Essays on the Social Impacts of Climate

Solomon M. Hsiang

Submitted in partial fulfillment of the
requirements for the degree of
Doctor of Philosophy
in the Graduate School of Arts and Sciences

COLUMBIA UNIVERSITY

2011

Abstract

Essays on the Social Impacts of Climate

Solomon M. Hsiang

It has been hypothesized that local or global climatic conditions can affect societies in a variety of ways. However, to date, it has been difficult to measure the social impact of climate, so the scale and scope of its influence on populations remains mostly theoretical. This dissertation integrates data and quantitative methods from climate science, economics and political science to develop new techniques for empirically measuring the the social impacts of climate. These techniques are used to measure large-scale dynamical relationships between climatological conditions and the response of the societies that are exposed to them. In general, the response of societies to climatological forcing is found to be larger than previously thought. The concluding chapter discusses how these findings may inform policies that govern the global environment and economic development.

Contents

List of Figures

List of Tables

Acknowledgments

I would like to sincerely thank my advisors Mark Cane and Bentley MacLeod.

I am also especially indebted to my teachers Douglas Almond, Scott Barrett, Alessandra Casella, Wojciech Kopczuk, Leigh Linden, Matthew Neidell, Jeffrey Sachs, Bernard Salanié, Wolfram Schlenker and Adam Sobel.

I also thank to those who have stood behind this entrepreneurial doctoral program, Mona Khalidi, John Mutter, Joshua Graff Zivin, Geoffrey Heal, Joseph Stiglitz, John Coatsworth and Lisa Anderson; as well as the many faculty and colleagues who helped me along the way: David Autor, Michela Biasutti, Suzana Camargo, Janet Currie, Kerry Emanuel, Raymond Fisman, Alessandra Giannini, Macartan Humphreys, Navin Kartik, Nathaniel Keohane, James Kossin, Edward Miguel, Suresh Naidu, Neville Nicholls, Serena Ng, Cristian Pop-Eleches, David Rind, Robert Solow, Bahvin Sampat, Kerry Smith, Eric Verhoogan, Xiaojia Bao, Charlene Chi, Walker Hanlon, Geoff Johnston, Chandra Kiran Krishnamurthy, Lily Parshall, Geoffrey McCarney, Gordon McCord, Daiju Narita, Andrew Neal, Matthew Notowidigdo, Nicole Ngo, Anisa Khadem Nwachuku, Jose Carlos Orihuela, Mark Orrs, Aly Sanoh, Anna Tompsett, Reed Walker, Gernot Wagner and Marta Vicarelli.

I thank Jesse Anttila-Hughes, Ram Fishman, Xiaoming Jia and Kyle Meng for insight, support, and ensuring that I do not take myself too seriously.

Finally, I thank my grandparents, my parents, my sisters and Brenda for everything else.

For supporting my research, I thank Columbia University and the United States Environmental Protection Agency.

Dissertation Committee

Mark A. Cane
Columbia University
Department of Earth & Environmental Science
Department of Applied Physics & Applied Mathematics

W. Bentley MacLeod
Columbia University
Department of Economics
Department of International & Public Affairs

Edward Miguel
University of California, Berkeley
Department of Economics
The Center of Evaluation for Global Action

Jeffrey D. Sachs
Columbia University
The Earth Institute
Department of Economics

Wolfram Schlenker
Columbia University
Department of Economics
Department of International & Public Affairs

Chapter 1

Introduction

1.1 Context

Understanding how human and natural systems are coupled is a research priority that has rapidly risen in prominence. The interactions between human and natural systems are central to environmental policies, sustainability analysis and, in many cases, development policy. Yet, to date, a majority of research on coupled human-natural systems has focused on the impact that humans have on their environment; while little is known about the effect that environmental conditions have on humans. There are a number of general historical accounts that attribute human outcomes to geographic or environmental conditions, but very few careful analyses of specific causal links.

Our ability to characterize human impacts on the environment better than we can describe environmental impacts on ourselves generates important asymmetries in policy. For example, when an environmental policy is designed to balance costs and benefits of an environmental variable p, we are only able to balance the tradeoffs that we know exist. The canonical public finance problem boils down to maximizing the benefits of a policy that regulates parameter p:

$$\max_p \; value(p) = \max_p \left[\sum_i benefits_i(p) - \sum_j costs_j(p) \right] \tag{1.1}$$

In this case, the estimated costs of a policy come from our knowledge of how we affect environmental parameter p and the costs we associate with improving environmental conditions. In the example of anthropogenic climate change, these costs would be those associated with reducing greenhouse gas emissions. Because these costs are well studied, the term $\sum_j costs_j(p)$ is often well characterized. However, our limited understanding of the ways in which environmental conditions affect us means that the term $\sum_i benefits_i(p)$ is generally incomplete, often completely omitting some $benefit_i$ terms. In these scenarios, the potential for such omissions would suggest that environmental policies might generally be undervalued because cost estimates are generally more complete than benefits estimates.

Traditional approaches in empirical economics have been important for overcoming this asymmetry. Modern techniques for identifying counterfactual environments have allowed us to describe many environmental impacts on society that are otherwise impossible to measure and quantify. For example, traditional approaches have worked well at describing the health benefits of limiting local pollutants, such as soot. The largest contributions of these traditional approaches lie with their ability to identify causal effects, and they have worked well when environmental parameters of social importance are readily observable and measurable (for example, concentrations of soot in urban air). Unfortunately, the statistical tools and research designs used for causal inference have not, on their own, been sufficient for understanding environmental impacts on human societies when important environmental parameters are not readily accessible.

A central challenge to understanding the impact of climates on societies has been the measurement of environmental variables that climatological phenomena impose on societies. Unlike anthropogenic pollutants like soot, natural climatological variations exhibit complex spatial and temporal structures that originate from natural forcing. Further, because these forcings drive many phenomena in our environment, natural climatological variations exhibit important correlations over space and time. Both the complexity and correlation of climatological structures makes it difficult to parametrize and identify their components that are most relevant to society. It seems that the difficulty of measuring climatological phenomena may have been one of the important constraints for quantitative analysis of climatological influences on society.

1.2 Approach

This dissertation focuses on the measurement of climate impacts; and its contributions arise directly from new methods for generating socially-relevant measures of climatological phenomena. My interdisciplinary training in climate physics and economics allowed me to transform raw climatological data into socially-meaningful measures, which I apply in econometric studies of the climate's impact on society. In each paper I examine different components of the general model

$$outcome_t = f(\bar{C}_t, C'_t, \theta_t) \tag{1.2}$$

where social *outcome* at time t is some function of the expected climate state $\bar{C}$, a random environmental component C' and parameters θ which agents may control. Understanding the structure of this equation is essential to solving the problem posed in Equation 1.1 as well as for efficiently designing other social policies that affect θ, such as building irrigation systems in poor countries.

The structure of Equation 1.2 is complex and the four papers in this dissertation can only illuminate small pieces of it. However, each chapter highlights features that each individually have substantive social significance. Taken together, these chapters paint a picture of the world where social outcomes can be tightly coupled to environmental parameters $\bar{C}$ and C', however there are regions in the space of θ where this coupling clearly breaks down. As I discuss in Chapter 6, a central challenge moving forward will be to understand exactly how social parameters θ mitigate or exacerbate the impact of environmental forcing, a challenge that is not trivial because θ is highly endogenous.

The papers in this dissertation intentionally span several dimensions: I have tried to "fill in" as much as possible of what is unknown about Equation 1.2 without generating overlapping results. In terms of *outcomes*, these papers examine both market (Chapters 2, 3 & 4) and non-market outcomes (Chapters 3 & 4) by examining economic production (Chapters 2, 3 & 4), capital depreciation (Chapters 2 & 4), social & political stability (Chapters 3), the loss of human life (Chapters 3 & 4) and changes in risk structures (Chapters 3 & 4). They also focus on different arguments of $f(.)$: Chapter 2 studies unanticipated atmospheric changes (C'), Chapters 3 and 5 study changes in the underlying climate ($\bar{C}$), and Chapter 4 examines the scope for human actions to mitigate environmental events (θ). Further, the types of climatological variations examined vary across the papers from local temperature and rainfall anomalies (Chapter 2), to tropical cyclone strikes (Chapter 2 & 4), to the El Niño-Southern Oscillation (Chapter 3) and finally anthropogenic climate change (Chapter 5). At a more conceptual level, these papers also differ by both examining how environmental fluctuations directly interact with agents themselves, for example by making them less productive (Chapter 2) or killing them (Chapter 4), and examining how environmental fluctuations affect how agents relate to one another, for example by inducing them to fight (Chapter 3) or increasing inequality (Chapter 5). Nonetheless, despite my efforts to explore the space of climate-social coupling with broad brush strokes, this work only represents the beginning of what is a much larger research endeavor. A large number of climatological phenomena remain unexplored with a huge number of potential social impacts. Furthermore, each of the studies that follow are extremely "reduced form;" thus more work is needed to understand these patterns' underlying mechanisms. At a minimum, my work should be viewed as an attempt to establish a basic framework of facts and methods that will enable us to better design and organize future work on coupled human-climate systems.

The econometric approaches used in this work are similar to many of the approaches of applied micro-economics, however my analyses examine highly aggregated data and adopt a "big picture" perspective: three of the four chapters are fully global in scale, in cases utilizing summary statistics to describe the state of the entire planet. This big picture perspective is useful for making generalizations, however it is also an econometric necessity. Because the atmosphere and ocean are fluid bodies that dissipate energy gradients rapidly, natural climatological variations tend to be large in spatial extent. Thus, in order to observe enough variance in climatological variables that we can extract a signal in social data, it is generally necessary that we adopt a regional or global perspective. However, this requirement generates a new challenge: even though climatological phenomena may not vary rapidly over small spatial distances, social phenomena do. Social processes separated by a few kilometers, let alone a few hundred or thousand kilometers, may be entirely unconnected or dissimilar. Therefore, as we adopt a global perspective, we must constantly be aware of social inhomogeneities (basically variations in θ) that challenge the identification and external validity of my results.

The large-scale nature of climatological variations may have been one reason why several of the relationships I characterize were not previously described by observers "on the ground." When large scale environmental patterns change, all the individuals in a location will be exposed to them and it becomes difficult to find unexposed individuals for comparisons. Thus, without carefully tracking changes over time or observing societies far from one another, it becomes difficult for observers on the ground to identify a "treatment effect" when all observable units are treated simultaneously.

As mentioned, the large-scale perspective of these studies requires that they are interpreted with care, however their large-scale nature can also make their interpretation intellectually exciting. When we examine how the universe of societies respond to exogenous forcing of fixed magnitude (Chapters 3 & 4), we find evidence that social responses are strikingly similar around the globe. This consistency suggests that there may exist "laws" to human-environment interactions, an appealing idea that will require rigorous testing in the future.

1.3 Chapter summaries

Chapter 2: Temperature strongly affects economic output probably through worker productivity. In Chapter 2, I examine why temperature variations are so strongly associated with economic output. Following up on the observation that high temperatures are correlated with lower than average growth rates [Dell et al., 2009a], I isolate the impact of temperature from two economically important correlates (rainfall and tropical cyclones) in a region with many small, relatively isolated and economically similar countries. Following a panel of countries, I show that inter-temporal fluctuations in temperature appear to have nonlinear impacts and are focused in labor intensive industries. These results, when compared to laboratory results from ergonomics research, suggest these large macroeconomic fluctuations probably originate in the response of workers to thermal stress. This mechanism appears to have large economic impacts but has been omitted from both previous analyses of climate change and development policies in currently poor and hot countries. In Chapter 5, I compute the global economic cost of this mechanism under anthropogenic climate changes (with limited adaptation) and find that it is similar in magnitude to the sum of all other previously estimated costs. However, while these results do not conflict with cross-sectional correlations in temperature and economic output [Nordhaus, 2006b], further work is required to understand whether or not this mechanism can actually generate differences in incomes across countries.

Chapter 3: Evidence from ENSO that the global climate influences civil conflicts. In Chapter 3, Kyle Meng, Mark Cane and I examine whether the global climate can induce civil conflicts within societies. Building on historical accounts and drawing from extensive literatures in the climate sciences and social sciences, we are able to map the timing of modern civil conflicts onto variations in the El Niño-Southern Oscillation (ENSO). By demonstrating that global patterns of conflict contain a signal that originates from the global climate, our results overcome the previously unsolved challenge of attributing violence to the global climate. Moreover, we find that variations in ENSO describe inter-temporal variations in conflict risk more consistently, generally and robustly than any other commonly used variables. These results may have important implications for how we interpret political history and how we conceptualize the costs of future climate changes. They also may have practical implications for the management of current conflicts, allowing us to reduce overall conflict incidence or at least limit their humanitarian costs. Future work will focus on understanding the mechanisms through which ENSO influences conflict, however it is unclear whether sufficient data exists so that these mechanisms can be disentangled in a satisfying way.

Chapter 4: Vulnerability to tropical cyclones declines rapidly but unevenly. In Chapter 4, Daiju Narita and I examine the rate at which societies become less vulnerable to tropical cyclones (TCs). By improving and scaling-up the method I developed in Chapter 2 for reconstructing TC incidence, we are able to compare how physically similar events lead to different social costs around the world and over time. We are able to reject the hypotheses of previous studies that losses to TCs are rising. Instead, we find that highly visible losses (deaths and economic damages) have been declining rapidly for all but the most extreme TC events; and that this decline does not appear to be driven by rising incomes. In contrast, we find that lost agricultural revenues, which are less visible, have not declined in recent decades. Thus, unearned income now dominates global losses to TCs, a situation very different from that observed mid-century when immediate damages dominated losses. These findings demonstrate that societies can decouple their lives from climatological events at remarkable rates when actions and technologies effectively mitigate risk; but at the same time these findings identify ways in which societies may fail to decouple their lives from these events. By highlighting where vulnerabilities may persist "naturally," i.e. when events are exceptionally extreme or losses are not visible, these results may help policy focus on social vulnerabilities that would not otherwise be addressed. Future work will be needed to understand exactly what kind of social changes, such as technological innovations or developments in political institutions, have lead to the effective reductions in social vulnerability to TCs.

Chapter 5: Summarizing the global economic exposure to anthropogenic temperature changes. In Chapter 5, I characterize the temperature changes that the global economy may be exposed to if anthropogenic climate change proceeds unmitigated. This chapter differs from the others because it is not concerned with causal inference but instead focuses on producing a useful tool to streamline future research. Unlike smaller scale regional analyses, global evaluations of climate change are notoriously complex and opaque. A particular weakness of these global studies, identified by the modelers themselves, is our ability to describe the global costs of unmitigated climate changes. To aid the process of constructing, augmenting and evaluating such global "damage functions," I compute temperature exposures for the global economy's "primitive economic units": people, croplands and dollars of value added. By designing simple, useful and quantified measures of future exposure, I hope that econometricians will more regularly project locally-derived response functions onto the global economy. In this way, the research community can begin to be more systematic and transparent about whether global cost estimates are "reasonable." In ancillary findings we also document that: (1) the cost of thermal stress on productivity is potentially large, (2) summarizing global changes with traditional global averages may introduce large errors to economic analysis, (3) temperature changes are likely to be highly regressive, even before one considers the ability for wealthy populations to protect themselves, and (4) the global economic impacts of warming seem unlikely to be positive.

Appendix

1.A Methodological lessons learned

The central methodological contributions of this dissertation lie in the techniques used for quantifying social exposure to climatological fluctuations. In each paper, a new technique is developed to describe physical exposure to a different phenomena. The methods for doing this vary, but in general they follow these principles/rules-of-thumb, which have emerged through trial and error and which I collect here for reference:

1. **Physical processes should be described with physical measures.** In the study of coupled human-natural systems, there is frequently confusion between *exposure* to a physical process, *vulnerability* to a physical process and the *social cost* of a physical process. Because *exposure* is a physical event (sometimes called a "hazard" or "dosage"), it should be described in terms of physical variables. For unclear reasons, many researchers try to describe physical processes in terms of non-physical units, such as "the number of people affected by a cyclone." It is not obvious how such measures can be interpreted or reproduced.

2. **Physical processes should be described by the parameters that are plausibly most relevant to the social outcome of interest.** Most environmental observations are recorded by physical scientists whose interest is in developing a physical model of an environmental process; and so the observations and measurements taken by these scientists are usually aimed at this goal. Thus, there should be no *a priori* belief that raw environmental observations should map onto social systems in any meaningful way. The analyst should be cognizant of how they expect "the rubber to hit the road" when they study the interaction of climate and society and transform their independent variables accordingly. Some researchers have used raw physical data which

has no direct social significance, such as "the minimum central pressure of a cyclone." Such measures are difficult to interpret for non-scientists and will probably be out-performed by more socially-relevant measures.

3. **Physical processes should be measured in ways that are not manipulatable by society.** Modern econometrics emphasizes the importance of exogenous variation for independent variables. Environmental fluctuations are often strictly exogenous, however if they are measured by social systems they may be biased by the measurement procedure. When constructing measures of societies' physical exposure to a process, the influence of agency should be minimized as much as possible. For example, previous studies have used datasets where cyclone reporting clearly increases with an expanding monitoring network, which itself is correlated with many other social processes.

4. **Physical understanding of a problem can augment weaknesses in data.** Like all datasets, many environmental datasets are unreliable or incomplete. However, understanding the ways in which physical variables are related may allow a single process to be measured with different datasets. For example, when rainfall data in the tropics is incomplete, it is possible to use surface temperature data as a proxy because the two are coupled through the tropical atmosphere's static stability.

5. **Scale-free intensive variables are probably the most generalizable.** The social units in a single dataset may differ in scale by orders of magnitude (eg. countries have different sizes and populations). When comparing environmental impacts on social objects of different size, both dependent and independent variables should be transformed into an intensive, rather than extensive, form.

6. **Construction of physical measures should be checked for robustness.** Because there are few or no standard techniques for projecting environmental variables onto social systems, all procedures remains *ad-hoc*. However, the properties of a physical process should remain qualitatively unchanged if the measurement process is pertubed slightly. This is important to ensure that the measurement procedure does not itself generate artifacts in analyses.

7. **If multiple events are to be aggregated, they probably should be measured in terms of conserved values.** In physical systems, it always makes sense to sum conserved values but

often makes no sense to sum other summary statistics. This differs from many approaches in social science where conservation is not always a central concept.

Chapter 2

Temperatures and Cyclones Strongly Associated with Economic Production in the Caribbean and Central America

Solomon M. Hsiang [1]

[1]This chapter was published in the Proceedings of the National Academy of Sciences in August, 2010.

Abstract

Understanding the economic impact of surface temperatures is an important question for both economic development and climate change policy. This study shows that in 28 Caribbean-basin countries, the response of economic output to increased temperatures is structurally similar to the response of labor productivity to high temperatures, a mechanism omitted from economic models of future climate change. This is demonstrated by isolating the direct influence of temperature from that of tropical cyclones, an important correlate. Notably, output losses occurring in non-agricultural production ($-2.4\%/+1°C$) substantially exceed losses occurring in agricultural production ($-0.1\%/+1°C$). Thus, these results suggest that current models of future climate change that focus on agricultural impacts but omit the response of workers to thermal stress may underestimate the global economic costs of climate change.

2.1 Introduction

Understanding what drives and constrains economic growth is a classical problem in economics [Smith, 1776, Solow, 1956, Ramsey, 1928, Barro and Sala-i-Martin, 2003]. While the relationship between environmental conditions and economic performance is debated [Daly, 1996, Gallup et al., 1999, Acemoglu et al., 2002, Easterly and Levine, 2003, Barro and Sala-i-Martin, 2003, Arrow et al., 2004, Miguel et al., 2004, Auffhammer et al., 2006, Dasgupta, 2008] it is central to cost-benefit analyses of environmental policies, such as the global regulation of greenhouse gases [Stern, 2006, Tol, 2009, Fankhauser, 1995, Nordhaus, 2008, Tol, 2002, Mendelsohn et al., 2006]. In this study, the economic histories of geographically and economically similar Caribbean-basin countries are analyzed to understand whether year-to-year variations in surface temperature and tropical cyclones (hurricanes and tropical storms) could be responsible for country-level economic fluctuations. The central finding is that short-term increases in surface temperature are associated with large reductions in economic output across a set of industries previously considered "not vulnerable" to climate changes. A temporary 1°C increase in surface temperature is associated with contemporaneous 2.5% reductions in economic output.

Recent work by Dell, Jones and Olken (2009) [Dell et al., 2009a] and Jones and Olken (2010) [Jones and Olken, 2010] observe similar magnitude losses in, respectively, total production (-1.1%/+1°C) and exports ($-2.0\%/+1°$C to $-5.7\%/+1°$C) for a larger and more heterogenous sample of countries. They hypothesize that this response may be driven by (1) a temperature-sensitive agricultural sector that in turn has repercussions for the entire economy and/or (2) the response of human labor to thermal stress. This second mechanism has largely been dismissed by modelers of future climate change in favor of the first (for a review and discussion, see Tol (2009) [Tol, 2009]). However, this study suggests that it is implausible for agricultural temperature responses to directly or indirectly drive the observed economy-wide variations in these Caribbean-basin countries.

In the sample of countries examined here, total temperature-related losses in non-agricultural industries exceed the [statistically insignificant] losses of agricultural industries by a factor of 29. Three of six non-agricultural industries suffer large and robust reductions in annual output that are dominated by temperatures experienced during the hottest season and are non-linear in temperatures during that season. The magnitude, structure and coherence of these responses support the hypothesis that the underlying mechanism is a reduction in the productivity of human labor when workers are exposed to thermal stress. The ergonomics and physiology of thermal stress in humans is well-studied [Ramsey and Morrissey, 1978, Wyon, 2001, Pilcher et al., 2002, Hancock and Vasmatzidis, 2003, Seppänen et al., 2003, Hancock et al., 2007], but has been absent from previous integrated assessments of global climate change impacts [Stern, 2006, Tol, 2009, Fankhauser, 1995, Nordhaus, 2008, Tol, 2002, Mendelsohn et al., 2006].

To isolate the direct economic impact of local thermal conditions, the impacts of correlated atmospheric processes must also be accounted for. Because temperatures in the tropical Atlantic and local tropical cyclone activity have been correlated since 1950 [Emanuel, 1999, Mann and Emanuel, 2006, Elsner et al., 2008, Swanson, 2008], the economic impact of tropical cyclones must be estimated and removed from the estimated effect of temperature. If correlations in temperature and output were measured without accounting for the impact of cyclones, it would be difficult to know whether local thermal conditions were directly responsible for reductions in output or if the correlation simply measured the effect of cyclones on output by proxy. To measure the impact of cyclones so it may be separated from the impact of temperature, wind-field histories for every storm passing through the region is numerically reconstructed (Fig. 2.1A). Energy dissipation per square-meter is then computed for each location in the region (Fig. 2.1B and 2.4) and spatially-averaged over each country for every year (see Methods). When this measure of cyclone incidence is compared to raw economic data (for example, Fig. 2.1C), it is clear that cyclones are a major factor in some economic processes and must be accounted for. Annual rainfall is also controlled for in all of the statistical models, however the results are not presented here.

Transient production losses associated with tropical cyclones exhibit an entirely different structure from those associated with temperature; and are most strongly exhibited in agriculture and tourism, the two sectors where adaptation via geographic relocation are plausibly the most costly. In contrast, the construction industry expands production in response to cyclones, probably due to its role in reconstruction. While the economic impacts of temperature changes only appear contemporaneously with temperature fluctuations, the direct impacts of cyclones may persist for several years.

Annual longitudinal data from 28 countries in Central America and the Caribbean (1970-2006, see Supplementary Section 2.A and Table 2.4) are analyzed with multiple regression analyses that simultaneously control for precipitation, average country-level differences in production for each industry, country-industry time-trends in production and year-level shocks to regional-industry production (see Methods and Section 2.B). Throughout this study the effects of temperature and cyclones are estimated simultaneously, however they are presented in sequence for clarity.

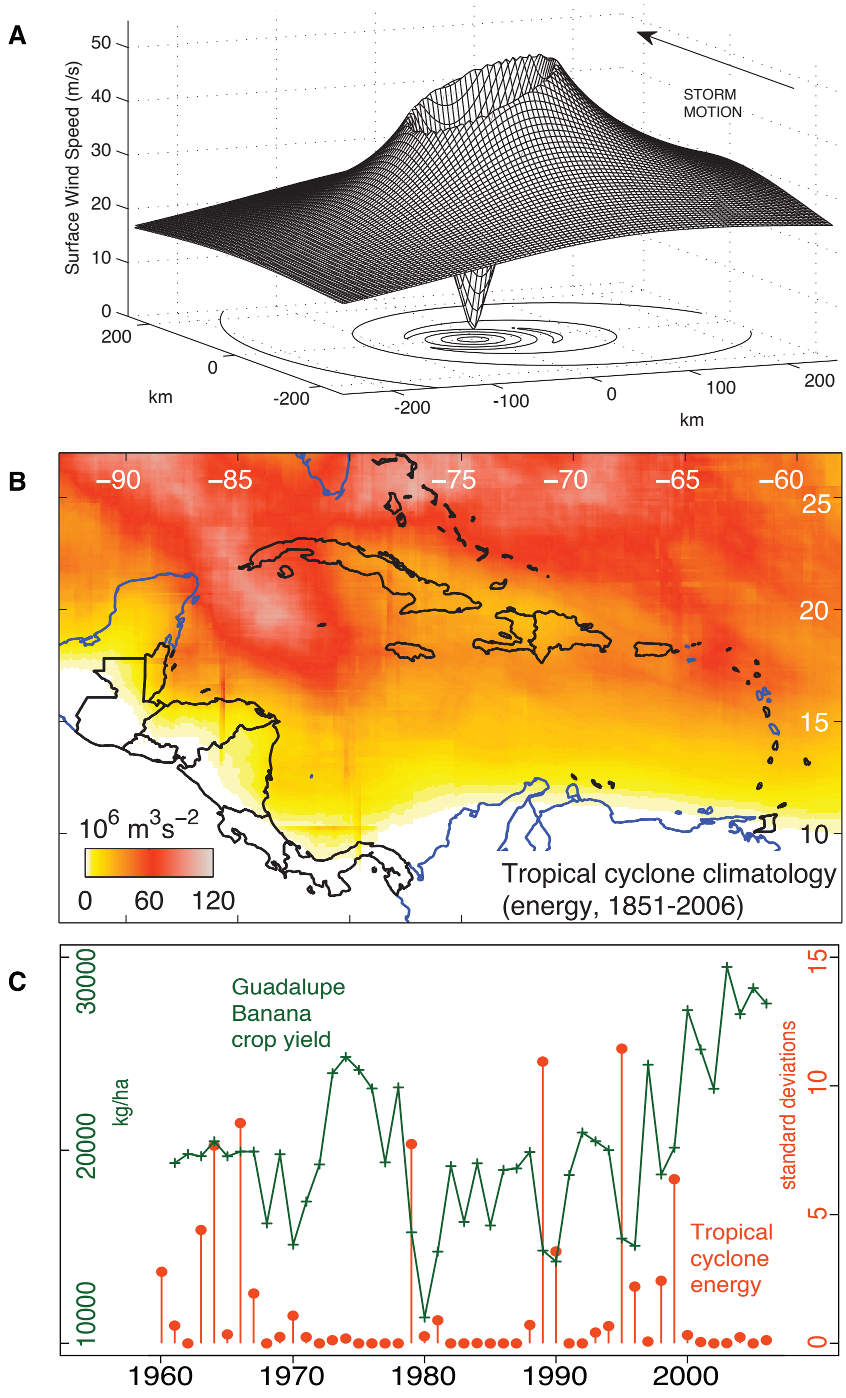


Figure 2.1: **Estimating tropical cyclone exposure and impacts.** (A) An example idealized surface wind speed function used to reconstruct the distribution of cyclone energy dissipated for each storm (contours reflect the overlying surface). The direction of wind flow is irrelevant to energy dissipation, so azimuthal flow is combined with the translational velocity of the storm (arrow) generating the observed asymmetry in the wind speed field about the storm's vector of motion. (B) The average density of tropical cyclone wind energy annually dissipated throughout the Caribbean Basin over the period 1851-2006. Countries included in this study are black, those excluded are blue. Inclusion is based only on geographical extent and the availability of economic data. (c) An example of economic impacts: banana crop yield (green) [source: FAOstat] and annual tropical cyclone energy dissipation (orange) in Guadeloupe.

