Lecture 14

Climate Change

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AEM 6510

Roadmap

- Estimating the effects of climate change
  - Ricardian model
  - Weather / two way fixed effects approach
- Integrated assessment
  - Dynamic Integrate Climate-Economy (DICE) model

Estimating the effect of climate change: ideal

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This is the gold standard in science: a randomized control trial (RCT)

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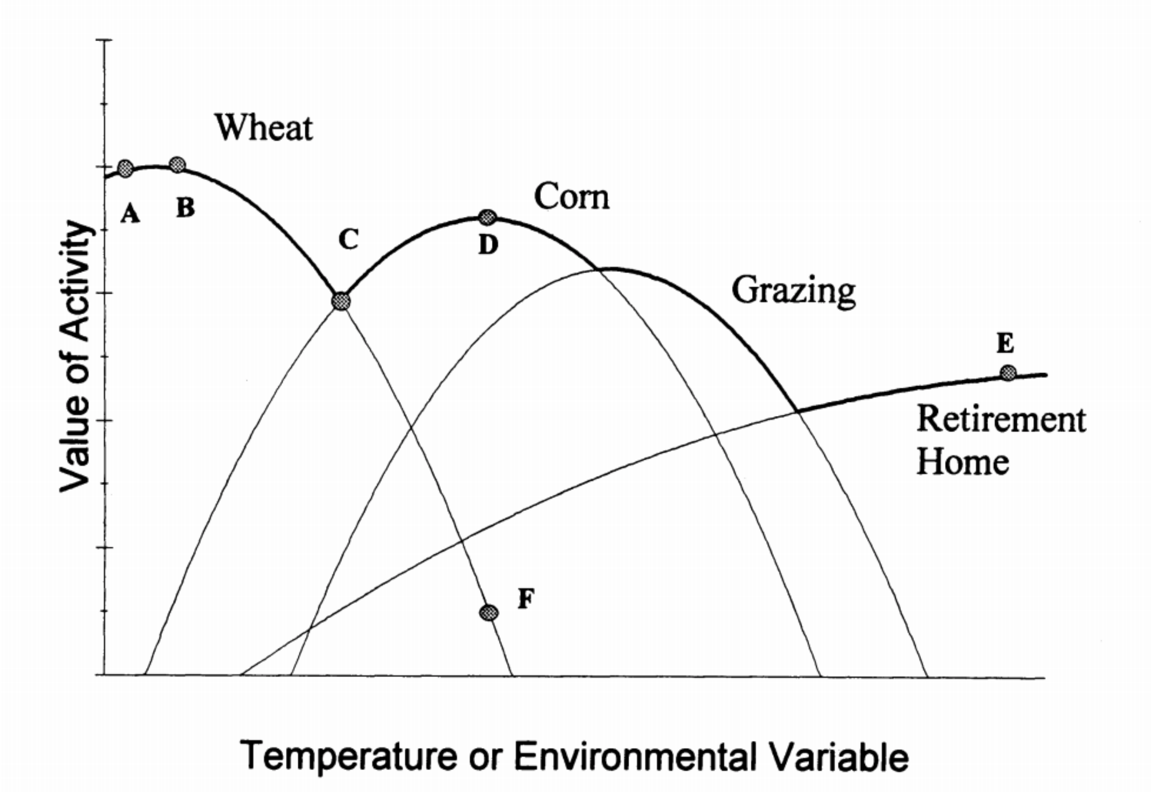
Main idea: Compare *farmland values* in areas with different climates, conditional on other relevant variables



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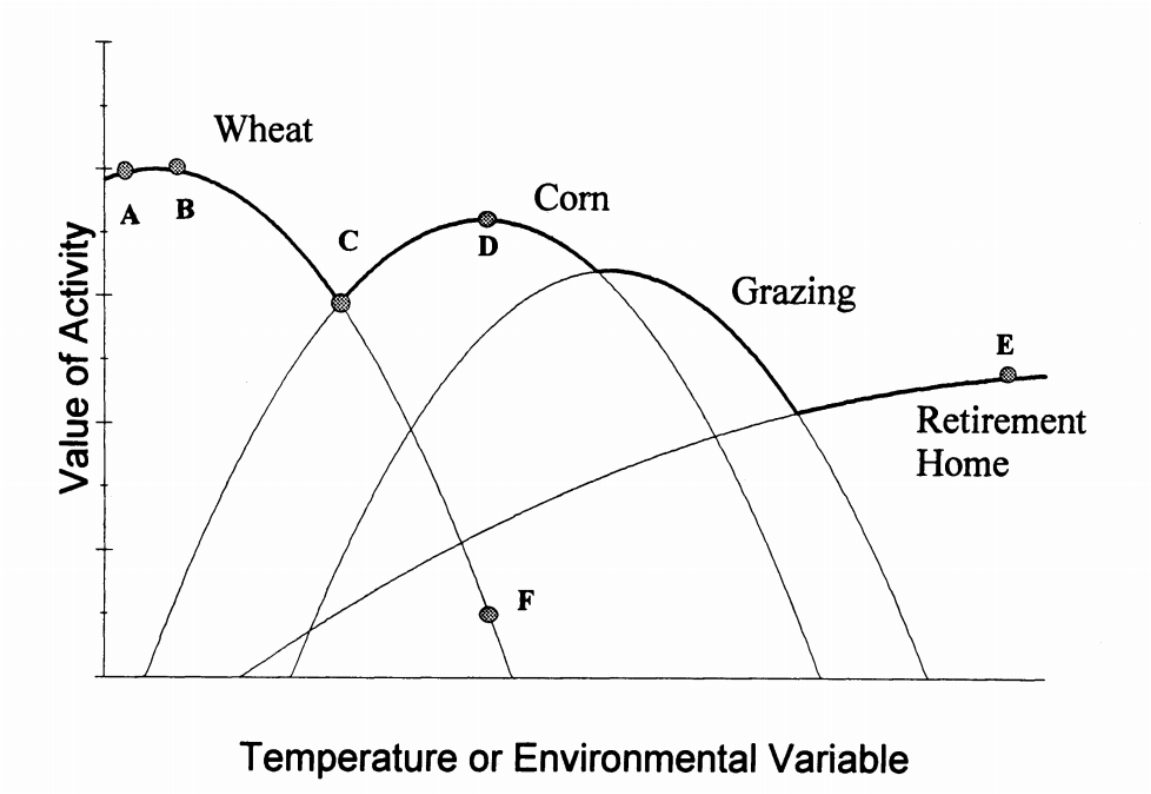

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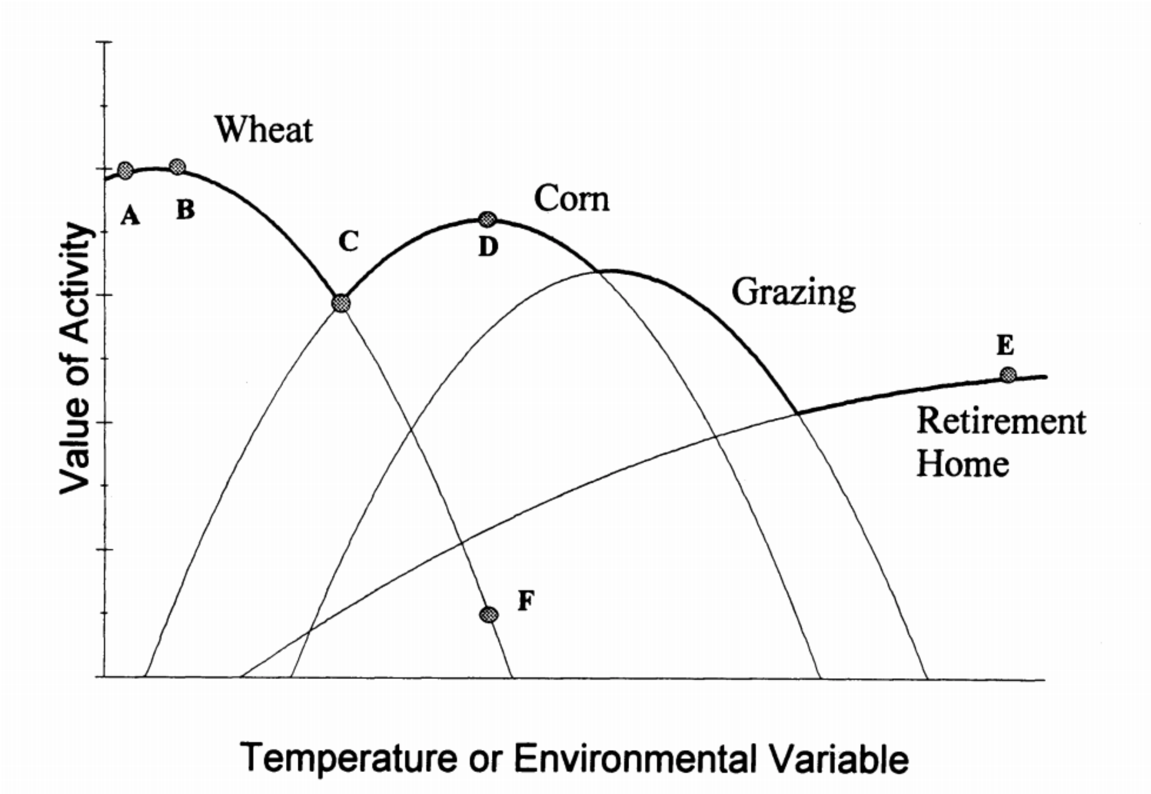
What do farmland values tell us?



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1. Agriculture is expected to be very climate sensitive
2. Lots of good data relative to other sectors (for 1994)

Mendelsohn, Nordhaus, Shaw (1994): Data

Ag data: 1982 Census of Agriculture

Climate data: 30 year average temperature and precipitation (normal) from 1951-1980

Socio-economic data

Soil data

Mendelsohn, Nordhaus, Shaw (1994): Estimation

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Climate must be uncorrelated with omitted variables (conditional on controls), **no omitted variable bias** -- examples later

Mendelsohn, Nordhaus, Shaw (1994)

TABLE 3—REGRESSION MODELS EXPLAINING FARM VALUES

Independent variables	Cropland weights 1982 (i)	Cropland weights 1982 (ii)	Cropland weights 1978 (iii)	Crop-revenue weights 1982 (iv)	Crop-revenue weights 1978 (v)
Constant	1,490	1,329	1,173	1,451	1,307
	(71.20)	(60.18)	(57.95)	(46.36)	(52.82)
January temperature	−57.0	−88.6	−103	−160	−138
	(6.22)	(9.94)	(12.55)	(12.97)	(13.83)
January temperature squared	−0.33	−1.34	−2.11	−2.68	−3.00
	(1.43)	(6.39)	(11.03)	(9.86)	(14.11)
April temperature	−137	−18.0	23.6	13.6	31.8
	(10.81)	(1.56)	(2.23)	(1.00)	(2.92)
April temperature squared	−7.32	−4.90	−4.31	−6.69	−6.63
	(9.42)	(7.43)	(7.11)	(9.44)	(11.59)
July temperature	−167	−155	−177	−87.7	−132
	(13.10)	(14.50)	(18.07)	(6.80)	(12.55)
July temperature squared	−3.81	−2.95	−3.87	−0.30	−1.27
	(5.08)	(4.68)	(6.69)	(0.53)	(2.82)
October temperature	351.9	192	175	217	198
	(19.37)	(11.08)	(11.01)	(8.89)	(9.94)
October temperature squared	6.91	6.62	7.65	12.4	12.4
	(6.38)	(7.09)	(8.93)	(12.50)	(15.92)
January rain	75.1	85.0	56.5	280	172
	(3.28)	(3.88)	(2.81)	(9.59)	(7.31)
January rain squared	−5.66	2.73	2.20	−10.8	−4.09
	(1.86)	(0.95)	(0.82)	(3.64)	(1.72)
April rain	110	104	128	82.8	113
	(4.03)	(4.44)	(5.91)	(2.34)	(4.05)
April rain squared	−10.8	−16.5	−10.8	−62.1	−30.6
	(1.17)	(1.96)	(1.41)	(5.52)	(3.35)
July rain	−25.6	−34.5	−11.3	−116	−5.28
	(1.87)	(2.63)	(0.94)	(6.06)	(0.34)
July rain squared	19.5	52.0	37.8	57.0	34.8
	(3.42)	(9.43)	(7.54)	(8.20)	(6.08)
October rain	−2.30	−50.3	−91.6	−124	−135
	(0.09)	(2.25)	(4.45)	(3.80)	(5.15)
October rain squared	−39.9	2.28	0.25	171	106
	(2.65)	(0.17)	(0.02)	(14.17)	(11.25)

Data are weighted either by cropland or crop-revenue

Results are pretty sensitive to this choice: cropland weights

Mendelsohn, Nordhaus, Shaw (1994)

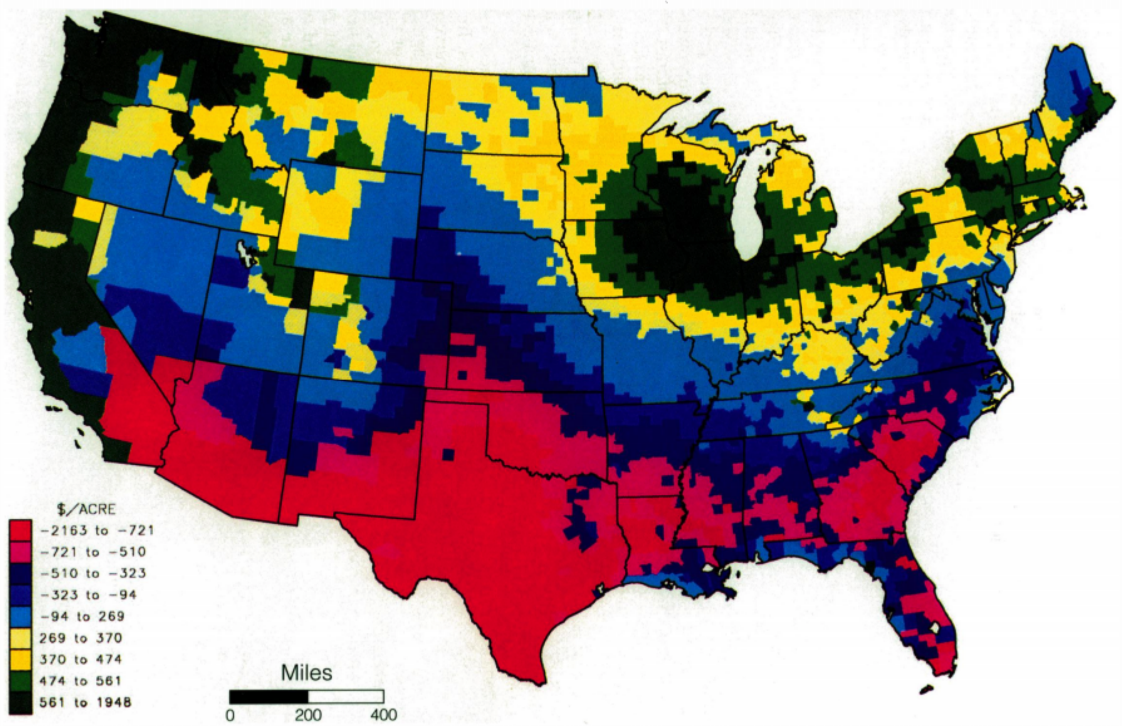

FIGURE 2. INFLUENCE OF CURRENT CLIMATE ON FARM VALUES: CROPLAND WEIGHTS
Note: Farm value is measured as the difference in dollars per acre from the sample average, 1982 prices.

