Using empirical evidence to calibrate economic models of climate change

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Committee on Assessing Approaches to Updating the SCC
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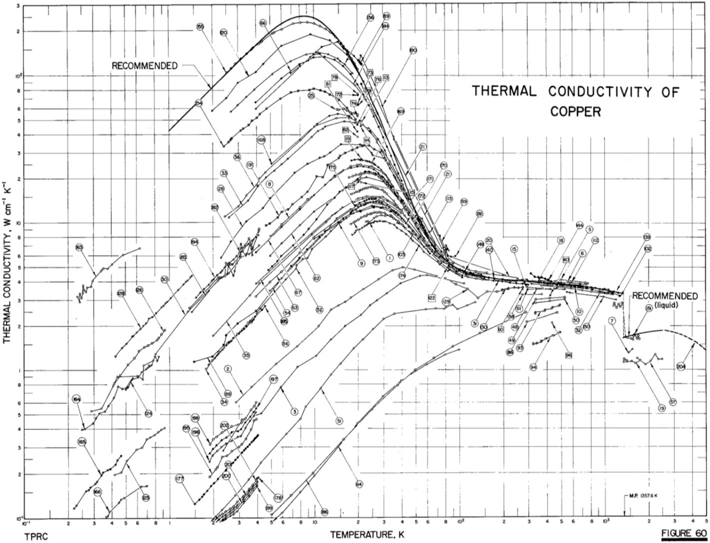
Cell phones and toasters work because they are built on a foundation of empirical measurements.



Ho et al. (1974)

Model	Damage type	Study	Basis	Interlinkages to SCC models
DICE	Aggregate non-SLR	IPCC (2007), Tol (2009)[1]	Calibration	DICE, FUND, PAGE
	SLR coastal impacts	Undocumented		
FUND	Agriculture	Kane et al. (1992), Reilly et al. (1994), Morita et al. (1994), Fischer et al. (1996), Tsigas et al. (1996)	Calibration	
		Tol (2002b)	Income elasticity	
	Forestry	Perez-Garcia et al. (1995), Sohngen et al. (2001)	Calibration	
		Tol (2002b)	Income elasticity	
	Energy	Downing et al. (1995), (1996)	Calibration	
		Hodgson and Miller (1995)	Income elasticity	
	Water resources	Downing et al. (1995, 1996)	Calibration	
		Downing et al. (1995, 1996)	Income elasticity	
	Coastal impacts	Hoozemans et al. (1993), Bijlsma et al. (1995), Leatherman and Nicholls (1995), Nicholls and Leatherman (1995), Brander et al. (2006)	Calibration	
	Diarrhoea	WHO Global Burden of Disease (2000)	Calibration	
		WHO Global Burden of Disease (2000)	Income elasticity	
	Vector-borne diseases	Martin and Lefebvre (1995), Martens et al. (1995, 1997), Morita et al. (1995)	Calibration	
		Link and Tol (2004)	Income elasticity	
	Cardiovascular and respiratory mortality	Martens (1998)	Calibration	
	Storms	CRED EM-DAT database, WMO (2006)	Calibration	
		Toya and Skidmore (2007)	Income elasticity	
	Ecosystems	Pearce and Moran, (1994), Tol (2002)	Calibration	
PAGE	SLR	Anthoff et al. (2006)[2]	Calibration & income elasticity	FUND
	Economic	Warren et al. (2006)[3]	Calibration	DICE, FUND, PAGE
	Noneconomic	Warren et al. (2006)	Calibration	DICE, FUND, PAGE
	Discontinuity	Lenton et al. (2008), Anthoff et al. (2006), Nordhaus (1994)[4]	Calibration	DICE, FUND
	Adaptation costs	Parry et al. (2009)	Calibration	

Diaz (2015)

What is holding us back?

1) **Not enough empirical studies –** academic publications do not sufficiently reward reliable socially valuable measurements (for policy, "tested and true" often preferred to novelty)

2) **Econometric methods linking climatological and economic data are challenging** → requires additional training

3) **Replication / harmonization of existing studies requires data sharing**

4) **Collection and comparison of results is labor intensive and costly** → Web 2.0 can help

5) **Disagreement over what is being measured**, weather or climate impacts? → this is gradually getting resolved

6) **Coordination/integration with climate modeling community is required but challenging** → interdisciplinary training/teams work

7) **Adoption/integration with IAM community is required but challenging** → interdisciplinary training/teams work

8) **IAM models are not falsifiable, so models with erroneous calibrations are never rejected.** Trusting models that cannot generate testable predictions requires faith.

Core messages regarding empirical calibrations

Current calibrations are very far from modern empirical standards and missing major known impacts. We know how to fix this.

We are simultaneously updating calibrations and building infrastructure to prevent future gaps, but not the standard yet.

- Harmonization and consolidation of empirical findings is possible and happening – this is difficult and bloody
- Research community is organizing to improve training and efficient allocation of research – needs support
- Development of public goods computational infrastructure is possible and happening – needs support and incentives to participate
- Applications of empirical results often fundamentally change priors/results in IAMs – need to reduce transaction costs, create incentives to ensure calibrations are up to date, require IAM validation (e.g. hindcasts).

Clearing the climate-vs-weather logjam

Cross sectional analyses are confounded by omitted variables, it is impossible to know by how much. Researchers cannot empirically demonstrate this is not fatal to causal inference.

Identification of causal effects has improved dramatically by leveraging high frequency variation in climate variables.
e.g. Schlenker & Roberts (PNAS, 2009)

Heuristic argument that climate $\neq$ weather has created impasse.

Expectations clearly matter, but expectations over *what* matters too.

Claims against high frequency results generally do not compare apples-to-apples.

Use of high-frequency variation does not assume away adaptation as often claimed. It allows precise measurement of adaptation.

Clearing the climate-vs-weather logjam

Theory: weather identifies climate effects (Hsiang, *in prep*)

Proposition 1: If agents are optimizing the outcome and technologies are "continuous," then weather variations *exactly* identify the effect of marginal climate changes.

Proposition 2: If technologies are "continuous," then the assumptions needed (regarding cross-unit conditional homogeneity) to integrate non-marginal climate effects using marginal climate effects is *strictly weaker* than the assumptions needed to use cross-sectional estimates.

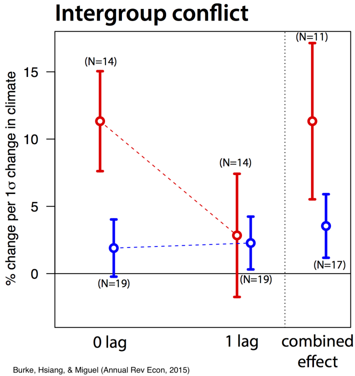
(*Note:* Not all studies using weather variation satisfy these criteria.)