Table 2.1: The effect of annual average surface temperature on production (1970-2006)

Industry	$\%\Delta/{+1}°C$	s.e.m.	% output
Total production	-2.5%**	[1.0]	-
Wholesale, retail, restaurants & hotels	-6.1%***	[1.7]	20.4
Other services	-2.2%**	[1.1]	35.0
Transport & communications	-2.2%	[1.7]	10.7
Construction	-0.6%	[3.1]	7.4
Manufacturing	$+1.4\%$	[2.6]	12.0
Agriculture, hunting & fishing	-0.8%	[2.5]	10.5
Mining & Utilities	-4.2%*	[2.4]	4.2

*** p<0.01, ** p<0.05, * p<0.1

2.2 Temperature impacts

Annual average temperatures are associated with statistically significant reductions in total domestic output and the outputs for three of six non-agricultural industries. These results are presented in Table 2.1 and they suggest that it is implausible for agricultural losses to drive these economy-wide responses in the Caribbean and Central America. First, the statistically significant responses of *wholesale, retail, restaurants & hotels* (-6.1%/+1°C), *mining & utilities* (-4.2%/+1°C) and *other services* (-2.2%/+1°C) are substantially larger than the estimated [statistically insignificant] response of *agriculture, hunting & fishing* (-0.8%/+1°C) when measured in percentage points. Second, these responses dwarf the losses in agriculture further if they are measured in terms of their "economic size." The last column of Table 2.1 lists the average contribution of each industry to total production. *Wholesale, retail, restaurants & hotels* and *other services* together constitute 55.4% of value-added in the region's average economy, compared to the 10.5% represented by agriculture. Thus, production losses in the two former industries account for approximately $-2.0\%/{+1}°C$ in the economy-wide losses of $-2.5\%/{+1}°C$. This is twenty-fold the losses in *agriculture, hunting & fishing*, estimated at $-0.1\%/{+1}°C$ in economy-wide losses.

The sheer scale of the economic response to temperature suggests it cannot be driven by agriculture alone, and the centrality of labor to production in *wholesale, retail, restaurants & hotels* and *other services* is suggestive that ergonomic considerations may be important. However, additional evidence substantially strengthens the case for ergonomic impacts. Meta-analyses of over 150 laboratory and observational ergonomic studies agree that most forms of human performance deteriorate under levels of thermal stress beyond a threshold [Ramsey and Morrissey, 1978, Wyon, 2001, Pilcher et al., 2002, Hancock and Vasmatzidis, 2003, Seppänen et al., 2003, Hancock et al., 2007]. Thus, performance losses appear to be non-linear, with little or no performance loss from temperature increases in moder-

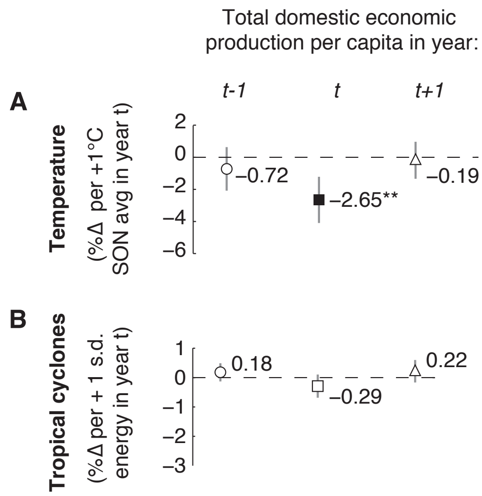


Figure 2.2: **The estimated impact of transient atmospheric changes in year t on total domestic output.** (A) Reductions in total output the year before (circle), the year of (square) and the year following (triangle) a 1° increase in Sep-Oct-Nov temperature. (B) The same, but for a 1 standard deviation increase in cyclone energy dissipation. Whiskers are 90% confidence intervals, a filled marker is statistically significant. Significance: *** 1%, ** 5%, * 10%.

ate temperature regimes and large performances losses associated with temperature increases in high temperature regimes. If the economic responses to annual average temperature are driven by performance losses, then they should be similarly non-linear and driven primarily by high temperatures. Two techniques are used to detect the presence of this non-linearity. First, the effect of annual average temperature is decomposed into four seasonal contributions: December-January-February (DJF), March-April-May (MAM), June-July-August (JJA) and September-October-November (SON). If the economic response to temperature is non-linear and in agreement with ergonomic studies, temperature changes during the hottest season (SON in this region) should have a larger economic impact than temperature changes in other seasons. Second, spline regressions on degree-days are used to look for non-linearities within this hottest season.

In all industries except *mining & utilities* and *manufacturing*, temperature increases during SON (the hottest season) are associated with the largest reductions in production. Each column in Table 2.2 presents coefficients for seasonal average temperatures that are estimated simultaneously. Most of the production losses associated with increased annual average temperatures are due to temperature increases in SON. The effects of temperature changes during all other seasons are not statistically different from zero (except one coefficient for *mining & utilities*). This is consistent with the hypothesis

Table 2.2: The effect of seasonal average temperature on production (1970-2006)

	Total production	Wholesale ...hotels	Other services	Transport & comm.	Constr.	Manuf.	Agr., hunt. & fishing	Mining& utilities
T_t^{DJF}	-0.5%	-1.4	0.1	-0.2	0.2	-2	-0.9	-3.5**
	[0.6]	[1.0]	[0.7]	[1.1]	[2.4]	[1.6]	[2.0]	[1.7]
T_t^{MAM}	-0.3	0.4	-0.6	0.4	2.6	1.3	0	-1.2
	[0.8]	[1.0]	[0.8]	[1.0]	[2.9]	[1.4]	[1.6]	[1.5]
T_t^{JJA}	0.6	-0.8	0.6	1.2	0.7	1.5	2	0.3
	[1.2]	[1.8]	[1.4]	[1.5]	[4.2]	[2.3]	[2.3]	[2.8]
T_t^{SON}	-2.9***	-4.6***	-2.6**	-4.3***	-5	-1.8	-3.9	1.2
	[1.0]	[1.7]	[1.0]	[1.4]	[3.1]	[2.4]	[2.4]	[2.5]
Obs.	972	972	972	968	972	962	972	959

*** $p<0.01$, ** $p<0.05$, * $p<0.1$, units: $\%\Delta/+1°C$

that production losses are nonlinear in temperature, with production dropping most strongly at the highest temperatures. Furthermore, the coefficients for SON temperature are more precise than those for annual temperature (Table 2.5). This suggests that annual average temperatures served as a noisy measure of SON temperature for the results in Table 2.1, and that SON temperature is the measure most strongly associated with economic output. Therefore, for statistical parsimony, SON temperature is used as the sole predictor of output unless otherwise noted[1]. Using this model, both *transport & communications* and *construction* exhibit significant production losses, compared to their statistically insignificant responses to annual average temperatures.

Only current SON temperature is associated production losses, rather than future or past temperatures, further supporting the hypothesis that thermal stress during the production process is driving losses. If temperature-induced losses in agriculture were driving the losses in other industries, one might expect the losses in non-agricultural industries to lag behind temperature changes since it would take time for the "temperature signal" to propagate through the entire economy. Fig. 2.2A plots the response of *total production* to a 1°C increase in future, current and past SON temperature. Only the effect of current SON temperature is statistically different from zero. Fig. 2.3 plots similar results for all seven industries. In the four industries significantly impacted by SON temperature, neither future (Table 2.6) nor past temperatures have a significant impact on current production.

Estimating linear coefficients in Figs. 2.2-2.3 is a good approximation of the data. To show this, Fig. 2.4A plots non-parametric estimates of *total production*, *wholesale, retail, restaurants & hotels*, *other services* and *transport & communications*, each against SON temperature (once the effects of other

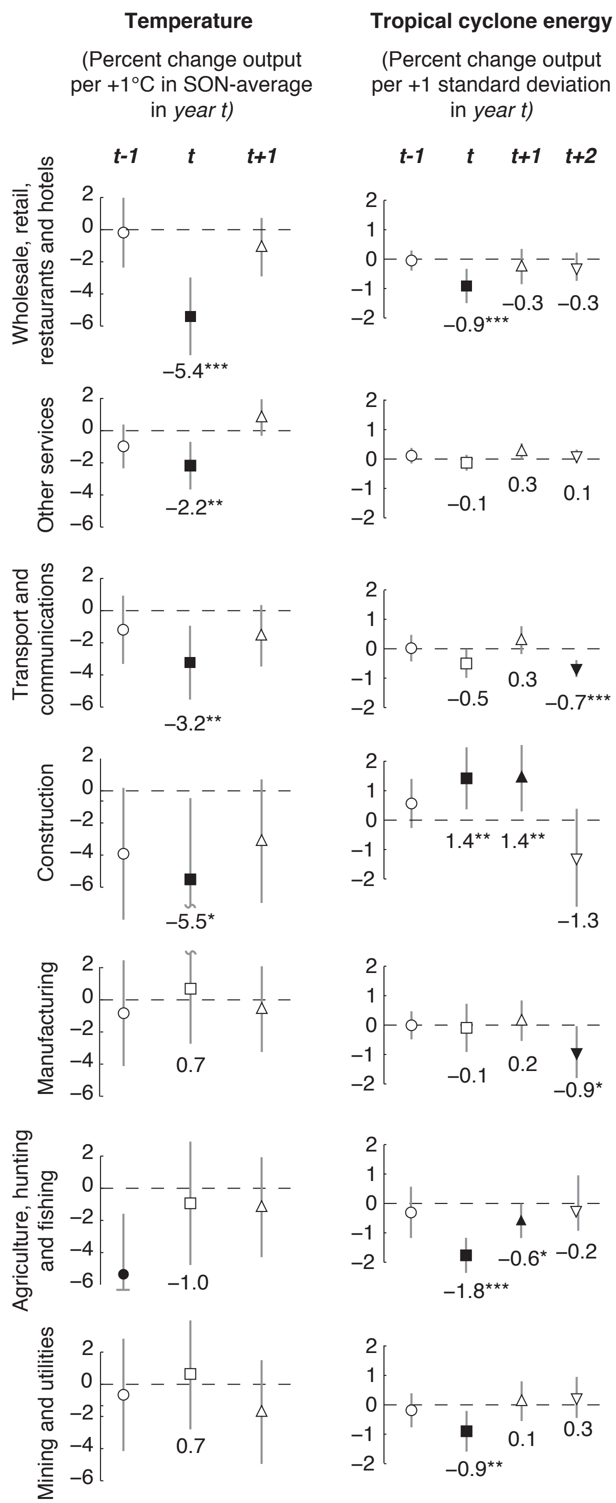


Figure 2.3: **Industry-level production responses to temperature and tropical cyclones.** Rows are industries. The left column plots responses to average Sep-Oct-Nov temperature, the right column plots responses to cyclone energy dissipation. Markings and units are the same as Fig. 2.2.

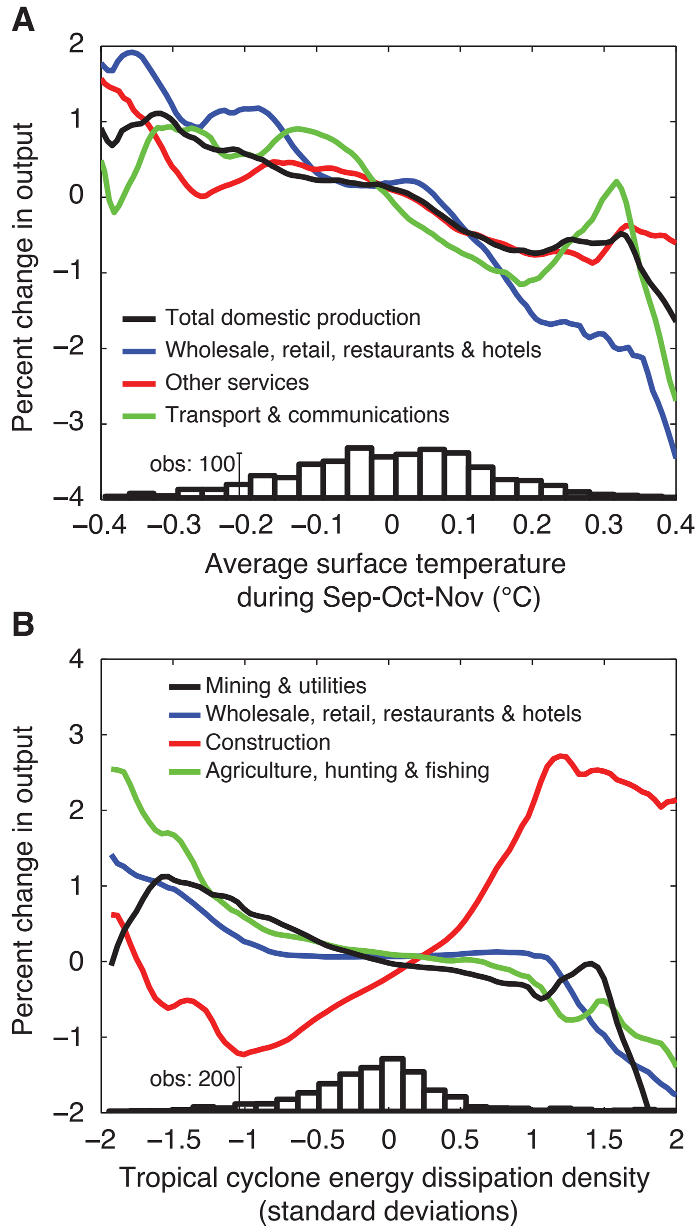


Figure 2.4: **Validating the appropriateness of a linear regression model.** The responses to (A) average *SON* surface temperature and (B) tropical cyclone energy. Measures are residuals following regression on all remaining regressors. Histograms plot observational densities. The response functions are most precisely estimated near zero residual values (abscissa), where observational density is high; distortion near the tails is expected from sampling noise. These relationships are well approximated by linear functions for residual values near zero. Panel (A) also shows that the estimated responses to temperature are not driven by outliers.

variables have been removed; see Fig. 2.7 for all sectors and confidence intervals). These estimated responses are also broadly robust to the statistical model used. The estimated effects of current SON temperature do not change substantially with the number of lags used, whether country-specific trends are included, whether output is measured relative to the previous year's output (rather than relative to a trend) or if structural breaks following large cyclone events are allowed (Tables 2.7-2.8).

As a second test for the non-linear economic response to surface temperature, the response to daily variations in temperature within the SON season are estimated. Even though economic data is only available annually, daily production responses can be estimated using "degree days" (see Methods). Fig. 2.5A plots the estimated response to daily average surface temperatures during SON for the robustly temperature-sensitive industries (Table 2.9 provides coefficients and SE). Except for *total production*, economic responses to temperature changes below 27°C are not statistically different from zero. For temperature changes between 27-29°C, the responses become slightly steeper for all industries and statistically different from zero for *wholesale, retail, restaurants & hotels* and *transport & communications*. Above 29°C, the response steepens further for all industries and becomes significant for *other services* (although it is no longer significant for *wholesale, retail, restaurants & hotels*). Taken together, these results suggest that it is the years with a large number of very hot days during the hottest season that exhibit the largest production losses.

Production's transition from weak dependance on temperature to strong dependence on temperature occurs near a daily average temperature of 27-29°C. For normal sea-level conditions, this roughly corresponds to a "Wet Bulb Globe Temperature" (WBGT) at or above 25°C, the level of thermal stress near which human performance begins to deteriorate in laboratory experiments [Ramsey and Morrissey, 1978, Wyon, 2001, Pilcher et al., 2002, Hancock and Vasmatzidis, 2003, Seppänen et al., 2003, Hancock et al., 2007]. Fig. 2.5b shows "average" performance losses from three meta-analyses [Ramsey and Morrissey, 1978, Pilcher et al., 2002, Seppänen et al., 2003], a literature that informed the "Recommended Exposure Limits" of the National Institute for Occupational Safety and Health of the United States (1986) [NIOSH, 1986] (red line, Fig. 2.5b). Because humidity, radiation and air flow affect the intensity of thermal stress experienced by workers, ergonomics research utilizes measures that capture their impact. WBGT, expressed in °C and plotted along the abscissa in Fig. 2.5b, is one such measure. Insufficient data is available to calculate daily WBGT for this analysis, however the WBGT equivalents of 27 and 29°C at 80% relative humidity and 1000hPa ("normal" sea level conditions) are orange crosses in Fig. 2.5 for reference. Daily average temperatures in the region regularly exceed

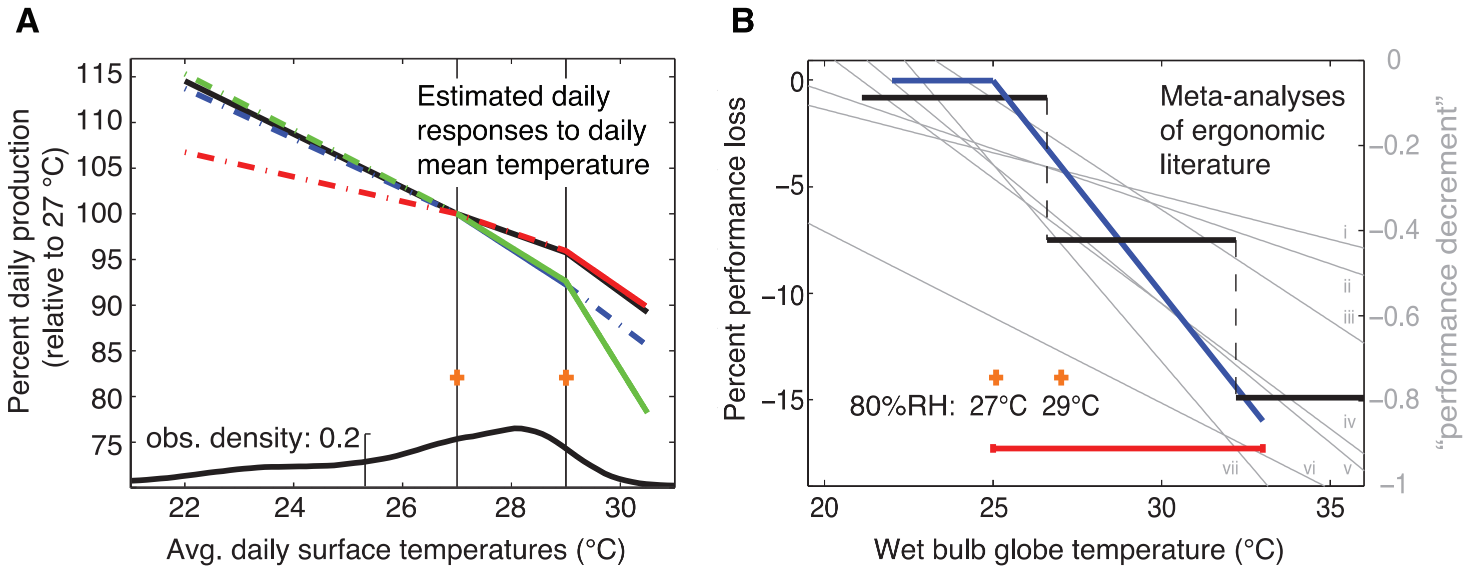


Figure 2.5: **Nonlinear industry responses mirror laboratory ergonomic studies.** (A) Production responses to daily SON surface temperatures using "degree days." Production at 27°C is normalized to 100%. Industries and colors are the same as those in Fig. 2.4A. Solid lines indicate the slope is statistically significant, otherwise lines are dashed. (B) Productivity surfaces from meta-analyses of ergonomic studies. Orange crosses correspond to crosses in Panel (A) under "normal" sea level conditions. Black (Pilcher et al., 2002) and blue (Seppänen et al. 2003): "average" performance losses (left axis). Grey (Ramsey and Morrissey, 1978): unitless "performance decrement" following two hours of thermal stress for tasks: *i* mental, *ii* mental/reaction time, *iii* reaction time, *iv* tracking/vigilance/complex, *v* complex, *vi* vigilance, *vii* tracking. Red: range of "Recommended [1 hour] Exposure Limits" from the National Institute for Occupational Safety (1986).

these threshold temperatures (black curve, bottom of Fig. 2.5A) and are associated with years in which labor-intensive industries experience the largest economic losses. This is consistent with the hypothesis that country-level production losses associated with high-temperature years reflect individual-level responses to thermal stress.

2.3 Addressing cyclones as confounding phenomena

To ensure the estimated impact of surface temperature on production captures direct thermal effects, not the influence of cyclones, the influence of cyclones must be modeled simultaneously. This is important because tropical Atlantic sea surface temperatures have been correlated with basin cyclone activity during the last half century [Emanuel, 1999, Mann and Emanuel, 2006, Elsner et al., 2008, Swanson, 2008]. If the responses to cyclones and surface temperature are not modeled simultaneously, the effects of the omitted variable might contaminate the estimates of the modeled response. Using a parametric "storm kernal" (Fig. 2.1A) the historical exposure of countries to cyclones was reconstructed for every year and every country (see Methods). For this analysis, "exposure" is measured as dissipated wind energy per unit area and normalized to the observed standard deviation ($mean = 0.32$, $min = 0$, $max = 13.1$).

Regression of *total production* on cyclone energy (Fig. 2.2B) suggests that the overall effect of cyclones on output is not distinguishable from zero, but this is misleading. Decomposition of this response by industry (Fig. 2.3) reveals that there are both large negative and positive output responses to cyclone events. Also, contrasting with the impact of temperature changes, significant cyclone impacts may persist beyond the year of the initial event. *Agriculture, hunting & fishing* ($-1.8\%/+1$ s.d. and $-0.6\%/+1$ s.d. the year following), *wholesale, retail, restaurants & hotels* ($-0.9\%/+1$ s.d.) and *mining & utilities* ($-0.9\%/+1$ s.d.) all reduce output in response to cyclones, while *construction* ($+1.4\%/+1$ s.d. and $+1.4\%/+1$ s.d. the year following) expands, presumably because of its role in reconstruction. Fig. 2.4B demonstrates that a linear model of income is a good approximation for the production response to cyclones for all but the most extreme observations (see Fig. 2.8 for all industries and confidence intervals). These impacts are broadly robust to the statistical model used (Tables 2.7-2.8).

The impact of cyclones on tourism-related income is disproportionately large. Data on total income attributed to tourists, across all industries, is available for a shorter period (1995-2006) and reveals substantial losses that persist multiple years. Table 2.3 displays reductions in tourism income relative

Table 2.3: The effect of cyclones on tourism (1995-2006)

	Deviations from a trend			Change from prior year		
Dependent var:	receipts	visitors	$ per visit	receipts	visitors	$ per visit
$Cyclones_t$	-1.6%	-0.9	-0.6	-1.0*	-1.5**	0.3
	[1.0]	[0.6]	[1.1]	[0.5]	[0.5]	[0.4]
$Cyclones_{t-1}$	-3.5***	-2.8**	-0.7	-1.8**	-2.0**	0.1
	[1.2]	[1.1]	[1.0]	[0.8]	[0.8]	[0.4]
$Cyclones_{t-2}$	-2.5**	-0.9	-1.4	1.1	1.4	-0.3
	[1.0]	[1.2]	[0.9]	[0.7]	[1.4]	[0.8]
$Cyclones_{t-3}$	-3.0**	-2.0*	-1.0*	-	-	-
	[1.4]	[1.2]	[0.6]			
$Cyclones_{t-4}$	-1.8*	-1.2	-0.7	-	-	-
	[1.0]	[0.9]	[0.7]			
$Cyclones_{t-5}$	-0.4	-0.3	-0.2	-	-	-
	[0.7]	[0.7]	[0.7]			
$Cyclones_{t-6}$	0.0	-0.9	0.6	-	-	-
	[0.6]	[0.7]	[0.6]			
Obs.	275	273	273	252	250	250

*** p<0.01, ** p<0.05, * p<0.1, units: $\%\Delta/+1$ s.d. cyclone energy dissipation m^{-2}

to a trend and relative to the previous year. The response in both models is large and driven primarily by reductions in tourist visits, rather than by reductions of income per visit.

2.4 Discussion

Economies recover from shocks slowly, so the short-term impact of temperature changes have larger long-term consequences. The estimated 2.5% reduction in output associated with a 1°C temperature increase in year t is the direct effect of temperature on output in year t. However, it is well known that output in one year will affect output in the following year [Barro and Sala-i-Martin, 2003]. Thus, a temperature change in one year (t) will *indirectly* affect output in the following year ($t+1$) by altering output in the first year (t). This is true even though it was shown in Fig. 2.2 that temperature in the first year (t) did not *directly* influence output the following year ($t+1$). In this sample, total production in any year is observed to be approximately 0.9 times output the year before. Therefore, a one-time reduction in output of 2.5% at time t leads to additional indirect reductions over all future years that sum to 22.5% of output[2] (as measured at time t).

