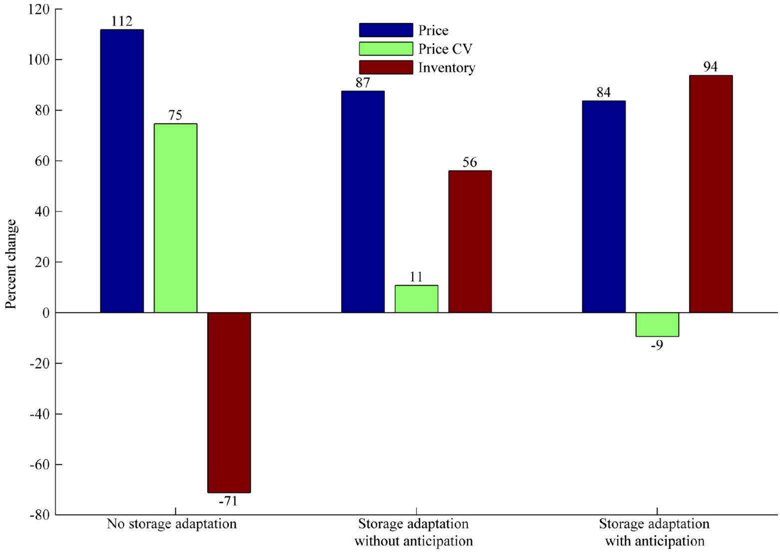
Yield Variability in the Future

- Highly nonlinear relationship between yields and temperature
- Increase in mean temperature
  - Reduction in average yields
    - Increase in frequency of extreme heat
  - Increase in yield variability
    - Even if weather variability does not change
    - Relationship between yields and weather have higher curvature
    - Same weather fluctuation result in larger yield swings
- Will food prices become more variable?
  - Calibrate a storage model
  - Storage driven by arbitrage between periods
    - If production more variable, incentive to hold more stock
    - Higher stock levels: higher average price as storage costly, but less variability

Adaptation: Storage can Smooth Variability



Adaptation: Storage can Smooth Variability



Back to Adaptation to Change in Variability

Outline

6 Water versus Temperature

7 Yields in Africa

8 Rice Yields in Asia

9 Kansas Wheat Trials

10 Cross-Section in US Farmland Values

11 Adaptation to Production Variability

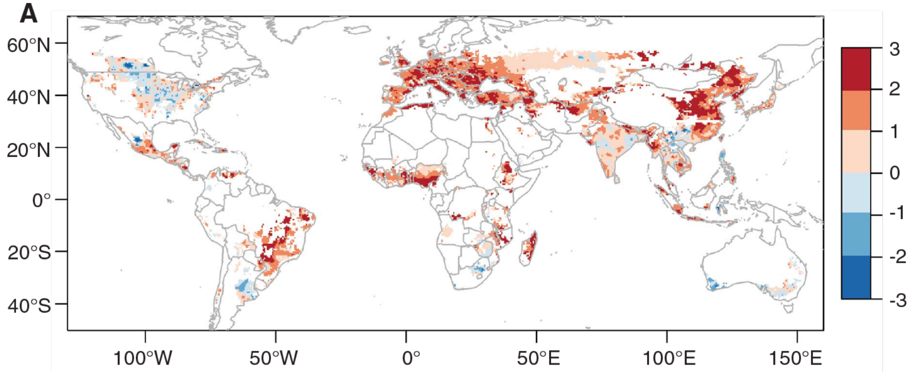
12 Observed Climate Change and Global Production Trends

13 Statistical Model: Recent Performance

Observed Climate Trends and Food Prices

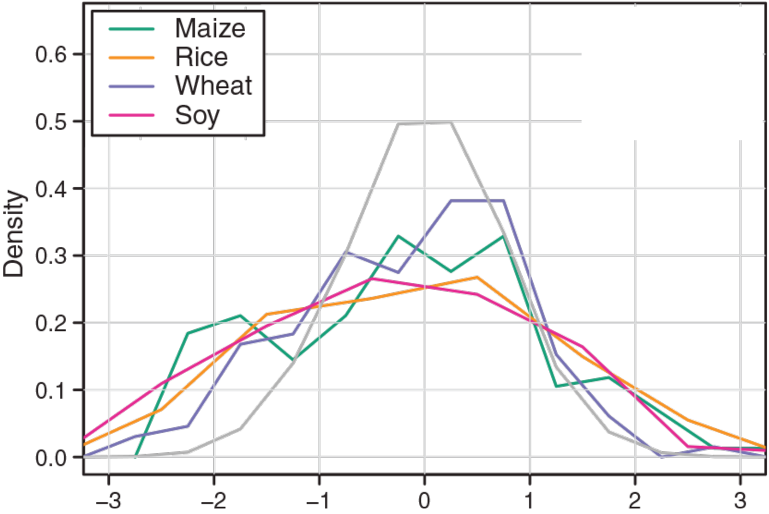
- Do climate trends already have an effect on food production
  - Statistical model linking yields to weather
    - Predicted production under observed trend
    - Predicted production if trend is removed
  - Difference in global production
- Focus on four major staples
  - Maize, rice, soybeans, wheat
  - Responsible for 75% of global caloric production
- Panel of country-level yields (FAO data)
  - Matched with weather data (University of Delaware)
  - Averaged over area where crop is grown
    - Monfreda, Ramankutty & Foley 2008
  - Averaged over crop-specific growing season
    - Sacks, Deryng, Foley & Ramankutty (2010)