The value of current climate for farmland across the US

Mendelsohn, Nordhaus, Shaw (1994)

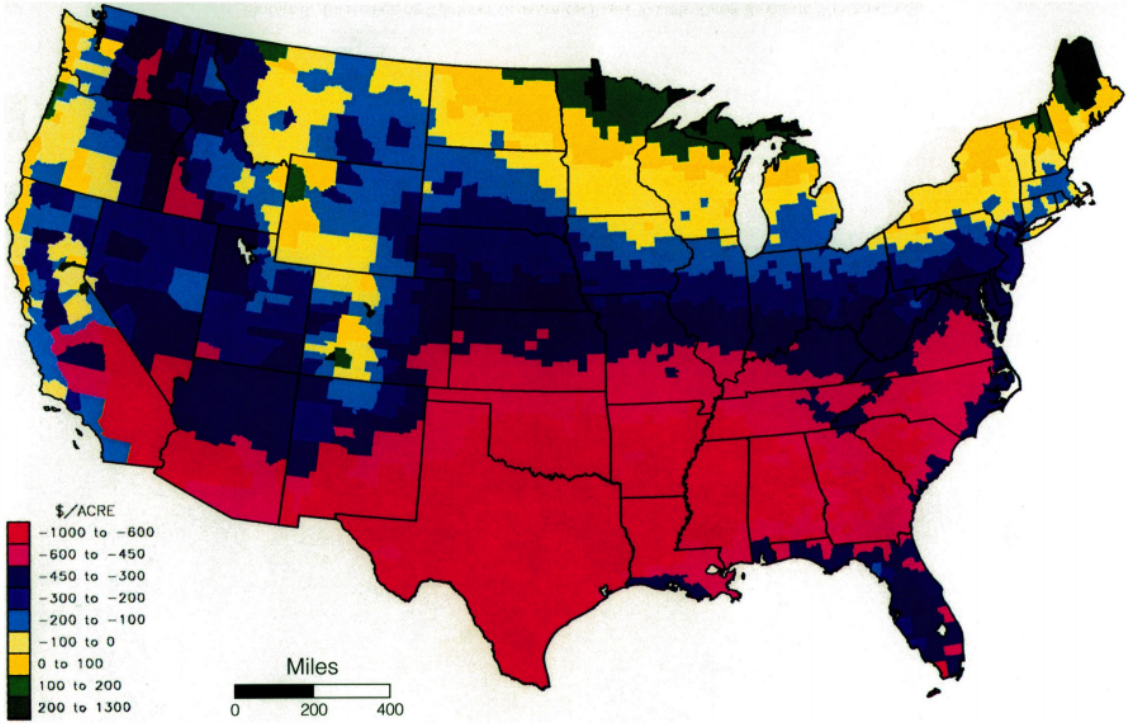

FIGURE 4. CHANGE IN FARM VALUE FROM GLOBAL WARMING: CROPLAND WEIGHTS
Note: The map shows the change in terms of dollars per acre for a 5° F uniform warming and an 8-percent increase in precipitation, 1982 prices.

The value of 5°C of warming and 8% increase in precipitation under farmland weighting

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The value of 5°C of warming and 8% increase in precipitation under crop-revenue weighting

This shows a very different story because crop-revenue weights put more emphasis on irrigated land and products which will likely do better under a warmer, more humid climate

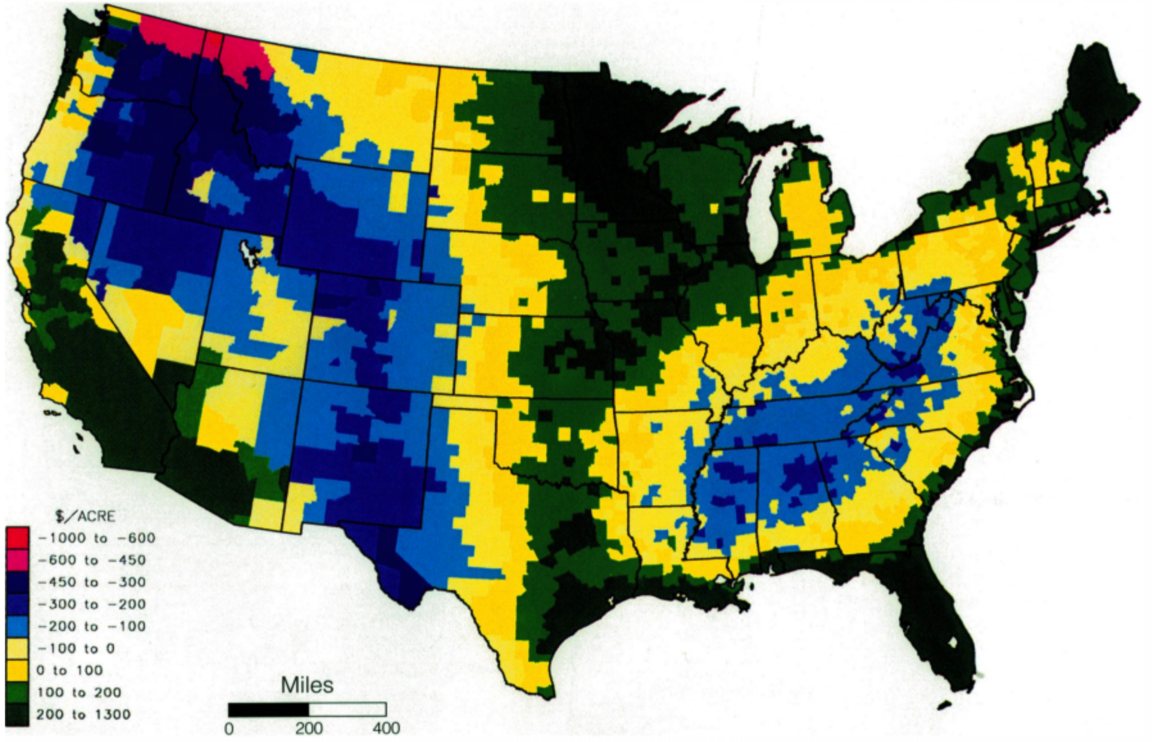

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TABLE 5—PREDICTED IMPACT OF GLOBAL WARMING ON FARMLAND VALUES AND FARM RENTS

		Change in farmland values (billions of dollars, 1982 prices)		Change in farmland rents (percentage of 1982 farm marketings)	
Year	Weight	Impact	Truncated impact	Impact	Truncated impact
1982	Cropland	−\$125.2	−\$118.8	−4.4	−4.2
1978	Cropland	−\$162.8	−\$141.4	−5.7	−4.9
1982	Crop revenue	\$34.5	\$34.8	1.2	1.2
1978	Crop revenue	−\$14.0	\$21.0	−0.5	0.7

Notes: The global-warming scenario is a uniform 5°F increase with a uniform 8-percent precipitation increase. The "impact" column shows the estimated loss; the "truncated impact" columns show the impact when the loss in farmland value in each county is limited to the original value of the land. The last two columns are annualized impacts, as explained in the text, as a percentage of 1982 farm marketings.

Results are pretty different depending on weighting

Overall takeaway: climate change could be moderately bad (4-6% losses), or mildly positive

Cross-section issues

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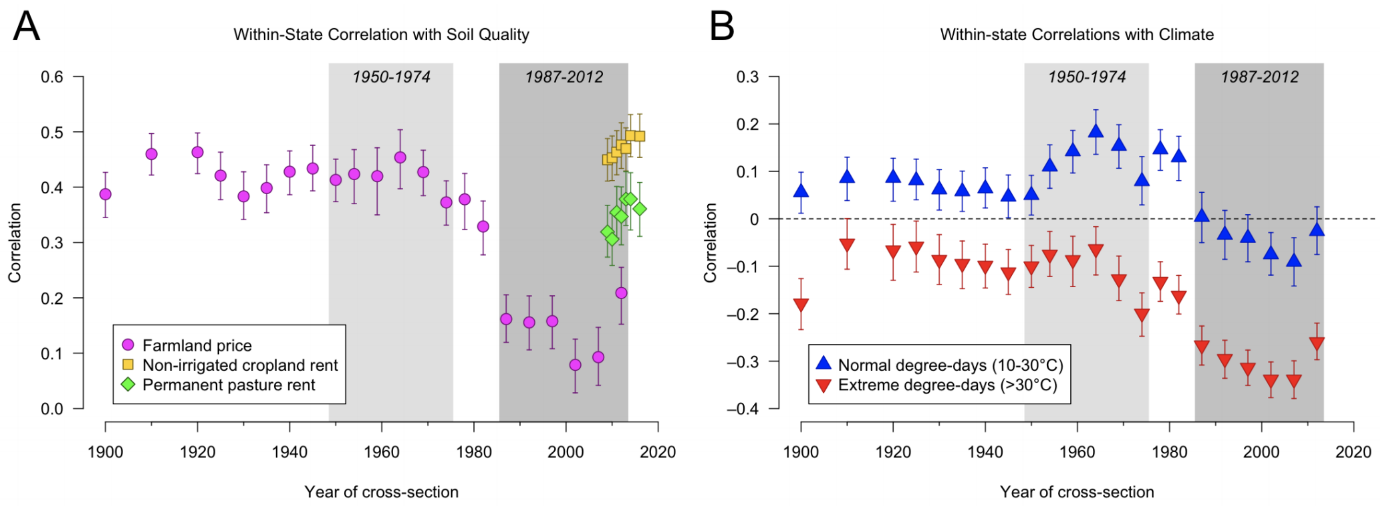
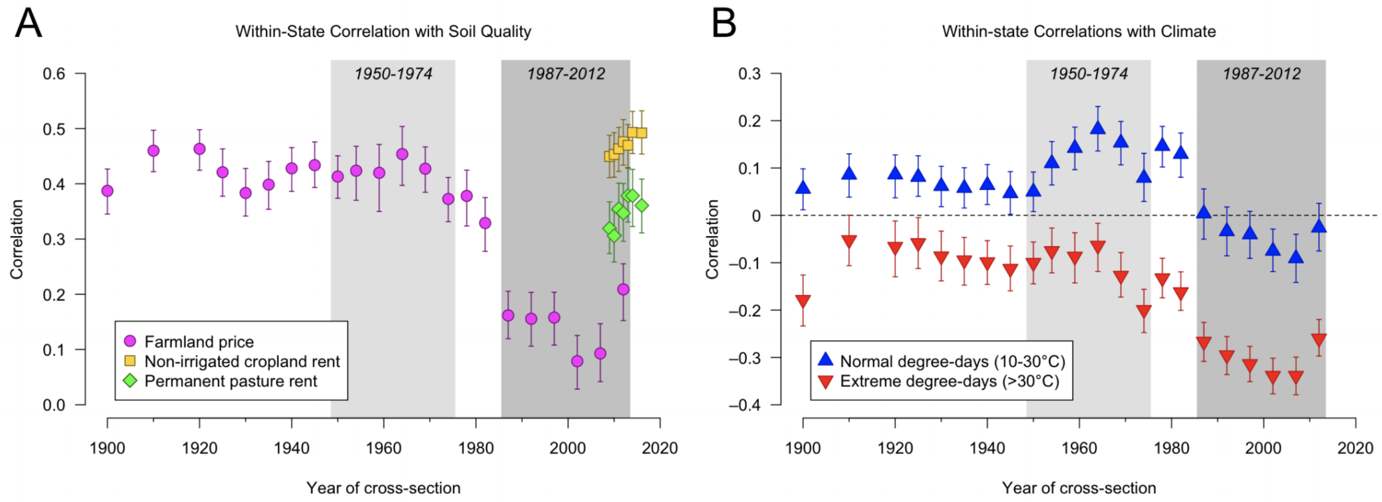
Ozone, wealth, other productive uses of land besides agriculture, lots of things

Ortiz-Bobea (2019)



Ortiz-Bobea (2019)

Since 1900, correlations between farmland values and soil quality and measures of climate are decreasing



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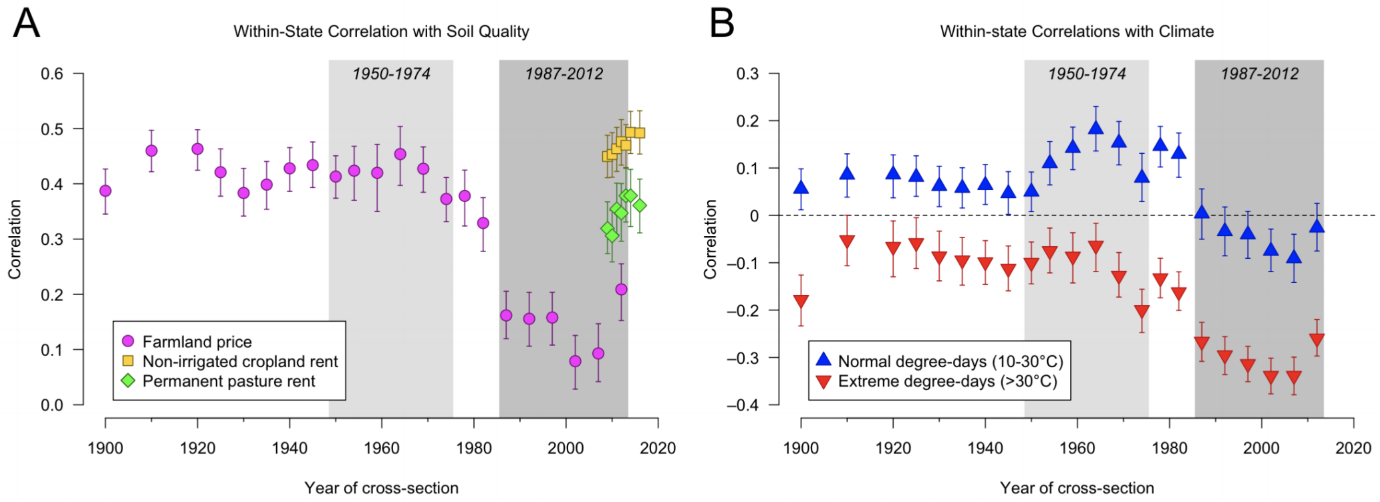