This work analyzes only transient and unexpected variations in the atmosphere around the expected climatological state. When individuals adapt to changes in climatological conditions, the response may differ [Smith et al., 2006, Deschenes and Greenstone, 2007]. Agriculture and tourism, industries where geographic location plays a central role in production, suffer most from tropical cyclones. This suggests that other industries, where relocation is a less costly adaptive strategy, may have adapted successfully to cyclones. Adaptation to thermal stress may take many forms and some strategies will be available to individuals even over short time horizons. For example, individuals may work less if high temperatures make their efforts more exhausting [Graff Zivin and Neidell, 2010], although the costs of these strategies may themselves be considerable. For this reason, it is possible that as countries become wealthier, they are better able to cope with environmental changes [Dell et al., 2009a, Stern, 2006]. Within this sample of countries, when the response to temperature changes and cyclones are allowed to be functions of income (Section 2.C and Table 2.10-2.11) there is suggestive evidence that this intuition is generally true.

While these results are specific to the Caribbean and Central America, the mechanisms are plausibly quite general. Nonetheless, future work should evaluate the extent to which similar patterns hold in other regions, taking into account those regions' meteorological patterns and correlates of temperature.

Projected impacts from global climatic change have included capital losses from cyclones [Nordhaus, 2006a, Narita et al., 2009] and the impact of temperature on agriculture and health [Stern, 2006, Tol, 2009, Fankhauser, 1995, Nordhaus, 2008, Tol, 2002, Mendelsohn et al., 2006]. None of these integrated assessments have accounted explicitly for the impacts of thermal stress on human labor. While agriculture's vulnerability to high temperature is a focus of most estimates, this may be only a small fraction of our economic vulnerability to changes in local temperature. It is estimated here that output in the studied region would drop 2.5% in response to a temporary increase of 1°C, but only 0.1% of this is attributable to reductions in agricultural output. The remaining 2.4% occurs in industries that have been omitted from existing cost estimates of global climatic change [Stern, 2006, Tol, 2009, Fankhauser, 1995, Nordhaus, 2008, Tol, 2002, Mendelsohn et al., 2006].

2.5 Methods

Annual economic data is available for 28 of 31 countries in the region (see blue boundaries in Fig. 2.1B). Their combined population in 2007 was 81 million people. Details on the data are in Supplementary Section 2.A, Table 2.4 contains summary statistics.

Atmospheric data The local energy dissipated at the surface per square meter by tropical cyclone winds are estimated and denoted C. Flooding, landslides and storm surges are not modeled explicitly. Storm locations and intensities are taken from the Best Track record [Neumann et al., 1999]. Storms are parametrically modeled as translating Rankine vortices [Kossin et al., 2007] out to a radius of 250 km on a 10 km grid (see Fig. 2.1a). Surface temperature T and rainfall R estimates are spatially averaged over each country. Surface temperatures are from NCEP-NCAR Climate Data Assimilation System 1 reanalysis [Kalnay et al., 1996]. Rainfall estimates are from the CPC Merged Analysis of Precipitation [Xie and Arkin, 1996] (CMAP), with missing observations replaced with NOAA's Climate Anomaly Monitoring System (CAMS) [Ropelewski et al., 1985] estimates.

Economic data The production of goods and services is measured by per capita value-added and its logarithm taken (denoted V) so percentage changes can be estimated linearly. National accounts are collected and maintained by the United Nations [UN, 2007] (UN) . Production in each country is aggregated into industries according to the International Standard Industrial Classification of All Economic Activities (ISIC): *agriculture, hunting & fishing* (ISIC code: A + B); *mining & utilities* (C + E); *manufacturing* (D); *construction* (F), *wholesale, retail, hotels & restaurants* (G + H), *transport & communication* (I), and *other services* (J-P). Tourism data is collected by the UN World Tourism Organization [UN, 2008].

Regressions The dependence of production on exogenous fluctuations in atmospheric states is estimated by multivariate panel regressions using ordinary least squares (Section 2.B). Such connections are identified by comparing only year to year variations in local conditions that do not follow the secular time trend of the country and are distinct from regional shocks. This methodology differs from cross-sectional analyses that compare levels of production between economies exposed to different average environments [Tol, 2009, Nordhaus, 2006b, Dell et al., 2009b]. If the relation of interest is approximately linear, short-run impacts can be identified by comparing idiosyncratic, year-to-year variations. To account for simultaneous variations in temperature, rainfall and cyclone exposure, all responses are estimated simultaneously using a distristributed-lag, auto-regressive (2) regression

$$V_{it}^{j} = \rho_1^j \times V_{i,t-1}^j + \rho_2^j \times V_{i,t-2}^j + \sum_{L=0}^{\tau} \left[\beta_T^{jL} \times T_{i,t-L} + \beta_C^{jL} \times C_{i,t-L} + \beta_R^{jL} \times R_{i,t-L} \right] + \gamma_i^j \times t + \delta_i^j \times t^2 + \eta_t^j + \mu_i^j + \epsilon_{it}^j \tag{2.1}$$

for industry j. ρ_{1-2} represent auto-regressive coefficients, γ and δ are country-specific trends for each industry, η is a region-industry by year constant, μ is an industry by country constant and ϵ is a disturbance term. The variables of interest are the coefficients β, the derivatives of production with respect to fluctuations in surface temperature T, tropical cyclone energy C and rainfall R. These coefficients are assumed to be the same for all 28 countries, motivating the restriction of analysis to a small group of countries with limited heterogeneity. Positive "lags" L are used to track and measure the impact of events from previous years, up to some maximum lag $\tau \leq 5$. ϵ characterizes variations in output not explained by temporary atmospheric changes. Equation 2.1 is adjusted when estimating seasonal impacts by replacing T with T^{SON} and/or a vector of seasonal temperatures (in the case of Table 2.2). A second regression model that omits the lagged values of the dependent variable and the country-specific trends while replacing V_{it}^{j} with $\Delta V_{it}^{j} = V_{it}^{j} - V_{i,t-1}^{j}$ is also estimated (Table 2.7-2.8) and provides similar estimates to Equation 2.1. Because this second model provides a more consistent description of cyclone responses (across lag specifications) it is the model displayed in cyclone panels of Figs. 2.2-2.3.

Figure 2.4 The non-parametric curve in Fig. 2.4 is a Nadaraya-Watson moving average with an Epanechnikov kernel [Nadaraya, 1964, Watson, 1964]. The bandwidth in Panel A (B) is 0.1°C (1 s.d.). Bootstrapped standard errors for these curves are in Figs. 2.7-2.8. Both variables are residuals from regressions on all remaining regressors in Equation 2.1 [Frisch and Waugh, 1933].

Daily production Daily production data is unavailable, however analysis of "accumulated degree-days" can recover the response to daily average conditions if the response to temperature is constant throughout the year [Schlenker and Roberts, 2009]. In Equation 2.1, the temperature term is replaced by four terms representing the accumulated degree-days in four temperature bins: <27, 27-29 and >29°C. Temperature variations within each bin are treated as separate variables, with the OLS coefficient for a bin representing the response of production to daily temperature variations only within that bin. A full derivation of this model is in the Supplementary Information Appendix.

Uncertainty Uncertainty in the estimated values of β are calculated using generalized method of moments estimates for variance of β. Non-parametric estimation of the variance-covariance matrix for ϵ allows for contemporaneous spatial correlations between countries whose centroids lie within 300 km of one another [Conley, 1999]. Following Conley (2008) [Conley, 2008], weights in this matrix are uniform up to that cutoff distance. In addition, non-parametric estimates of country-specific serial-correlation are estimated using linear weights that decays to zero after a lag length of five years [Newey and West, 1987]. This technique ensures that uncertainty in β is adjusted to account for heteroscedasticity, country-specific serial correlation and cross-sectional spatial correlation. Due to computational difficulties, uncertainty for tourism-related regressions is computed with a variance-covariance matrix that allows for uniformly-weighted clustering by country [Bertrand et al., 2004,Newey and West, 1987], but no spatial correlation. Significance tests are two-tailed t-tests. For details, see Supplementary Information Appendix.

Appendix

2.A Data Supplement

Table 2.4 contains summary statistics for the primary variables used in the analysis.

Countries Included in this study are Anguilla, Aruba, the Bahamas, Barbados, Belize, the British Virgin Islands, the Cayman Islands, Costa Rica, Cuba, Dominica, Dominican Republic, Antigua and Barbuda, El Salvador, Grenada, Guatemala, Haiti, Honduras, Jamaica, the Netherlands Antilles, St. Lucia, Montserrat, Nicaragua, Panama, Puerto Rico, St. Kitts and Nevis, St. Vincent and the Grenadines, Trinidad and Tobago and the Turks and Caicos Islands. Note that not all countries are independent states for all or any of the years in the sample.

Temperature Observations are extracted from gridded reanalysis estimates from the NOAA NCEP-NCAR Climate Data Assimilation System I [Kalnay et al., 1996]. Temperature is spatially averaged over each country.

Rainfall Climate Prediction Center (CPC) Merged Analysis of Precipitation (CMAP) estimates of rainfall are preferred because they merge available gauge readings with satellite data. When CMAP observations are unavailable, they are replace by CPC's Climate Anomaly Monitoring System (CAMS) observations that interpolate gauge readings only. When combined, rainfall estimates are available for the period 1950-2007. Like temperature, spatial averages are used.

Cyclones Storms trajectories and intensities are taken from the HURDAT Best Track database [Neumann et al., 1999], with the wind field of each storm numerically reconstructed to estimate the "storm experience" of individuals on the ground. This novel technique is implemented with the Limited Information Cyclone Reconstruction and Integration for Climate and Economics (LICRICE) model, which uses statistical relationships about key parameters to rebuild storm structures using information collected prior to the satellite era.

The radius of maximum wind is predicted using a linear function of latitude and maximum wind speed [Kossin et al., 2007], even when satellite data is available for statistical consistency. The field of absolute surface wind speed is estimated by combining azimuthal winds and the translational velocity of the storm. An example wind-speed function is pictured in Fig. 2.1A.

Holding constant surface wind speed and drag (and thus the working rate), cyclone energy dissipation at a fixed location will increase when a storm remains over that location longer. For this reason, power dissipation must be multiplied by the length of time a storm spends at a location, which is inversely proportional to the storm's translational speed. The translational speed of a storm's center is calculated for each six-hour interval of the Best Track record and then smoothed once with a 1-2-1 filter to prevent large jumps in storm velocity. Fig. S2.6 plots an example field of total estimated energy dissipation for all points in the region during 2004.

All else equal, larger countries have more total energy dissipated over them, so energy dissipation is normalized by a country's area. Thus, the measure of energy dissipation is an energy dissipation *density* that describes the expected quantity of energy dissipated over a square kilometer conditional only on the year and the country containing that square.

The cyclone energy density C is an annual estimate, so it is summed over all storms affecting country i in year t:

$$C_{it} = \frac{\kappa}{A_i} \sum_{z \in i} \sum_{s \in t} \frac{V_s^{wind}(z)^3}{V_s^{storm}}$$

where V_s^{storm} is the translational velocity of the center of a storm indexed by s, $V_s^{wind}(z)$ is the velocity of wind at grid cell z, A_i is the area of country i, and κ is a constant capturing drag and the density of air. This measure is analogous to a density of *accumulated cyclone energy* (ACE), a commonly used alternative measure [**?**].

Economic output National statistical agencies, government ministries, central banks and other international institutions provide national accounts data to the United Nations where it is standardized into estimates of annually averaged production for twenty-eight countries from 1970-2007 [UN, 2007]. Details on the methodology for data estimation can be found at `data.un.org`.

Tourism *Tourism receipts* are the income earned by destination countries from visitors' consumption across multiple industries (lodging, transport, food, etc.) [UN, 2008]. It excludes income related to international transport contracted by residents of other countries. The data is maintained by the Secretariat of the United Nations World Tourism Organization (UNWTO), details are at `unwto.org`. Tourism data are available for twenty-five countries for the shorter period 1995-2006.

2.B Method Supplement

The objective of this study is to empirically determine if the production of value in individual industries has any statistical dependance on interannual variations in the state of the local atmosphere. Previous work used a cross-sectional approach where patterns in production are correlated with the *average* state of the local atmosphere [Nordhaus, 2006b, Dell et al., 2009b, Tol, 2009]. A critique of this approach is that the average state of the atmosphere (a fixed parameter) may be correlated with other fixed parameters (for example, altitude) which may themselves directly affect patterns of production [Tol, 2009]. This is the *omitted-variables problem*: without describing all fixed variables affecting an outcome, statistical inference on any single fixed variable may be biased [Greene, 2003]. Since it is impossible to characterize this full set of fixed variables, this study removes all fixed differences between countries and only examines trends related to dynamic variations. The average atmospheric states of any two countries are never compared here. Instead, the influence of the atmosphere on production is identified by looking at the response of production to perturbations in the atmospheric state around its mean value. This should only compare a country to itself at different points in time when it is experiencing a different atmospheric state. While each country may respond slightly differently to atmospheric variations, a collection of countries is analyzed as if they responded identically to increase statistical power, producing a single estimate (β) for the "average effect" of atmospheric conditions on production within that collection. If the effects differ dramatically between countries, this average effect will not describe the true structure of the relation well. For this reason, analysis is restricted to a small region where atmospheric variations and productive processes share reasonable commonalities.

For industry j, let production of value be some function

$$V_{it}^{j} = f^{j}(\mathbf{V^{j}_{i,t-1}}, t, \mathbf{X_i}, \mathbf{C_{it}}, \mathbf{R_{it}}, \mathbf{T_{it}}) + \epsilon_{it}^{j} \tag{2.2}$$

where $\mathbf{V}^{j}_{i,t-1}$ is a vector of historical production, $\mathbf{X_i}$ is some vector of fixed country-specific traits and $\mathbf{C_{it}}$, $\mathbf{R_{it}}$ and $\mathbf{T_{it}}$ are vectors of historical incidence of cyclones, rainfall and surface temperature respectively. Atmospheric variations that impact production at time t may include events from the recent past. Time t enters $f^j(...)$ directly for three reasons: (1) there may be trends in productive output due to technological innovations that occur gradually over time, (2) production in a given industry may be expanding over time due to economic growth or (3) specific years may be "abnormal" for reasons unrelated to atmospheric processes, such as large variations in world commodity prices. ϵ_{it}^{j}

describes variations in output not explained by the data.

Equation 2.2 can be approximated by a Taylor-series expansion in which non-linear terms are dropped (except a t^2 term, which is kept). The following linear approximation for f^j is estimated:

$$V_{it}^{j} \approx \rho_1^j \times V_{i,t-1}^{j} + \rho_2^j \times V_{i,t-2}^{j} + \gamma_i^j \times t + \delta_i^j \times t^2 + \eta_t^j + \mu_i^j + \sum_{L=0}^{\tau} \left[\beta_C^{jL} \times C_{i,t-L} + \beta_R^{jL} \times R_{i,t-L} + \beta_T^{jL} \times T_{i,t-L} \right] + \epsilon_{it}^{j} \tag{2.3}$$

by applying ordinary least squares to the data. The variables of interest are the parameters denoted by β, the derivatives of production with respect to atmospheric fluctuations. The terms lagged by L measure the impact of events from previous years, up to some maximum lag τ. If τ is larger than the actual number of historical years that affect production at t, the estimates for β will be consistent [Greene, 2003] ($\tau = 5$ for all industries in all estimates unless otherwise noted). Each industry in each country is assumed to have a mean output that varies smoothly in time. This variation is thought to be different for each country, as different economies will expand in different industries at different rates: γ_i and δ_i describe these changes over time. If a certain year has unusual properties that affect all the countries in the sample (for example, world oil prices are high), then this variation will be captured in the estimate of η_t. This term is an additive constant that is common to all countries in the data, but only added for a single year. μ_i is a constant term that is unique to each country. This term is critical because countries will have different baseline levels of production in different industries for reasons unrelated to variations in atmospheric processes. This term captures all static differences between production levels in countries described earlier as dependent on $\mathbf{X}_i$. The autocorrelation coefficients ρ_{1-2} describe the extent to which output in year t (relative to the trends described by γ_i and δ_i) is correlated with the previous year's output, holding all environmental variables fixed. Because the sum $\rho_1 + \rho_2$ is large (but always less than unity), controlling for these lagged dependent variables is essential to avoiding spuriously large estimates of β. However, because ρ_{1-2} may be underestimated by Equation 2.3, a model in "first-differences" that constrains $\rho_1 = 1$ (it assumes V has a unit-root) is also estimated as a robustness check (see below).

The model in Equation S2.3 is equivalent to writing the model in terms of de-trended "anomalies" of economic and weather variables (as is often done in the climate sciences). The two models produce identical estimates for the β's [Frisch and Waugh, 1933].

The omitted variables problem also applies to dynamic variables, such as temperature anomalies. If the dynamic variation of two variables are correlated and both affect production, the exclusion of one from Equation S2.3 will produce biased estimates of β for the other [Greene, 2003]. Previous literature has established correlations between cyclogenisis, cyclone intensity, surface temperatures and rainfall [Mann and Emanuel, 2006, Camargo et al., 2007, Rosenzweig and Hillel, 2008]. Of particular concern is the contamination of the estimated impact of surface temperature by tropical cyclones. "Potential intensity theory" [Bister and Emanuel, 1998, Emanuel, 1991] predicts that the maximum attainable intensity of cyclones will be determined by local sea surface temperatures (holding other atmospheric variables fixed). Empirically, variations in the number and intensity of extremely intense hurricanes are well predicted by local sea surface temperatures [Emanuel, 1999, Elsner et al., 2008]. If intense hurricanes dominate the magnitude of economic responses, as suggested by Nordhaus (2006) for capital damages in the United States [Nordhaus, 2006a], then a small number of cyclones may seriously contaminate the estimated response of industries to surface temperatures. This may occur even if the correlation between surface temperatures and cyclones is weak, should the response to cyclones be nonlinear and the response to surface temperatures be small.

Table 2.12 displays the correlation coefficients (ρ) between C', T' and P'. When integrated over countries, cyclone energy dissipation is only weakly positively correlated with surface temperature ($\rho = 0.08$) and weakly negatively correlated with rainfall ($\rho = -0.04$). Temperature and rainfall are weakly negatively correlated ($\rho = -0.14$). Table 2.13 demonstrates that when the effect of temperature or cyclones are estimated alone, they do not differ substantially from their values when they are estimated simultaneously. Thus, it appears that in the region studied, regressions on temperature without controlling for rainfall and cyclones would have revealed similar estimates. However, such a study would have left the interpretation of these coefficients ambiguous. It would be unclear whether the the included variable was directly affecting production or appeared to affect production because an excluded variable actually affected production. Using the approach of this study, it is possible to attribute the estimated impact of surface temperatures to direct impacts of local thermal energy (enthalpy) and not to the primary secondary process associated with surface heating: intense tropical cyclones. In the Caribbean Basin, cyclones are likely the most economically significant form of correlated environmental variation. However, different regions around the world exhibit a variety of environmental variations that are correlated with surface heating and which have plausible economic significance. The environmental variables included in this study are limited to measures of major processes in the local atmosphere and may not be comprehensive insofar as environmental variation in the region is concerned (eg. earthquakes).

Table 2.12 also displays correlations between variables in year t and the previous year $t-1$. Following quadratic de-trending, C' ($\rho = 0.10$), T' ($\rho = 0.55$) and R' ($\rho = 0.49$) still all exhibit serial correlation. As production is also auto-correlated, there is potential for spurious correlations between weather variations and economic output. Thus, an important check on the main results is to estimate the effect of weather changes on *changes in output*, rather than output itself. If output is an integrated process of order one, differencing output between periods will produce a stationary time series that should not lead to spurious correlations. As mentioned in the main text, results from the model

$$V_{it}^j - V_{i,t-1}^j = \eta_t^j + \mu_i^j + \sum_{L=0}^{\tau} \left[\beta_C^{jL} \times C_{i,t-L} + \beta_R^{jL} \times R_{i,t-L} + \beta_T^{jL} \times T_{i,t-L} \right] + \epsilon_{it}^j \tag{2.4}$$

are estimated and listed in Tables 2.7-2.8 in the columns marked "Δ_{t-1}." The values for β estimated by this model remain highly significant for the relationships highlighted in the main text. In fact, the coefficients estimated for Equation 2.4 are actually larger than those estimated for Equation 2.3 for *total production*, *wholesale, retail, restaurants & hotels* and *other services*.

Equations S2.3 and S2.4 relate annually-averaged temperature to production. In the main text, Equation 2.3 is modified to decompose the seasonal contributions ($L = 0$ only) to this annual average:

$$V_{it}^j = \beta_T^{j,DJF} \times T_{it}^{DJF} + \beta_T^{j,MAM} \times T_{it}^{MAM} + \beta_T^{j,JJA} \times T_{it}^{JJA} + \beta_T^{j,SON} \times T_{it}^{SON} + g(\mathbf{V^j_{i,t-1}}, t, \mathbf{C}_{it}, \mathbf{R}_{it}, \mathbf{T}_{it}) \tag{2.5}$$

where $g(...)$ contains all of the terms ($\tau = 1$) of Equation S2.3 except the $L = 0$ term for temperature. The superscripts indicate the average surface temperature over three months: December-January-February (DJF), March-April-May (MAM), June-July-August (JJA) and September-October-November (SON). Table 2.2 in the main text presents these seasonal coefficients for all industries.

To test whether average or extreme temperatures are driving reductions in productivity, the relative impact of extremely warm days is compared to the impact of "normal" days. If high temperatures affect productivity more than average temperatures, then incremental changes in temperature will affect production more at higher temperatures than the same incremental changes in temperature at average temperatures. This will produce non-linearities in the response of productivity to surface temperature, with the response function becoming steeper at high temperatures if they have larger impacts on production. To detect such non-linearity, it may be insufficient to examine only the impact of annually or seasonally averaged surface temperatures. To estimate the structure of non-linear production responses to temperature, the response to daily average temperature is estimated.

To construct such an estimate, let $\tilde{P}(T_d)$ be a continuous function describing production as a function of temperature T on day d:

$$\tilde{P}(T_d) = \tilde{P}(T_0) + \int_{T_0}^{T_d} \frac{\partial \tilde{P}}{\partial T} dT$$

that is approximated by a piece-wise linear function $\bar{P}$:

$$\bar{P}(T_d) = \bar{P}(T_0) + \sum_{k=1}^{N} \beta_k D_k(T_d) \tag{2.6}$$

where β_k is the slope of the kth linear segment and

$$D_k(T_d) = \int_{\underline{x}_k}^{\bar{x}_k} \mathbf{1}[T_d \leq x] dx$$

where $\mathbf{1}[...]$ is equal to one if the statement in the brackets is true and zero otherwise. Here, $\underline{x}_k$ is the lower-valued limit of the kth segment and $\bar{x}_k$ is the higher-valued limit of that segment.

If $\tilde{P}$ is *assumed* to be a function that is independent of the day of the year, than $\bar{P}$ can be still be recovered if daily temperature observations and *only* annual production observations are available. (Schlenker and Roberts (2008) test this assumption and the assumption of piece-wise linearity, they find them both to be reasonable for primary crops in the United States [Schlenker and Roberts, 2009]). Under these assumptions, annual production $\mathbf{P}_t$ in year t is then:

$$\begin{aligned}
\mathbf{P}_t &= \sum_{d \in t} \bar{P}(T_d) \\
&= \sum_{d \in t} \left[\bar{P}(T_0) + \sum_{k=1}^{N} \beta_k D_k(T_d) \right] \\
&= \mathbf{P}_0 + \sum_{k=1}^{N} \beta_k \cdot \left[\sum_{d \in t} D_k(T_t) \right]
\end{aligned}$$

by substitution of Equation S2.6 and interchanging the order of summation. The bracketed term $\left[\sum_{d \in t} D_k(T_t)\right]$ is constructed for each year using daily temperature observations for each of the N segments. This term is in units of "degree-days," as it is referred to in the literature [Schlenker and Roberts, 2009].

Fig. 2.5A in the main text is constructed by estimating such an equation for $N = 3$ segments with boundaries at 27 and 29°C. The following equation is estimated with ordinary least squares:

$$V_{it}^{j} = \beta_1^j \left[\sum_{d\in t} D_1(T_d)\right] + \beta_2^j \left[\sum_{d\in t} D_2(T_d)\right] + \beta_3^j \left[\sum_{d\in t} D_3(T_d)\right] + g(\mathbf{V^j_{i,t-1}}, t, \mathbf{C}_{it}, \mathbf{T}_{it}, \mathbf{R}_{it})$$

where $g(...)$ is the same as in Equation S2.5. Here, the subscript d denotes daily observations and t yearly observations. The estimated coefficients $\beta_1^j - \beta_3^j$ are the slopes of the segments in Fig. 2.5A (main text) and are tabulated with their standard errors in Table 2.9.

2.C Weather impact reductions with higher income

In the discussion of the main article, it was noted that as countries become wealthier, they may become better able to cope with environmental changes [Parry et al., 2007, Stern, 2006, Dell et al., 2009a]. Within this sample of countries, the response to temperature changes and cyclones can be modeled as linear functions of income. This is done by "interacting" income and temperature or income and cyclone exposure in the statistical model. This means that a new variable is constructed by multiplying temperature by income, so that the effect of temperature becomes a linear function of income ($\tilde{\beta} + \tilde{\zeta} \times income$). However, because income in any year is also affected by temperature in that year, income levels observed three years earlier is used in constructing the "interaction variable". The new model for temperature impacts becomes

$$V_{it}^{j} = \tilde{\beta}_T^{j,SON} \times T_{it}^{SON} + \tilde{\zeta}_T^{j,SON} \times \left[T_{it}^{SON} \times income_{i,t-3}\right] + \omega \times income_{i,t-3} + g(\mathbf{V^j_{i,t-1}}, t, \mathbf{C}_{it}, \mathbf{R}_{it}, \mathbf{T}_{it}). \tag{2.7}$$

If increases in income make countries more susceptible to temperature impacts, than the estimated values for $\tilde{\zeta}$ should be negative; and if increases in income make countries more resilient to temperature changes, then $\tilde{\zeta}$ should be positive. Table 2.10 presents the estimated values of $\tilde{\beta}$ and $\tilde{\zeta}$ for SON temperature using models analogous to Equation S2.3 and Equation S2.4. Th structure across these estimates is not entirely consistent. However, for temperature-sensitive industries other than *transport & communications* it appears that increases in income generally increases resilience to high temperatures. The disagreement in coefficients and significance levels for the two statistical models suggests the need for additional analysis to determine what models are appropriate for modeling adaptation. Table 2.11 presents analogous results for tropical cyclones. Again, these results are suggestive that higher income countries experience smaller losses to cyclones (in % of current income), however they are not entirely compelling. One concern is that those sectors with significant, positive-valued interaction terms are not those sectors identified in the main text as most vulnerable to cyclones. A related concern is that several industries that are vulnerable to cyclones do not exhibit significant interaction terms. Thus, it is only with strong caution that these results can be taken as suggestive evidence that increases in income generally reduce productive vulnerability to weather shocks. Future work will focus on understanding this relationship better.