Data: weather and climate effects generally look the same

Careful apples-to-apples comparisons reveal panel, long-difference, and cross-sectional results are indistinguishable in agriculture (Schlenker & Roberts, 2009; Burke & Emerick, 2012), conflict (Burke et al., 2015) and fertility (Barecca et al., 2015).

Calibrate to what?

Harmonization and consolidation is currently painful and costly.



Burke, Hsiang, & Miguel (Annual Rev Econ, 2015)

Climatic Change
DOI 10.1007/s10584-014-1266-1

COMMENTARY

One effect to rule them all? A comment on climate and conflict

H. Buhaug • J. Nordkvelle • T. Bernauer • T. Böhmelt • M. Brzoska • J. W. Busby • A. Ciccone • H. Fjelde • E. Gartzke • N. P. Gleditsch • J. A. Goldstone • H. Hegre • H. Holtermann • V. Koubi • J. S. A. Link • P. M. Link • P. Lujala • J. O′Loughlin • C. Raleigh • J. Scheffran • J. Schilling • T. G. Smith • O. M. Theisen • R. S. J. Tol • H. Urdal • N. von Uexkull

In science, not all priors can be right.

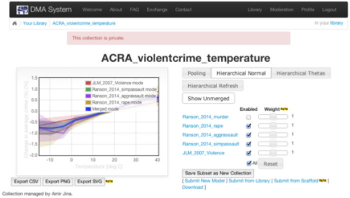
How can we foster an intellectual environment that encourages inter-study comparisons and consolidations of findings?

Modern computing infrastructure reduces transaction costs

Cross-comparisons and meta-analysis for calibration are public goods. They are currently under provided. Concept:

Distributed Meta-Analysis System

Researcher 1
Researcher 2
Researcher 3
→



→ Damage Function

dmas.berkeley.edu

(Rising & Hsiang, 2014)

Modern computing infrastructure reduces transaction costs

Cross-comparisons and meta-analysis for calibration are public goods. They are currently under provided. Concept:

Distributed Meta-Analysis System

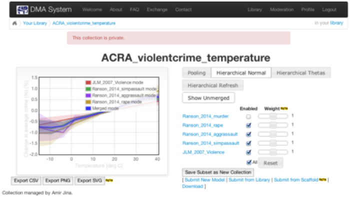
Bayesian updating

Researcher 1

Researcher 2

Researcher 3

Researcher 4



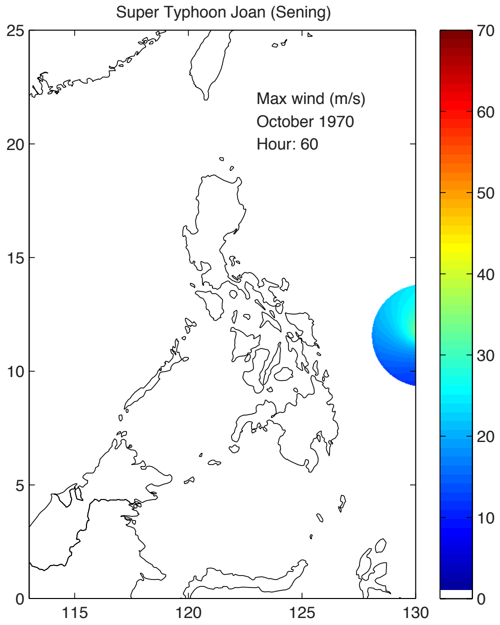
Revised Damage Function

dmas.berkeley.edu

(Rising & Hsiang, 2014)

Why empirical calibration matters

Example 1: “Top down” measurement of tropical cyclone impacts



Super Typhoon Joan (Sening)
Max wind (m/s)
October 1970
Hour: 60
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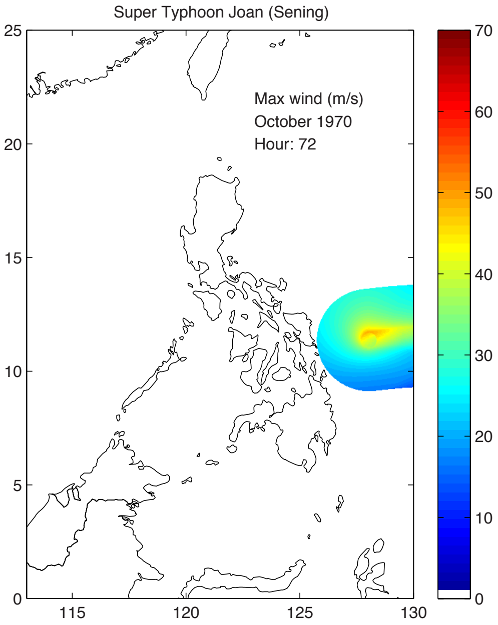
Super Typhoon Joan (Sening)
Max wind (m/s)
October 1970
Hour: 72
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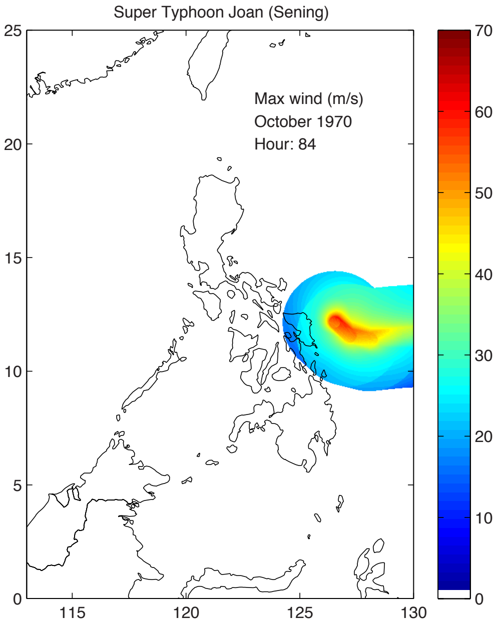

Super Typhoon Joan (Sening)
Max wind (m/s)
October 1970
Hour: 84
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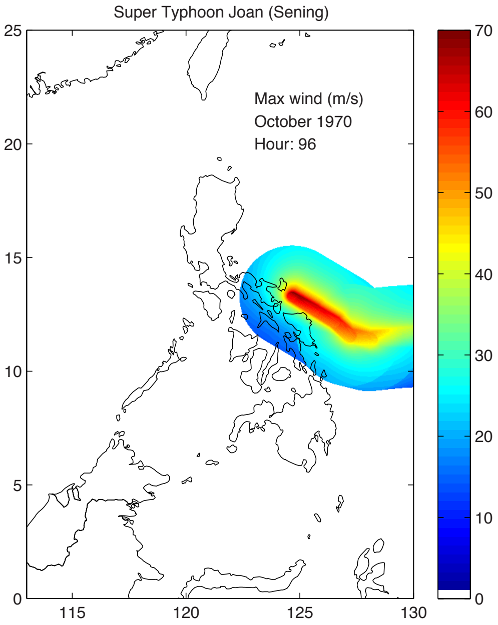