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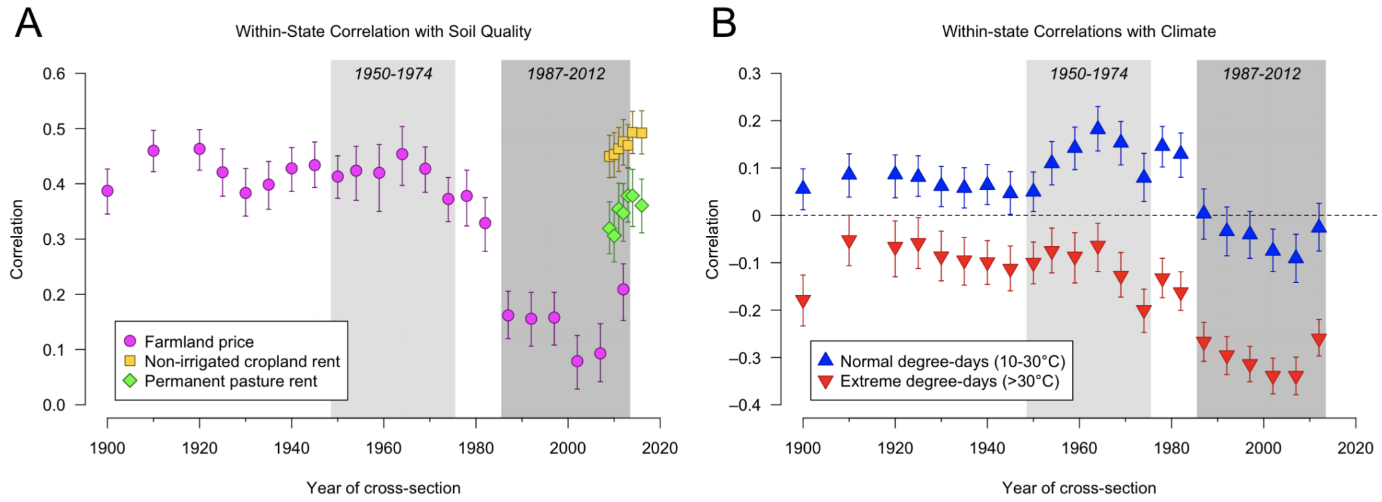

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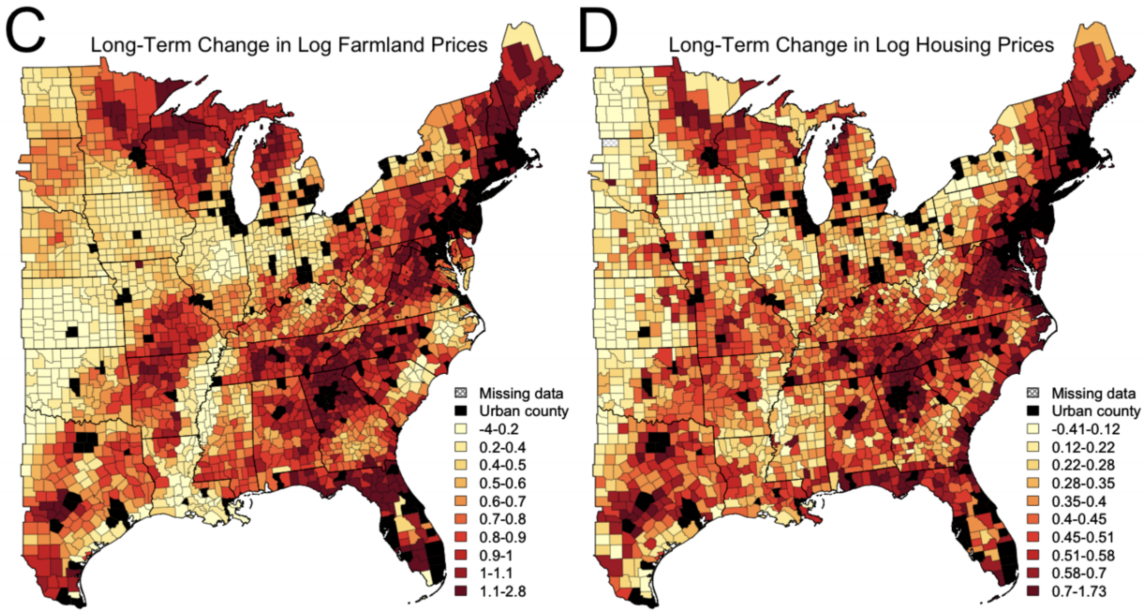
What could be driving this?

Ortiz-Bobea (2019)

Big increases in farmland value in weird places (Ozark and Appalachin Mountains, Vermont, upper Minnesota)



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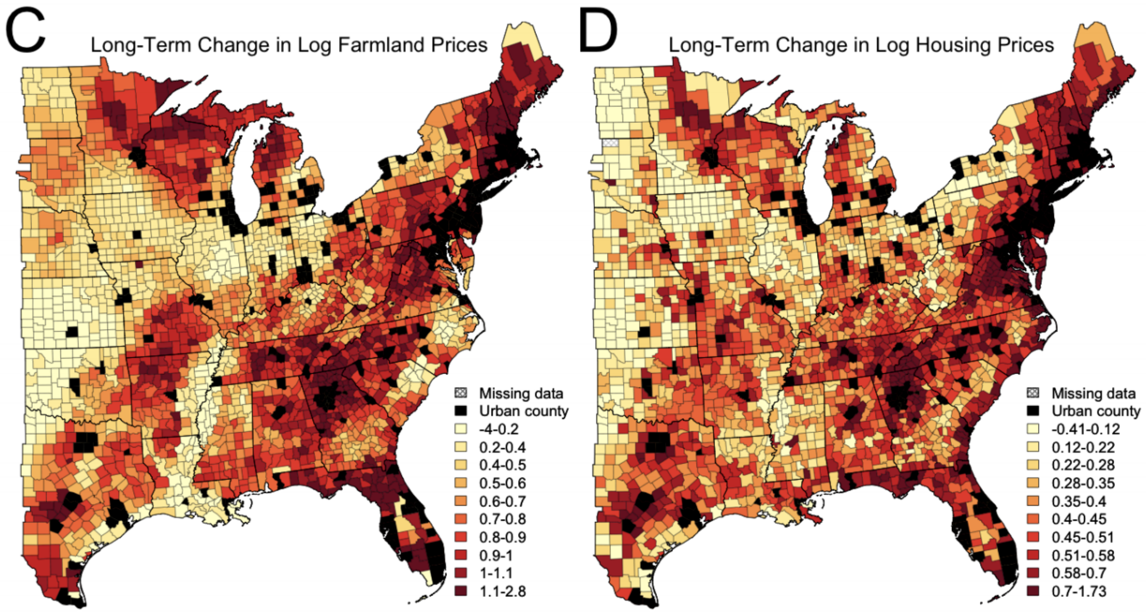

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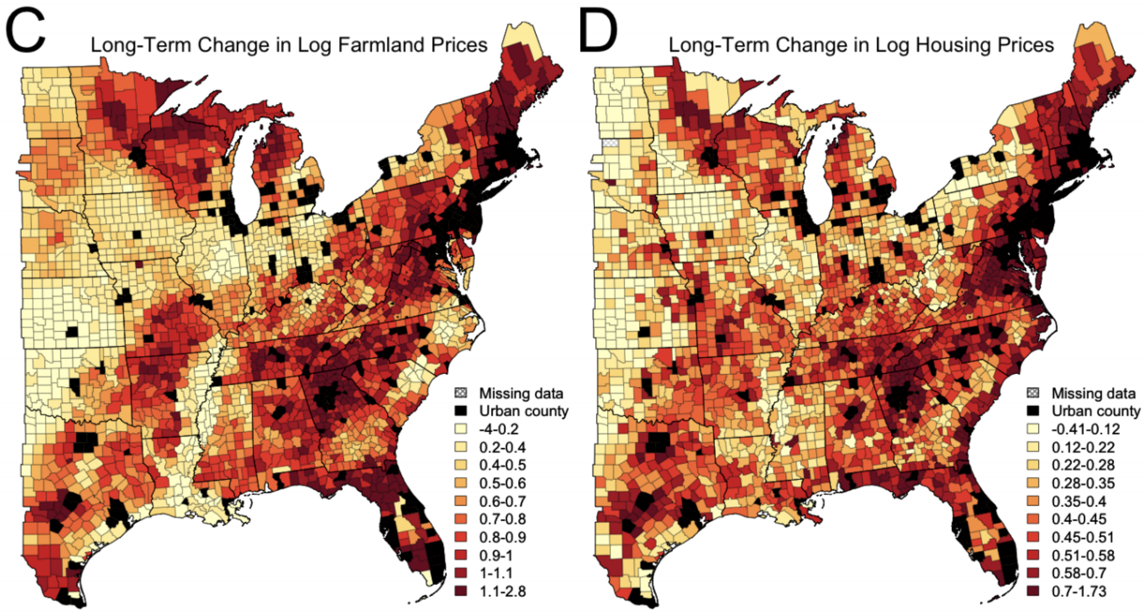

This points to demand for land for non-farm purposes (vacation homes!) as a primary driver of farmland values

Ortiz-Bobea (2019)

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Estimates may be biased up or down depending on how housing demand depends on climate

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It is difficult to control for lots and lots of variables in the cross-section so this approach has fallen out of favor in recent years

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Climate is spatially correlated with economic development: countries in cooler climates are generally richer, have more safety net policies, etc

- Comparing in the cross-section will **overstate** the effect of climate change on mortality: countries in cooler climates are healthier because they're rich, not only because their climate is cooler

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Will not account for adaptation: mortality doesn't capture expected future outcomes like farmland values do, people will migrate, buy air conditioning, etc

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- Comparing in the cross-section will **understate** the effect of climate change: we are ignoring the fact that we can't draw upon groundwater forever

Panel approaches to estimation

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How? Let's find out

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Suppose that the true relationship for climate change on farmland value is

$$\text{farmland value}_{it} = \textbf{time invariant vars}_i \cdot \alpha + \textbf{climate vars}'_{it} \cdot \beta + \textbf{controls}'_{it} \cdot \gamma + \varepsilon_{it}$$

It is the same as before but now we have observations for each county i and year t

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We are going to show how to control for **all** of these in a simple way

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This effectively demeans all the data **within each i** (for each location i, subtract the mean within i across t off each it observation), let bars indicate means within i, demeaning gives us:

$$\text{farmland value}_{it} - \overline{\text{farmland value}_{it}} =$$
$$(\textbf{time invariant vars}_i' - \overline{\textbf{time invariant vars}_i}') \cdot \alpha +$$
$$(\textbf{climate vars}_{it}' - \overline{\textbf{climate vars}_{it}}') \cdot \beta +$$
$$(\textbf{controls}_{it}' - \overline{\textbf{controls}_{it}}') \cdot \gamma + \varepsilon_{it}$$

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$$\overline{\textbf{time invariant vars}_i} = \textbf{time invariant vars}_i$$

It falls out of the estimating equation!

Panel approaches to estimation

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This is why this approach is called **fixed effects:** we can control for anything 'fixed' (i.e. time-invariant) within i by demeaning the data within i

Panel approaches to estimation

$$\text{farmland value}_{it} - \overline{\text{farmland value}_{it}} = $$
$$(\textbf{climate vars}'_{it} - \overline{\textbf{climate vars}_{it}}') \cdot \beta + (\textbf{controls}'_{it} - \overline{\textbf{controls}_{it}}') \cdot \gamma + \varepsilon_{it}$$

What does this mean?

Panel approaches to estimation

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What does this mean?

All variables that are time-invariant within a county over time are implicitly controlled for when we demean the data!

This means we do not need to explicitly control for time-invariant things like soil quality, elevation, average sunlight, etc for which we might not have data

Panel approaches to estimation

We re-write the equation by including county fixed effects $\alpha_{\mathbf{i}}$

$$\text{farmland value}_{it} = \alpha_{\mathbf{i}} + \textbf{climate vars}'_{it} \cdot \beta + \textbf{controls}'_{it} \cdot \gamma + \varepsilon_{it}$$

where α_i is a dummy variable equal to 1 for county i and 0 otherwise

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Since α_i is always the same for county i no matter which year t, it effectively controls for all things in county i that are not changing over time, $\textbf{time invariant vars}'_i$, just like demeaning the data

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Mathematically, it just gives each county i its own intercept term $\alpha_{\mathbf{i}}$

Panel approaches to estimation

Notice that there's nothing special about doing this with respect to i

Panel approaches to estimation

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We could easily do this with respect to t for variables that are changing over time but are common across all counties so there is no i index

$$\text{farmland value}_{it} = \textbf{common vars}_t' \cdot \alpha + \textbf{climate vars}_{it}' \cdot \beta + \textbf{controls}_{it}' \cdot \gamma + \varepsilon_{it}$$

Panel approaches to estimation

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$$\text{farmland value}_{it} = \textbf{common vars}_t' \cdot \alpha + \\ \textbf{climate vars}_{it}' \cdot \beta + \textbf{controls}_{it}' \cdot \gamma + \varepsilon_{it}$$

Take the average of the all the variables within a given year t (across all counties), and then demean the variables

Panel approaches to estimation

$$
\begin{gathered}
\text{farmland value}_{it} - \overline{\text{farmland value}_{it}} = \\
(\mathbf{common\ vars}_t' - \overline{\mathbf{common\ vars}_t}') \cdot \alpha + \\
(\mathbf{climate\ vars}_{it}' - \overline{\mathbf{climate\ vars}_{it}}') \cdot \beta + \\
(\mathbf{controls}_{it}' - \overline{\mathbf{controls}_{it}}') \cdot \gamma + \varepsilon_{it}
\end{gathered}
$$

where now the bar indicates the average within each year t

Panel approaches to estimation

$$
\begin{gathered}
\text{farmland value}_{it} - \overline{\text{farmland value}_{it}} = \\
(\mathbf{common\ vars}'_t - \overline{\mathbf{common\ vars}_t}') \cdot \alpha + \\
(\mathbf{climate\ vars}'_{it} - \overline{\mathbf{climate\ vars}_{it}}') \cdot \beta + \\
(\mathbf{controls}'_{it} - \overline{\mathbf{controls}_{it}}') \cdot \gamma + \varepsilon_{it}
\end{gathered}
$$

where now the bar indicates the average within each year t

Similar to before, $\mathbf{common\ vars}'_t = \overline{\mathbf{common\ vars}_t}$ since these variables are not changing within a given t

Panel approaches to estimation

This gives us:

$$\text{farmland value}_{it} - \overline{\text{farmland value}_{it}} =$$
$$(\textbf{climate vars}'_{it} - \overline{\textbf{climate vars}_{it}}') \cdot \beta + (\textbf{controls}'_{it} - \overline{\textbf{controls}_{it}}') \cdot \gamma + \varepsilon_{it}$$

This is the same idea as when we demeaned within each county i so its equivalent to each year having its own intercept:

$$\text{farmland value}_{it} = \eta_{\mathbf{t}} + \textbf{climate vars}'_{it} \cdot \beta + \textbf{controls}'_{it} \cdot \gamma + \varepsilon_{it}$$

where $\eta_{\mathbf{t}}$ is called a year fixed effect

Panel approaches to estimation

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What does this control for?