2.D Supplementary Tables and Figures

Table 2.4: Sample sizes and summary statistics

Variable	N	Countries	Years	Units	Mean	SD	Min	Max
Temperature (T), annual	1789	31	1950-2007	°C	26.73	0.33†	22.55	28.59
Sep-Oct-Nov (SON) only	1824	31	1950-2007	°C	27.45	0.36†	21.75	29.80
Tropical Cyclone Energy (C)	1767	31	1950-2006	$10^9\ m^3s^{-2}$	0.0302	0.0784	0	1.0299
Rainfall (R)	1786	31	1950-2007	mm/month	105.58	42.67†	11.75	300.51
Total production	1060	28	1970-2007	2000 US$	6678.24	8679.33	297.38	64630.30
Wholesale, Retail, Hotels & Restaurants	1060	28	1970-2007	% of total production	20.40	6.96	5.72	48.47
Other Services	1052	28	1970-2007	% of total production	35.02	9.76	14.15	60.72
Transport & Communications	1060	28	1970-2007	% of total production	10.70	4.69	1.74	27.02
Construction	1060	28	1970-2007	% of total production	7.38	3.64	0.85	32.89
Manufacturing	1060	28	1970-2007	% of total production	11.98	9.35	0.64	43.28
Agriculture, Hunting & Fishing	1052	28	1970-2007	% of total production	10.46	9.18	0.34	46.88
Mining & Utilities	1052	28	1970-2007	% of total production	4.17	4.12	0.00	31.48
Tourism Receipts	287	24	1995-2006	current US$	7.67E8	8.01E8	4.20E7	3.79E9

† demeaned by country

Table 2.5: Comparing the effects of annual-average and SON-average temperatures

	Panel (a)							
	Total production		Wholesale, retail, restaurants & hotels		Other services		Transport & communications	
	SON	AVG	SON	AVG	SON	AVG	SON	AVG
$Temp_t$	-2.65%***	-2.50**	-5.41***	-6.13***	-2.21**	-2.16**	-3.24**	-2.16
	[0.87]	[1.01]	[1.47]	[1.68]	[0.90]	[1.07]	[1.39]	[1.70]
$Temp_{t-1}$	-0.19	0.17	-1.11	0.69	0.79	0.82	-1.57	-0.72
	[0.70]	[1.00]	[1.10]	[1.54]	[0.69]	[1.00]	[1.16]	[1.41]
Obs.	968	968	968	968	968	968	964	964
	Panel (b)							
	Construction		Manufacturing		Agriculture, hunting & fishing		Mining & Utilities	
	SON	AVG	SON	AVG	SON	AVG	SON	AVG
$Temp_t$	-5.51*	-0.55	0.70	1.41	-0.97	-0.76	0.67	-4.24*
	[3.07]	[3.12]	[2.08]	[2.61]	[2.33]	[2.48]	[2.09]	[2.44]
$Temp_{t-1}$	-3.13	1.41	-0.57	-1.86	-1.21	-1.83	-1.70	-1.74
	[2.34]	[3.87]	[1.62]	[2.29]	[1.89]	[2.27]	[1.96]	[2.86]
Obs.	968	968	958	958	968	968	955	955

*** p<0.01, ** p<0.05, * p<0.1. Standard errors (in brackets) account for spatial correlation (uniformly weighted up to 300 km) and country-specific serial correlations using a Bartlett window of five years. Units: % output per 1°C.

Table 2.6: Falsification test: the effect of future weather on current production

Panel (a)

	Total production	Wholesale ...hotels	Other services	Transport & comm.
$Temp_{t+1}^{SON}$	-0.7%	-0.2	-1.0	-1.2
	[0.8]	[1.3]	[0.8]	[1.3]
$Cyclones_{t+1}$	0.1	-0.1	0.1	-0.1
	[0.2]	[0.2]	[0.1]	[0.2]

Panel (b)

	Constr.	Manuf.	Agr., hunt. & fishing	Mining& utilities
$Temp_{t+1}^{SON}$	-3.9	-0.8	-5.4**	-0.6
	[2.5]	[2.0]	[2.3]	[2.1]
$Cyclones_{t+1}$	0.1	-0.2	0.1	-0.2
	[0.5]	[0.3]	[0.4]	[0.3]

*** p<0.01, ** p<0.05, * p<0.1. Standard errors (in brackets) account for spatial correlation (uniformly weighted up to 300 km) and country-specific serial correlations using a Bartlett window of five years. Model includes regressors from the "true" model in Equation 1. Each coefficient is a separate regression. Units for temperature coefficients: % output per 1°C, cyclone coefficients: output per 1 standard deviation in cyclone energy dissipated.

Table 2.7: Robustness of main results

Panel (a)

	Total production					Wholesale, retail, restaurants & hotels				
	Δ from trend			Δ_{t-1}	Δ_{trend}	Δ from trend			Δ_{t-1}	Δ_{trend}
$Temp_t^{SON}$	-2.5%***	-2.7***	-2.2***	-2.9***	-2.8***	-4.3***	-5.4***	-4.6***	-5.0***	-5.5***
	[0.8]	[0.9]	[0.8]	[0.8]	[0.9]	[1.4]	[1.5]	[1.3]	[1.2]	[1.9]
$Temp_{t-1}^{SON}$	0.3	-0.2	0.6	-0.8	-0.6	-1	-1.1	0.2	-1.2	-1.8
	[0.7]	[0.7]	[0.8]	[0.7]	[0.7]	[1]	[1.1]	[1.1]	[1]	[1.2]
$Cyclones_t$	-0.3	-0.4	-0.3	-0.3	-0.3	-0.7*	-0.8**	-0.7**	-0.9**	-0.4
	[0.2]	[0.2]	[0.2]	[0.2]	[0.4]	[0.3]	[0.3]	[0.3]	[0.4]	[0.6]
$Cyclones_{t-1}$	0.3*	0.2	0.4	0.2	0.2	-0.1	-0.3	0	-0.3	-0.1
	[0.2]	[0.2]	[0.2]	[0.2]	[0.2]	[0.3]	[0.3]	[0.4]	[0.4]	[0.4]
$Cyclones_{t-2}$		-0.3	-0.2	-0.2	-0.2		-0.2	0	-0.3	-0.1
		[0.2]	[0.3]	[0.2]	[0.3]		[0.3]	[0.3]	[0.3]	[0.3]
Lags	1	5	5	5	5	1	5	5	5	5
FE & YE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
country trends	Y	Y	N	N	Y	Y	Y	N	N	Y
trend breaks	N	N	N	N	Y	N	N	N	N	Y
Obs.	972	968	968	996	968	972	968	968	996	968

	Other services					Transport & communications				
	Δ from trend			Δ_{t-1}	Δ_{trend}	Δ from trend			Δ_{t-1}	Δ_{trend}
	-2.2***	-2.2**	-1.9**	-3.2***	-2.5*	-3.5***	-3.2**	-2.9**	-2.8**	-3*
$Temp_t^{SON}$	[0.8]	[0.9]	[0.8]	[0.8]	[1.3]	[1.3]	[1.4]	[1.3]	[1.2]	[1.7]
	1	0.8	1.4	0.4	0.4	-0.3	-1.6	-0.8	-1.9	-2
$Temp_{t-1}^{SON}$	[0.6]	[0.7]	[0.7]	[0.7]	[1]	[1.1]	[1.2]	[1.2]	[1.2]	[1.2]
$Cyclones_t$	-0.2	-0.2	-0.1	-0.1	-0.2	-0.3	-0.5	-0.5	-0.5*	-0.4
	[0.1]	[0.2]	[0.2]	[0.2]	[0.3]	[0.3]	[0.3]	[0.3]	[0.3]	[0.7]
$Cyclones_{t-1}$	0.3**	0.3	0.4**	0.3	0.3	0.4*	0.2	0.3	0.3	0.3
	[0.2]	[0.2]	[0.2]	[0.2]	[0.2]	[0.2]	[0.3]	[0.3]	[0.3]	[0.4]
$Cyclones_{t-2}$		0	0	0.1	0.1		-0.6**	-0.6**	-0.7**	-0.5
		[0.1]	[0.1]	[0.1]	[0.3]		[0.2]	[0.2]	[0.2]	[0.6]
Lags	1	5	5	5	5	1	5	5	5	5
FE & YE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
country trends	Y	Y	N	N	Y	Y	Y	N	N	Y
trend breaks	N	N	N	N	Y	N	N	N	N	Y
Obs.	972	968	968	996	968	968	964	964	992	964

Models denoted "Δ from trend" or "Δ_{trend}" are regressions of $ln(output)$ which control for two lagged values of $ln(output)$ and quadratic country-specific time trends. Models denoted "Δ_{t-1}" use a dependant variable that is $ln(output)_t - ln(output)_{t-1}$ and do not control for deterministic trends. In all models, for each industry, country specific constants and year specific constants (so-called "Fixed effects" and "Year effects") are estimated ("FE &YE"). In the model with "trend breaks," only linear country-specific trends are included but two country-specific trend-breaks are estimated for the largest cyclone events experienced by each country. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Standard errors (in brackets) account for spatial correlation (uniformly weighted up to 300 km) and country-specific serial correlations using a Bartlett window of five years. Units for temperature coefficients: % output per 1°C, cyclone coefficients: % output per 1 standard deviation in cyclone energy dissipated.

Table 2.8: Robustness of main results (Continued)

Panel (b)

	Construction					Manufacturing				
	Δ from trend			Δ_{t-1}	Δ_{trend}	Δ from trend			Δ_{t-1}	Δ_{trend}
$Temp_t^{SON}$	-3.6%	-5.5*	0.4	-2.8	-7.9*	0.1	0.7	0.7	-0.3	0.7
	[2.9]	[3.1]	[3]	[2.7]	[4.3]	[2]	[2.1]	[2.1]	[2]	[2.9]
$Temp_{t-1}^{SON}$	-1	-3.1	2.5	0.5	-5	-0.5	-0.6	-1.1	-1.6	-0.3
	[2.4]	[2.3]	[2.5]	[2.5]	[3]	[1.6]	[1.6]	[1.6]	[1.6]	[2.4]
$Cyclones_t$	1.2*	0.9	1.6**	1.4**	1	0	-0.3	-0.1	-0.1	-1.2
	[0.7]	[0.7]	[0.6]	[0.6]	[1.4]	[0.5]	[0.5]	[0.5]	[0.5]	[1.2]
$Cyclones_{t-1}$	1.4**	1.3*	1.5**	1.4**	1.2	0.1	0	0.2	0.1	-0.8
	[0.7]	[0.7]	[0.7]	[0.7]	[1.1]	[0.4]	[0.3]	[0.4]	[0.4]	[1.0]
$Cyclones_{t-2}$		-0.9	-0.9	-1.3	-0.6		-1.2**	-0.9	-0.9*	-2.1
		[0.8]	[0.9]	[1]	[0.9]		[0.6]	[0.5]	[0.5]	[1.5]
Lags	1	5	5	5	5	1	5	5	5	5
FE & YE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
country trends	Y	Y	N	N	Y	Y	Y	N	N	Y
trend breaks	N	N	N	N	Y	N	N	N	N	Y
Obs.	972	968	968	996	968	962	958	958	987	958

	Agriculture, hunting & fishing					Mining & Utilities				
	Δ from trend			Δ_{t-1}	Δ_{trend}	Δ from trend			Δ_{t-1}	Δ_{trend}
$Temp_t^{SON}$	-1.7	-1	-3.3	-2	-0.3	0.5	0.7	2.2	0.5	2.3
	[1.9]	[2.3]	[2.2]	[2.1]	[2.2]	[2]	[2.1]	[1.8]	[2]	[3.7]
$Temp_{t-1}^{SON}$	-0.8	-1.2	-2.7	-2.2	-1.9	-2	-1.7	-0.9	-1.2	-0.1
	[2]	[1.9]	[1.8]	[1.9]	[2.7]	[1.8]	[2]	[1.8]	[1.9]	[3.1]
$Cyclones_t$	-1.1***	-1.3***	-1.6***	-1.8***	-1.4***	-0.8**	-0.9**	-0.6	-0.9**	-0.5
	[0.3]	[0.3]	[0.3]	[0.4]	[0.8]	[0.3]	[0.4]	[0.4]	[0.4]	[0.8]
$Cyclones_{t-1}$	-0.8**	-0.8**	-0.7**	-0.6*	-1.2*	-0.1	-0.3	0.1	0.1	-0.2
	[0.3]	[0.4]	[0.3]	[0.4]	[0.7]	[0.3]	[0.3]	[0.3]	[0.4]	[0.6]
$Cyclones_{t-2}$		-0.7	-0.2	-0.2	-1.3		-0.1	0.4	0.3	0.2
		[0.6]	[0.6]	[0.6]	[1.2]		[0.4]	[0.4]	[0.4]	[0.6]
Lags	1	5	5	5	5	1	5	5	5	5
FE & YE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
country trends	Y	Y	N	N	Y	Y	Y	N	N	Y
trend breaks	N	N	N	N	Y	N	N	N	N	Y
Obs.	972	968	968	996	968	959	955	955	985	955

Models denoted "Δ from trend" or "Δ_{trend}" are regressions of $ln(output)$ which control for two lagged values of $ln(output)$ and quadratic country-specific time trends. Models denoted "Δ_{t-1}" use a dependant variable that is $ln(output)_t - ln(output)_{t-1}$ and do not control for deterministic trends. In all models, for each industry, country specific constants and year specific constants (so-called "Fixed effects" and "Year effects") are estimated ("FE &YE"). In the model with "trend breaks," only linear country-specific trends are included but two country-specific trend-breaks are estimated for the largest cyclone events experienced by each country. *** p<0.01, ** p<0.05, * p<0.1. Standard errors (in brackets) account for spatial correlation (uniformly weighted up to 300 km) and country-specific serial correlations using a Bartlett window of five years. Units for temperature coefficients: % output per 1°C, cyclone coefficients: % output per 1 standard deviation in cyclone energy dissipated.

Table 2.9: Non-linear response to daily mean surface temperature [$\%\Delta/+1°$C in bin]

	Total production	Wholesale ...hotels	Other services	Transport & comm.
$Temp_t^{SON} < 27°$C	-2.9**	-2.7	-1.4	-3.1
	[1.4]	[2.4]	[1.3]	[2.1]
27°C$< Temp_t^{SON} < 29°$C	-2.1*	-3.9**	-2.0	-3.7**
	[1.1]	[1.8]	[1.2]	[1.7]
29°C$< Temp_t^{SON}$	-4.4*	-4.5	-4.1*	-9.6**
	[2.5]	[4.4]	[2.4]	[4.2]
Obs.	973	973	973	969

*** p<0.01, ** p<0.05, * p<0.1. Standard errors (in brackets) account for spatial correlation (uniformly weighted up to 300 km) and country-specific serial correlations using a Bartlett window of five years. Units: % output per 1°C.

Table 2.10: The effect of temperature on production for different income levels

Panel (a)

	Total production		Wholesale, retail, restaurants & hotels		Other services		Transport & communications	
	Δ_{trend}	Δ_{t-1}	Δ_{trend}	Δ_{t-1}	Δ_{trend}	Δ_{t-1}	Δ_{trend}	Δ_{t-1}
$Temp_t^{SON}$	-4.2%	-11.9***	-9.4	-16.9***	-6.5	-12.4***	11.8*	-3.2
	[4.2]	[3.5]	[9.9]	[5.0]	[4.7]	[4.0]	[6.8]	[6.1]
$Temp_t^{SON} \times$ ln(income)	0.3	1.2***	0.6	1.6***	0.6	1.3***	-1.7**	0.0
	[0.5]	[0.4]	[1.1]	[0.6]	[0.6]	[0.5]	[0.8]	[0.7]
Obs	806	806	806	806	806	806	806	806

Panel (b)

	Construction		Manufacturing		Agriculture, hunting & fishing		Mining & Utilities	
	Δ_{trend}	Δ_{t-1}	Δ_{trend}	Δ_{t-1}	Δ_{trend}	Δ_{t-1}	Δ_{trend}	Δ_{t-1}
$Temp_t^{SON}$	-28.0*	-37.6***	-14.7	-5.7	1.8	-1.4	17.4*	-8.5
	[15.4]	[8.7]	[11.0]	[5.0]	[12.6]	[7.6]	[9.9]	[11.6]
$Temp_t^{SON} \times$ ln(income)	3.0	4.3***	1.8	1.0	-0.3	0.1	-1.9	1.4
	[1.9]	[0.9]	[1.4]	[0.6]	[1.5]	[0.8]	[1.1]	[1.4]
Obs.	806	806	802	804	806	806	802	804

Models denoted "Δ from trend" or "Δ_{trend}" are regressions of $ln(output)$ which control for two lagged values of $ln(output)$ and quadratic country-specific time trends. Models denoted "Δ_{t-1}" use a dependant variable that is $ln(output)_t - ln(output)_{t-1}$ and do not control for deterministic trends. ln(income) for the average country in the sample is 8.0 $\pm$1.0 (s.d.). The minimum is 5.4 (Haiti, 2004), the maximum is 10.8 (British Virgin Islands, 2007). *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Standard errors (in brackets) account for spatial correlation (uniformly weighted up to 300 km) and country-specific serial correlations using a Bartlett window of five years.

Table 2.11: The effect of cyclones on production for different income levels

Panel (a)

	Total production		Wholesale, retail, restaurants & hotels		Other services		Transport & communications	
	Δ_{trend}	Δ_{t-1}	Δ_{trend}	Δ_{t-1}	Δ_{trend}	Δ_{t-1}	Δ_{trend}	Δ_{t-1}
$Cyclones_t$	-6.9***	-3.6	-10.4**	-7.0*	-4.9***	-1.9	-8.9***	-5.9***
	[2.7]	[2.7]	[4.3]	[3.7]	[1.7]	[2.0]	[2.8]	[2.3]
$Cyclones_{t-1}$	-0.7	1.7	-3.4	-0.2	-0.8	1.7	-3.5	0.2
	[1.9]	[1.7]	[4.5]	[4.3]	[1.7]	[1.5]	[2.2]	[2.1]
$Cyclones_t \times$ ln(income)$_{t-3}$	0.8**	0.4	1.1**	0.7*	0.5**	0.2	1.0***	0.6**
	[0.3]	[0.3]	[0.5]	[0.4]	[0.2]	[0.2]	[0.3]	[0.3]
$Cyclones_{t-1} \times$ ln(income)$_{t-3}$	0.1	-0.2	0.4	0.0	0.1	-0.2	0.4*	0.0
	[0.2]	[0.2]	[0.5]	[0.5]	[0.2]	[0.2]	[0.2]	[0.2]
Obs.	806	806	806	806	806	806	806	806

Panel (b)

	Construction		Manufacturing		Agriculture, hunting & fishing		Mining & Utilities	
	Δ_{trend}	Δ_{t-1}	Δ_{trend}	Δ_{t-1}	Δ_{trend}	Δ_{t-1}	Δ_{trend}	Δ_{t-1}
$Cyclones_t$	-1.0	5.7	-8.0	-2.3	-8.7	-6.1	-1.6	-2.5
	[5.0]	[3.9]	[4.9]	[4.1]	[5.4]	[4.3]	[4.5]	[3.2]
$Cyclones_{t-1}$	6.0	9.3*	-0.7	4.6	-9.6**	-5.1	2.4	3.0
	[5.3]	[5.1]	[3.1]	[3.6]	[3.8]	[4.2]	[4.6]	[2.3]
$Cyclones_t \times$ ln(income)$_{t-3}$	0.2	-0.5	0.9	0.3	0.8	0.5	0.1	0.2
	[0.6]	[0.4]	[0.5]	[0.5]	[0.6]	[0.5]	[0.5]	[0.4]
$Cyclones_{t-1} \times$ ln(income)$_{t-3}$	-0.6	-0.9	0.1	-0.5	1.0**	0.5	-0.3	-0.3
	[0.6]	[0.6]	[0.3]	[0.4]	[0.4]	[0.5]	[0.6]	[0.3]
Obs.	806	806	802	804	806	806	802	804

Models denoted "Δ from trend" or "Δ_{trend}" are regressions of $ln(output)$ which control for two lagged values of $ln(output)$ and quadratic country-specific time trends. Models denoted "Δ_{t-1}" use a dependant variable that is $ln(output)_t - ln(output)_{t-1}$ and do not control for deterministic trends. ln(income) for the average country in the sample is 8.0 ±1.0 (s.d.). The minimum is 5.4 (Haiti, 2004), the maximum is 10.8 (British Virgin Islands, 2007). *** p<0.01, ** p<0.05, * p<0.1. Standard errors (in brackets) account for spatial correlation (uniformly weighted up to 300 km) and country-specific serial correlations using a Bartlett window of five years.

Table 2.12: Correlation coefficients between residuals (anomalies) of atmospheric variables

	C'_t	C'_{t-1}	T'_t	T'_{t-1}	R'_t	R'_{t-1}
Cyclones (C'_t)	1					
C'_{t-1}	0.1015	1				
Temperature (T'_t)	0.0753	0.0454	1			
T'_{t-1}	0.1127	0.0892	0.5517	1		
Rainfall (R'_t)	-0.0376	-0.1055	-0.1428	-0.1575	1	
R'_{t-1}	-0.1073	-0.0426	-0.2766	-0.1309	0.4911	1

Table 2.13: Comparing models for the effect of SON temperature (T^{SON}) and cyclones (C) on production

Panel (a)

	Total production				Wholesale, retail, restaurants & hotels				Other services				Transport & communications			
	Δ off trend		Δ off $t-1$		Δ off trend		Δ off $t-1$		Δ off trend		Δ off $t-1$		Δ off trend		Δ off $t-1$	
T_t^{SON}	-2.8%***	-2.7***		-2.9***	-5.2***	-5.4***		-5.0***	-2.4***	-2.2***		-3.2***	-3.4**	-3.2**		-2.8**
	[0.8]	[0.9]		[0.8]	[1.4]	[1.5]		[1.2]	[0.9]	[0.9]		[0.8]	[1.3]	[1.4]		[1.2]
T_{t-1}^{SON}	-0.1	-0.2		-0.8	-0.9	-1.1		-1.2	0.7	0.8		0.4	-0.9	-1.6		-1.9
	[0.7]	[0.7]		[0.7]	[1.1]	[1.1]		[1.02]	[0.7]	[0.7]		[0.7]	[1.1]	[1.2]		[1.2]
C_t		-0.4	-0.1	-0.3		-0.8**	-0.7**	-0.9**		-0.2	-0.01	-0.1		-0.5	-0.3	-0.5*
		[0.2]	[0.2]	[0.2]		[0.3]	[0.3]	[0.4]		[0.2]	[0.2]	[0.2]		[0.4]	[0.3]	[0.3]
C_{t-1}		0.2	0.2	0.2		-0.3	-0.3	-0.3		0.3	0.3	0.3		0.3	0.4	0.3
		[0.2]	[0.2]	[0.2]		[0.3]	[0.4]	[0.4]		[0.2]	[0.2]	[0.2]		[0.3]	[0.3]	[0.3]
C_{t-2}		-0.3	-0.2	-0.2		-0.2	-0.3	-0.3		-0.0	0.1	0.1		-0.6**	-0.6**	-0.7***
		[0.3]	[0.2]	[0.2]		[0.3]	[0.3]	[0.3]		[0.1]	[0.1]	[0.1]		[0.2]	[0.2]	[0.2]
Obs.	1008	968	1008	996	1008	968	1008	996	1008	968	1008	996	1004	964	1004	992

Panel (b)

	Construction				Manufacturing				Agriculture, hunting & fishing				Mining & Utilities			
	Δ off trend		Δ off $t-1$		Δ off trend		Δ off $t-1$		Δ off trend		Δ off $t-1$		Δ off trend		Δ off $t-1$	
T_t^{SON}	-5.9**	-5.5*		-2.8	-0.4	0.7		-0.3	-1.7	-1.0		-2.1	1.0	0.7		0.5
	[2.8]	[3.1]		[2.7]	[1.9]	[2.1]		[2.0]	[2.0]	[2.3]		[2.1]	[2.0]	[2.1]		[2.0]
T_{t-1}^{SON}	-2.7	-3.1		0.5	-0.7	-0.6		-1.6	-0.7	-1.2		-2.3	-1.6	-1.7		-1.2
	[2.3]	[2.3]		[2.6]	[1.6]	[1.6]		[1.6]	[1.9]	[1.9]		[1.9]	[1.9]	[2.0]		[1.9]
C_t		1.0	1.7***	1.4**		-0.3	-0.0	-0.1		-1.3***	-1.5***	-1.8***		-0.9**	-0.7**	-0.9**
		[0.7]	[0.7]	[0.6]		[0.5]	[0.5]	[0.5]		[0.3]	[0.4]	[0.4]		[0.4]	[0.4]	[0.4]
C_{t-1}		1.3*	1.5**	1.4**		-0.0	0.3	0.2		-0.8**	-0.7*	-0.6*		-0.3	0.2	0.1
		[0.7]	[0.7]	[0.7]		[0.3]	[0.4]	[0.4]		[0.4]	[0.4]	[0.4]		[0.3]	[0.4]	[0.4]
C_{t-2}		-0.9	-1.2	-1.3		-1.2**	-0.9*	-0.9**		-0.7	-0.2	-0.2		-0.1	0.3	0.3
		[0.8]	[1.0]	[1.0]		[0.6]	[0.5]	[0.5]		[0.6]	[0.5]	[0.6]		[0.4]	[0.4]	[0.4]
Obs.	1008	968	1008	996	998	958	999	987	1008	968	1008	996	995	955	997	985

Models denoted "Δ off trend" are regressions of $ln(output)$ which control for two lagged values of $ln(output)$ and quadratic country-specific time trends. Models denoted "$\Delta off t-1$" use a dependant variable that is $ln(output)_t - ln(output)_{t-1}$ and do not control for deterministic trends. *** p<0.01, ** p<0.05, * p<0.1. Standard errors (in brackets) account for spatial correlation (uniformly weighted up to 300 km) and country-specific serial correlations using a Bartlett window of five years. Units for temperature coefficients: % output per 1°C, cyclone coefficients: % output per 1 standard deviation in cyclone energy dissipated.