Super Typhoon Joan (Sening)
Max wind (m/s)
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Hour: 96
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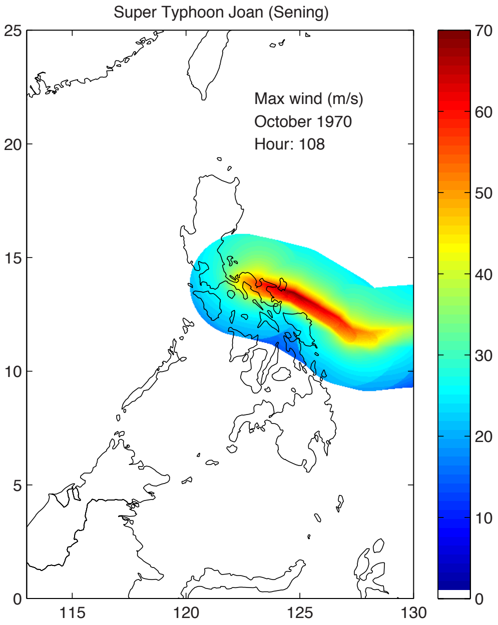

Super Typhoon Joan (Sening)
Max wind (m/s)
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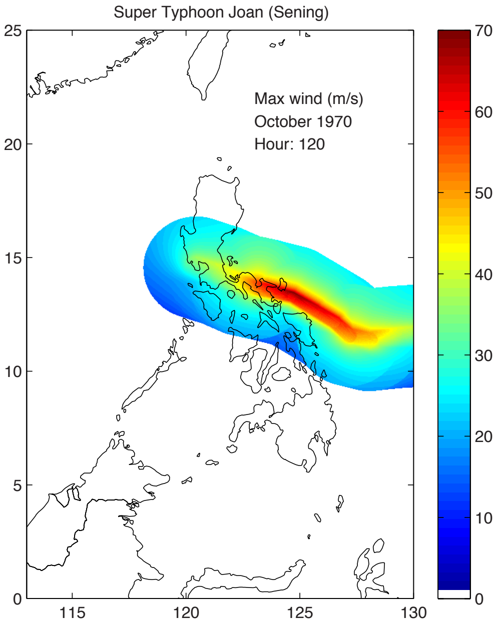
Super Typhoon Joan (Sening)
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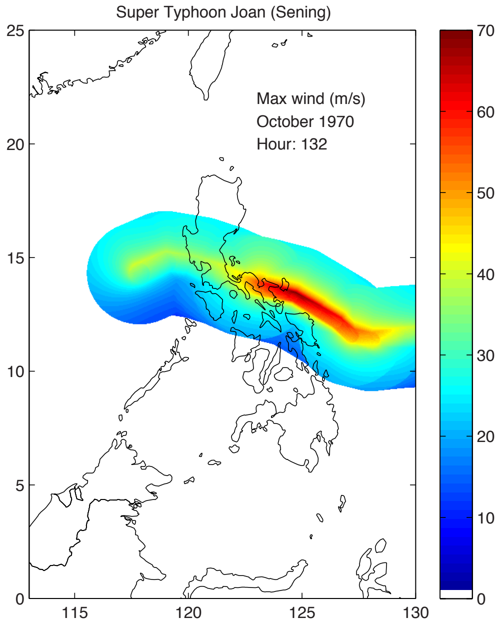

Super Typhoon Joan (Sening)
Max wind (m/s)
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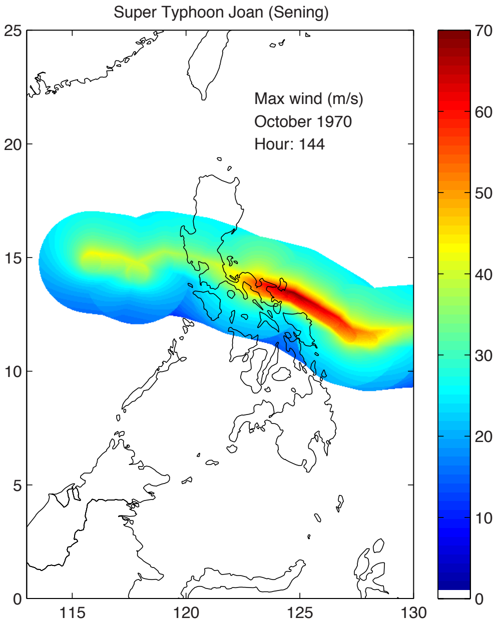

Super Typhoon Joan (Sening)
Max wind (m/s)
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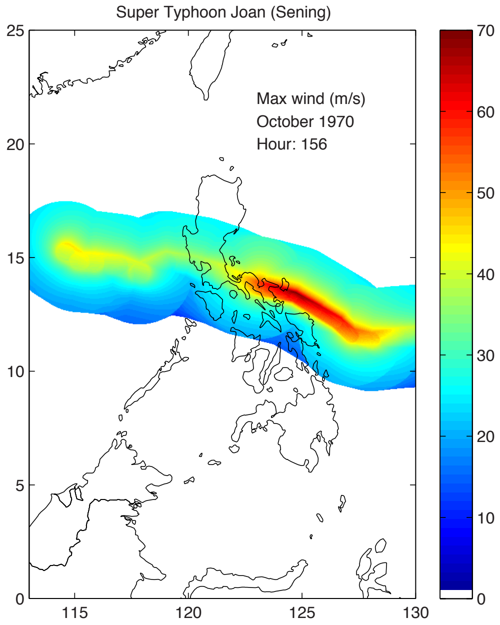

Super Typhoon Joan (Sening)
Max wind (m/s)
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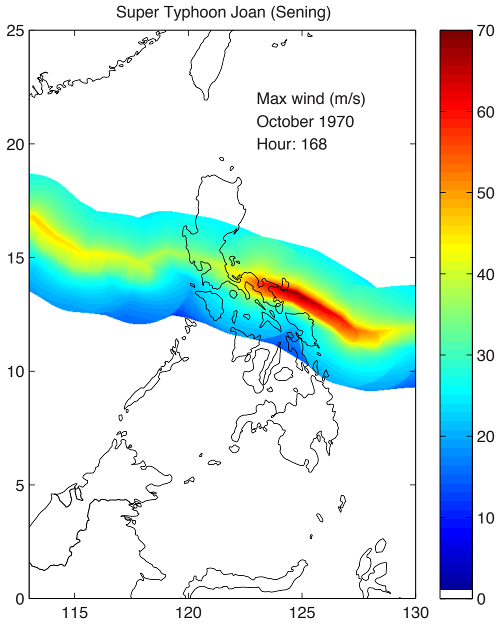