Recessions, the current president, nationwide ag policy, etc

Panel approaches to estimation

What does this mean?

All variables that are invariant across all counties within a year are implicitly controlled for when we demean the data

What does this control for?

Recessions, the current president, nationwide ag policy, etc

This effectively gives each **year** t its own unique intercept $\eta_{\mathbf{t}}$

Two way demeaning: fixed effects

Key thing: we can have fixed effects for i and t at the same time to simultaneously control for:

1. Variables that are constant within a county over time
2. Variables that are constant across counties within a given year

$$\text{farm outcome}_{it} = \alpha_{\mathbf{i}} + \eta_{\mathbf{t}} + \textbf{climate vars}'_{it} \cdot \beta + \textbf{controls}'_{it} \cdot \gamma + \varepsilon_{it}$$

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This is the norm for panel regressions in applied economics (although you can't do this with farmland values)

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Note that you can't have a fixed effect with respect to i **and** t here

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A county-by-year fixed effect controls for all things that are time-invariant within a county-year (e.g. things not changing in Tompkins County in 2019)

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Our data only vary at the county-year level

A county-by-year fixed effect would control for everything on which we have data: we can't actually estimate anything

Alternative explanation for FE in climate economics

What's the "gold standard" for estimating causal effects?

Alternative explanation for FE in climate economics

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Randomized control trials

Alternative explanation for FE in climate economics

What's the "gold standard" for estimating causal effects?

Randomized control trials

Suppose we have a group of 100 people and want to know the effect of a drug on hypertension

We randomly assign 50 people to get treatment (e.g. drugs), and the other 50 people are controls (e.g. no drugs)

Alternative explanation for FE in climate economics

Since we randomly assigned treatment, both groups should be identical **on average**

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Alternative explanation for FE in climate economics

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The difference we see between the two groups in average hypertension outcomes after the drug treatment can be attributed to the drug

Randomization is key for estimating the effect of different kinds of treatments

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Is climate random from our (the economist's) perspective?

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Tourist economies are selected to be in specific climates

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But in Ithaca in January, *there's some randomness in how cold it is on any given day relative to long-run average January temperature*

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Is weather random from our (the economist's) perspective?

Sort of i: We know Ithaca's generally cold in January and warm in July

But in Ithaca in January, *there's some randomness in how cold it is on any given day relative to long-run average January temperature*

This long-run average temperature/weather is what we call the **climate**: C_{it}

As good as random weather

If we demean the data to control for time-invariant climate features of a county i, and trends in climate t what are we estimating the effect of?

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When farmers decide to plant in spring, they can't predict deviations from average weather during the summer growing season for any day

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If we demean the data to control for time-invariant climate features of a county i, and trends in climate t what are we estimating the effect of?

Deviations in weather from average weather

We might think these are as good as random

When farmers decide to plant in spring, they can't predict deviations from average weather during the summer growing season for any day

The deviations from average are effectively random from the farmer's perspective

Weather vs climate

If weather is random, then we can estimate the **marginal effect of weather**

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Why?

Weather vs climate

Climate change is a long-run phenomenon: in the long-run we might have more ways to adapt

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Note: we did see an example earlier for why the bias might go the other way

Deschenes and Greenstone

This 'random weather' approach was used by Deschenes and Greenstone (2007) to estimate the effect of weather on **farm profits**

$$\text{farm profits}_{it} = \alpha_{\mathbf{i}} + \eta_{\mathbf{t}} + \textbf{climate vars}'_{it} \cdot \beta + \textbf{controls}'_{it} \cdot \gamma + \varepsilon_{it}$$

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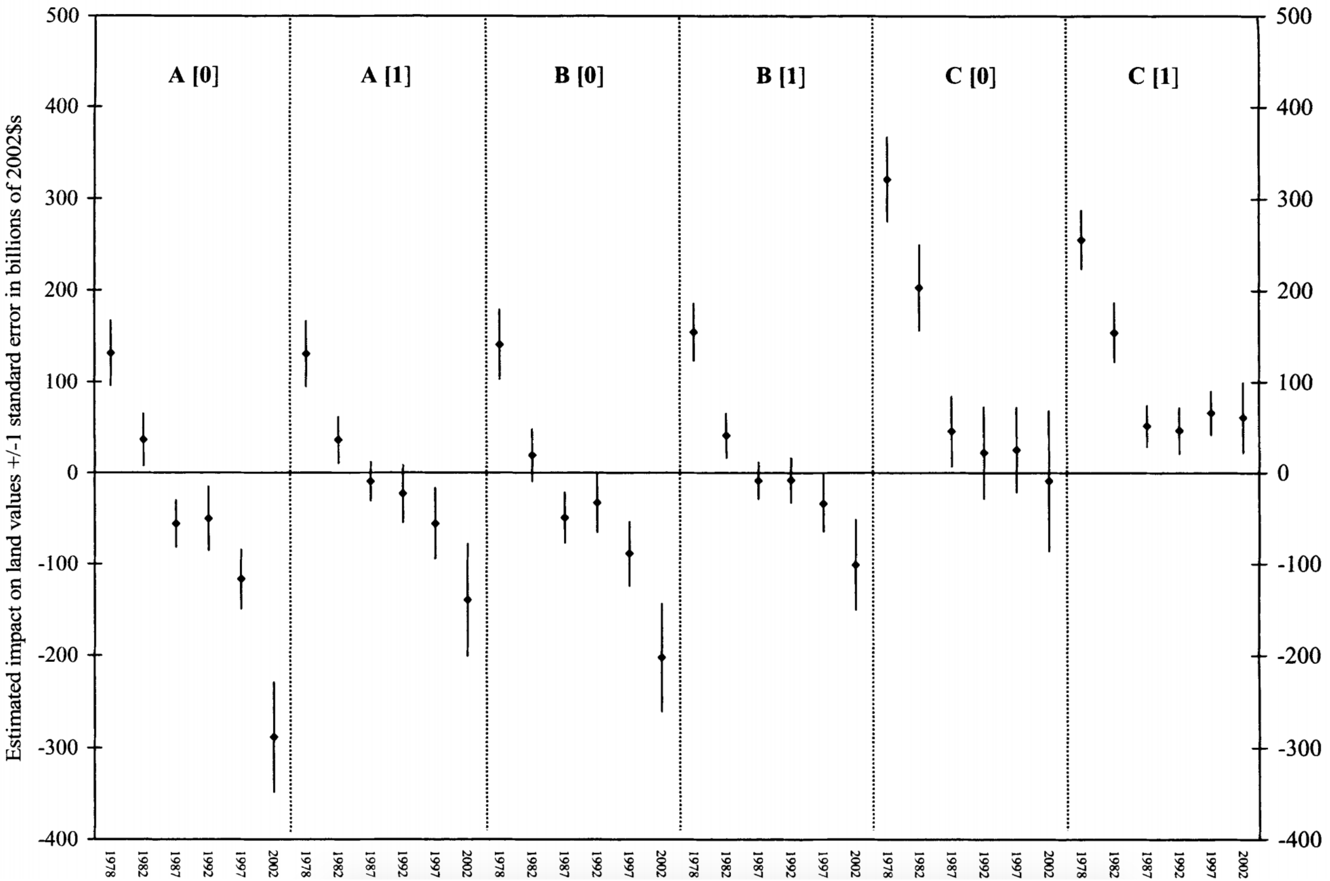
Why profits?

Because farmland values shouldn't change in response to random annual weather shocks

- Since they're random and transient, not permanent changes, they won't have lasting effects on land values

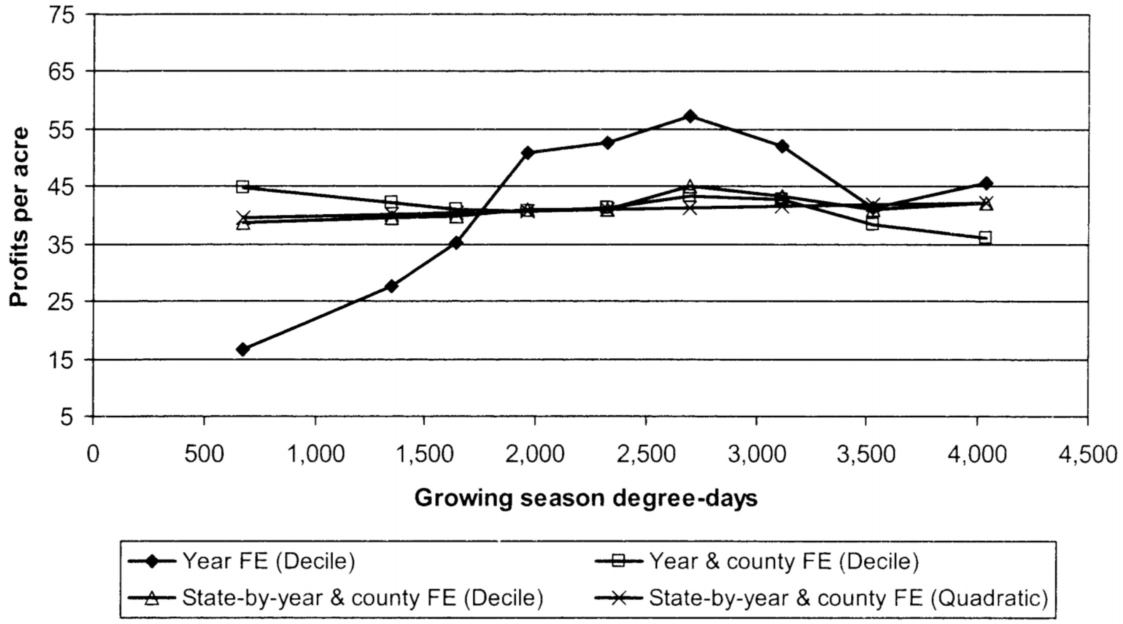
Deschenes and Greenstone: cross-section

DG shows why the cross-sectional approach doesn't cut it, the estimated effects are very sensitive to controls, sample



Deschenes and Greenstone: panel

DG use **degree days** to capture climate: the sum of daily average temperature during the growing season



Main takeaway: little effect of climate change!

Deschenes and Greenstone: panel

This is super surprising right?