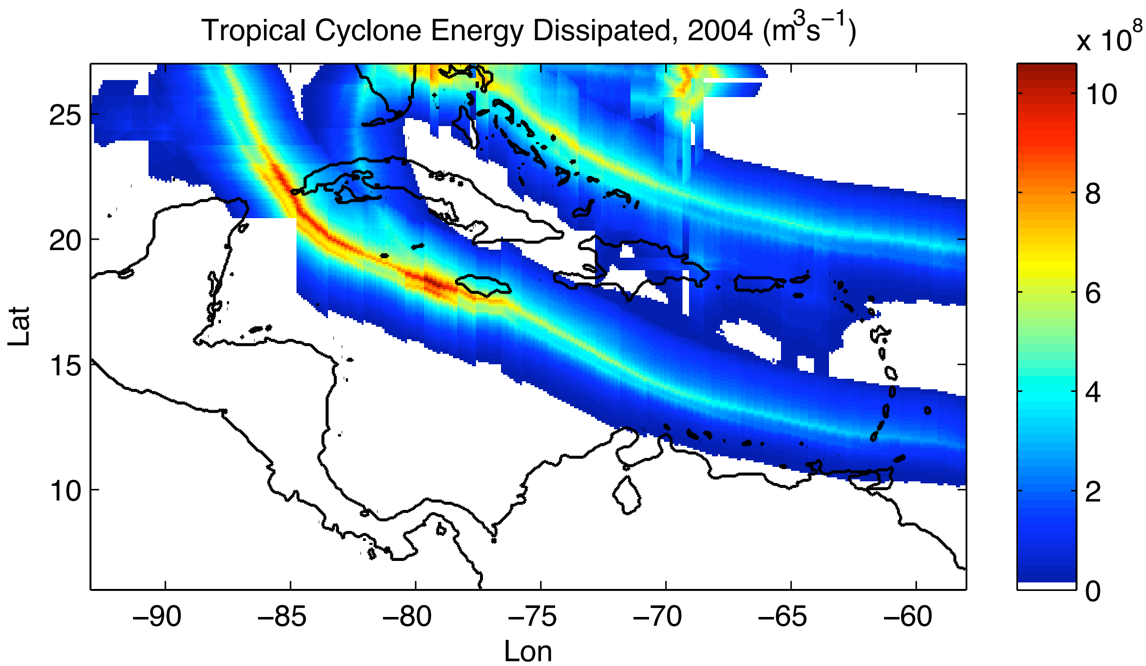


Figure 2.6: An example of the computed energy dissipated by tropical cyclones for a single year (2004).

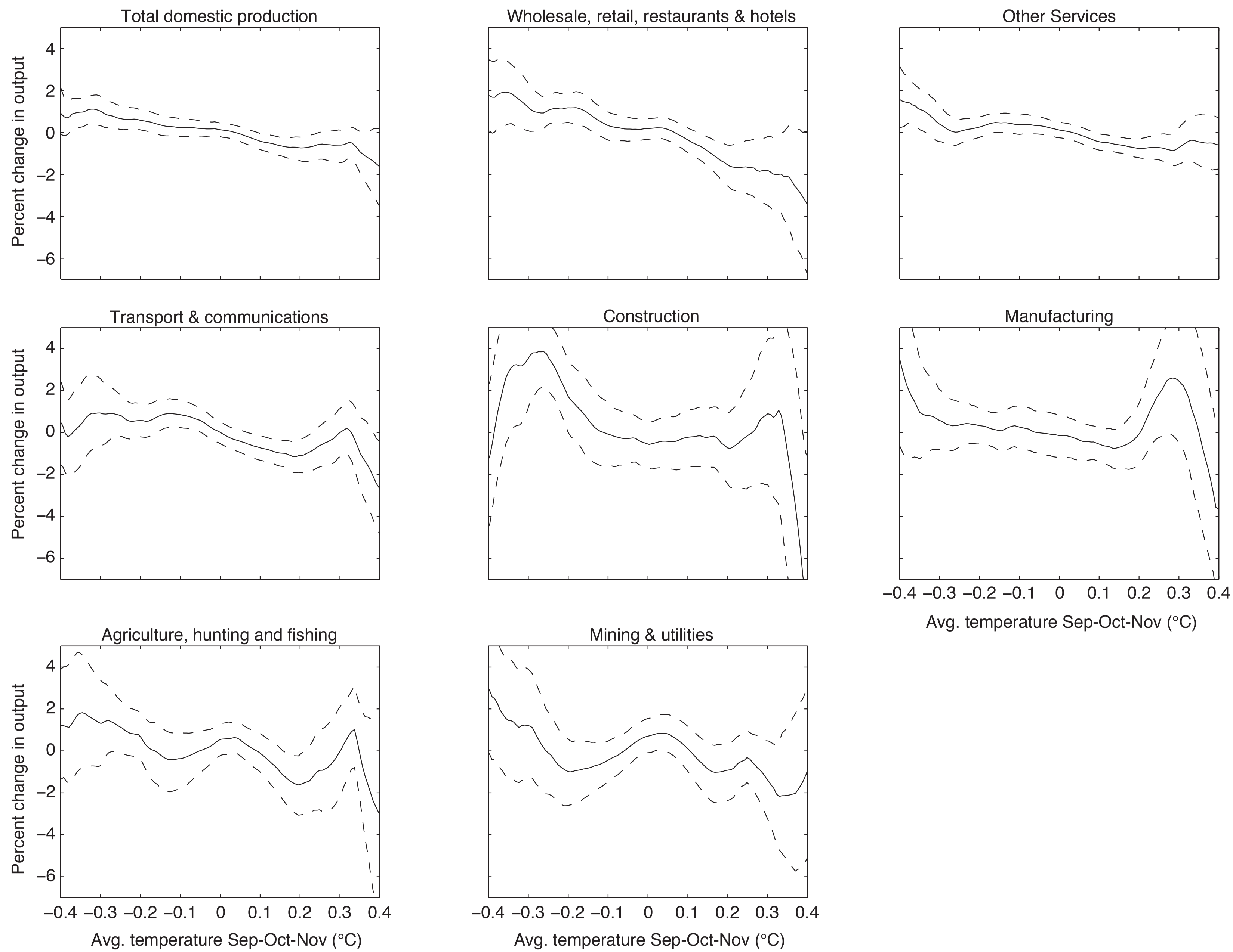


Figure 2.7: Same as Fig. 2.4A in the main text, but for all industries. Dashed lines are bootstrapped 90% confidence intervals using 10,000 resamples

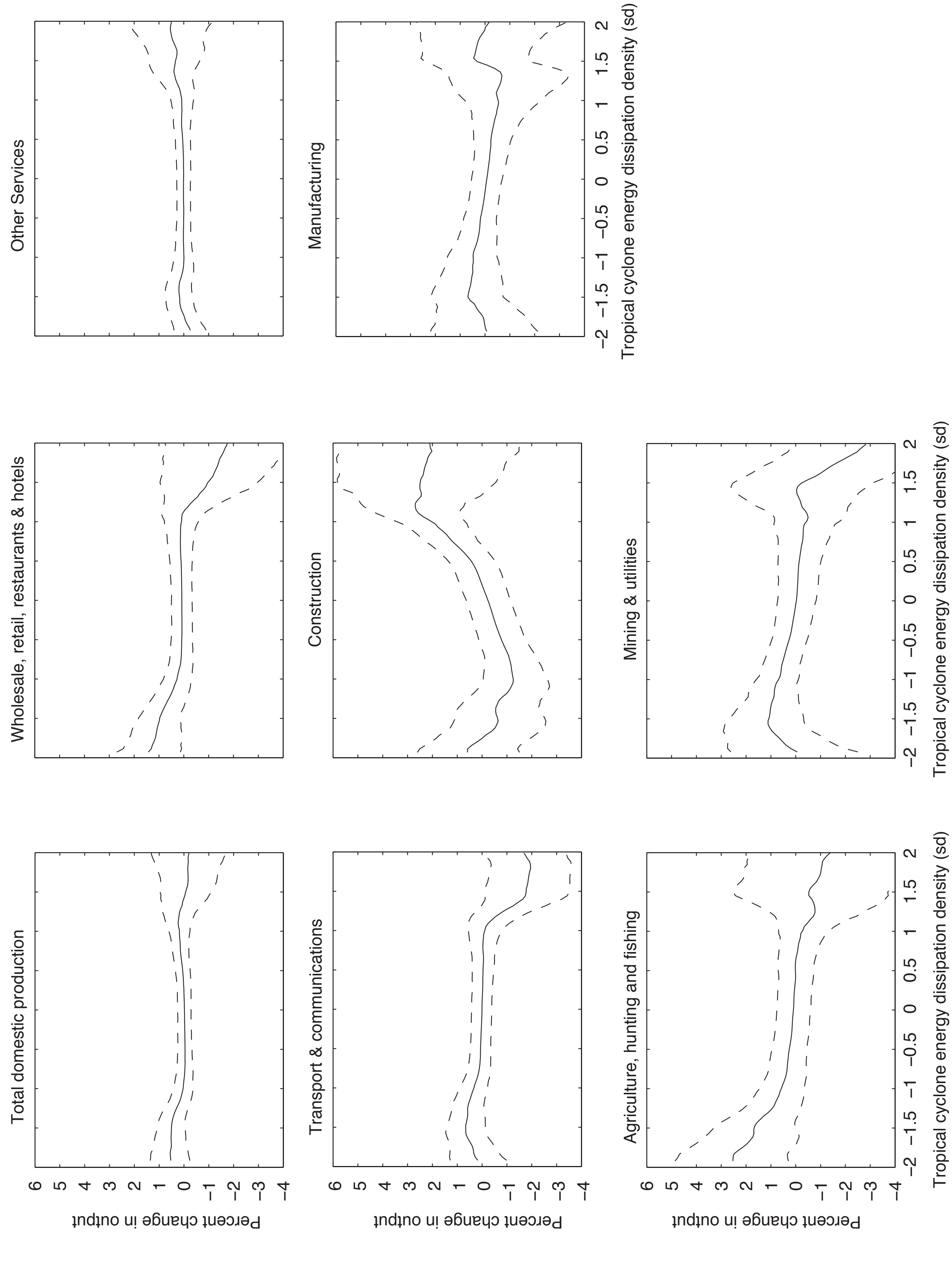


Figure 2.8: Same as Fig. 2.4B in the main text, but for all industries. Dashed lines are bootstrapped 90% confidence intervals using 10,000 resamples

Chapter 3

Global Climate Influences Civil Conflicts: Evidence from El Niño

Solomon M. Hsiang, Kyle C. Meng & Mark A. Cane

Abstract

It has been hypothesized that global climatic changes have been responsible for episodes of widespread violence and even the collapse of civilizations. Yet previous studies have not shown that violence can be attributed to the global climate, only that random weather events might be correlated with conflict in some cases. Here, we directly connect planetary-scale climate changes to global patterns of civil conflict by examining the dominant interannual mode of the modern climate, the El Niño-Southern Oscillation (ENSO). Historians have argued that ENSO may have driven global patterns of civil conflict in the distant past, a hypothesis that we extend to the modern era and test quantitatively. Using data from 1950 to 2004, we show that the probability of new civil conflicts arising throughout the tropics doubles during El Niño years relative to La Niña years. This result, which indicates that ENSO has played a role in 21% of all civil conflicts since 1950, is the first demonstration that the global climate has a strong impact on the stability of societies in the modern world.

3.1 Introduction

The idea that the global climate might influence the peacefulness of societies [Homer-Dixon, 1991, Diamond, 2005, Grove, 2007, Davis, 2002, Fagan, 2009] has motivated a growing body of research [?]. However, much of the support for this idea is anecdotal and the two methodologies dominating quantitative work on this problem have yielded inconclusive results [Salehyan, 2008]. The first of these approaches correlates multi-century trends in regional climate with trends in wars [Zhang et al., 2007, Tol and Wagner, 2009], but such correlations are weak [Tol and Wagner, 2009] and gradual social changes over multiple centuries confound results. The second approach avoids confounding trends by correlating random changes in local annual temperature or rainfall with local civil conflicts [Miguel et al., 2004, Levy et al., 2005, Burke et al., 2009, Jensen and Gleditsch, 2009, Buhaug, 2010], but different statistical assumptions have yielded different results and the notion that random local temperature or rainfall shocks are analogs for global climate changes have been criticized on three grounds: (1) The global climate may affect a large number of interacting environmental variables that influence conflict but are not adequately summarized by local temperature and rainfall; (2) Systematic environmental changes that occur on a planetary scale may influence markets, geopolitics or other social systems differently than location-specific weather shocks that are uncorrelated with weather in other locations; (3) Predictable changes in climate and unpredictable weather shocks may generate very different social responses, even if they are otherwise identical. We circumvent these issues by examining ENSO variations, which shift the planet's climate through a spectrum of states much faster than confounding social changes occur (Fig. 3.1a). An ENSO index summarizes global and multi-dimensional climatological changes that occur simultaneously at locations throughout the tropics and subtropics [Ropelewski and Halpert, 1987, Chiang and Sobel, 2002, Sarachik and Cane, 2010]. Furthermore, early-season ENSO processes inform populations about late-season events, allowing individuals to respond to foreseeable climate conditions. Our approach is to use a parsimonious statistical model to demonstrate a robust connection between a global climate variation, ENSO, and the onset of civil conflicts. This technique is methodologically clear, but is unable to provide direct insight into the mechanisms linking conflict to ENSO. We return to this issue below.

3.2 Approach

ENSO may plausibly influence multiple varieties of conflict, such as riots or genocides, however we restrict this analysis to organized political violence. We examine the Onset and Duration of Intrastate Conflict Dataset [Gleditsch et al., 2002,Strand, 2006] that codes a country as experiencing *conflict onset* if more than 25 battle-related deaths occur in a new civil dispute between a government and another organized party over a stated political incompatibility (see Supplementary Information Section 3.A and Supplementary Table 3.2 for data details). Following Strand [Strand, 2006] (2006), a dispute is "new" if it has been at least two years since that dispute was last active; however, individual countries may experience *conflict onset* in sequential years if the government has sequential disputes with different opposition groups. (Sensitivity to this criteria is explored in the Supplementary Information.) Using this statistic, we define *annual conflict risk* (ACR) in a collection of countries to be the probability that a randomly selected country in the set experiences *conflict onset* in a given year. Importantly, this ACR measure removes trends in conflict counts due to the growing number of countries [Gleditsch et al., 2002, Blattman and Miguel, 2010] (Fig. 3.1b and Supplementary Fig. 3.4).

In an impossible but ideal experiment, we would observe two identical Earths, change the global climate of one and observe whether ACR in the two Earths diverged. In practice, we can approximate this experiment if the one Earth that we do observe randomly shifts back and forth between two different climate states. Such a quasi-experiment is ongoing and is characterized by rapid shifts in the global climate between El Niño and La Niña, the phases of the El Niño-Southern Oscillation (ENSO).

In order to identify an effect of the global climate on conflict, we compare societies to themselves when they are exposed to different states of the global climate. Heuristically, a society observed during a La Niña is the "control" for that same society observed during an El Niño "treatment." We further sharpen this comparison by separating the world into two groups of countries, those whose climate is strongly coupled to ENSO and those weakly affected by ENSO. If climate influences ACR, we expect to observe the larger ENSO signal in ACR of the former group.

ENSO related changes in the tropical Pacific profoundly impact the global tropics primarily by radiating waves through the atmosphere, linking climates around the globe through so-called "teleconnections" [Ropelewski and Halpert, 1987, Chiang and Sobel, 2002]. Virtually the entire tropics are influenced by ENSO, with most land areas becoming warmer and dryer, while ENSO effects in mid-latitudes are generally smaller and less consistent [Chiang and Sobel, 2002, Sarachik and Cane, 2010]. We partition the globe into two groups based on how coupled their climates are to ENSO, separating

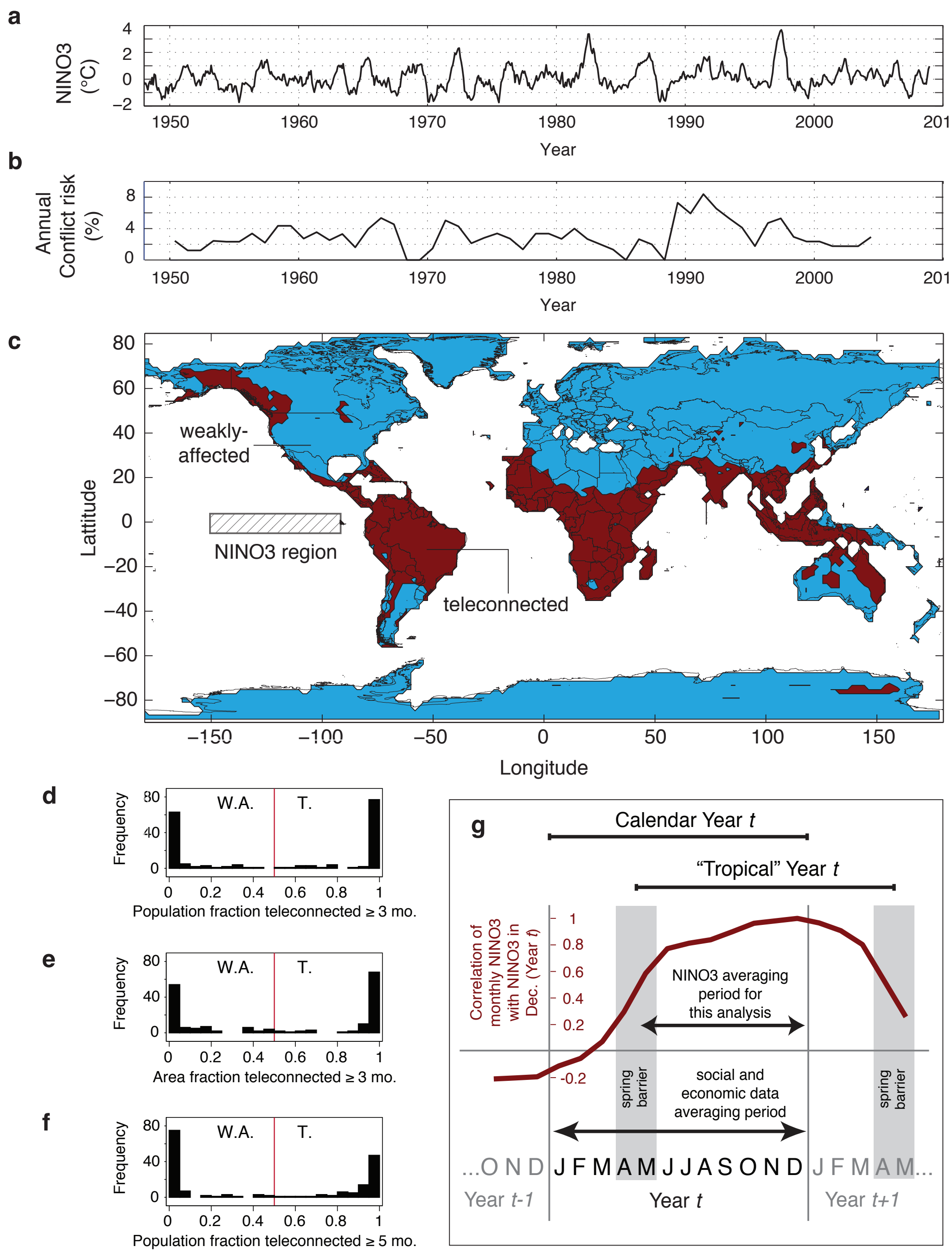


Figure 3.1: **Construction of global ENSO vulnerability partition.** (a) Monthly sea surface temperature anomaly over the NINO3 region (5°S-5°N, 150°W-90°W). (b) ACR for the whole world. (c) Red (blue) indicates an ENSO teleconnected (weakly-affected) grid cell; NINO3 region hatched. (d) Countries are coded as weakly-affected (W.A.) or teleconnected (T.) based on the fraction of their population that inhabited teleconnected cells in 2000. (e) The distribution of countries changes little if teleconnected area is used instead of populations. (d) The distribution of countries changes little if temperatures in teleconnected cells are required to correlate with NINO3 for five months instead of three. (g) Correlation of monthly NINO3 with NINO3 in December. The natural "tropical year" begins in May and ends the following April at the "spring barrier." To isolate the ENSO signal, an annual measure of ENSO was constructed by averaging May-December NINO3.

countries into "teleconnected" and "weakly-affected" groups. Guided by the analysis of Chiang and Sobel [Chiang and Sobel, 2002] (2002), we identify locations as "teleconnected" if local surface temperatures are positively correlated with sea surface temperatures in the equatorial Pacific (Fig. 3.1c-f, also see Methods Summary, Fig. 3.5-3.8 and Supplementary Information Section 3.B; Fig. 3.8 shows that only three Pacific island countries exhibit negative correlations that are spatially coherent and persistent). We identify teleconnected locations using surface temperature, rather than rainfall [Ropelewski and Halpert, 1987] or cloud cover [Klein et al., 1999], because the temperature signal is more reliable and the temperature data has more complete spatial coverage. In generating our partition we avoid using socioeconomic variables since these might themselves influence ACR, confounding our analysis. We validate our partition by confirming that it preserves the well-documented impact of ENSO on countries' average surface temperature [Chiang and Sobel, 2002], precipitation [Ropelewski and Halpert, 1987], and agricultural yields and revenues [Rosenzweig and Hillel, 2008] (Supplementary Fig. 3.9). In all cases the usual relationships hold in the teleconnected group and we find no significant correlations in the weakly affected group (see Table 3.3 and Supplementary Information Section 3.B.4). In the analysis of ACR which follows, all inference is based strictly on correlations over time between ENSO and ACR in the teleconnected group. Locations in the weakly affected group are not a perfect "control" for teleconnected locations because they differ in other ways. Nonetheless, analysis of ACR in the weakly affected group is a valid way to check that there are no unobserved confounding global variables that are correlated with ENSO.

Our preferred summary statistic for the global ENSO state is the NINO3 index (Fig. 3.1a), the average sea surface temperature anomaly in the equatorial Pacific region shown in Fig. 3.1c. Our results are insensitive to which index of ENSO is chosen (Fig. 3.10), but detecting ENSO impacts requires that we account for the "spring barrier" [Sarachik and Cane, 2010] by averaging NINO3 from May to December only rather than over the entire calendar year (see Fig. 3.1g, Table 3.4-3.5 and Supplementary Information Section 3.C).

3.3 Results

We regress the conflict measure ACR on NINO3 for both groups and detect a large and significant increase in ACR associated with warmer NINO3 values only in the teleconnected group (see Table 3.1, Fig. 3.2a and Supplementary Materials Section 3.D). We build a multiple regression model by including linear time trends and an additive constant to all years after 1989 (inclusive), a common

Table 3.1: Multiple regression of annual conflict risk (%) on NINO3 averaged May-Dec. (°C): 1950-2004

	Model	Teleconnected (%/°C)	Weakly-Affected (%/°C)
(1)	group aggregate	0.76*	0.16
		[0.39]	[0.31]
		n = 54	n = 54
(2)	group aggregate	0.85**	0.06
	linear trend	[0.40]	[0.30]
		n = 54	n = 54
(3)	group aggregate	0.81**	0.04
	linear trend	[0.32]	[0.31]
	post-1989 constant	n = 54	n = 54
(4)	same as (3)	0.95**	0.33
	1975-2004 only†	[0.34]	[0.45]
		n = 29	n = 29
(5)	country-level panel	0.89**	0.04
	country-specific trends	[0.38]	[0.29]
	country-specific constants	n = 3978	n = 3400
(6)	same as (5)	0.84**	-0.01
	non-African countries only	[0.41]	[0.29]
		n = 2084	n = 3203

Standard errors in brackets ** $p<0.05$, * $p<0.1$. Coefficients are probability responses in units of %/1°C, 1.0 means the probability of conflict in a given year (ACR) rises 0.01 for each 1°C in NINO3. Heteroscedasticity robust SE for rows 1-4. SE in rows 5-6 are robust to heteroscedasticity, serial correlation and spatial correlation. 1989 dropped in all models (3-σ outlier). †After 1974, the set of countries in the teleconnected group stabilized at 87-91 countries.

technique [Buhaug, 2010] to account for mean shifts in ACR following the end of the Cold War (rows 1-3). The dashed lines in Fig. 3.2b depict the estimated relationship when a linear response is assumed. Relaxing this assumption, we use a weighted moving-average that permits arbitrary non-linear responses to NINO3 (solid curves in Fig. 3.2b). The red curve indicates that ACR in the teleconnected group is most responsive to strong ENSO events and is less affected by smaller deviations from the neutral state.

In the teleconnected group, ACR is 3% in the La Niña state and rises to 6% in the El Niño state; this contrasts with the weakly-affected group where ACR remains at 2% for all ENSO states (Fig. 3.2b). This suggests that ENSO affected one-fifth (21%) of all civil conflicts during this period (see Methods Summary).