Super Typhoon Joan (Sening)
Max wind (m/s)
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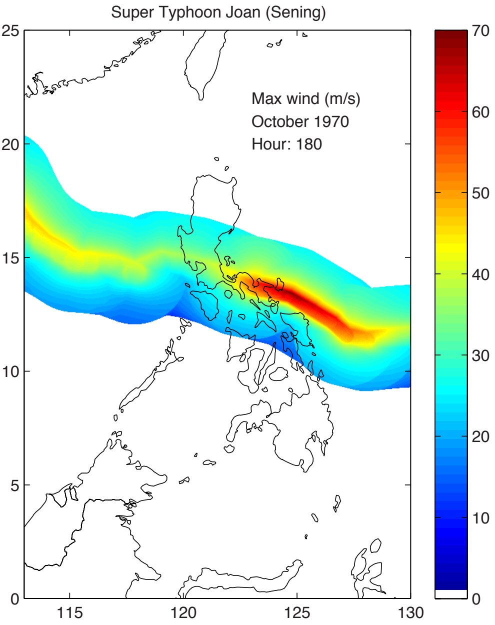
Super Typhoon Joan (Sening)
Max wind (m/s)
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Hour: 180
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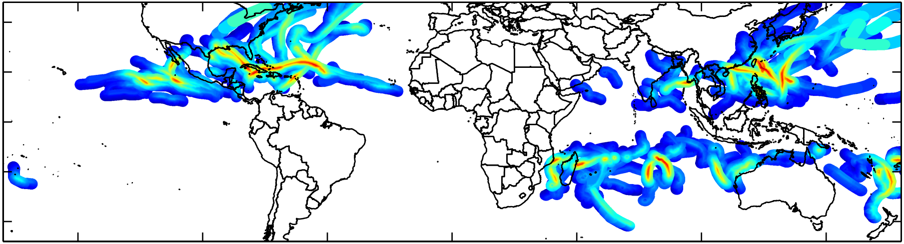
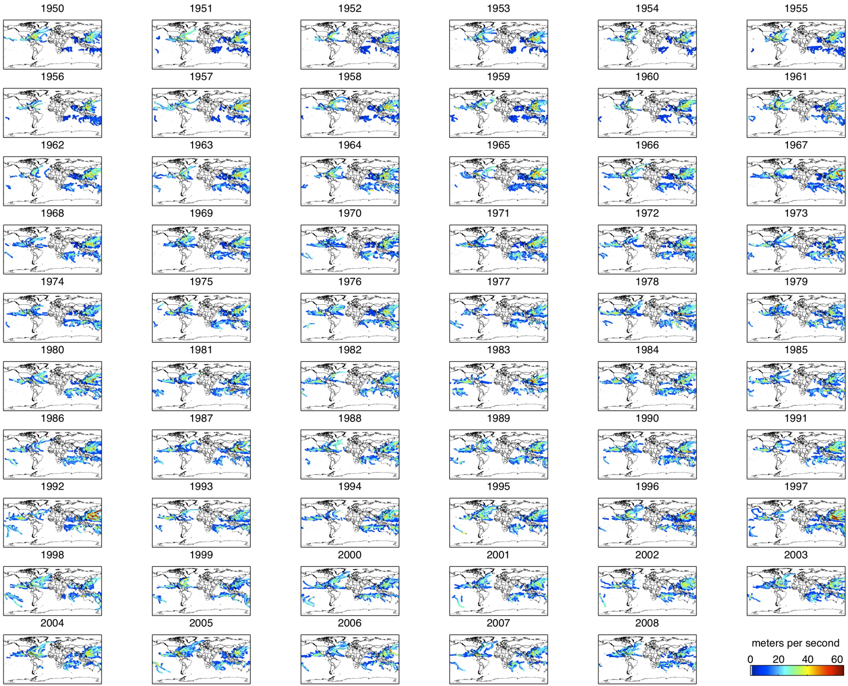
Maximum Wind Speed (m/s) 2008

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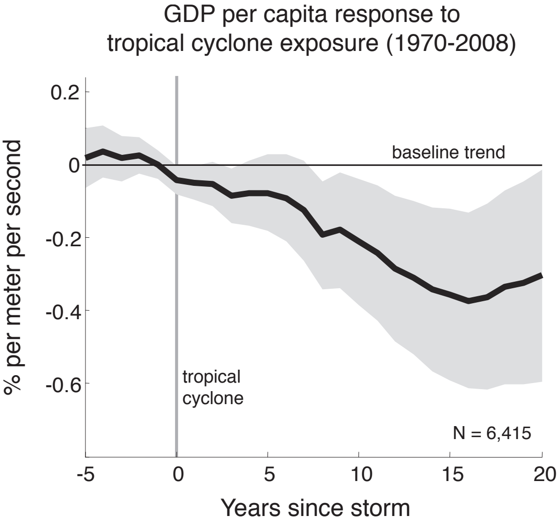
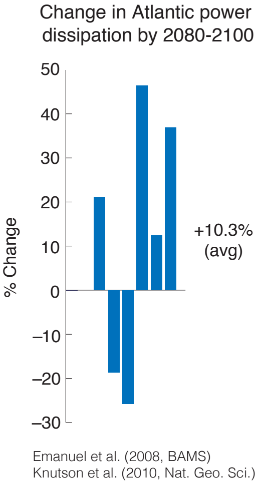
A globally generalizable response



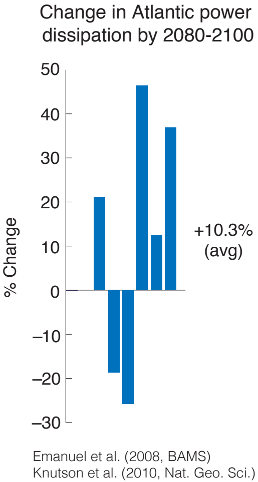
Hsiang & Jina (2014);
corroborating micro evidence in Deryugina (2013), Anttila-Hughes & Hsiang (2012)

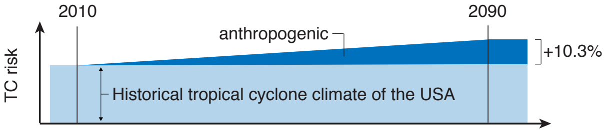
Example implications for climate change: USA



Hsiang & Jina (2014)

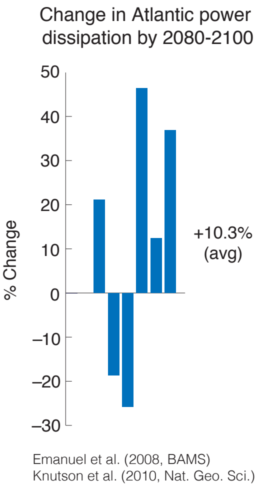
Example implications for climate change: USA