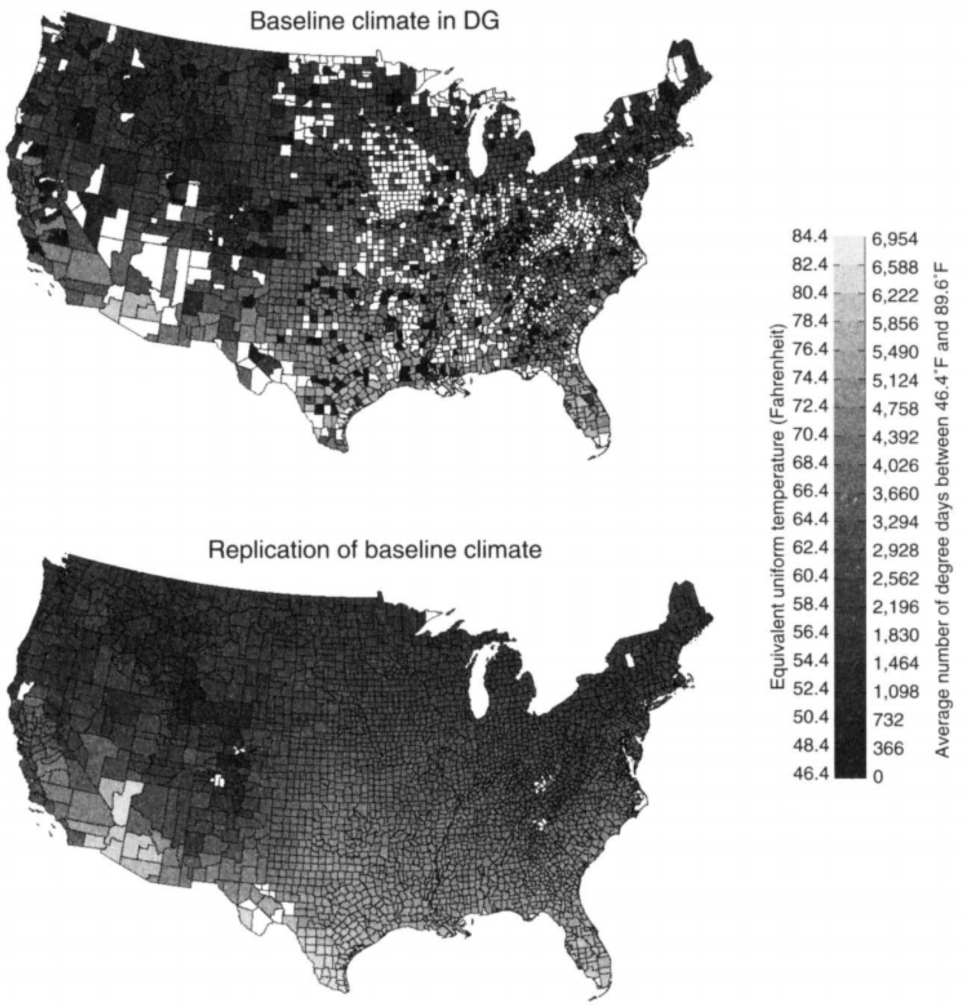


FIGURE 1. BASELINE CLIMATE IN DESCHÊNES AND GREENSTONE

Deschenes and Greenstone: panel

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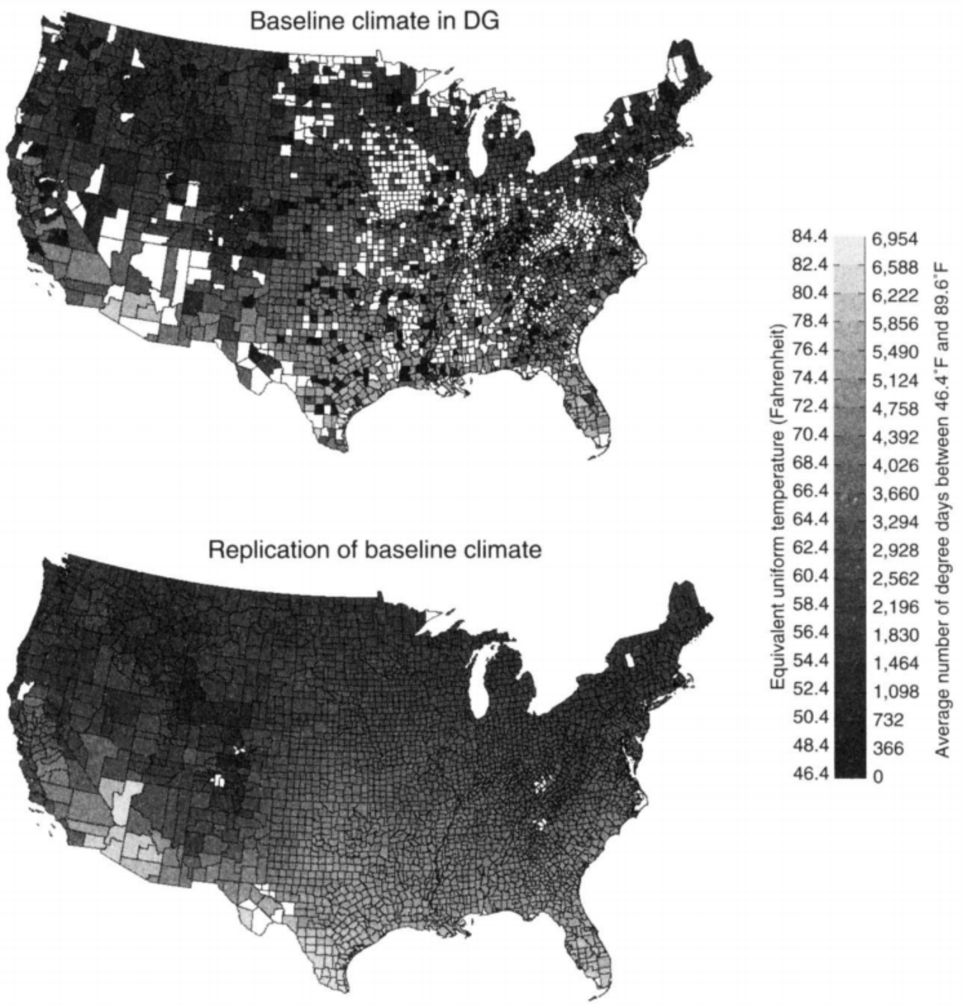

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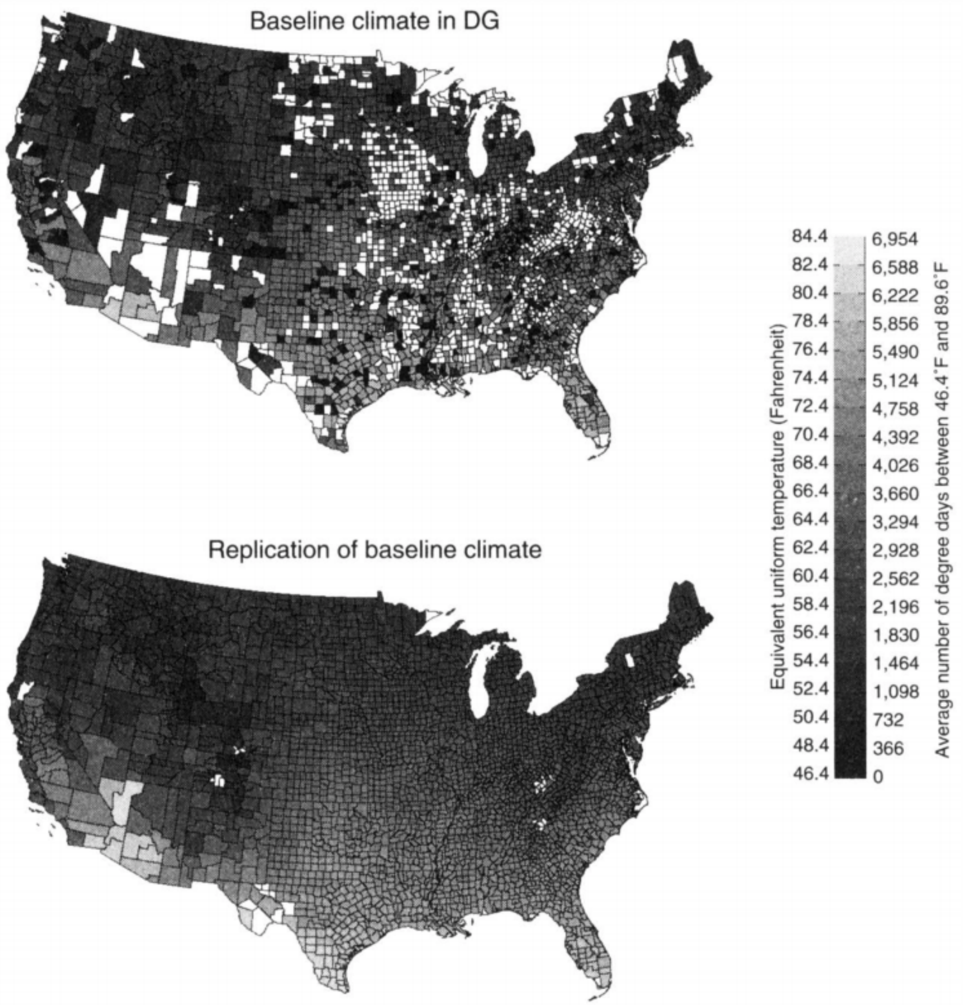

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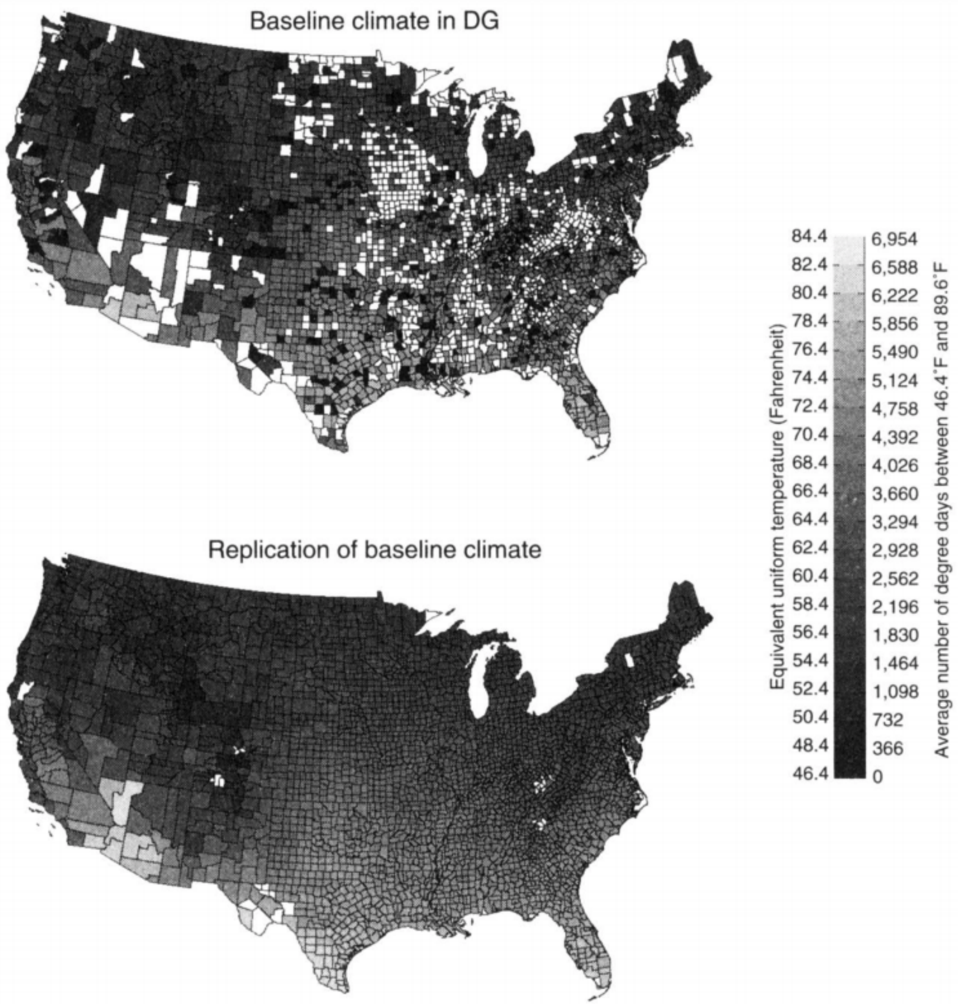
In the short run, we'd think very hot weather would be bad for crops

We'd expect farmers have little ability to adapt to (randomly) hot weather during the growing season



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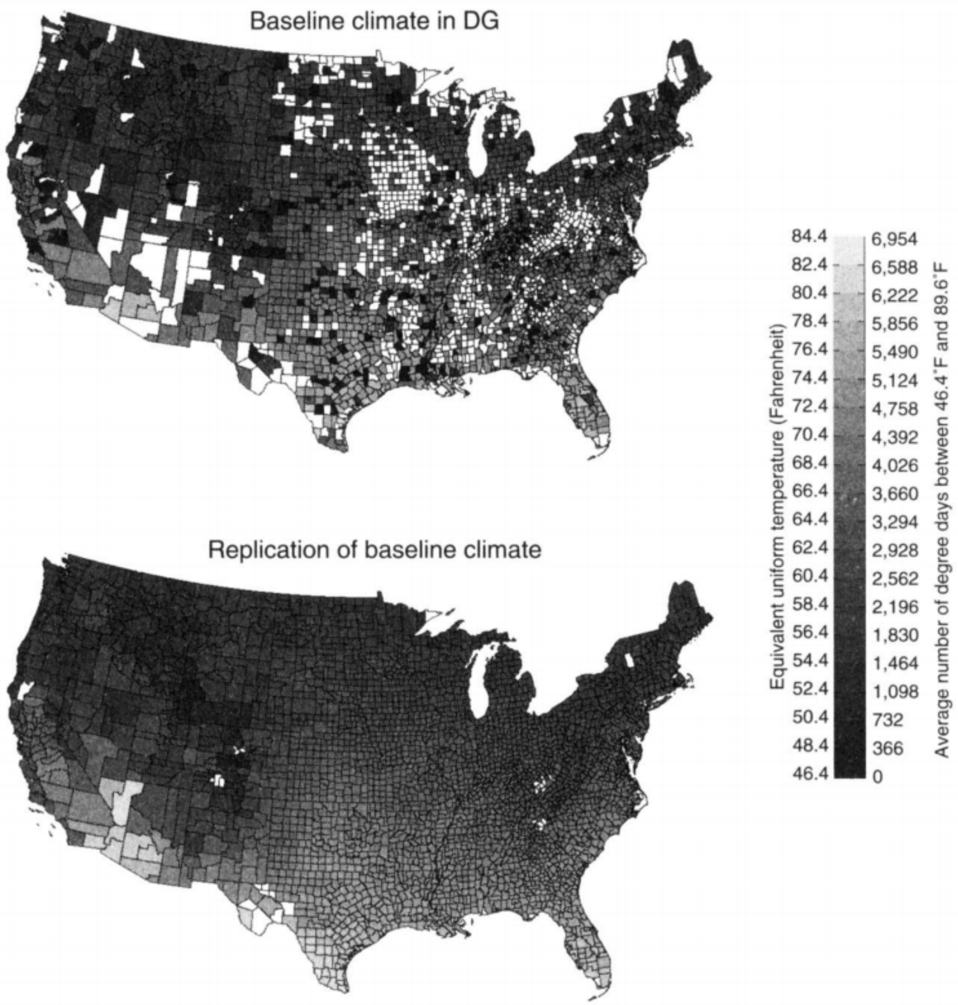
In the long run, it would be less surprising to find little effect since farmers can change crops or add irrigation if its persistently hot



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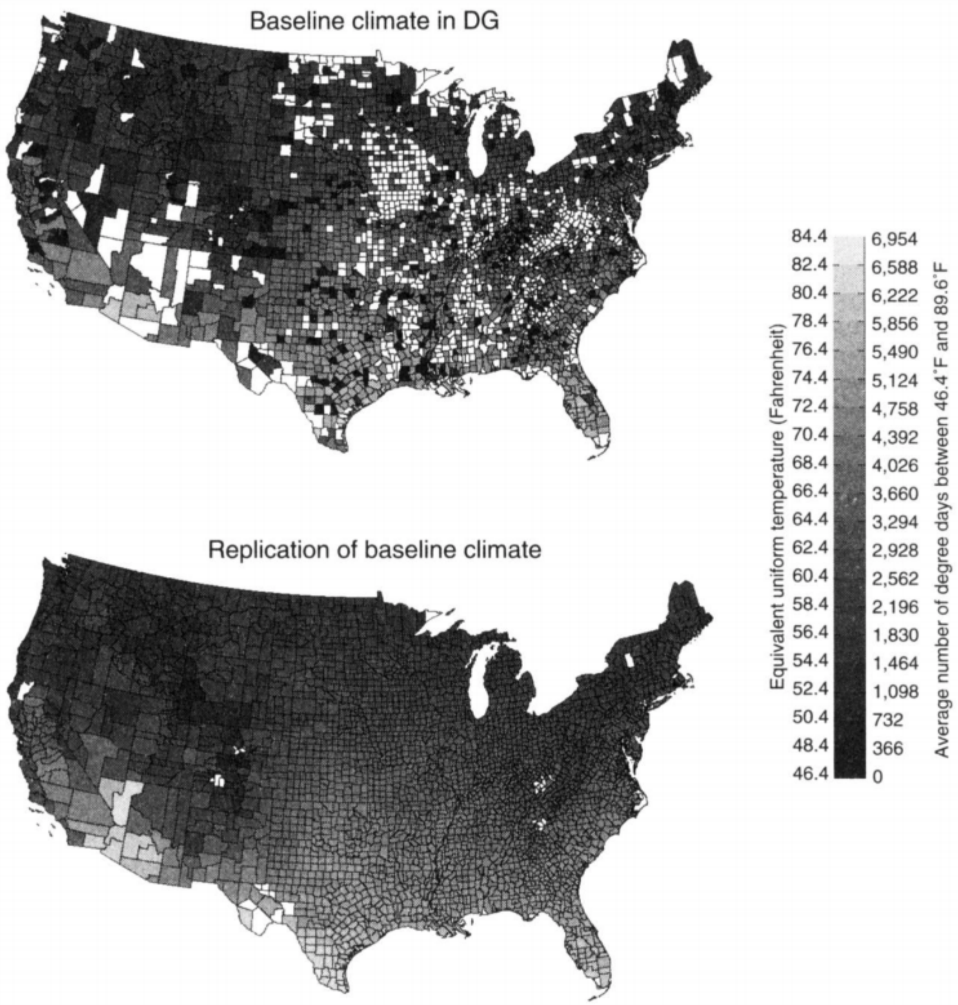