Because ENSO events occur after the April/May "spring barrier" [Sarachik and Cane, 2010] as

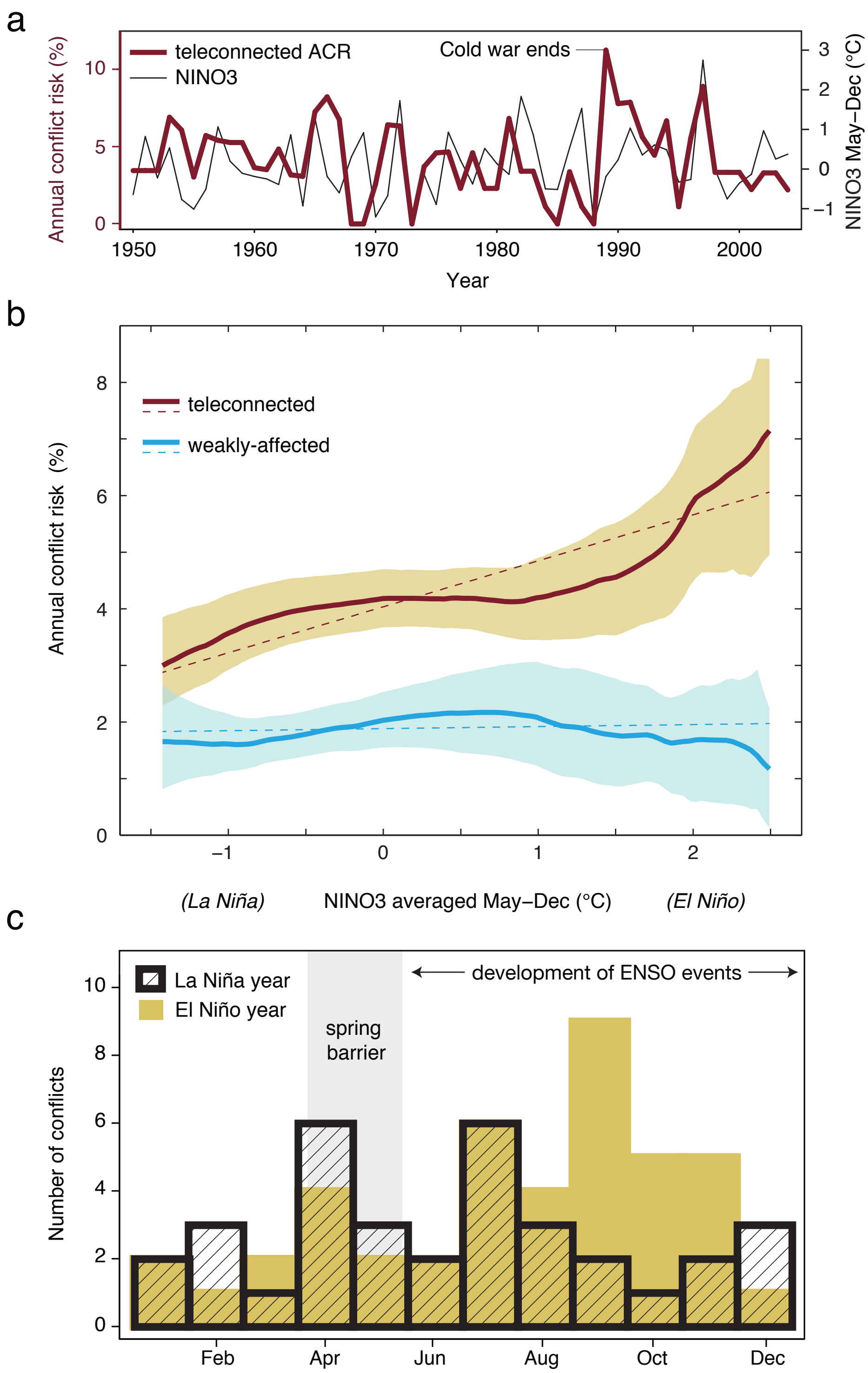


Figure 3.2: **Conflict risk response to ENSO.** (a) Time series of ACR for the teleconnected group and NINO3. (b) Dashed lines are linear fits of ACR on NINO3 for the two regions. Solid curves are weighted moving-averages of ACR (90% CI shaded) against NINO3. Conditional means control for linear trends and a post-Cold War constant. (c) Solid (hatched) bars show total monthly *conflict onsets* in teleconnected countries during 18 most El Niño-like (La Niña-like) years. Monthly data are available for only half of the conflicts.

shown in Fig 1g, we should expect conflicts triggered by ENSO to occur in the later part of the calendar year. Fig. 3.2c, based on the subset of conflict data available at monthly resolution, shows the within-year distributions of *conflict onsets* for the teleconnected group in El Niño and La Niña years (defined here as the highest and lowest terciles of NINO3 values). The distributions of conflicts are similar early in the year with substantial differences appearing only after El Niño events are underway.

The correlation we observe between ACR and NINO3 is robust to the battery of statistical models advanced by previous studies [Miguel et al., 2004,Burke et al., 2009,Jensen and Gleditsch, 2009,Buhaug, 2010] (see Supplementary Materials Section 3.E). To ensure the entrance of new countries into the sample do not drive our result, we restrict our sample to the post-colonial period [Burke et al., 2009] (Table 3.1, row 4) and also estimate a country-level linear probability model [Burke et al., 2009,Buhaug, 2010] (row 5). Further, we find that non-linear probability models (Fig. 3.11), count models (Fig. 3.12) and survival models (Table 3.6) produce indistinguishable results. We limit the sample to exclude African countries (Table 3.1, row 6) and find that the correlation is not driven exclusively by Africa [Miguel et al., 2004,Burke et al., 2009,Buhaug, 2010]. We find the relationship persists when alternative ENSO indices are used (Table 3.7). We estimate dynamic-panel and first-difference models (Table 3.8) and find no evidence that patterns of serial correlation in either variable drives our results. We expand our sample to include several influential outlying observations (1946, 1948 and 1989, see Fig. 3.13) and find the correlation persists (Table 3.9). We remove country-specific constants and trends from our longitudinal model [Buhaug, 2010] and find our estimates unchanged (Table 3.10). When we include controls for contemporaneous temperature and precipitation (Table 3.11) or for lagged income, political institutions and population (Table 3.12; and see Fig. 3.14) we continue to find a large and significant influence of ENSO on ACR. We then estimate a model with all of the above controls, as well as controls for gender balance, urbanization, age-structure, income growth, agricultural reliance and cyclone disasters (Table 3.13; and see Fig. 3.15) and find that our results persist across African and non-African countries. Using standard definitions [Strand, 2006], we find that neither large (>1000 battle deaths) nor small ($25 < \#$ battle deaths < 1000) conflicts dominate our result (Table 3.14). However, we find that increasing the required peaceful period between conflicts [Strand, 2006] reduces the correlation between ENSO and large conflicts, indicating that many of the large conflicts associated with ENSO are reoccurring conflicts (Table 3.14). Finally, we note that all of these techniques are robust to spatial correlation in disturbances [Jensen and Gleditsch, 2009] (see Methods Summary).

It may be that ENSO influences the timing of conflicts that would have occurred sooner or later.

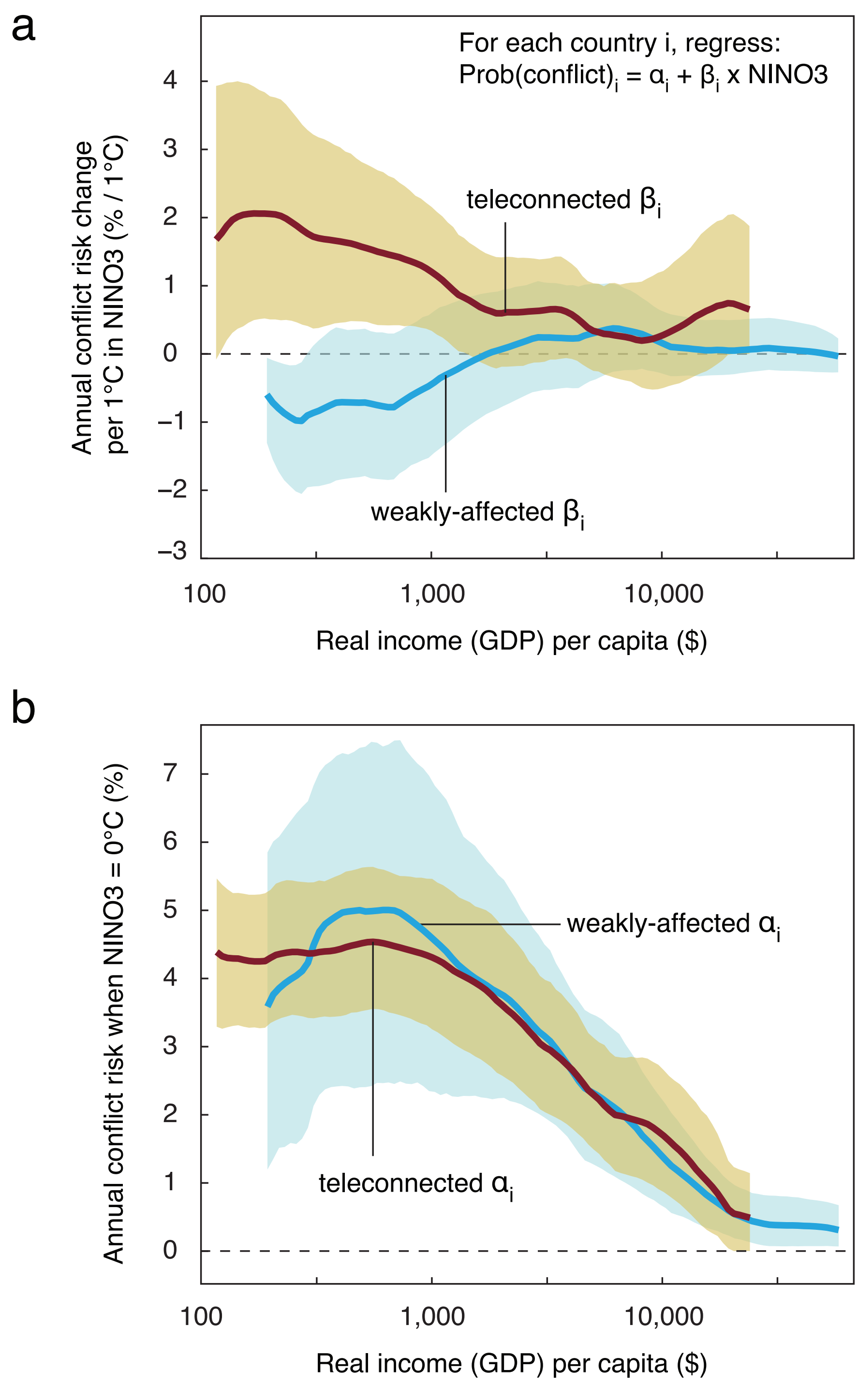


Figure 3.3: **Conflict risk and income.** (a) Red (blue) is a weighted moving-average (90% CI shaded) of ENSO sensitivity β of ACR on log income per capita (2007) for countries in the teleconnected (weakly-affected) region. (b) Same, for baseline ACR α.

By examining years following ENSO events, we find suggestive but statistically insignificant evidence that approximately 40% of the conflicts associated with ENSO are displaced in time (Table 3.15).

We evaluate the relative sensitivities of different countries by estimating a separate regression for each country, decomposing ACR for each country into a baseline component (α) independent of ENSO and a component (β) that varies linearly with NINO3 (see Supplementary Materials Section 3.D). Fig. 3.3a shows that in the teleconnected group (red curve) low income countries are the most responsive to ENSO (i.e. β is larger), while similarly low income countries in the weakly-affected group (blue curve) do not respond significantly to ENSO. It is noteworthy that the dependence of baseline ACR α on income is statistically indistinguishable between the two groups (Fig. 3.3b).

While we observe that those countries whose ACR responds most strongly to ENSO are low income, we cannot determine if (1) they respond strongly because they are low-income, (2) they are low income because they are sensitive to ENSO, or (3) they are sensitive to ENSO and low income for some third unobservable reason. Relationship (1) is frequently hypothesized based on the argument that low income countries lack the resources to mitigate the effects of environmental changes [Homer-Dixon, 1991, Hsiang, 2010, Jones and Olken, 2010]. However, relationship (2) is consistent with the observations that ENSO existed well before the invention of agriculture [Sarachik and Cane, 2010] and conflict induces economic underperformance [Miguel et al., 2004, Blattman and Miguel, 2010].

3.4 Discussion

Our results do not provide an estimate of the full social value of a global climate state, but a comparison of the influence of income and of ENSO on ACR is instructive. In a teleconnected country where average income per capita is \$1000, a 1°C increase of NINO3 increases ACR by 1% (Fig. 3.3a), so the 3°C shift associated with a change from La Niña to El Niño increases ACR by 3%. A similarly sized 3% decrease in its baseline ACR α would be associated with an order of magnitude increase in average income (Fig. 3.3b).

Since the strong ENSO events that have the greatest influence on ACR may be predictable up to two years in advance [Chen et al., 2004] use of our findings may improve global preparedness for some conflicts and their associated humanitarian crises.

While we find that the changes in the global climate associated with ENSO influence global patterns of conflict, our results might not generalize to gradual trends in average temperature or particular characteristics of anthropogenic climate change. Generalizing our results to global climate changes other than ENSO will require an understanding of the mechanisms that link conflict to climate. ENSO has a proximate influence on a variety of climatological variables, each of which may plausibly influence how conflict-prone a society is. Precipitation, temperature, sunlight, humidity and ecological extremes can adversely influence both agrarian [Rosenzweig and Hillel, 2008, Schlenker and Roberts, 2009] and non-agrarian economies [Hsiang, 2010, Jones and Olken, 2010]. In addition, ENSO variations affect natural disasters, such as tropical cyclones [Carmargo and Sobel, 2005], and trigger disease outbreaks [Kovats et al., 2003]. All of these have adverse economic effects, such as loss of income or increasing food prices, and it is thought economic shocks can generate civil conflict through a variety of pathways [Homer-Dixon, 1991, Miguel et al., 2004, Blattman and Miguel, 2010]. Furthermore, altered environmental conditions stress the human psyche, sometimes leading to aggressive behavior [Anderson et al., 2000]. We hypothesize that El Niño can simultaneously lead to any of these adverse economic and psychological effects, increasing the likelihood of conflict. Further, the influence of ENSO may exceed the sum influence of these individual pathways because it is a global-scale process that generates simultaneous and correlated conditions around the world. This is possible if non-local processes, such as increasing global commodity prices [Brunner, 2002] or conflict contagion [Blattman and Miguel, 2010, Jensen and Gleditsch, 2009], strongly influence local conflict risk. Future work will examine the relative importance of these various mechanisms.

3.5 Methods summary

Pixels with surfaces temperatures significantly and positively correlated with NINO3 for ≥ 3 months out of the year (Fig. 3.5-3.6) are coded "teleconnected" (red, Fig. 3.1c). Remaining pixels are coded "weakly affected" (blue, Fig. 3.1c). Countries are coded "teleconnected" ("weakly affected") if $> 50\%$ of the population in 2000 inhabited teleconnected (weakly affected) pixels (Fig. 3.7). Group-level time-series regressions use a continuous variable for ACR with linear trends and post-1989 constants; we drop 1989 because it is a 3-σ outlier, presumably because of the collapse of the Soviet Union (Fig. 3.13). Group-level standard errors are robust to unknown forms of heteroscedasticity. Country-level longitudinal regressions are linear probability models for ACR with country constants and country-time trends. Country-level standard errors are robust to unknown forms of spatial correlation over distances ≤ 5000 km, serial correlation over periods ≤ 5 years and heteroscedasticity. We estimate the number of conflicts affected by ENSO by assuming all conflicts in the weakly-affected group were unaffected and a baseline ACR of 3% for the teleconnected group would have remained unchanged in the absence of ENSO variations. We then project the observed sequence of NINO3 realizations onto our linear conflict model ($\partial ACR/\partial NINO3 = 0.0081$) and find 48.2 conflicts (21%) were influenced by ENSO.

Appendix

3.A Data sources and definitions

Table 3.2 contains summary statistics for the main variables in this study.

Climate data To determine the relative teleconnectedness of local climates to ENSO, we use the National Centers for Environmental Prediction (NCEP) Climate Data Assimilation System 1 (CDAS1) reanalysis of monthly surface temperatures during 1949-2009 [Kalnay et al., 1996]. ENSO variations can be detected using different indices, with the most commonly used being equatorial Pacific sea surface temperature (SST) anomalies. We utilize monthly means of three such indices: NINO12 (10°S-Eq, 90°W-80°W), NINO3 (5°S-5°N, 150°W-90°W), and NINO4 (5°S-5°N, 160°E-150°W) [Kaplan et al., 1998]. These indices measure SST in different locations in the Pacific Ocean, with NINO12 measured furthest east and NINO4 measured furthest west (see Fig. 3.10). These three indices differ both in the magnitude and timing of their variations, but are correlated with one another. For example, the standard deviation of our NINO12 measure (1.02°C) is substantially larger than that of our NINO4 measure (0.58°C). Our main text presents results for NINO3 because it is less influenced by coastal perturbations (compared to NINO12) and captures "medium-scale" events reliably (compared to NINO4), although we find that the choice of NINO index is inconsequential.

Conflict data We use the Onset and Duration of Intrastate Conflict dataset compiled by the Uppsala Conflict Data Program (UCDP) at Uppsala University and the International Peace Research Institute in Oslo (PRIO) [Gleditsch et al., 2002, Strand, 2006]. This dataset contains information on the magnitudes and recurrence periods of conflicts. A *conflict* is defined as "a contested incompatibility that concerns government and/or territory where the use of armed force between two parties, of which at least one is the government of a state, results in at least 25 battle-related death" [Gleditsch et al., 2002, Strand, 2006]. A *conflict onset* is the date on which a certain fatality threshold has been crossed in specific conflict between a unique government-opposition dyad (note that a country can experience *conflict onset* in sequential years if its government fights with different opposition groups in sequential years). The dataset uses fatality thresholds of 25 and 1000 battle-related deaths to distinguish events of different intensities. Should a conflict that has subsided be reinitiated, it is counted as a new conflict only if the last time it surpassed the 25 battle-deaths cutoff was more than X years ago, where $2 \leq X \leq 9$. For example, "Onset2" records a new *conflict onset* only if that conflict is new or if that specific conflict has been quiescent for at least two years. Our main results utilize this 25 fatality, 2-year definition of *conflict onset*. We check the robustness of this choice in a later section.

A subsample of this data set (approximately half of the full data set) has monthly dates associated with the timing of conflict onset [Gleditsch et al., 2002, Strand, 2006]. This subsample is used to construct Fig. 3.2c in the main text.

Agricultural data To validate our partition of the world into ENSO teleconnected and weakly-affected groups, we estimate the differential impact of ENSO on agricultural yields and agricultural revenue in each. Cereal yields are obtained from the Food and Agricultural Organization's (FAO) FAOStat database [Food and Agriculture Organization, 2009] and are available for 1961-2007. Agriculture revenue is acquired from the United Nations National Accounts database [UN, 2007] and is available for 1970-2008. The total annual agricultural revenue for each group is simply the sum of agricultural revenue across all countries in the given year (see Fig. 3.9).

Income data Income data is obtained from the United Nations National Accounts database [UN, 2007]. Incomes are available for 1970-2008 and are converted to 2007 US dollars per capita.

Demographic data Population data is obtained from United Nations World Development Indicators [World Bank, 2008] and are available for 1950-2008.

Political institutions data Polity IV data describes the level of democratization embodied by the political institutions of a country and is obtained from the Polity IV Project sponsored by the Political Instability Task Force [Marshall et al., 2009] and are available for 1950-2008. Polity IV scores take integer values ranging from -10 (hereditary monarchy) to +10 (consolidated democracy).

Rainfall data Data merged from gauges, satellite observations and numerical simulations is obtained from the Climate Predicition Center (CPC) Merged Analysis of Precipitation [Xie and Arkin, 1996] (CMAP) and are available for 1979-2008.

Tropical Cyclone data Hurricane, typhoon, cyclone and tropical storm data are obtained from the Limited Information Cyclone Reconstruction and Integration for Climate and Economics (LICRICE) model [Hsiang, 2010] and are available for 1950-2008. The data describe the annual maximum wind-speed spatially averaged over each country.

3.B The ENSO-teleconnection partition

3.B.1 ENSO teleconnections

A central contribution of this work is to develop a simple and robust partition of the continents based on their teleconnectedness to ENSO. Previous analyses have identified different types of ENSO teleconnections using a number of statistical techniques on different data sets [Ropelewski and Halpert, 1987, Ropelewski and Halpert, 1989, Nicholls, 1989, Nicholson and Kim, 1997, Klein et al., 1999, Chiang and Sobel, 2002, Giannini et al., 2003, Rosenzweig and Hillel, 2008, Sarachik and Cane, 2010]. Because of the heterogeneity in these approaches, there are variations in the patterns of teleconnections that they characterize. Nonetheless, there are many common patterns and we attempt to summarize this agreement with a simple approach that partitions the world into locations that are either strongly teleconnected or weakly affected. While this a crude simplification of the high dimensional and continuous structure of ENSO teleconnections, it provides a surprising amount of power to global analyses of ENSO impacts, despite its simplistic nature.

El Niño events are associated with abnormally warm sea surface temperatures in the central and eastern equatorial Pacific, releasing large fluxes of thermal energy into the atmosphere. This warming of the tropical Pacific free troposphere induces warming throughout the tropical free troposphere, generally stabilizing the air column to vertical motions, inhibiting rainfall and warming the surface. For a fully developed discussion of these dynamics, see Sarachik and Cane [Sarachik and Cane, 2010] (2010). While there are many other local impacts of ENSO variations with complex structure in space and time, the simplest and most general fingerprint throughout impacted regions is near-surface warming induced by the increased static stability [Chiang and Sobel, 2002]. Furthermore, using surface temperatures to identify teleconnections benefits from the fact that temperature data is the most reliably collected atmospheric statistic and is well modeled in reanalyses [Kalnay et al., 1996].

3.B.2 Construction method

To construct our global partition of ENSO teleconnections, we examine whether reanalysis grid cells exhibit surface temperatures that are positively correlated with NINO3 on a monthly basis (with a two month lag) for at least three months out of the year. The details of this construction are as follows:

Let $NINO(m, y)$ = the value of the ENSO index in calendar month $m \in \{1, ..., 12\}$ and year $y \in Y \equiv \{1950, ..., 2004\}$. Similarly, let $T(x, m, y)$ be the surface temperature at location x, month m and year y. Let $\rho(x, m, L)$ be the correlation coefficient (over all years $y \in Y$) of $NINO(m, y)$ and $T(x, m + L, y)$ (ρ is plotted for each month in Fig. 3.5). Note that T lags NINO3 by $L > 0$ months to account for the fact that signals from the tropical Pacific where NINO3 is measured need some time to propagate and influence the rest of the world [Chiang and Sobel, 2002]. In the main analysis $L = 2$. Now let $\tilde{\rho}(x, m, L) = 1$ if $\rho(x, m, L)$ is positive and statistically different from zero at $\alpha = 0.1$; $\tilde{\rho} = 0$ otherwise. Then

$$M_{xL} = \sum_{m=1}^{12} \tilde{\rho}(x, m, L)$$

is the number of months that grid point x exhibits interannual surface temperature variations that are significantly correlated at a level ≤ 0.1 with NINO3 L months earlier.

Even with no mechanistic connection between surface temperatures at x and NINO3, most values of M_{xL} should be ≥ 1 since 1 in 10 random draws will be correlated at the $\alpha = 0.1$ level. If the monthly draws of temperature were all completely independent, $M_{xL} \geq 3$ would occur randomly 11 percent of the time[1] ($M_{xL} \geq 5$ would occur 0.4% of the time). Independence is not a valid assumption in this case, but it is a useful benchmark. For a cutoff value R, a point x is denoted ENSO “teleconnected” if $M_{xL} \geq R$. We define a binary measure of “teleconnectedness” $V_x(L, R) = 1$ if $M_{xL} \geq R$ and $= 0$ otherwise. In the main analysis, $R = 3$. Fig. 3.6A displays V_x (for $L = 2$ and $R = 3$, the values used in the main analysis); points with $V_x = 1$ are marked in red.

To estimate country-level teleconnection index $\bar{V}_i$ for country i, we take a weighted average of V_x over all points in country i, denoted by $x \in X_i$:

$$\bar{V}_i = \frac{1}{(\sum_{x \in X_i} w_x)} \sum_{x \in X_i} (V_x \times w_x).$$

Values for $\bar{V}_i$ will range from 0 in the least teleconnected countries to 1 for the most teleconnected countries. The histogram in Fig. 3.1d (main text) displays the distribution of $\bar{V}_i$ for the values used in the main analysis ($L = 2$, $R = 3$ and w_x = the population of pixel x in the year 2000). Because it is so strongly bimodal, a partition into just two groups appears to be an excellent approximation. It is surely an attractive simplification. We assign those countries with $\bar{V}_i > 0.5$ to the teleconnected

[1] $\sum_{m=3}^{12} \left[0.1^m 0.9^{12-m} \binom{12}{m} \right] = 0.1109$

group and those with $\bar{V}_i \leq 0.5$ to the weakly-affected group (see Fig. 3.7).

3.B.3 Robustness of the ENSO-teleconnection partition

In this subsection, we examine the sensitivity of our partition under different choices for w, L, and R. We find that the gross features of the global partition are unchanged for a range of reasonable parameter choices and we document that it agrees well with previous analyses of regional ENSO teleconnections.

Pixel Assignment Fig. 3.6 illustrates changes to the partition that occur when L and R are modified. Panel a depicts teleconnected pixels ($V_x(L, R) = 1$) as red for $L = 2$ and $R = 3$, the values used in the main analysis. Panel b is the same, except $L = 0$. Almost no features change, suggesting that the selection of L is inessential. Panel c displays the changes that occur when L is held fixed at 2 and R is changed. As described before, setting $R < 3$ would admit too many chance assignments, but perhaps $R = 3$ is also too low. When $R = 5$ is used, those pixels that are teleconnected are marked as green. Pixels that are teleconnected when a cutoff $R = 3$ is used but are no longer teleconnected when $R = 5$ are yellow. Pixels that are weakly-affected when either $R = 3$ or $R = 5$ are blue. Note that the red region in Panel a is the union of the green and yellow regions in Panel c. When R is increased from 3 to 5, only the group assignment of the yellow region changes. This region is small and represents the boundary of the moist tropics and the arid subtropics; it is the region where the annual monsoonal rains stop in their meridional translation and reverse direction. The primary effect of increasing R from 3 to 5 is to simply omit relatively dry pixels that do not have five rainy months in a normal year.

Country Assignment Figures 1d-f in the main text illustrate the redistribution of country-level assignments when the weighting values w_x are changed from area to population weights and when R is changed from 3 to 5 months. (Fig. 3.7 displays countries assigned to the teleconnected group in red and the weakly-affected group in blue, using the values from the main analysis, $L = 2, R = 3$.) The histogram in Fig. 3.1d (main text) displays the distribution of the country-level ENSO teleconnection index $\bar{V}_i$ when pixels are aggregated using weights w_x that reflect the population of each pixel. The histogram in Panel e displays how this distribution changes if the weights are changed to reflect the area of each pixel; the overall distribution is virtually unchanged. The histogram in Panel f displays how the distribution changes if population weights are used but $R = 5$ instead of 3. Again, the structure hardly changes.

Negative temperature correlations When designating pixels and countries as teleconnected, we only examined whether surface temperatures were positively correlated with NINO3 or not. One might be concerned that we ignore significant negative correlations with NINO3 because such correlations are well known [Sarachik and Cane, 2010], however most locations with negatively correlated temperatures are oceanic and not continental [Chiang and Sobel, 2002]. If large continental regions were negatively correlated with NINO3, we might expect that ACR in those countries would have a response to ENSO that was opposite the response in the teleconnected group. To check that such a pattern does not influence our results, we document that only three countries in our sample ($< 2\%$) have most of their population in locations where surface temperatures that are negatively correlated with NINO3 (see Fig. 3.8). Northern Mexico, the western United States, eastern Russia and eastern Indonesia also contain locations where surfaces temperatures anticorrelate with NINO3, however these locations contain only a small fraction of these countries' total populations. Fiji, the Solomon Island and New Zealand are the three countries that could plausibly be coded as "negatively teleconnected," yet none experience any civil conflict during the period of observation.