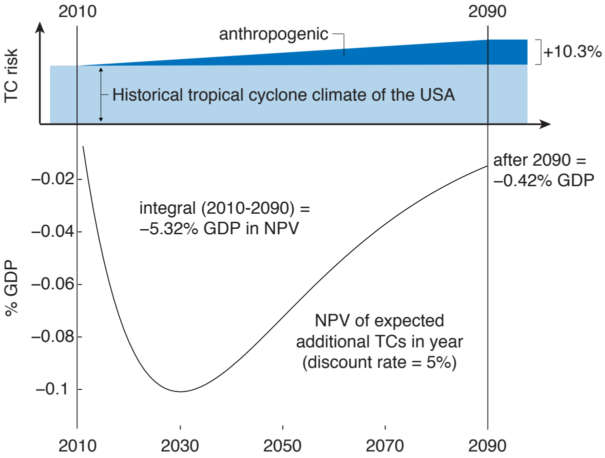




Hsiang & Jina (2014)

Example implications for climate change: USA





Hsiang & Jina (2014)

Implications for climate policy

Net Present Value of anthropogenic cyclone risk (A1B, 5% discount)

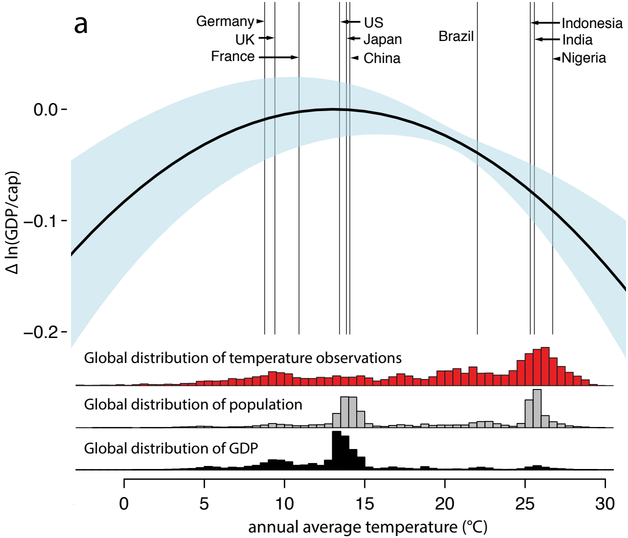
	% current GDP	billion US$
Japan	-101%	-4,461
China	-12.6%	-1,364
USA	-5.9%	-855
Philippines	-83.3%	-299
Mexico	-17.2%	-260
Vietnam	-56%	-160
Haiti	-27.8%	-4
Bangladesh	+11.1%	+26
Australia	+13.1%	+140
India	+5.6%	+264
World	**-13.8%**	**-9,704 (±2,938)**

Hsiang & Jina (2014)

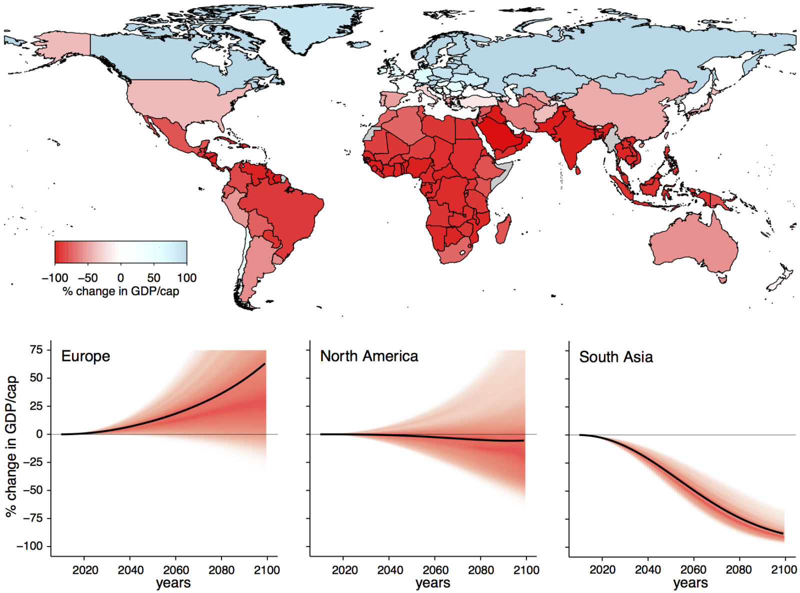
Why empirical calibration matters

Example 2: "Top down" measurement of temperature impacts

Global nonlinear effect of temperature on growth

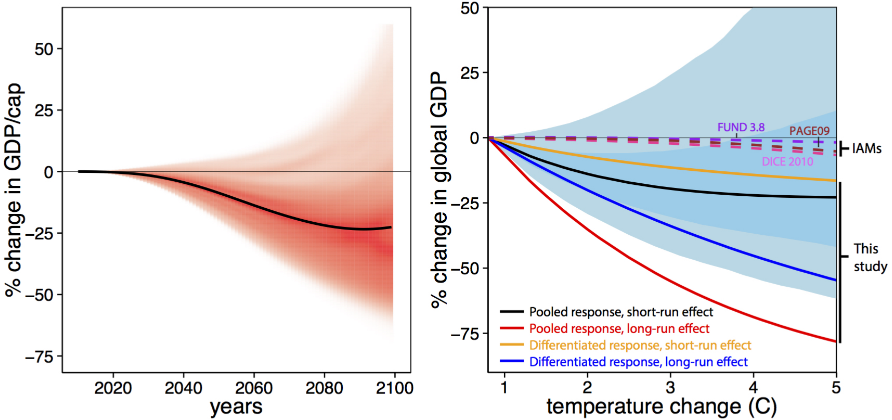


Burke, Hsiang & Miguel (Nature, 2015)



Burke, Hsiang & Miguel (Nature, 2015)

Aggregating globally



Burke, Hsiang & Miguel (Nature, 2015)

Comparing SCC accounting for nonlinear growth effects

Table: **Current Social Cost of Carbon (\$ per metric ton CO_2)**

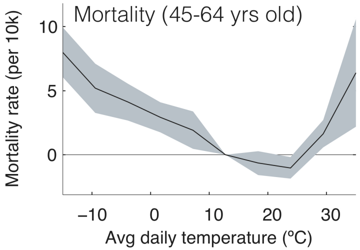
Model† (3% discount)	USG2 (BAU)
DICE	20
FUND	9
PAGE	25
BHM pooled*	348
(SSP5)	549
BHM rich-poor*	233
(SSP5)	455

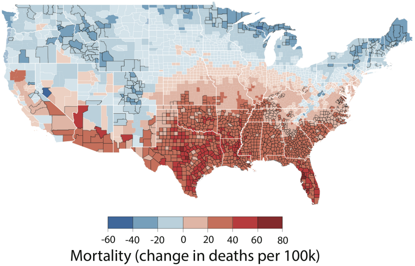
†3°C climate sensitivity, IAWG socioeconomic scenario except "SSP5" cases. *5-yr lagged model.