Temperature Trend (1980-2008) in Historic Std. Deviation



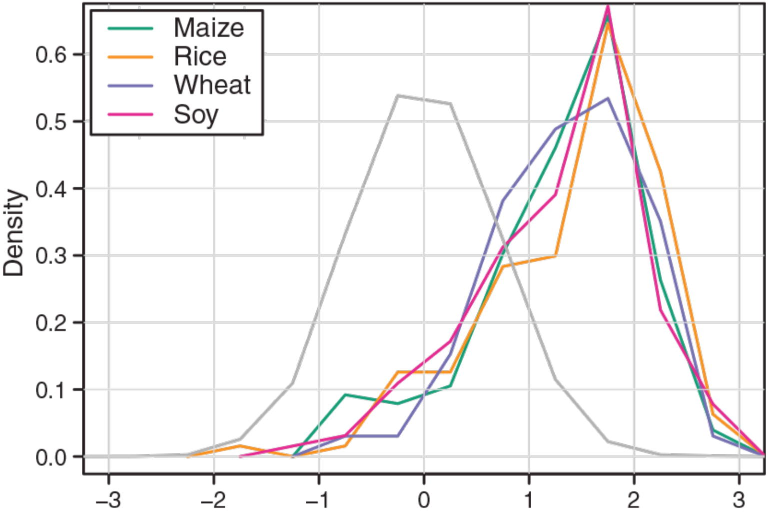
Lobell, Schlenker & Costa-Roberts (2011)

Country-Crop Specific Temperature Trends (1960-1980)



Lobell, Schlenker & Costa-Roberts (2011)

Country-Crop Specific Temperature Trends (1980-2008)



Lobell, Schlenker & Costa-Roberts (2011)

Predicted Impact of Observed Trend

Crop	Global production, 1998–2002 average (millions of metric tons)	Global yield impact of temperature trends (%)	Global yield impact of precipitation trends (%)	Subtotal	Global yield impact of CO_2 trends (%)	Total
Maize	607	−3.1 (−4.9, −1.4)	−0.7 (−1.2, 0.2)	−3.8 (−5.8, −1.9)	0.0	−3.8
Rice	591	0.1 (−0.9, 1.2)	−0.2 (−1.0, 0.5)	−0.1 (−1.6, 1.4)	3.0	2.9
Wheat	586	−4.9 (−7.2, −2.8)	−0.6 (−1.3, 0.1)	−5.5 (−8.0, −3.3)	3.0	−2.5
Soybean	168	−0.8 (−3.8,1.9)	−0.9 (−1.5, −0.2)	−1.7 (−4.9, 1.2)	3.0	1.3

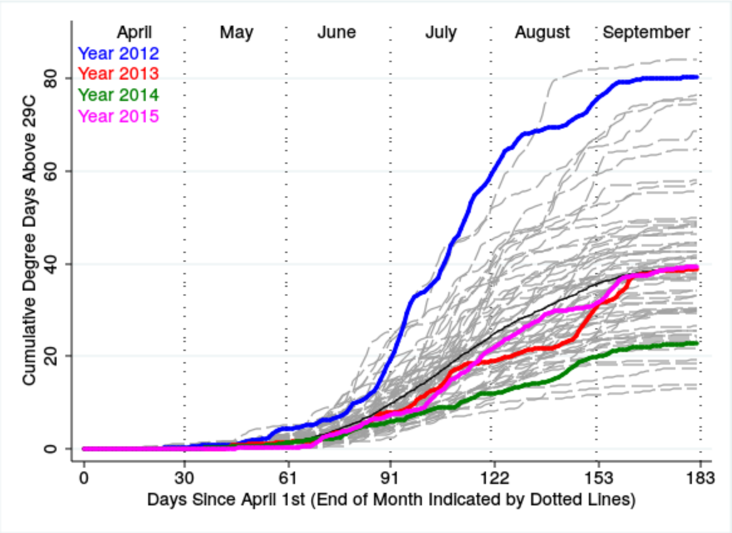
Combined Price Effect: 18.9% (no CO_2 fertilization), 6.4% (including CO_2 fertilization)

Lobell, Schlenker & Costa-Roberts (2011) Back to Price Elasticities

Outline

6. Water versus Temperature
7. Yields in Africa
8. Rice Yields in Asia
9. Kansas Wheat Trials
10. Cross-Section in US Farmland Values
11. Adaptation to Production Variability
12. Observed Climate Change and Global Production Trends
13. Statistical Model: Recent Performance

Statistical Model: 2012-2015 Compared to 1950-2010



Source: Berry, Roberts & Schlenker (2013)