Agreement with previous analyses Several previous studies have illustrated different types of ENSO teleconnections using different environmental variables and statistical techniques [Ropelewski and Halpert, 1987,Ropelewski and Halpert, 1989,Nicholls, 1989,Nicholson and Kim, 1997,Chiang and Sobel, 2002,Giannini et al., 2003,Rosenzweig and Hillel, 2008]. The pixels we designate as teleconnected to ENSO (Fig. 3.1c in main text) is approximately the union of regions previously found to be teleconnected to ENSO. The seminal work by Ropelowski and Halpert [Ropelewski and Halpert, 1987,Ropelewski and Halpert, 1989] demonstrated that several regions in the tropics and subtropics exhibited rainfall anomalies (of both signs) in association with ENSO (see Fig. 21 p. 1625 in [11]). Nicholls [Nicholls, 1989] showed the dependence of rainfall throughout eastern Australia (see Fig. 4b p. 969 in [13]). Nicholson and Kim [Nicholson and Kim, 1997] illustrated impacts throughout sub-Saharan Africa by utilizing more complete data sets than earlier work could access (see Fig. 7 p. 125 in [14]). Chiang and Sobel [Chiang and Sobel, 2002] explained the propagation of teleconnections with Kelvin wave dynamics and demonstrated their results using 1000-200mb temperature anomalies, which were correlated with ENSO throughout the tropics and some of the subtropics (see Fig. 2 p. 2618 in [15]). Giannini, Saravanan and Chang [Giannini et al., 2003] demonstrated the dependance on ENSO of rainfall and surface temperatures in the Sahel (see Fig. 4E-F p. 1029 in [16]). A large number of other studies have illustrated flooding or ecological responses in more limited regions, many of which are summarized in Rosenzweig and Hillel [Rosenzweig and Hillel, 2008].

Our binary teleconnection partition is a dramatic simplification of the rich relationships studied in earlier work. For many purposes it would be an oversimplification, but it serves our purposes here by providing a structurally simple inclusive description of worldwide ENSO impacts. The binary assignment is justified *a posteriori* by the sharpness of the division. However, this strong generalization does not allow us to identify the specific mechanisms that are driving our main findings.

3.B.4 Partition validation using weather and agricultural outcomes

As a validation exercise of our global partition of ENSO teleconnection, we explore the effect of ENSO on surface temperatures, rainfall and agricultural output (Table 3.3) because these relationships are well established [Ropelewski and Halpert, 1987, Chiang and Sobel, 2002, Cane et al., 1994, Rosenzweig and Hillel, 2008, Sarachik and Cane, 2010].

Temperature and rainfall First we check that temperature and rainfall at the country-level are correlated with interannual variations in ENSO in the teleconnected group and not in the weakly affected group. The partitioning technique was designed to isolate those countries that are strongly influenced by ENSO, however it is possible that countries that have temperatures positively correlated with NINO3 for three months also exhibit negative correlations in other months or do not exhibit annually averaged signals for some other reason. Moreover, it is important to verify that rainfall patterns are negatively correlated with NINO3 in the teleconnected countries because rainfall was not explicitly used in the construction of the partition. (Rainfall was not used in the partition construction because rainfall signals are more variable and rainfall data is both less complete and noisier.)

To verify our partition with weather data, we estimate

$$W_i(t) = \beta NINO3(t) + \gamma_i + \theta_{i1}t + \theta_{i2}t^2 + \epsilon_i(t) \tag{3.1}$$

where $W_i(t)$ is either temperature or rainfall for country i in year t, $NINO3$ is averaged May-December, γ_i is a country-specific constant (fixed effect) and θ_{i1} and θ_{i2} are country-specific linear and quadratic time trends. This equation is estimated once for each country group and the results are in rows 1 and 2 of Table 3.3. In the teleconnected group, annual average temperature (precipitation) is significantly and positively (negatively) correlated with the dominant NINO3 signal in each year. In the weakly affected group, the estimated values of β are near zero and statistically insignificant.

Cereal yields Next we compare inter-temporal variations in cereal yields for individual countries in the two groups with inter-temporal variations in ENSO. Using a longitudinal dataset of all countries between 1961-2007 we estimate the following dynamic model:

$$\log(Y_i(t)) = \beta_1 NINO3(t) + \beta_2 \log(Y_i(t-1)) + \gamma_i + \theta_{i1} t + \theta_{i2} t^2 + \epsilon_i(t) \tag{3.2}$$

where $Y_i(t)$ is the $Cereal\ Yield$ for country i in year t. The trend terms are intended to account for technological innovation such as the "green revolution". Equation 3.2 is estimated separately for the teleconnected and weakly-affected groups. Standard errors are clustered by country [Liang and Zeger, 1986, Arellano, 1987, Bertrand et al., 2004] to account for unknown patterns of within-country autocorrelation. Row 3 of Table 3.3 presents the NINO regression coefficient and associated standard errors for the two groups. For the teleconnected group, the coefficient is significantly negative while for the weakly-affected group the coefficients are positive but insignificant, a result that is consistent with observed increases in rainfall for some locations in the mid-latitudes [Rosenzweig and Hillel, 2008].

Agricultural revenue Finally, we check our teleconnection partition against agricultural outcomes by using agricultural revenue data from another source [UN, 2007]. In row 4 of Table 3.3, we estimate equation 3.2 using country-level agricultural revenue and find that relative to the impact of ENSO on the teleconnected group, the drop in agricultural revenue for weakly affected countries is smaller and not significant. We also aggregate a single time-series of total agricultural revenue A per capita for the entire teleconnected and weakly-affected groups for 1970-2007. For each group, this number represents the total value of all agricultural output for roughly half of the world population (see Fig 3.9). Specifically, for each group, we estimate the following auto-regressive model

$$A(t) = \beta_0 + \beta_1 NINO3(t) + \beta_2 A(t-1) + \theta_1 t + \theta_2 t^2 + \epsilon(t). \tag{3.3}$$

Row 5 of Table 3.3 shows the regression coefficient β_1. Consistent with the other panels in Table 3.3, we find that in the teleconnected group, an increase in NINO3 leads to large and significant negative impacts in agricultural revenue while the coefficient for the weakly-affected group is smaller and not statistically significant. (We have verified that these different agricultural responses are also robust across NINO12 and NINO4 indices, results that are available on request.)

These results, which are consistent with previous regional and local-scale analyses [Ropelewski and Halpert, 1987, Chiang and Sobel, 2002, Cane et al., 1994, Rosenzweig and Hillel, 2008, Sarachik and Cane, 2010], broadly validate our global partition of ENSO teleconnections.

3.C ENSO timing and measurement error

Annual conflict onset data is organized by years that begin in January and end in December [Gleditsch et al., 2002, Strand, 2006]. NINO indices are collected for individual months and therefore must be aggregated into years in order to match the conflict data. The simplest approach would be to average NINO indices over years that begin in January and end in December, producing measures of ENSO that are exactly contemporaneous with the conflict onset observations. However, ENSO "events" do not begin in January nor end in December. ENSO events generally begin in May/June and persist until they break down in March/April of the following year. For this reason, the period April-May is often termed the "spring barrier" and separates "tropical years" from one another. Fig. 3.1g in the main text illustrates the spring barrier by plotting monthly correlations between NINO3 values in December and other months. Importantly, the values of the NINO3 index in January-April of *Calendar Year t* are unrelated to the dominant event observed in *Tropical Year t*.

To demonstrate that ENSO events are organized this way, Table 3.4 tabulates the correlation coefficients for monthly NINO3 values over the period 1950-2008. Entries describe the correlation between the NINO3 values that are observed in two months of the same calendar year. The first three columns, marked *early season*, have values near one for the first three rows, indicating that months prior to the spring barrier have NINO3 values that are highly correlated with one another. The bottom seven rows have values close to zero, indicating that NINO3 values before and after the spring barrier are not correlated. In any given year, the annual average NINO value is dominated by measurements following the spring barrier. Thus, if an El Niño or La Niña "event" occurs, the calendar year in which it begins (referred to as "Year 0" in the climate literature) is the calendar year that exhibits the largest annually averaged signal. These events are generally coherent across the months June-December, as indicated by the high values in the last seven columns of Table 3.4. The correlation coefficients associated with spring barrier months (April and May) have intermediate values as this is the transition period between "tropical years".

Because El Niño or La Niña events are dominated by signals following the spring barrier, including early season measurements that are uncorrelated with these late season signals is equivalent to introducing noise into estimates of a given year's dominant climatology. Therefore, we omit early season months and estimate the ENSO state of the global climate by averaging NINO index values over May-December only. The NINO index values for January-April of the following year are omitted, despite their occurrence in the same "tropical year," because they follow all conflicts that are recorded in the matching calendar year.

Table 3.7 demonstrates the result when the spring barrier is ignored in the "naive" approach described above. Panel f displays the coefficients and standard errors when ACR for the teleconnected group is regressed on annual average NINO indices using all months, ignoring the existence of the spring barrier. Contrast this with Panel c displaying the results when index values for January-April are omitted from the annual averages of NINO. Including January-April NINO values reduces the magnitude of the coefficients by about 11-16% and increases the size of the standard errors by 13-49%. Thus, a "naive" estimate ignoring the timing of ENSO events would suggest that there is no statistically significant relation between ENSO and conflict onset. Tables 3.4, 3.5 and 3.7 suggest that the inclusion of January-April NINO values lead to "attenuation bias," a well known statistical problem associated with classical (additive) measure error in a regressor variable [Greene, 2003, Angrist and Pischke, 2008].

In addition, recall that Fig. 3.2c of the main text displays the within-year distribution of additional conflicts associated with El Niño-like conditions. It demonstrates that conflict onsets preceding the spring barrier are not driving our main result.

3.D Main statistical models

Table 3.1 in the main text presents the main results of this study: a shift in the global climate from a strong La Niña to a strong El Niño increases the probability of conflict onset in the teleconnected group from 3% to 6% whereas the probability of conflict onset in the weakly-affected group remains unchanged at 2%. Estimating the magnitude of these changes requires the use of statistical models, which are detailed here.

Time series model of *conflict risk*: In our primary results, presented in Table 3.1 row 3, we define *annual conflict risk(t)* = $\left(\frac{conflict\ onsets(t)}{countries in region(t)}\right)$. We use a time series model with the following specification:

$$annual\_conflict\_risk(t) = \alpha + \beta NINO(t) + \theta t + post\_cold\_war(t) + \epsilon(t) \tag{3.4}$$

where α is a constant, θ is a linear trend and $post\_cold\_war(t)$ is a constant term for all years following 1989 (inclusive) and zero otherwise. The coefficient of interest is β, which describes how many more conflict onsets per country are associated with a 1°C increase in NINO. This model is estimated once for the teleconnected group and once for the weakly-affected group. In each case, the observational unit is a "group-year" and the comparison is between the time series of NINO and the time series of a group's *annual conflict risk*, each of which has 54 observations. The linear trend captures slow increases in overall conflict risk and NINO. It also ensures that the estimated coefficients only represent high-frequency variations in ENSO and not correlated trends. The introduction of a cold war constant is a common practice in statistical analyses of conflict [Buhaug, 2010] because overall conflict levels changed qualitatively following the collapse of the Soviet Union. The standard errors presented for these time-series models are White standard errors and are robust to heteroskedasticity of arbitrary form [White, 1980].

One drawback of Equation 3.4 is that country-level trends in conflict cannot be accounted for (eg. some countries may have become more conflict-prone over the observation period). The stationarity of NINO indices suggest that this is not a major threat to unbiased estimation of β. However, the entry of new countries into our sample (see Fig. 3.4) may bias our estimates if new countries are systematically different from older countries (eg. they may be more violent) and they enter the sample differentially during different ENSO states (eg. during more El Niño-like conditions). It is for these reasons that we check our estimates with the following second estimation procedure.

Longitudinal linear probability model of *conflict risk*: Rows 5 and 6 of Table 3.1 in the main text presents the coefficients from a country-level panel data linear probability model. These results come from the following specification:

$$C_i(t) = \beta NINO(t) + \mu_i + \theta_i t + \epsilon_i(t) \tag{3.5}$$

where $C_i(t)$ is unity if country i begins a conflict in year t and zero otherwise, μ_i is a country-specific constant and θ_i is a country-specific trend. Unlike the time-series model in Equation 3.4, the unit of observation for this model is a "country-year". For each country and year combination, there is one observation for a total of 3978 observations in the teleconnected group and 3400 observations in the weakly-affected group. The advantage of this technique is that it allows us to remove country-level trends in violence with the term θ_i because each country is observed multiple times. It also allows us to control for new countries that enter the sample during different ENSO states: the country-specific term μ_i removes any time-invariant characteristics of a country that might make it more or less conflict prone.

One disadvantage of the longitudinal data approach is that it is more difficult to calculate appropriate standard errors for our estimates of β. First, there may be serial correlation in conflict onset that are observed for an individual country. For example, countries may go through violent periods when they experience several conflict onsets over a short period. Second, all countries in a region are exposed to the same NINO index in a given year. If there are other factors that give rise to spatial correlation in conflict onsets, then our observations will not be independent and we will underestimate the size of our standard errors [Bertrand et al., 2004, Angrist and Pischke, 2008]. We address these concerns by computing standard errors using the generalized method of moments proposed by Conley [Conley, 1999] (1999) to account for unknown forms of spatial correlation. Because ENSO is regional to global in scale, we allow for spatial correlations in errors over distances up to 5000 km. In addition, we allow for serial correlation over periods less than six years and heteroskedasticity of unknown form.

A second issue associated with this longitudinal data model is that the variable $C_i(t)$ can only take on the values of zero or one (i.e. it is a "binary response" model) [Greene, 2003]. Several methods have been developed to estimate probabilities when only a binary outcome is observable. The linear model in Equation 3.5 represents the simplest of these models and is the easiest to interpret. However, when using this type of model, two issues must be examined to ensure that a linear model is appropriate. First, the predicted probabilities of an event should not be lower than zero nor higher than one. Figure 3.11 plots the predicted ACR for both regions (labeled "OLS") over the values of NINO3 that are observed. All predicted ACR values are well within the unit interval. Second, the probability response function should be well approximated by a linear function. Probit and logit models are two commonly used models that have been developed to deal with the type of non-linearity commonly observed in probability response functions [Greene, 2003]. Fig. 3.11 also plots the predicted ACR using these two other methods (labeled "Logit" and "Probit"). These response functions are indistinguishable from the linear model, suggesting that linearity is a good approximation.

The similarity of the results between rows 3 and 5 of Table 3.1 in the main text provides strong support for our main results. Two estimation procedures with different strengths and weaknesses provide almost identical results.

Note on 1989 In the regressions presented in the main text, observations from 1989 are dropped. Fig. 3.13a illustrates why we have done this. It plots the residuals for a regression in row 2 of Table 3.1 from the main text. The number of conflicts in 1989 for the teleconnected group was three standard deviations from the conditionally expected value. It seems likely that the large number of conflicts in that year were related to events associated with the end of the Cold War. Yet, we note that once a constant for the post-Cold War period is included in Equation 3.5 (a common technique in the literature [Buhaug, 2010]) our main result appears robust to the reintroduction of 1989 to the sample (see Table 3.7). Fig. 3.13b plots the estimated residuals using this second model.

Non-parametric estimates of conflict risk: Fig. 3.2b in the main text provides local non-parametric estimates of our time-series model. Non-parametric techniques are employed to (1) validate that linearity between NINO3 and conflict risk is a reasonable assumption, and (2) obtain a better sense of local behavior around different parts of the NINO3 distribution. For Fig. 3.2b, a Nadaraya-Watson estimator [Nadaraya, 1964,Watson, 1964] was fit to the data using a Epanechnikov kernel with a 1°C bandwidth. The 90% confidence intervals are bootstrapped.

Hierarchical regression model of ENSO teleconnection and income: Fig. 3.3 in the main text uses a hierarchical regression model to decompose conflict risk for each country into ENSO unaffected (α_i) and ENSO-affected (β_i) components. Specifically, for each country i, we run the regression:

$$C_i(t) = \alpha_i + \beta_i NINO3(t) + \epsilon_i(t) \tag{3.6}$$

where the variables are defined as they were in Eq 3.5. We next conduct a local non-parametric estimate for the relationship between income per capita and the two estimated terms α_i and β_i. Fig. 3.3a in the main text plots β_i against log income per capita in 2000 using a Epanechnikov kernel with a 0.6 log income per capita bandwidth. The 90% confidence intervals are bootstrapped. Fig. 3.3b uses the same method for α_i.

3.E Robustness of the main result

Earlier, we showed that the bimodal distribution of the country-level teleconnection index is largely insensitive to parameters in the construction of the global teleconnection partition. Here we further test the robustness of our results by altering the independent variables of the statistical model, explicitly modeling potential serial correlations, altering the sample of years used in the model, including a large number of potentially confounding control variables, estimating a distributed lag model, altering the definition of ACR and examining whether our results hold outside of Africa. Our main findings survive all of these checks.

NINO index Table 3.7 provides results when NINO12, NINO3 and NINO4 are used to check that our results are robust to different measures of the global ENSO state. While the coefficients in thise table may look as if they change substantially as the NINO index changes, this is partly driven by differences in the scale of variation observed for each index. These coefficients are in units of $\frac{\%\ year^{-1}}{1°\mathrm{C}}$, however the range of degrees Celsius over which each index varies is not fixed. Table 3.2 presents the standard deviations for the three NINO indices. When the coefficients from our preferred specification (panel d in Table 3.7) are converted to units of $\frac{\%\ year^{-1}}{1\ standard\ deviation}$, they look similar, ranging from 0.51-0.47.

Serial correlation In our time series analysis of ACR and NINO3, one might be concerned that patterns of serial correlation in one or both variables could be affecting our central findings, however we do not find that this is the case. Table 3.8 presents our baseline results in models 1 and 6. The Durbin-Watson d-statistic for the teleconnected group rejects the null hypothesis of serial correlation in errors, however the same test for the weakly affected group fails to reject the null. When the residuals from the baseline model are regressed on their lagged values (models 2 and 7) we again find no serial correlation in the teleconnected group but some serial correlation in the weakly affected group. When we explicitly add lagged values of ACR to the baseline model (models 3 and 8) we find no substantive change in our coefficient of interest. We also model changes in ACR as a response to changes in NINO3 (models 4 and 9) and find that our results are not statistically different from the baseline model. Finally we re-estimate our standard errors for our baseline model using a Newey-West estimator [Newey and West, 1987] that is robust to both serial correlation and heteroscedasticity (rather than the White estimator [White, 1980] that we used previously and is only robust to heteroscedasticity). Regardless of whether we use a lag cutoff of three, five or ten years[2], our estimated standard errors and significance levels do not change in a meaningful way.

Sample selection In our main analysis, we focus on the period 1950-2004 and omit the observation in 1989. We begin our analysis in 1950 because the post-war years were extraordinary, containing two extreme outliers (1946 and 1948). In addition, no other data sets except NINO reconstructions are available prior to 1950. We omit 1989 because it is also an influential outlier, probably related to the end of the Cold War. Retaining these obvious outliers in our analysis would likely bias our estimates, however we examine whether their inclusion in our analysis substantially changes our finding. In model 1 of Table 3.9 we present our baseline sample. In model 2 we add 1989 only and in model 3 we add the years 1946-1949 only. In model 4 we exclude only 1948 and 1989 (the largest outliers) and in model 5 we restrict the sample to years following 1975 (inclusive), when the sample of teleconnected countries stabilized. In model 6 we include all years in the Conflict Onset and Duration Dataset. In all of these samples, we find that the coefficient on NINO3 is statistically significant and statistically indistinguishable from our baseline model. However, these outliers exert a large and probably unreasonable influence on our model, so they remain omitted in our primary analysis.

Semi-parametric control variables In a recent paper, Buhaug [Buhaug, 2010] (2010) suggested that the compelling longitudinal-based results in studies such as this should not depend critically on using country-specific constants (fixed-effects) or country-specific trends. Burke et al. [Burke et al., 2010] (2010) respond that such controls are essential to reliable statistical inference. It is our view that such controls are generally appropriate, however we check that our results are robust to their omission. Table 3.10 presents results from our longitudinal linear-probability model (Equation 3.5) with and without country fixed-effects (μ_i) and country-specific trends (θ_i). None of these alterations affects our estimated coefficient of interest, however the omission of country fixed-effects increases our estimated standard errors slightly.

Other control variables Because previous studies have identified many parameters that are correlated with conflict, it may be worth it to try and include these variables in our longitudinal analyses. We do this to check the robustness of our results in light of previous work, but do not present heavily-controlled regression results as our main findings because we feel that such control is not methodolog-

[2] Greene [Greene, 2003] (2003) recommends using a cutoff length that is at least as large as the fourth-root of the number of observations, which in this case is 2.7 years.

ically sound [Greene, 2003, Angrist and Pischke, 2008], especially when our independent variable of interest (ENSO) is unquestionably exogenous. Moreover, our preferred model generates results that appear weaker than the following heavily-controlled models, suggesting that our preferred approach is the more conservative one.

We begin by introducing idiosyncratic country-level temperature and precipitation shocks that others [Levy et al., 2005, Miguel et al., 2004, Burke et al., 2009, Bruckner, 2010] have suggested influence civil conflicts. ENSO may influence conflict through temperature and precipitation, however it may also affect conflict through a variety of other mechanisms including (but not limited to) the timing of rainfall, altered wind patterns, humidity, cloud cover, disasters, ecological events, or other environmental changes. It may also be the case that ENSO induced changes in temperature and precipitation have a fundamentally different impact on conflict than idiosyncratic weather shocks because ENSO induced changes are experienced by a large number of countries. Thus, it is not surprising that when monthly temperature or rainfall are included in our longitudinal model, the coefficient on NINO3 remains large and statistically significant (Table 3.11). When rainfall is introduced to the model our coefficient of interest becomes larger, however this is partially an artifact of the subsample of years (post 1979) for which reliable global rainfall data is available. We do not believe that this is a well-specified model because ENSO is known to affect temperature and rainfall [Angrist and Pischke, 2008], however we present it here for completeness.

We now turn to three of the most commonly suggested correlates of civil conflict: income [Collier and Hoeffler, 2004, Miguel et al., 2004, Blattman and Miguel, 2010], population [Urdal, 2008, Bruckner, 2010] and political institutions [Buhaug, 2010]. When all of our data is pooled together (Fig. 3.14) it appears that ACR increases with population, decreases with income and is greatest for countries that are "anocracies" (Polity IV scores near zero). We include lagged values for these controls one by one and jointly into our fixed-effects model and present the results in Table 3.12. In all of these models, the effect of ENSO on ACR is large and statistically significant. This contrasts with the weakly affected region, where correlations between ACR and NINO3 continue to be absent even in the presence of these controls. Further, when we stratify the teleconnected sample according to whether countries are in Africa or not (models 9-10), both regions exhibit similar results. This contrasts with the effects of income, population and Polity IV, all of which change in magnitude and/or sign between the African and non-African subsamples. Polity IV is the only control that exhibits a reasonably consistent and significant correlation with ACR, however the amount of variation it explains is small (Fig. 3.14) and it is known to be extremely endogenous [Miguel et al., 2004, Angrist and Pischke, 2008, Burke et al., 2010].

Finally, we estimate a "kitchen sink" model that contains the following controls. The paper that motivates each variable's inclusion is listed in as a citation.

1. country fixed-effects [Fearon and Laitin, 2003]
2. country-specific time trends [Burke et al., 2010]
3. log income per capita [Collier and Hoeffler, 2004] (lagged)
4. income growth [Miguel et al., 2004] (lagged)
5. Polity IV score [Buhaug, 2010] [linear & quadratic] (lagged)
6. agriculture industry share (%) [Burke et al., 2009] (lagged)
7. percent urbanized [Fearon and Laitin, 2003] (lagged)
8. log population [Bruckner, 2010] (lagged)
9. percent female [Urdal, 2008] (lagged)
10. percent below 15 yrs old [Urdal, 2008] (lagged)
11. percent above 65 yrs old [Urdal, 2008] (lagged)
12. cyclone maximum windspeed [Barron et al., 2004] (area average)
13. monthly temperature [Burke et al., 2009] (12 variables)
14. monthly rainfall [Miguel et al., 2004, Levy et al., 2005] (12 variables)

Results from this heavily controlled model are presented in Table 3.13. The full-sample estimates with or without the weather controls (rows 1 and 4) exhibit large and statistically significant correlations between ACR and NINO3 in the teleconnected group only. We check that a linear model for the ACR response to NINO3 is a good approximation for the data in this "kitchen-sink" model (Fig. 3.15) and observe that these results are not driven by outliers. When the sample is split into African and non-African countries, we again see large coefficients for all groups. Only one teleconnected coefficient (model 3) is not significant despite being larger in magnitude that the analogous coefficient in our baseline model (Table 3.1 in the main text, row 3). This is hardly surprising and occurs because our standard errors grow substantially with such dramatic "over-fitting" in our statistical specification [Greene, 2003]. Again, it is our view that including so many endogenously determined and/or irrelevant control variables is not the correct approach to causal inference since ENSO is known to vary over time exogenously. We only present these results as a robustness exercise.

Lag and lead NINO terms As discussed in the main text, we conduct tests to determine whether or not (1) the conflicts induced by ENSO in the teleconnected group would have occurred in its absence and (2) our main results might be spurious.

To check if ENSO simply advances inevitable conflicts, we add a one-year lagged NINO term into Eq. 3.4. Model 1 of Table 3.15 replicates our main result for the teleconnected group. Model 2 includes a lagged NINO3 term while model 3 also includes an interaction term between current NINO3 and lagged NINO3 because sequential ENSO events may have compounding impacts. Model 4 includes two lagged NINO3 terms. Observe that the only significant coefficients in the four models are for current NINO3. Columns 2 and 4 show that when lagged NINO3 terms are included, the coefficient on the lagged terms are of lesser magnitude than the current NINO3 coefficient. The point estimate suggests that about 40% of the observed conflicts might be displaced, however we cannot reject the null that no displacement occurs.

As an additional check against potentially spurious results, model 5 of Table 3.15 includes a future NINO3 term which, as expected, is not a statistically significant predictor of current ACR.

Columns 6-10 replicate the analysis for the weakly-affected group and do not yield any statistically significant coefficients.

Conflict size Next, we check whether our main result is driven by large or small conflicts and find that neither is dominating our result. The UCDP/PRIO Onset and Duration of Intrastate Conflict database separates conflict onsets into three categories: *large conflicts* that exhibit more than one-thousand battle-related deaths in a single year, *small conflicts* that exhibit more than twenty-five battle-related deaths in the year of onset but never exceed one-thousand cumulative deaths throughout the conflict, and *intermediate conflicts* that exhibit more than one-thousand cumulative battle related-deaths throughout the conflict, but never exceed one-thousand deaths in a given year. Because there are a very small number of *intermediate conflicts*, they are dropped from the following analysis (although they are included in the main analysis). Also note that the scale of conflicts is determined by the absolute number of battle related-deaths, not by the fraction of individuals in a country that are killed. Thus, a large conflict in a large country may not be of the same "intensity" as a large conflict in a small country. Nonetheless, we follow the existing literature and use these cutoffs [Strand, 2006, Burke et al., 2009, Buhaug, 2010] despite their imperfections.