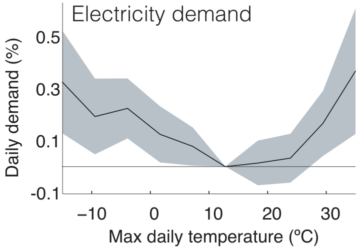
Why empirical calibration matters

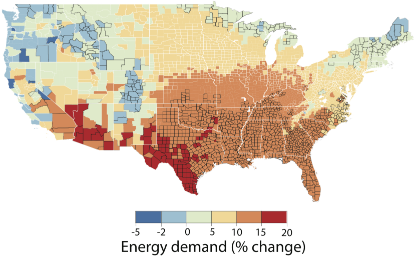
Example 3: "Bottom up" estimates from the American Climate Prospectus

Identifying major distributional effects in RCP 8.5



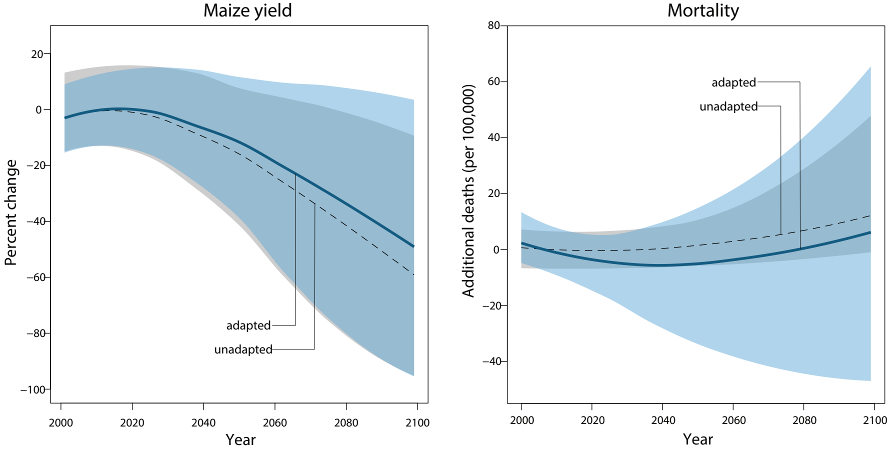






Houser et al. (2015)

Correcting confusion: **This approach captures historical adaptations. We can also model adaptation that is trending (due to warming).**



Innovation:

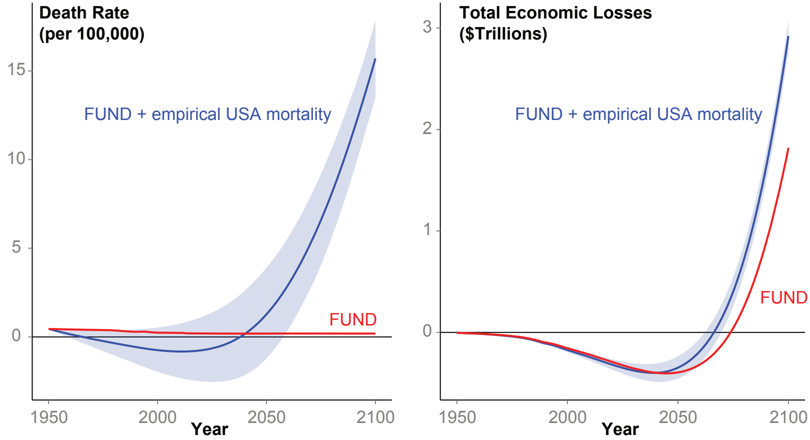
Link historical adaptation in cross-section (e.g. Schlenker & Roberts, 2009) and measured rates of adjustments (e.g. Burke & Emerick, 2012).

Applying ACP empirical mortality in USA to FUND/MIMI

Accounting for empirical mortality projections

→ **+15.5 deaths per 100k** in 2100 (>8,000% of base calibration)

→ **+ $1.1 trillion** in lost VSL in 2100



Where are we going from here?

"Bottom up" empirical estimates of a global damage function

Building a global damage function from the bottom up

Close collaboration between economics (Berkeley, UChicago), climate modeling (Rutgers), numerical modeling (Rhodium Group).
$\rightarrow$ 14+ researchers.

Integration of >40 climate models, >196 empirical impact studies, and micro-level municipal and remote sensing data.

Identification of "gaps" in the literature, in-house analysis to fill them.

Voluntary training and collaboration with 15 doctoral students through summer workshop in climate econometrics.

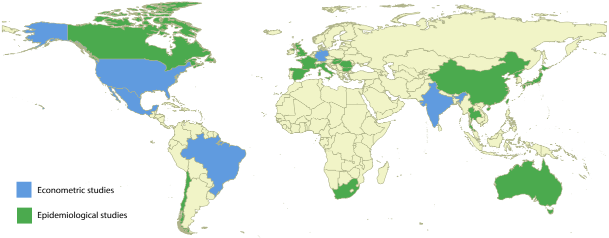
Develop "plumbing" for seamless flow of results

empirical researchers → DMAS → aggregation → API → IAMs

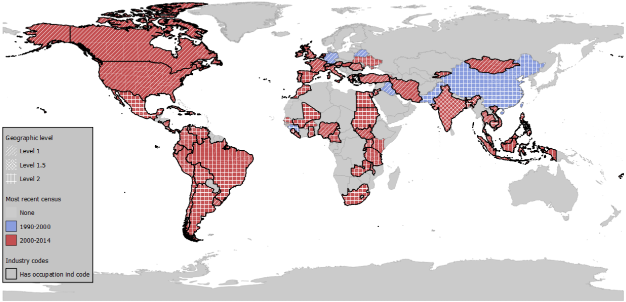
Close coordination with David Anthoff (MIMI).

We will have initial global estimates by summer 2016.

Mortality analyses (published + in-house)



Domestic migration micro-data sets available for in-house analysis



State of current evidence we use

Sector	Subsectors	# Studies	"Grade"	w/ Reanalysis
Agriculture	Staple crops	24	A	A
	Livestock	5	D	C
Crime & Conflict	Intergroup	39	A	A
	Interpersonal	18	B	B
Labor	Absenteeism	8	B	A
	Productivity	5	D	C
Health	Mortality	17	A	A
	Early Life Impacts	5	D	C
	Hospital Admissions	8	D	C
	Vector-borne Disease	32	C	A
Migration	Internal	10	B	A
	International	9	B	A
Coastal	Economic Damages	11	A	A
	Health Damages	3	C	C
Energy	Demand	22	B	B
	Supply	3	D	C

Lowest hanging fruit: update existing analyses w/ current econometric standards.

Potentially major remaining unknowns, limited empirics

- ecosystems / biodiversity
- amenity valuations
- water issues
- prices
- trade
- energy supply
- high value crops
- infrastructure
- ocean acidification
- morbidity (e.g. vector borne disease)
- human capital formation
- innovation
- financial / capital markets
- distributional effects
- tipping points
- covarying losses
- things we haven't thought of yet

Explicit measurement of adaptation is missing or highly uncertain in most sectors. (Although limited impact in ACP).