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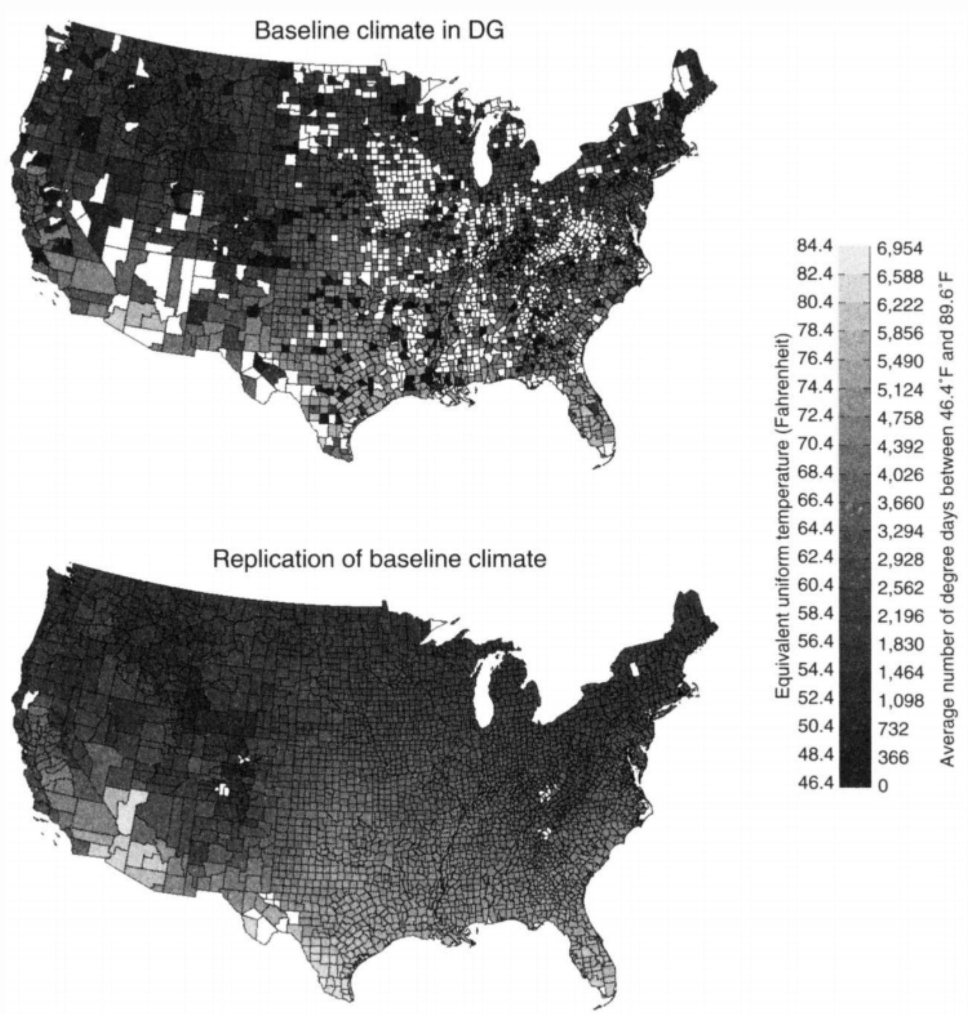
Moral of the story: data cleaning is the most important part of research, be extremely careful



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Burke, Hsiang, Miguel (2015)

BHM 2015 is one of the most influential papers in this area

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What do they do?

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What do they do?

Regress GDP growth on annual average temperature T_{it}:

$$\text{GDP Growth}_{it} = \beta_1 T_{it} + \beta_2 T_{it}^2 + \gamma \text{controls}_{it} + \text{Country FEs} + \text{Year FEs} + \varepsilon_{it}$$

Burke, Hsiang, Miguel (2015)

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$$\text{GDP Growth}_{it} = \beta_1 T_{it} + \beta_2 T_{it}^2 + \gamma \text{controls}_{it} + \text{Country FEs} + \text{Year FEs} + \varepsilon_{it}$$

The β_1 and β_2 terms allows for temperature to have a **non-linear** effect on growth

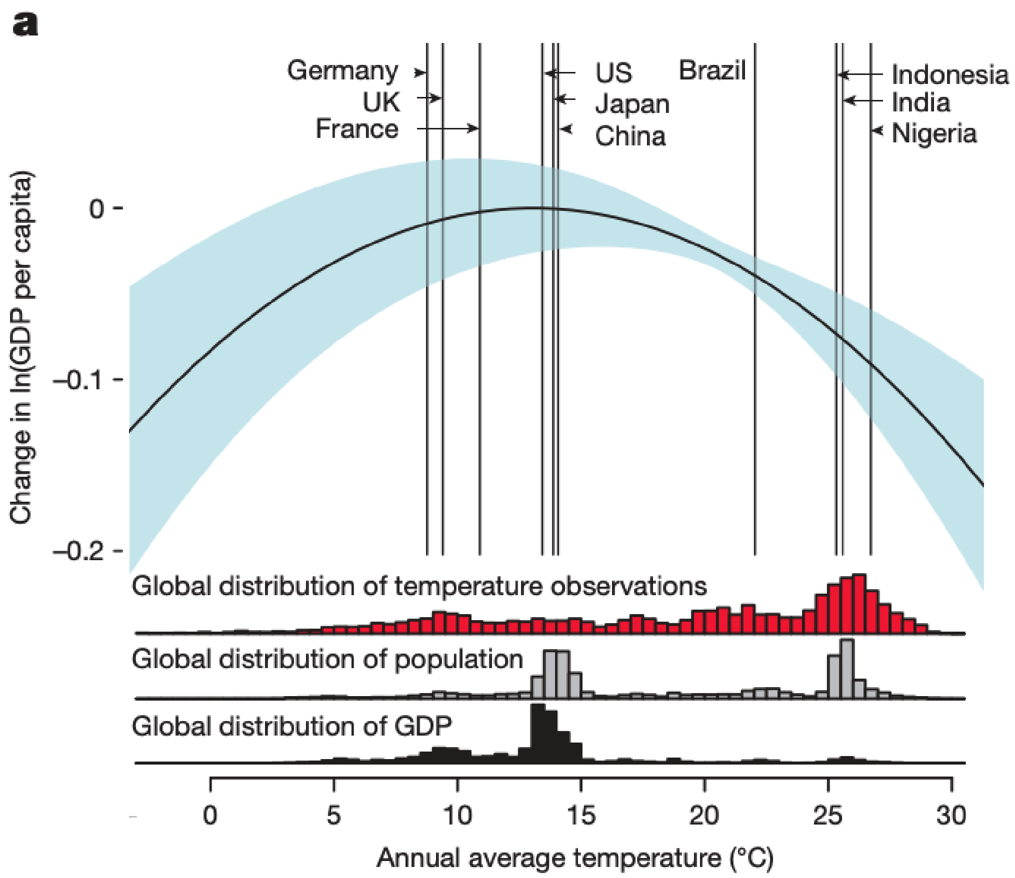
Burke, Hsiang, Miguel (2015)

Growth has an inverse-U shaped relationship with temperature

"Optimal" temperature is around 13°C

This is about where the US, Japan, and China are

Europe is colder, Africa and much of Asia are warmer

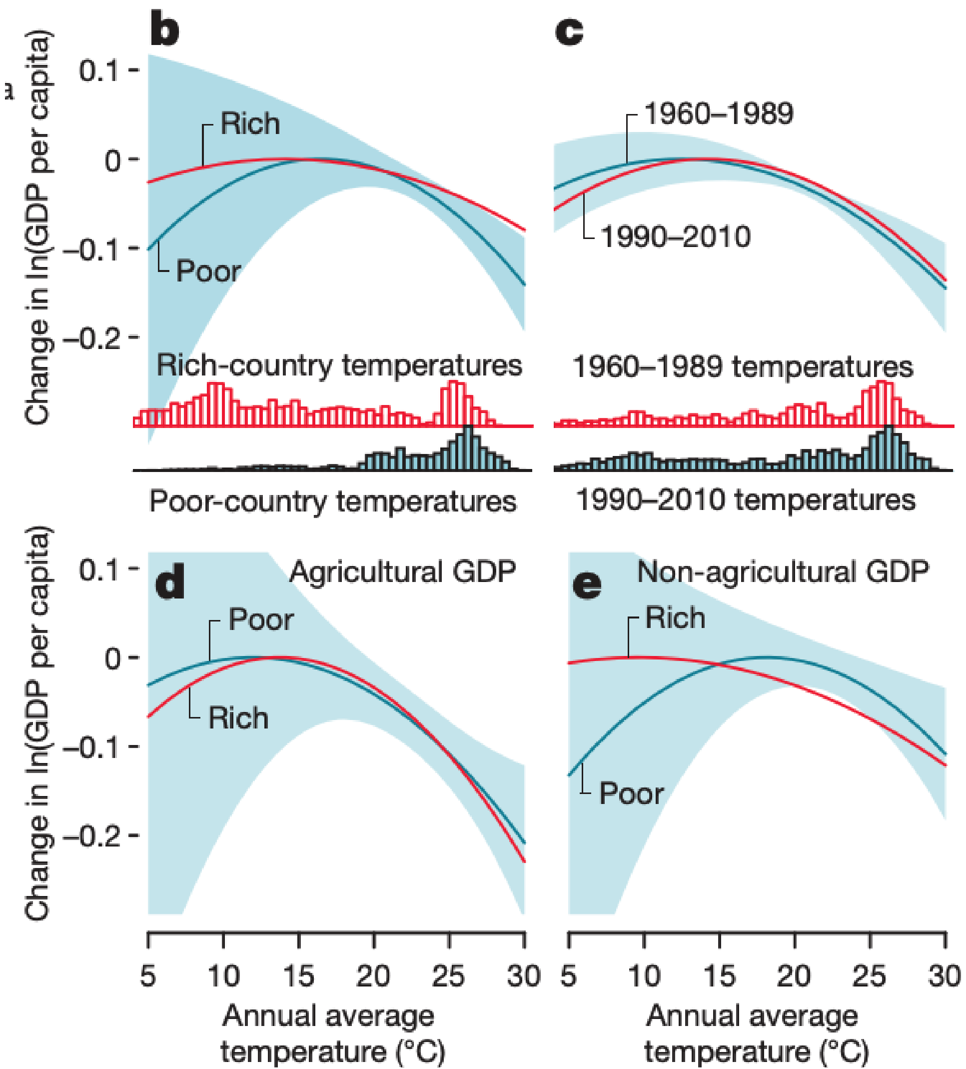


Burke, Hsiang, Miguel (2015)

Temperature has stronger effects on poor countries

Agriculture is a major factor in the effect of temperature on growth

Especially in poor countries (below median GDP)

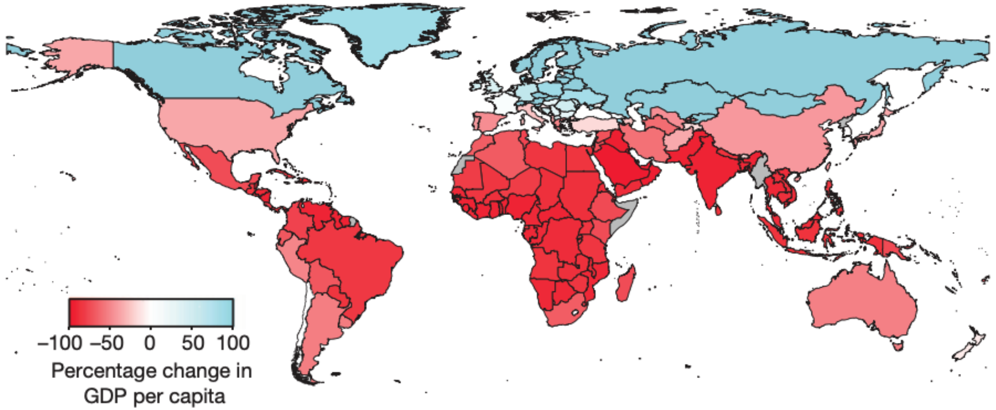


Burke, Hsiang, Miguel (2015)

Along RCP 8.5 (very high end of warming):