Usable estimates in some contexts: crime, agriculture, mortality, cyclones.

Thoughts on the path forward

Top-down approach

Benefits

- comprehensive within markets
- captures adaptation adjustments
- weather clearly identifies climate impacts
- easier

Challenges

- missing nonmarket impacts
- baseline projections are challenging
- distant from welfare
- may misrepresent depreciation
- growth effects not in IAMs

Bottom-up approach

Benefits

- mechanisms clearer
- captures distributional effects
- supports adaptation policies
- allows more credible welfare calculations
- can capture nonmarket impacts

Challenges

- requires prices, including nonmarket valuations (VSL)
- "missing sectors" and "missing samples" are a major challenge
- modeling adaptation explicitly sometimes required

Some remaining structural challenges to integration w/ IAMs

→ IAMs are not built to "accept" the output of many empirical findings (e.g. GDP growth, US maize yields).

→ Climatic forcing data not available for all scenarios (e.g. country-specific tropical cyclone exposure).

→ Climate models, socioeconomic scenarios, and damages are not mutually and internally consistent in many cases.

Some additional process recommendations

→ Intentional segregation of damage estimates to allow uncontaminated cross-comparison.

→ Promote practices in empirical study design that allow/encourage comparisons.

→ Require public documentation and replication files for all calibrations.

→ Standardize at least one top down and one bottom up damage scenario where possible for application and comparison across IAMs.

Conclusions

We can use credible identification strategies to measure climate impacts.

We can use empirical results to generate spatially explicit projections/damages.

We can integrate projections into IAMS by working closely with modelers.

When we do this, it has large and potentially important influence on SCC.

We can use modern computing technology to make this process easy, transparent, continuously updatable, with fewer errors.

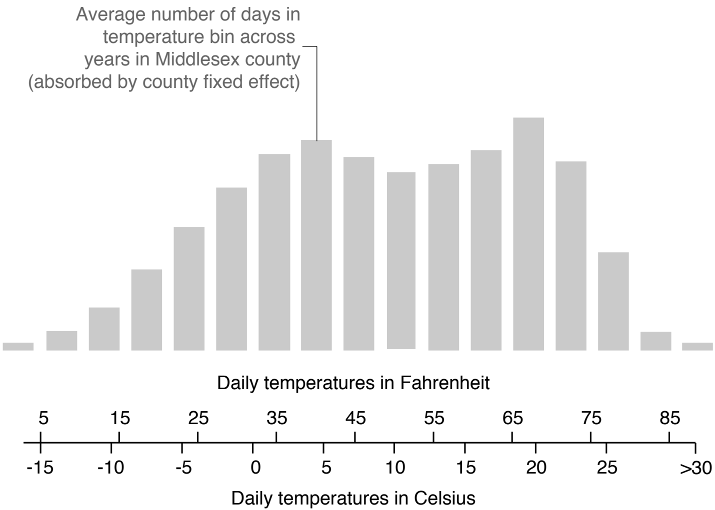
There is no intellectually or ethically defensible reason not to require complete integration and transparency in all IAMs used for the SCC.

Our teams are already doing all of this (ETA summer 2016).

This process should be supported and institutionalized to ensure SCC is constantly updated in real time with the best available numbers.

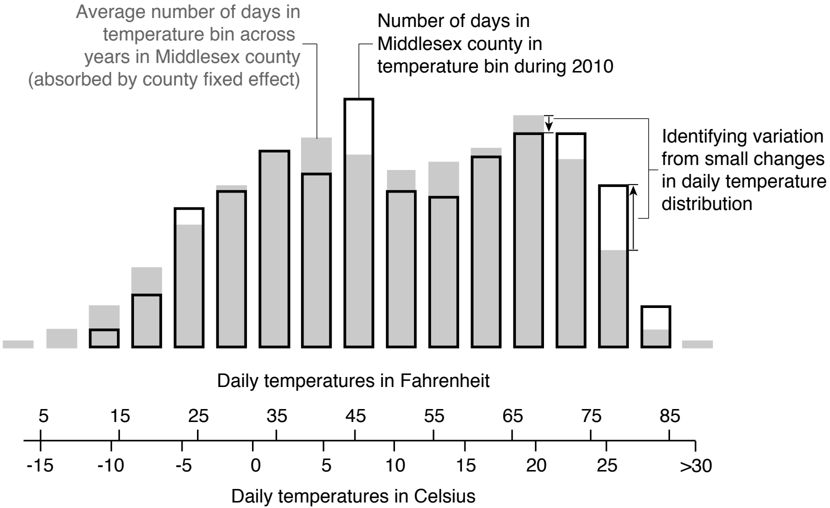
extra slides

Effect of temperature on income in the USA



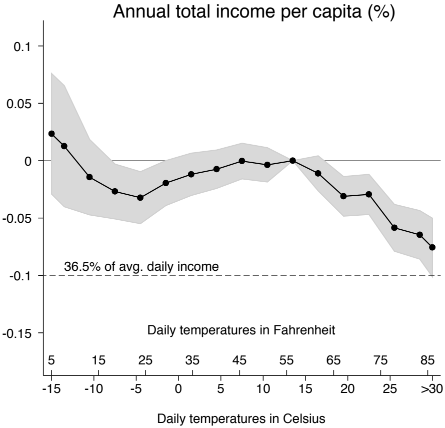
Deryugina & Hsiang (2014)

Effect of temperature on income in the USA



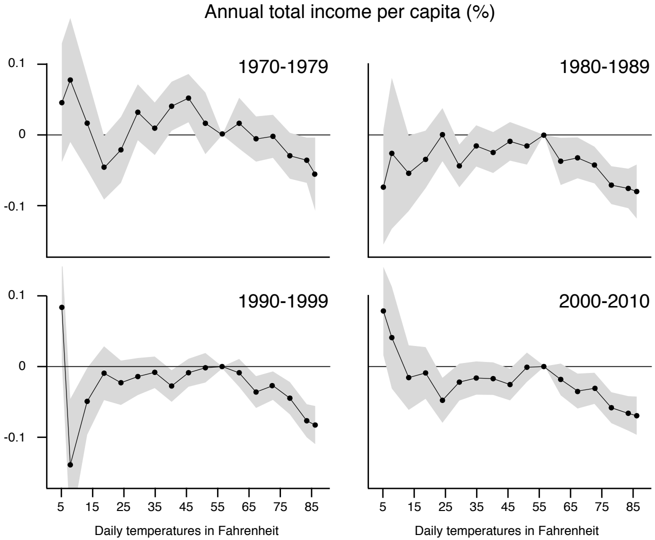
Deryugina & Hsiang (2014)