Most countries have major losses in GDP/capita

Canada, Europe, Russia tend to be better off

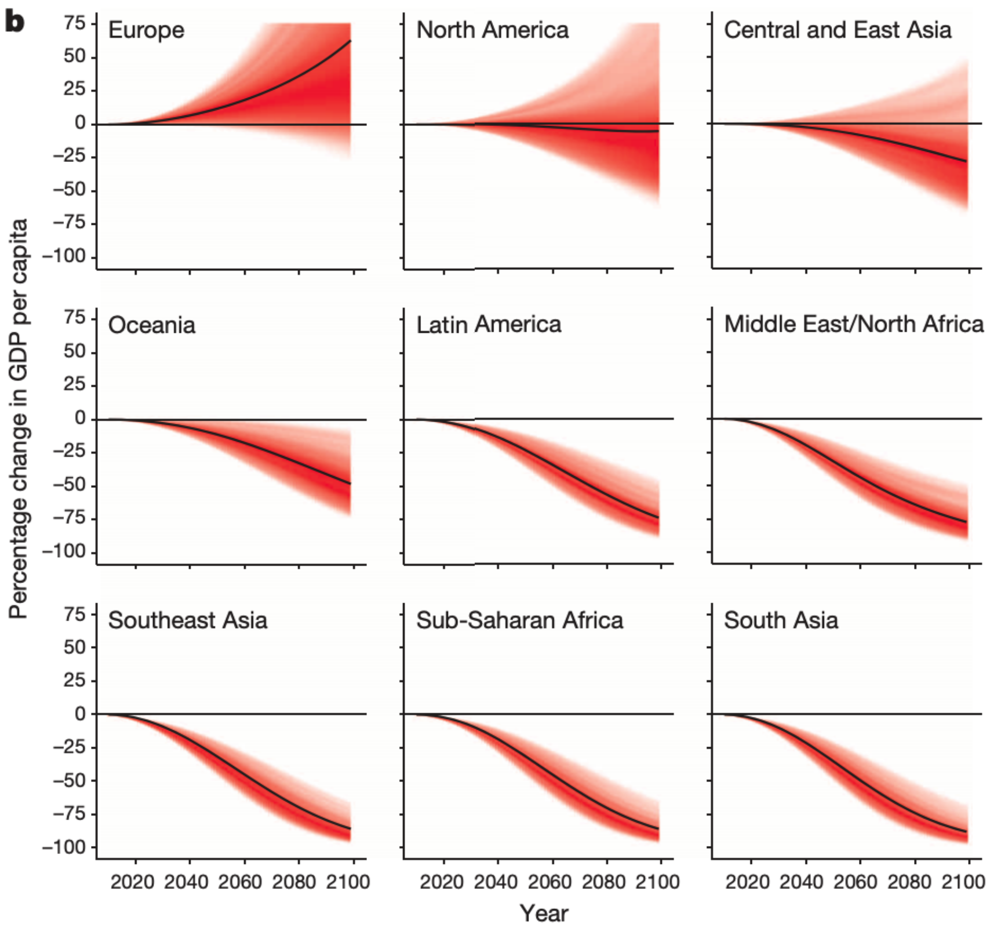


Burke, Hsiang, Miguel (2015)

Lots of uncertainty in the areas that gain

Some predictions are kind of nuts: South Asia and Sub-Saharan Africa lose virtually all GDP

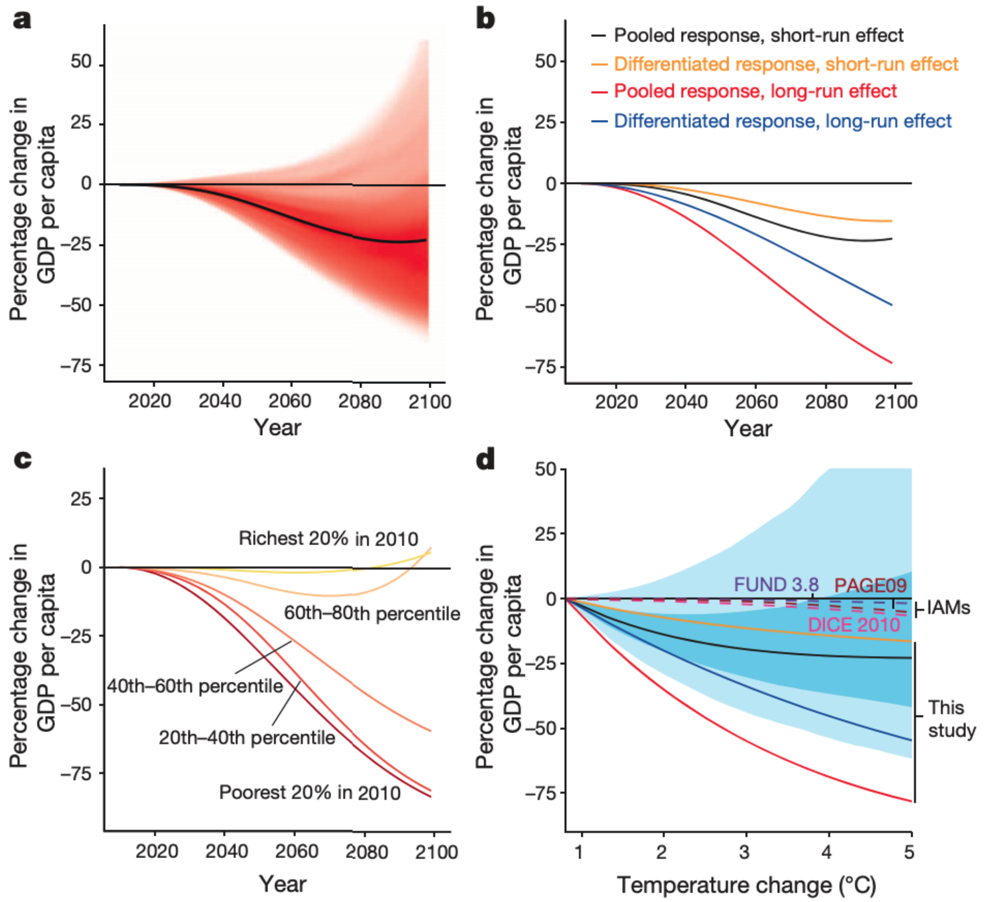
Why might this not be believable?



Burke, Hsiang, Miguel (2015)

Warming is highly regressive

The estimates from this paper are **much** larger than what comes out of the benchmark **integrated assessment models** (more later)



Burke, Hsiang, Miguel (2015)

Now let's actually play with their data

```
df <- read_csv("data/14-bhm.csv")
```

```
## Rows: 7351 Columns: 8
## ── Column specification ────────────────────────────────────────────────────────
## Delimiter: ","
## chr (2): iso, country
## dbl (6): year, gdp_growth, ag_gdp_growth, non_ag_gdp_growth, precip, temp
##
## ℹ Use `spec()` to retrieve the full column specification for this data.
## ℹ Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

Burke, Hsiang, Miguel (2015)

```r
df
```

```
## # A tibble: 7,351 × 8
##    iso   country      year gdp_growth ag_gdp_growth non_ag_gdp_growth precip  temp
##    <chr> <chr>       <dbl>      <dbl>         <dbl>             <dbl>  <dbl> <dbl>
##  1 AFG   Afghanistan  2003    0.0408        -0.0127            0.0747   328.  12.7
##  2 AFG   Afghanistan  2004   -0.0278        -0.290             0.103    276.  13.6
##  3 AFG   Afghanistan  2005    0.0715         0.129             0.0471   409.  12.5
##  4 AFG   Afghanistan  2006    0.0235        -0.0830            0.0675   472.  13.0
##  5 AFG   Afghanistan  2007    0.101          0.109             0.0979   361.  12.9
##  6 AFG   Afghanistan  2008    0.00989       -0.187             0.0768   360.  13.2
##  7 AFG   Afghanistan  2009    0.166          0.344             0.107    354.  12.8
##  8 AFG   Afghanistan  2010    0.0564        -0.0904            0.107    238.  14.2
##  9 AGO   Angola       1971   NA             NA                NA        979.  21.4
## 10 AGO   Angola       1972   NA             NA                NA       1019.  21.5
## # … with 7,341 more rows
```

Burke, Hsiang, Miguel (2015)

Let's run their same regression using `fixest::feols`

Burke, Hsiang, Miguel (2015)

Let's run their same regression using `fixest::feols`

`fixest::feols` works the same as `lm`, but we have another piece of the formula that is explicitly for fixed effects:

```
dependent variable ~ independent variables | fixed effects
```

Burke, Hsiang, Miguel (2015)

BHM's formula is:

`gdp_growth ~ temp + temp^2 + precip + precip^2 | country + year + country[year] + country[year^2]`

Note BHM include `country[year]`, a **country time trend**

We haven't discussed this much but it accounts for all variables that are trending *linearly* over time in each country

Burke, Hsiang, Miguel (2015)

```
fixest::feols(gdp_growth ~ temp + temp^2 + precip + precip^2 |
                country + year + country[year] + country[year^2],
              df)
```

```
## NOTE: 767 observations removed because of NA values (LHS: 767).

## OLS estimation, Dep. Var.: gdp_growth
## Observations: 6,584
## Fixed-effects: country: 166,  year: 50
## Varying slopes: year (country: 166),  I(year^2) (country: 166)
## Standard-errors: Clustered (country)
##                  Estimate   Std. Error  t value   Pr(>|t|)
## temp          1.271835e-02 3.737444e-03  3.40295 8.3664e-04 ***
## I(temp^2)    -4.870903e-04 1.168206e-04 -4.16956 4.9182e-05 ***
## precip        1.445150e-05 9.899750e-06  1.45978 1.4625e-01
## I(precip^2) -4.750000e-09 2.520000e-09 -1.88550 6.1120e-02 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## RMSE: 0.051968     Adj. R2: 0.220644
##                  Within R2: 0.004611
```

Burke, Hsiang, Miguel (2015)

```
reg_out <- fixest::feols(gdp_growth ~ temp + temp^2 + precip + precip^2 |
                 country + year + country[year] + country[year^2],
               df) %>% broom::tidy()
```

```
## NOTE: 767 observations removed because of NA values (LHS: 767).
```

```
reg_out
```

```
## # A tibble: 4 × 5
##   term         estimate     std.error statistic   p.value
##   <chr>           <dbl>         <dbl>     <dbl>     <dbl>
## 1 temp          1.27e-2 0.00374            3.40 0.000837
## 2 I(temp^2)    -4.87e-4 0.000117          -4.17 0.0000492
## 3 precip        1.45e-5 0.00000990         1.46 0.146
## 4 I(precip^2) -4.75e-9 0.00000000252     -1.89 0.0611
```

Optimal temperature is $-\beta_1/(2\beta_2) \approx 13^{\circ}$C

Burke, Hsiang, Miguel (2015)

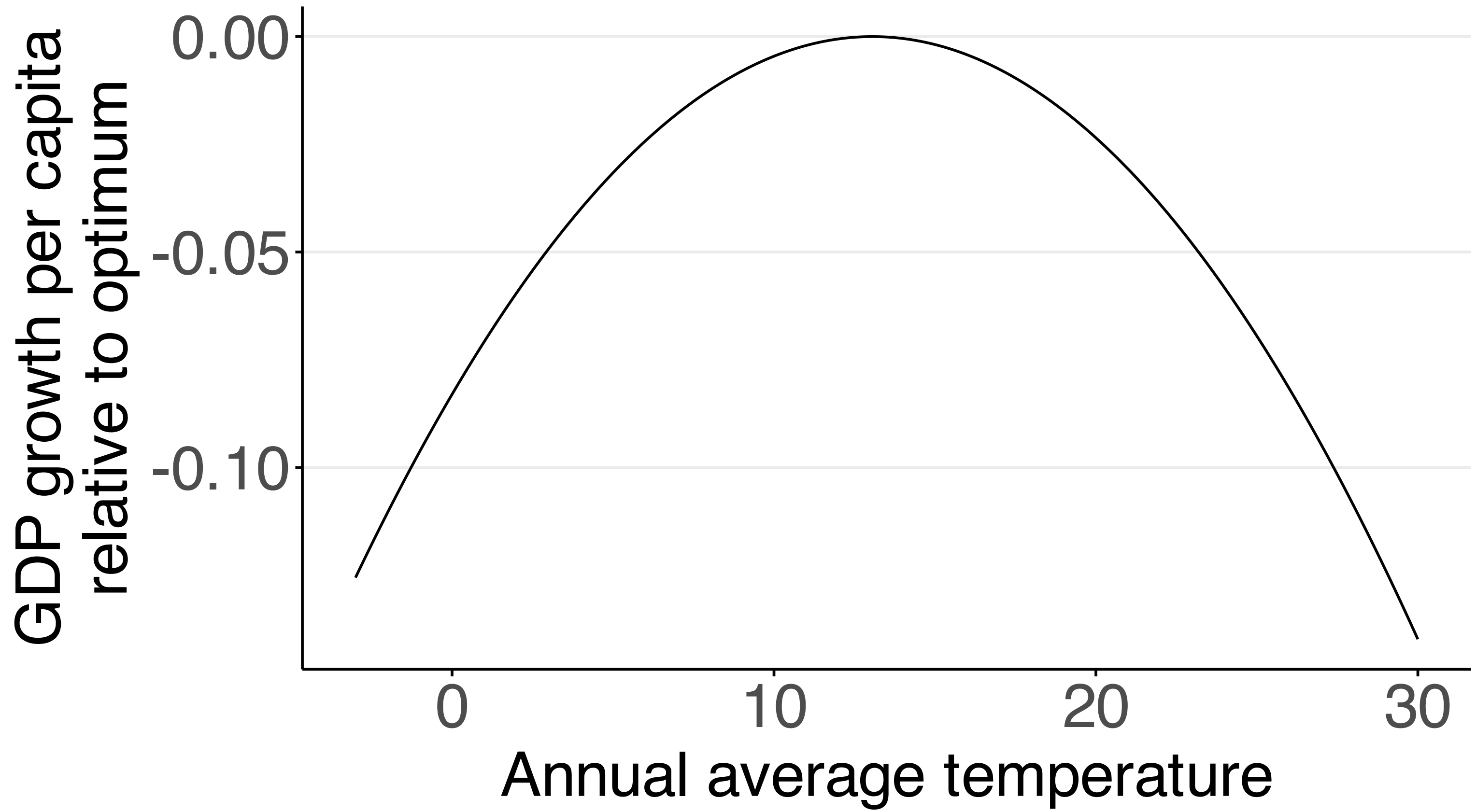
Let's plot the response function and see what we've got

```r
# Generate points to plot
points <- tibble(
  # make grid of x's from -3 to 30 degrees
  x = seq(-3, 30, .1),
  # effect on growth is given by: beta1*x + beta2*x^2
  y = reg_out$estimate[1]*x + reg_out$estimate[2]*x^2,
) %>%
  mutate(y = y - max(y)) # shift down so optimal temperature is at zero

# plot the change in growth
plot <- ggplot(points, aes(x = x, y = y)) +
  geom_line(size = 0.5) +
  theme_regular +
  labs(x = "Annual average temperature",
       y = "GDP growth per capita\nrelative to optimum")
```

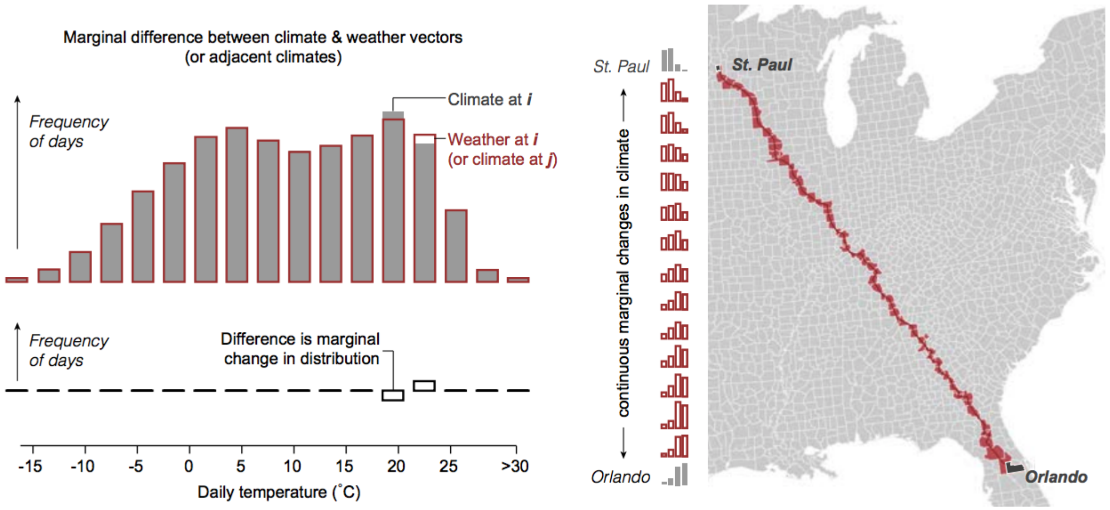
Burke, Hsiang, Miguel (2015)

Let's plot the response function and see what we've got



Deryugina and Hsiang

If we have the marginal effect of climate change, we can integrate across climates to get the **total effect of climate change**



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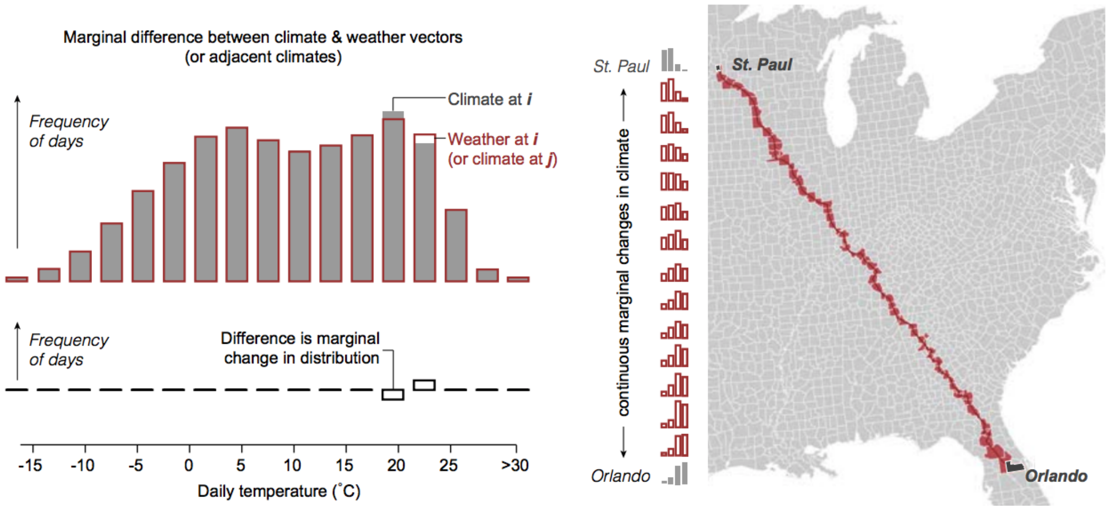
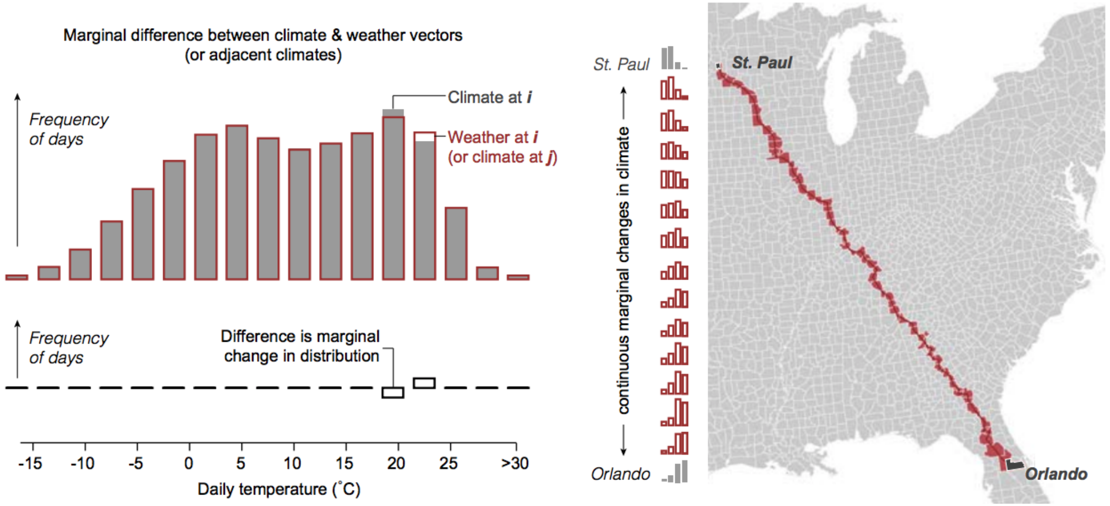


The left hand side shows the variation that allows us to estimate the marginal effect of climate change

Gray: The actual climate (average weather distribution)
Red: Weather as drawn from the distribution of climate
Difference: Deviations from average

Deryugina and Hsiang

The right side shows us how we can estimate the effect of non-marginal changes in climate: we integrate (sum) over marginal changes in climate



Deryugina and Hsiang

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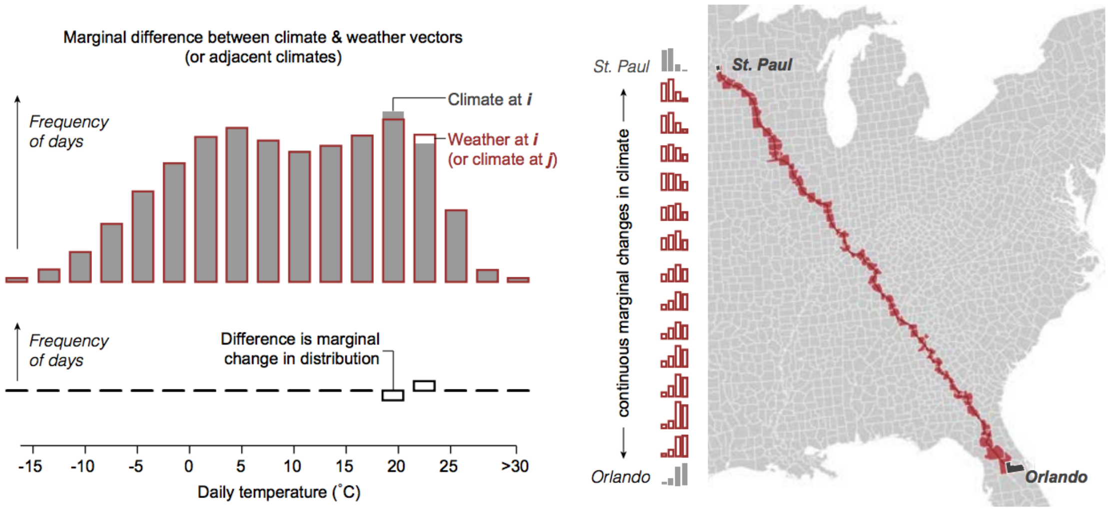
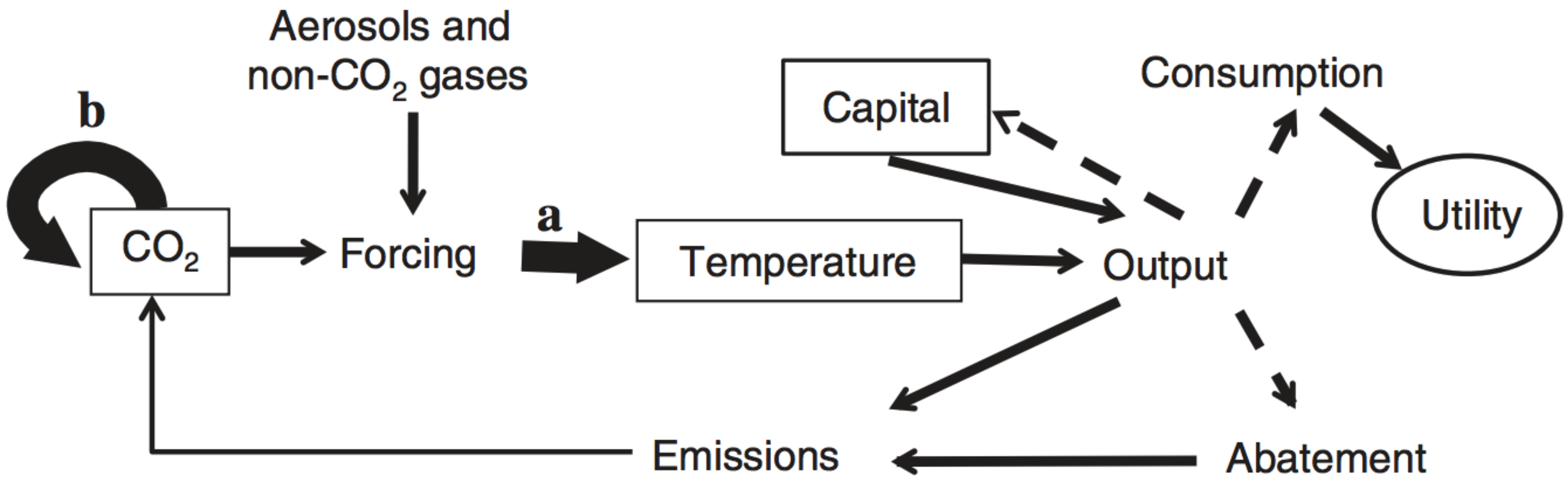


If we want to know what happens to St. Paul with Orlando's climate we just add up all the marginal effects for climates along the way (red)

Integrated assessment

Integrated assessment is the combination of both economic and climate models

The most famous integrated assessment model (IAM) is Bill Nordhaus' Dynamic Integrated Climate Economy (DICE) model



Integrated assessment

Why do we need integrated assessment models?

Integrated assessment

Why do we need integrated assessment models?

So we can compute the **social cost of carbon (SCC):** the present value of the marginal damage caused by an extra ton of CO_2 along a given economic trajectory

Integrated assessment

We compute the SCC at time t in a three step procedure:

1. Take a baseline economy (trajectories of emissions, consumption, temperature, etc)
2. Take this baseline and then increase CO_2 emissions at some time t by 1 ton
3. Compute the SCC at time t as the difference in present value of the sum of damage after time t between 1. and 2.

Integrated assessment

The baseline economy can be anything you want, business as usual, an optimal economy, whatever

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The social cost of carbon is defined for any particular future trajectory

Key: the social cost of carbon along the optimal trajectory will also be the socially optimal carbon tax

Integrated assessment

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Integrated assessment

The social cost of carbon depends on what we believe the economy and climate will be doing in the future

Consider two possible futures: high economic growth and low economic growth

The lower economic growth world is poorer $\rightarrow$ we should save more for the future

One way we can save for the future is by *avoiding the accumulation* CO_2

If we think of the environment as an asset we are saving for the future by preserving/saving environmental quality

Integrated assessment: economic module

We have iso-elastic utility: $U(c_t) = c_t^{1-\eta}/(1-\eta)$

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We produce output Y_t using a Cobb-Douglas production function: $Y_t = A_t K_t^{\alpha} L_t^{1-\alpha}$ where A_t measures productivity and L_t is labor

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We produce output Y_t using a Cobb-Douglas production function: $Y_t = A_t K_t^\alpha L_t^{1-\alpha}$ where A_t measures productivity and L_t is labor

The production process generates industrial emissions E_t as a by-product which go into the atmospheric CO_2 stock M_t^a

Integrated assessment: climate module

There are also exogenous non-industrial emissions B_t (e.g. land-use change) that enter the atmospheric CO_2 stock M_t^a

Net emissions are $e_t = (1 - \alpha_t)E_t + B_t$ where $\alpha_t \in [0, 1]$ is the percent of industrial emissions abated

Integrated assessment: climate module

There are three different CO_2 stocks: atmosphere M_t^a, upper ocean M_t^u, and lower ocean M_t^l

CO_2 can move according to the following linear system:

$$\begin{bmatrix} M_{t+1}^a \\ M_{t+1}^u \\ M_{t+1}^l \end{bmatrix} = \begin{bmatrix} \phi_{11} & \phi_{21} & 0 \\ \phi_{12} & \phi_{22} & \phi_{32} \\ 0 & \phi_{23} & \phi_{33} \end{bmatrix} \begin{bmatrix} M_t^a \\ M_t^u \\ M_t^l \end{bmatrix} + \begin{bmatrix} e_t \\ 0 \\ 0 \end{bmatrix}$$

CO_2 in the atmosphere can be exchanged with the upper ocean

The opper ocean can exchange with the atmosphere and lower ocean

The lower ocean can exchange only with the upper ocean

Emissions only directly enter the atmosphere

Integrated assessment: climate module

Atmospheric CO_2 traps heat and increases radiative forcing which is a function of the CO_2 stock and other exogenous forcers EF_t

$$F_t(M_t^a) = f_{2x}\, log_2(M_t^{atm}/M_{pre}) + EF_t$$

Integrated assessment: climate module

Temperature at the surface of the earth T_t^s and in the lower ocean T_t^o is:

$$T_{t+1}^s = T_t^s + C_1 \left[F_{t+1}(M_{t+1}^a) - \frac{f_{2x}}{s} T_t^s + C_3 \left(T_t^o - T_t^s \right) \right]$$
$$T_{t+1}^o = C_4 \, T_t^s + (1 - C_4) \, T_t^o$$

Surface temperature is a function of itself (first and third term), radiative forcing (second term), and heat transfer with the ocean (last term)

Ocean temperature is a convex combination of itself and surface temperature where C_4 determines how quickly the lower ocean warms

Integrated assessment: climate-economy linkage

Surface temperature causes damages to production of output so that output net of damages is:

$$Y_t^n = \frac{Y_t}{1 + d_1\, T_t^2}$$

Integrated assessment: climate-economy linkage

Surface temperature causes damages to production of output so that output net of damages is:

$$Y_t^n = \frac{Y_t}{1 + d_1 \, T_t^2}$$

Net output can be used for consumption, investment, and abatement

$$Y_t^n = c_t + I_t + Y_t^n G_t(\alpha_t)$$

where $G_t(\alpha_t)$ is the fraction of output spent on abatement

Integrated assessment: web version

Plug and play version of the DICE model: http://webdice.rdcep.org/

Under the parameters tab you can simulate outcomes that optimize policy, choose a particular kind of carbon tax, or enforce a climate treaty

You can also change parameters (e.g. growth, sensitivity of climate to emissions, etc)