Effect of temperature on income in the USA



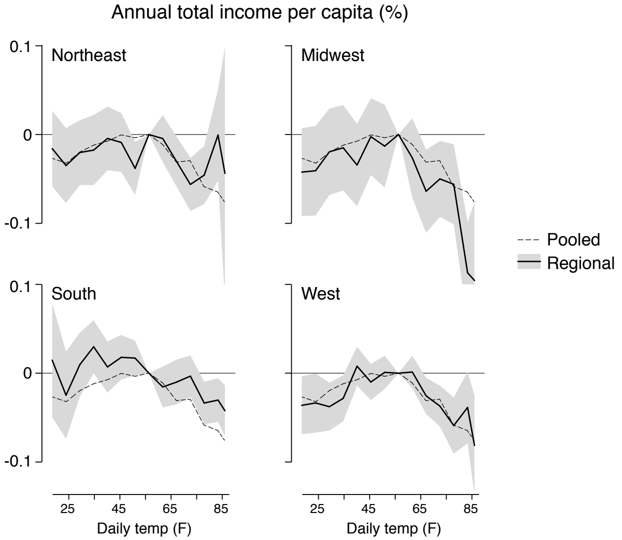
Deryugina & Hsiang (2014)

Little evidence of adaptation over time



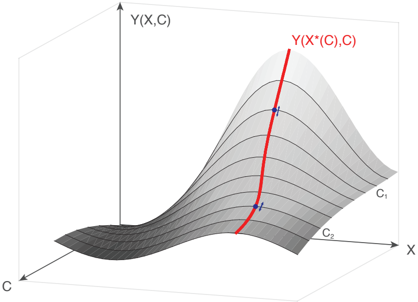
Deryugina & Hsiang (2014)

Limited evidence of adaptation over space



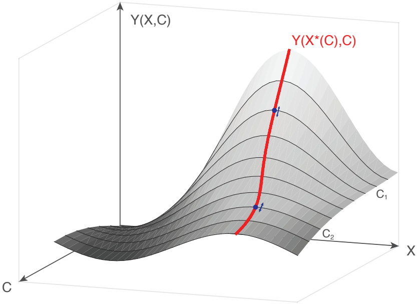
Deryugina & Hsiang (2014)

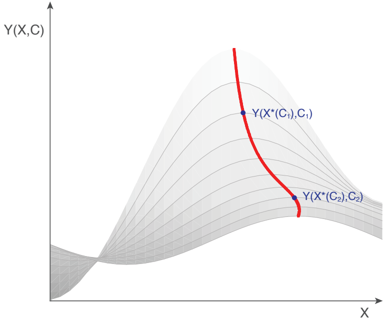
Weather vs. Climate



Hsiang (2016)

Weather vs. Climate





Hsiang (2016)

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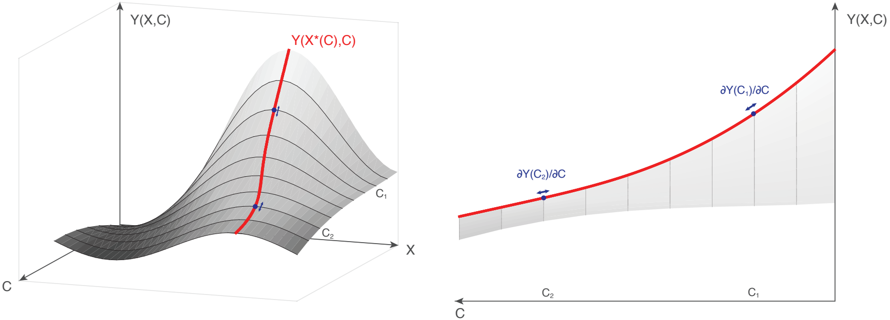

Hsiang (2016)

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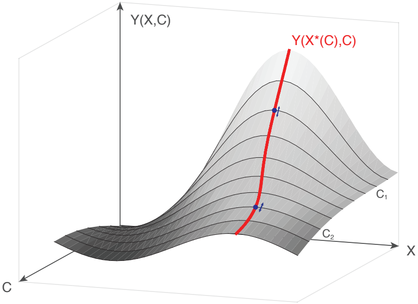

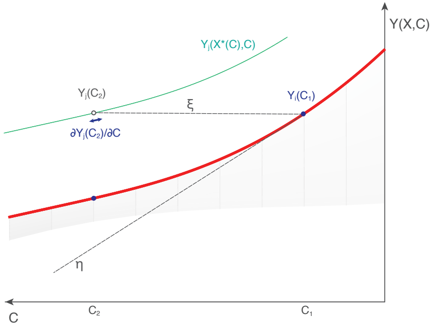

Hsiang (2016)

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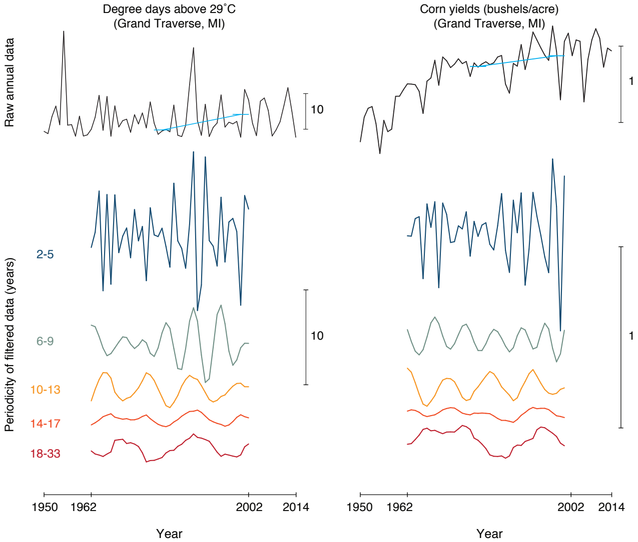

Hsiang (2016)

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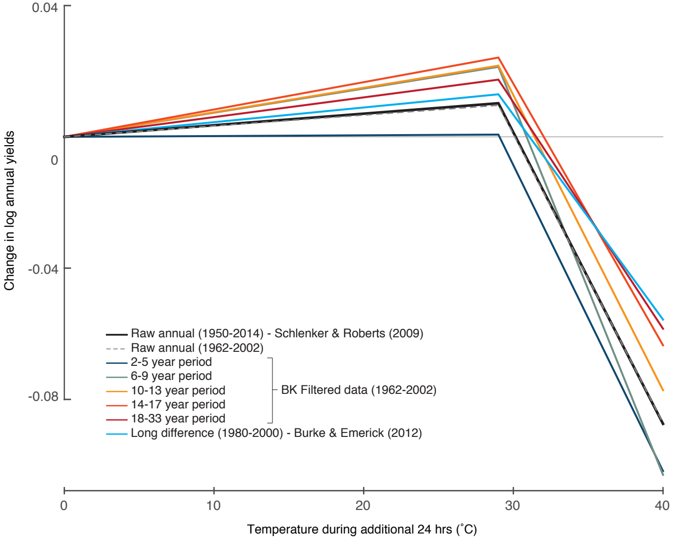

Hsiang (2016)