To check that our main results are not driven by only small or large conflicts, we re-estimate Equation 3.5 for *small conflicts* only and then again for *large conflicts* only (Table 3.14 column 1, titled "Onset2"). The sum of the coefficients for small and large conflicts should be approximately equal to the coefficient of NINO3 in row 5 of Table 3.1 in the main text. If the coefficient for small conflicts were much larger (smaller) than the corresponding coefficient for large conflicts, than that would indicate that small (large) conflicts were driving our main result in Table 3.1. We find no evidence this is the case. The increase in conflict onset risk associated with a 1°C increase is identical for large (0.45%) and small (0.45%) conflicts.

Intermittency threshold Previous statistical analyses of conflict have demonstrated that altering the definition of "conflict onset" may substantially influence their results [Gleditsch et al., 2002, Strand, 2006, Hegre and Sambanis, 2006]. One parameter that has been shown to affect results is the "intermittency threshold" for conflicts [Hegre and Sambanis, 2006]. Throughout our main analysis, if a specific conflict has been quiescent for at least two years and then becomes active again, it is coded as a new conflict onset. Borrowing the terminology of the UCDP/PRIO database, we call the binary variable that results from this coding rule $Onset2$ [Gleditsch et al., 2002, Strand, 2006]. We allow the number of quiescent years X to change when estimating Equation 3.5. Thus, $OnsetX$ denotes a new conflict onset that occurs only after X years of inactivity. Note that by construction all conflict onsets recorded in $OnsetX$ will also be recorded in $Onset(X-1)$, but the reverse is not true.

Table 3.14 shows how the results for large and small conflicts change when the intermittency threshold is increased[3]. As the intermittency threshold is increased, there is almost no effect on the coefficients for small conflicts. However, increasing the intermittency threshold for large conflicts causes

[3]One might be concerned that the existence of any intermittancy threshold may generate cyclical behavior in the ACR which could generate artificially large responses to the quasi-cyclical timing of ENSO events. To see why this type of bias is incapable of dramatically affecting our results, let

C_t = true ACR at time t

N_t = number of countries at time t

Assume conflict risk and the sample are stationary until the following year:

$$C_t = C_{t+1}, \quad N_t = N_{t+1}$$

We observe $C_t N_t$ conflicts in the data at time t. However, we only observe $C_{t+1}(N_{t+1} - C_t N_t)$ conflicts the following year because the $C_t N_t$ countries that had conflicts the preceding year were artificially excluded from observation (this is not true, as explained in the text, but suppose it were).

In year t we would accurately estimate conflict risk to be

$$\hat{C}_t = \frac{number\ of\ conflicts}{number\ of\ countries} = \frac{C_t N_t}{N_t} = C_t$$

however in the following year we would estimate

$$\hat{C}_{t+1} = \frac{number\ of\ observable\ conflicts}{number\ of\ countries} = \frac{C_{t+1}(N_{t+1} - C_t N_t)}{N_{t+1}} = C_t - C_t^2.$$

Therefore, the potential bias that would be introduced is of the magnitude C^2. Given that we estimate an average ACR of 4% in the teleconnected region, the introduced bias would be 0.16%. This bias is only $\frac{1}{25}$th of the signal's magnitude and is well below the estimated uncertainty of our preferred models (±0.84%).

the NINO coefficients to fall in magnitude. The coefficients are about half as large when $Onset4$ is used and one-fourth as large when $Onset9$ is used, compared to $Onset2$. These results suggest that all types of small conflicts are affected by the global ENSO state, while there may be two types of large conflicts: one of which occurs infrequently and is associated with ENSO and one of which is more frequent and exhibits cycles of "flaring up" and "cooling down" in association with the global ENSO state.

Non-African countries Most previous studies examining the relationship between weather and conflict have focused on Africa [Miguel et al., 2004, Hendrix and Glaser, 2007, Meier et al., 2007, Burke et al., 2009, Buhaug, 2010]. We find that while the effect of ENSO on conflict is strong in Africa, it appears similarly strong and statistically significant on other continents as well. Row 6 of Table 3.1 in the main text displays the baseline longitudinal regression model using non-African teleconnected countries only and the estimated coefficient is almost identical to the average value (row 5). Models 9-10 in Table 3.12 display results for African and non-African countries in the longitudinal model with commonly used control variables and the coefficients for NINO3 in both subsamples are similar to the average value (model 8). Contrast this with the coefficients for log(GDP/capita) which are opposite in sign and significant for the two subsamples. Finally, Table 3.13 displays the "kitchen sink" models for both subsamples and finds that the coefficients on both subsamples remain larger than the baseline model (Table 3.1 row 4 in the main text). In one of the specifications (row 3) the coefficient for non-African countries is not statistically significant, but this appears to be due to an inflation in standard errors. This is probably a result of over-fitting the model with too many irrelevant variables [Greene, 2003].

Conflict as a Poisson point process An alternative approach to modeling conflict onsets is to assume that conflict onsets can be represented by a non-homogenous Poisson point-processes. Two techniques can be applied in this setting: count analysis and survival analysis. We implement both and verify that our central findings remain unchanged.

In our count analysis, we model the number of conflicts observed in the teleconnected group as if these values were Poisson distributed, with a mean (variance) parameter that changed in response to NINO3. We estimate the model:

$$\mathrm{E}\left[\sum_i C_i(t)\right] = e^{(\alpha+\beta NINO3(t))} \tag{3.7}$$

via maximum likelihood (notation is the same as in Equation 3.5). Here, we assume that the structure of disturbances is such that $\sum_i C_i(t)$ can be represented by a Poisson distribution. Figure 3.12 shows $\sum_i C_i(t)$ in the teleconnected group against $NINO3(t)$ for the period 1975-2005 when the sample of countries is roughly constant. The regression line is an ordinary-least-squares fit to the data while the circles display predicted values using the Poisson regression described in Equation 3.7. Observe that movements in the predicted mean are the same, regardless of which statistical model is used.

In our survival analysis, we model how long peaceful periods "survive" before a "failure," i.e. a conflict, occurs. Assuming that conflict onsets can be represented by a non-homogeneous Poisson point-process, we allow the hazard rate h (instantaneous ACR) to change over time in response to ENSO. We estimate the model:

$$h(t) = e^{(\beta NINO3(t)+\mu_i+\theta_i t)} \tag{3.8}$$

again by maximum likelihood (notation is the same as in Equation 3.5). Table 3.6 presents our estimates for both the teleconnected and weakly affected groups. In row 1 we present our estimates of the hazard rate increase associated with a 1°C increase in NINO3. We find that the hazard rate response in the teleconnected group is significant and matches our main result: a 1°C increase in NINO3 increases the risk of transition from a peaceful state into conflict by 25%. If one uses the full temperature swing from La Nina to El Nino (roughly a 4°C increase), the total risk of conflict doubles. This magnitude matches our main results that we estimated with ordinary least squares (recall Fig 3.2 in the main text).

Finally, for a sense of scale, in row 2 of Table 3.6 we estimate how NINO3 influences the length of uninterrupted peaceful periods. This is an alternative but equivalent interpretation of Equation 3.8. We estimate that a 1°C increase in NINO3 reduces the length of an average peaceful period in the teleconnected group by 0.22 years. Thus, a shift from an La Niña to El Niño reduces the average peaceful period by 0.88 years. Summed over all eighty countries in the teleconnected group, this same shift in NINO3 reduces the global number of peaceful country-years by 70 ($0.22\ \frac{years}{1°C} \times 4°C \times 80\ countries = 70.4\ country\text{-}years$).

3.F Supplementary Tables and Figures

Table 3.2: Summary statistics of primary variables

variable	mean	SD	min	max	years
ENSO index [°C] *May-Dec average*					
NINO12	0.088	1.02	-1.49	3.53	1950-2008
NINO3	0.117	0.829	-1.38	2.75	1950-2008
NINO4	0.117	0.583	-1.36	1.11	1950-2008
Annual probability of conflict onset [%/yr]					
Whole world	3.08	2.51	0	11.2	1950-2004
Teleconnected region only	4.14	2.43	0	11.2	1950-2004
Weakly-affected region only	1.90	2.02	0	9.09	1950-2004
Agricultural output in teleconnected group					
Cereal yields [kg/ha] *country-level obs.*	1500	924	0	8900	1961-2007
Value-added per capita [2000 US$] *country-level obs*	168	105	12.4	771	1970-2007
Value-added per capita [2000 US$] *group*	142	12.8	128	181	1970-2007
Agricultural output in weakly-affected group					
Cereal yields [kg/ha] *country-level obs.*	2880	1720	0	9190	1961-2007
Value-added per capita [2000 US$] *country-level obs*	425	355	40.1	2500	1970-2007
Value-added per capita [2000 US$] *group*	254	45.2	202	352	1970-2007

Table 3.3: Validating the global partition with temperature, precipitation and agriculture responses to NINO3 (1950-2004)

	Independent Variable: NINO3 averaged May-Dec. (°C)			
	Dependant variable	**Model**	**Teleconnected**	**Weakly-Affected**
(1)	**Temperature**	country-level panel	0.048***	-0.017
	(°C)	country-specific trends	[0.009]	[0.011]
		country-specific constants	n = 4067	n = 3461
(2)	**Precipitation**	country-level panel	-0.12***	-0.00
	(mm/day)	country-specific trends	[0.02]	[0.01]
		country-specific constants	n = 2323	n = 1835
(3)	**Cereal yields**	country-level panel	-1.05***	0.71
	(%)	country-specific trends	[0.40]	[0.43]
		country-specific constants	n = 3934	n=2690
(4)	**Agricultural Income**	country-level panel	-0.57***	-0.33
	(%)	country-specific trends	[0.16]	[0.22]
		country-specific constants	n = 3187	n = 2399
(5)	**Agricultural Income**	group total	-1.06***	-0.22
	(%)	trends	[0.37]	[0.37]
			n = 37	n = 32

Standard error in brackets, *** $p<0.01$, ** $p<0.05$, * $p<0.1$. All trends have linear and quadratic terms. SE in rows 1-4 are clustered by country. SE in row 5 are robust to heteroscedasticity. In rows 3-5, coefficients are in units of %/1°C, 1.0 means yields (or income) decline 1% for each 1°C in NINO3. Models 3-5 include one lag dependent variable (see SI). Temperature and precipitation are spatially averaged. 1990-94 dropped in W.A. row 5 due to unreliability.

Table 3.4: Monthly correlation coefficients for NINO3 (1950-2008)

	early season			"spring barrier"		late season ("Year" 0)						
	J	F	M	A	M	J	J	A	S	O	N	D
	(high coherence)											
J	1											
F	0.96	1										
M	0.85	0.92	1									
	(transition)											
A	0.62	0.73	0.85	1								
M	0.39	0.50	0.66	0.86	1							
	(little/no correlation)			*(transition)*		*(high coherence)*						
J	0.15	0.25	0.41	0.64	0.88	1						
J	-0.00	0.09	0.25	0.47	0.71	0.90	1					
A	-0.08	0.01	0.20	0.44	0.68	0.85	0.96	1				
S	-0.05	0.03	0.20	0.44	0.68	0.80	0.88	0.94	1			
O	-0.10	-0.03	0.12	0.35	0.63	0.79	0.86	0.90	0.96	1		
N	-0.10	-0.03	0.10	0.31	0.59	0.77	0.825	0.86	0.92	0.98	1	
D	-0.11	-0.06	0.07	0.29	0.59	0.77	0.81	0.84	0.90	0.96	0.98	1

Table 3.5: The importance of accounting for ENSO dynamics for signal detection

Dependent Variable: Conflict Risk (%/yr)

	Independant variable	
(1)	**Jan-Dec. NINO3**	0.51
	all countries	[0.40]
		n = 54
(2)	**Jan.-Dec. NINO3**	0.76
	teleconnected only	[0.59]
		n = 54
(3)	**May-Dec. NINO3**	0.46*
	all countries	[0.24]
		n = 54
(4)	**May-Dec. NINO3**	0.85**
	teleconnected only	[0.40]
		n = 54

Heteroscedasticity robust S.E., ** $p<0.05$, * $p<0.1$.; 1989 dropped.
Models all contain a linear trend.

Table 3.6: Survival analysis for peaceful periods between civil conflicts (1950-2004)

	Independent Variable: NINO3 May-Dec	
	teleconnected	weakly affected
(1) Δ proportional hazard per 1°C	25%**	6%
	[11%]	[12%]
(2) Δ average survival time per 1°C	-0.22 yr**	-0.06 yr
	[0.09 yr]	[0.12 yr]
Observations	4929	4346

The peaceful periods between civil conflicts are modeled with survival analysis. The hazard function is assumed to have an exponential form (i.e. conflicts are a Poisson point-process) that varies in response to ENSO. Row (1) describes the proportional change in the hazard rate associated with a 1°C increase in NINO3. A value of "1%" implies that the probability a peaceful period ends is 1.01× the baseline hazard rate. Row (2) describes the same model, but interpreted in terms of survival time. A value of "-0.1 yr" implies that the average peaceful period (across all countries in a sample) decreases by 0.1 years for a 1°C increase in NINO3. All models include country-specific constants and country-specific trends. 1989 is dropped. Standard errors clustered by country in brackets: ** $p<0.05$, * $p<0.1$.

Table 3.7: Changes in *annual conflict risk* in response to ENSO (1950-2004)

Independent variable:	NINO12	NINO3	NINO4	NINO12	NINO3	NINO4
(a) Global time series *Dependent Variable: conflict onsets / countries*						
Jan-Dec NINO coeff.:	0.33	0.57	0.87*	-	-	-
	[0.24]	[0.39]	[0.49]	-	-	-
Observations:	54	54	54	-	-	-
R^2:	0.03	0.04	0.069	-	-	-
	teleconnected group			weakly-affected group		
(b) Regional time-series *Dep. Var.: conflict onsets in region / countries in region*						
May-Dec NINO Coeff	0.59*	0.762*	0.842	-0.022	0.160	0.623
	[0.304]	[0.390]	[0.535]	[0.215]	[0.307]	[0.495]
Observations:	54	54	54	54	54	54
R^2	0.073	0.080	0.048	0.000	0.004	0.032
(c) Same as (b) plus linear trend						
May-Dec NINO Coeff	0.625**	0.852**	1.07*	-0.071	0.059	0.430
	[0.310]	[0.396]	[0.555]	[0.202]	[0.300]	[0.470]
Observations:	54	54	54	54	54	54
R^2	0.095	0.112	0.086	0.053	0.053	0.066
(d) Same as (c) plus post-1989 dummy						
May-Dec NINO Coeff	0.634**	0.813**	0.879*	-0.065	0.036	0.319
	[0.252]	[0.318]	[0.482]	[0.208]	[0.305]	[0.446]
Observations:	54	54	54	54	54	54
R^2	0.273	0.277	0.237	0.124	0.123	0.130
(e) Same as (d) plus 1989 obs						
May-Dec NINO Coeff	0.589**	0.737**	0.679	-0.054	0.054	0.360
	[0.249]	[0.320]	[0.507]	[0.208]	[0.305]	[0.450]
Observations:	55	55	55	55	55	55
R^2	0.279	0.279	0.242	0.114	0.114	0.123
(f) Ignoring the "spring barrier" obscures signal						
Jan-Dec NINO coeff.:	0.542	0.762	0.901	-	-	-
	[0.374]	[0.586]	[0.622]	-	-	-
(g) Country-level longitudinal-data linear probability model *Dep. Var.: conflict onset in a country (binary)*						
May-Dec NINO coeff.:	0.674%	0.893	1.0	-0.108	0.038	0.414
	[0.38]*	[0.415]**	[0.522]*	[0.154]	[0.266]	[0.471]
Observations:	3978	3978	3978	3400	3400	3400

Heteroscedasticity-robust standard errors in brackets, *** p<0.01, ** p<0.05, * p<0.1. Coefficients are probability responses in units of %/1°C, 1.0 means the probability of conflict in a given year rises 0.01 for each 1°C increase in NINO averaged May-Dec. All panels except (e) drop 1989. Panel (f) includes a linear trend. Panel (g) includes county-specific constants (fixed-effects) and linear trends with estimated standard errors clustered by country.

Table 3.8: Results are not driven by patterns of serial correlation in ACR

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Teleconnected Dependent Variables					**Weakly-Affected** Dependent Variables				
	ACR_t	$Residuals_t$	ACR_t	ACR_t-ACR_{t-1}	ACR_t	ACR_t	$Residuals_t$	ACR_t	ACR_t-ACR_{t-1}	ACR_t
$NINO3_t$	0.813**		0.719**		0.737**	0.036		0.009		0.054
	[0.318]		[0.357]		$[0.319]^a$	[0.305]		[0.321]		$[0.321]^a$
					$[0.302]^b$					$[0.336]^b$
					$[0.285]^c$					$[0.339]^c$
$Residuals_{t-1}$		0.142					0.328**			
		[0.161]					[0.136]			
ACR_{t-1}			0.151					0.326**		
			[0.152]					[0.141]		
$NINO3_t$-$NINO3_{t-1}$				0.609*					-0.092	
				[0.307]					[0.249]	
year	-0.098***		-0.091***	-0.005	-0.107***	-0.014		-0.011	-0.006	-0.012
	[0.024]		[0.028]	[0.032]		[0.023]		[0.025]	[0.030]	
post 1989 const.	3.311***		2.893***	-0.400	3.954***	1.950*		1.412	0.355	1.799
	[0.885]		[1.040]	[1.295]		[1.063]		[0.993]	[1.225]	
Constant	197.125***	-0.025	181.989***	10.415	213.510***	29.840	-0.009	21.911	11.056	25.979
	[46.336]	[0.264]	[55.251]	[62.153]		[45.740]	[0.259]	[48.460]	[59.935]	
Durbin-Watson d-statistic:	1.656					1.339				
Observations	54	52	53	53	55	54	52	53	53	55
R-squared	0.277	0.021	0.308	0.097	-	0.123	0.107	0.216	0.005	-

Models 2 and 7 regress residuals from Models 1 and 6 (respectively) on their lagged values. Models 5 and 10 present three estimates for the SE of the main coefficient of interest: each is a Newey-West [Newey and West, 1987] estimate with lag lengths of a: 3 yrs, b: 5 yrs and c: 10 yrs. Greene [Greene, 2003] (2003) recommends a lag of at least $T^{0.25}$ (where T is the length of the time series) which is 2.7 in this case. All other SEs are White estimators [White, 1980].

Table 3.9: Results are not driven by sample selection: Teleconnected response to ENSO

	(1)	(2)	(3)	(4)	(5)	(6)
	BASELINE					FULL SAMPLE
Sample:	$t \geq 1950$	$t \geq 1950$	include 1946-49	$t \neq 1948$	$t \geq 1975^{a}$	include 1946-49
	$t \neq 1989$	include 1989	$t \neq 1989$	$t \neq 1989$	include 1989	include 1989
NINO3 May-Dec.	0.81**	0.74**	0.75**	0.77**	0.83**	0.68**
	[0.32]	[0.32]	[0.32]	[0.32]	[0.35]	[0.32]
Year	-0.10***	-0.11***	-0.12***	-0.10***	-0.36***	-0.13***
	[0.02]	[0.02]	[0.03]	[0.02]	[0.07]	[0.03]
Post Cold War Const.	3.31***	3.95***	3.90***	3.42***	7.51***	4.47***
	[0.88]	[1.03]	[0.97]	[0.87]	[1.41]	[1.07]
Constant	197.12***	213.51***	249.80***	206.30***	723.02***	261.14***
	[46.34]	[48.85]	[60.00]	[43.77]	[136.99]	[60.32]
Observations	54	55	58	57	30	59
R-squared	0.28	0.28	0.30	0.29	0.62	0.30

Heteroscedasticity robust standard errors in brackets *** p<0.01, ** p<0.05, * p<0.1. [a]After 1974, the set of countries in the teleconnected group stabilized, reaching 87 countries (the maximum of 91 was achieved 2002-4).

Table 3.10: Fixed effects or country-specific trends do not drive the result

Dependent Variable: Conflict Risk (% / yr)
Independent Variable: May-Dec NINO3 (°C)

	Panel model	Teleconnected (%/yr°C)	Weakly-Affected (%/yr°C)
(1)	**No controls**	0.85*	0.20
		[0.44]	[0.33]
(2)	**Country fixed effects**	0.89**	0.13
		[0.40]	[0.33]
(3)	**Country-trends**	0.90**	0.09
		[0.39]	[0.32]
(4)	**Country fixed effects**	0.89**	0.04
	Country-trends	[0.39]	[0.32]
	Observations	3978	3400

Conley [Conley, 1999] SE in brackets, *** p<0.01, ** p<0.05, * p<0.1.
1989 dropped.

Table 3.11: ENSO influences ACR holding local temperature and rainfall constant

Dependent Variable: Conflict Risk (% / yr)
Independent Variable: May-Dec NINO3 (°C)

	Panel model	Teleconnected (%/yr°C)	Weakly-Affected (%/yr°C)
(1)	**No weather**	0.89**	0.04
		[0.39]	[0.32]
		n=3978	n=3400
(2)	**Include temperature**	1.02***	0.13
	(monthly, 12 vars)	[0.39]	[0.30]
		n=3978	n=3400
(3)	**Include temp & rain**	1.66***	0.36
	(monthly, 24 vars)	[0.48]	[0.33]
		n=2234	n=1774

Conley [Conley, 1999] SE in brackets, *** p<0.01, ** p<0.05, * p<0.1. 1989 dropped. All models include country specific constants (fixed effects) and country-specific trends.

Table 3.12: Controlling for common time-varying controls

Dependent Variable: Conflict risk (% / yr)

	Teleconnected Group										***W. A.***
	All Countries								***Africa***	***Not Africa***	***All***
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
NINO3$_t$	0.893**		1.212***		1.046**		0.976**	1.229***	1.399*	1.004*	0.020
May-Dec.	[0.389]		[0.453]		[0.409]		[0.407]	[0.477]	[0.807]	[0.563]	[0.313]
log GDP$_{t-1}$ **/ capita**$_{t-1}$		3.348	3.224					3.988	10.765***	-11.025***	11.563***
(lagged)		[2.170]	[2.158]					[2.635]	[3.280]	[3.335]	[3.965]
Polity IV score$_{t-1}$				0.203**	0.200**			0.291**	0.418**	0.301	0.451***
(lagged)				[0.098]	[0.097]			[0.146]	[0.205]	[0.242]	[0.133]
Polity IV score$^2_{t-1}$				-0.033	-0.033			-0.039	0.016	-0.103**	0.031
(lagged)				[0.023]	[0.023]			[0.027]	[0.038]	[0.043]	[0.035]
Log population$_{t-1}$						10.822	10.466	4.118	-1.956	17.706*	21.308***
(lagged)						[10.393]	[10.348]	[13.413]	[20.822]	[9.839]	[6.533]
Observations	3,978	2,793	2,793	3,450	3,450	3,555	3,555	2,546	1,398	1,148	1,897

Conley [Conley, 1999] SE in brackets, *** p<0.01, ** p<0.05, * p<0.1. 1989 dropped. All models include country-specific constants (fixed-effects) and country-specific trends. Models 1-10 are for the teleconnected group only. Model 11 is for the weakly affected group only.

Table 3.13: The "kitchen sink" model

Dependent Variable: Conflict Risk (% / yr)
Independent Variable: May-Dec NINO3 (°C)

	Sample	**Teleconnected** (%/yr°C)	**Weakly-Affected** (%/yr°C)
	No Weather Controls		
(1)	**All Countries**	1.35***	0.03
		[0.47]	[0.31]
		n = 2464	n=1827
(2)	**Africa Only**	1.63**	0.27
		[0.76]	[0.53]
		n=1349	n=96
(3)	**Not Africa**	0.96	0.02
		[0.62]	[0.33]
		n=1115	n=1731
	With Weather Controls		
(4)	**All Countries**	1.83***	0.46
		[0.53]	[0.33]
		n=1973	n=1467
(5)	**Africa Only**	1.95*	0.54
		[1.01]	[1.79]
		n=1083	n=75
(6)	**Not Africa**	1.49**	0.50
		[0.66]	[0.34]
		n=890	n=1392

Conley [Conley, 1999] SE in brackets, *** p<0.01, ** p<0.05, * p<0.1. 1989 dropped in all models. Controls include country fixed-effects, country-specific linear trends, lagged log income per capita, lagged per capita income growth, lagged Polity IV score (with quadratic term), lagged agriculture industry share (%), lagged percent urbanized, lagged population, lagged percent female, lagged percent below 15 years old, lagged percent above 65 years old. Models 4-6 include 12 monthly temperature variables, 12 monthly precipitation variables and annual average maximum tropical cyclone windspeed.

Table 3.14: Robustness analysis under different definitions of conflict risk (1950-2004)

Dependent Variable: Binary conflict indicator for teleconnected group countries

	Onset2	Onset3	Onset4	Onset5	Onset6	Onset7	Onset8	Onset9
"Small" Conflicts	0.454	0.372	0.342	0.379	0.411	0.411	0.449	0.449
"Large" Conflicts	0.453	0.291	0.210	0.121	0.093	0.064	0.102	0.102

"Small" conflicts had between 25 and 1000 battle related deaths. "Large" conflicts had more than 1000 battle related deaths. Each coefficient is a separate regression. Coefficients are percent probability responses in units of %/1°C, 1 means the probability of conflict in a given year rises 0.01 for each 1°C increase in NINO3 sea surface temperature. Onset$N$ indicates that a conflict must be dormant for N years before renewed violence marks the "onset" of a new conflict. NINO3 SSTs are measured using May-December means. Models contain country constants (fixed effect) and country-specific time trends. 1989 dropped in all models.

Table 3.15: Conflict risk response to past and future ENSO

Dependent Variable: *annual conflict risk* (1950-2004)

	teleconnected group					weakly-affected group				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$NINO3_{t+1}$					0.472					0.101
					[0.342]					[0.223]
$NINO3_t$	0.813**	0.711**	0.707**	0.815**		0.036	0.085	0.077	0.190	
	[0.318]	[0.328]	[0.340]	[0.332]		[0.305]	[0.306]	[0.294]	[0.350]	
$NINO3_{t-1}$		-0.319	-0.305	-0.324			0.197	0.232	0.228	
		[0.317]	[0.313]	[0.309]			[0.317]	[0.336]	[0.315]	
$NINO3_t$			0.141					0.362		
$\times NINO3_{t-1}$			[0.365]					[0.513]		
$NINO3_{t-2}$				0.086					0.182	
				[0.306]					[0.289]	
Observations	54	53	53	52	53	54	53	53	52	53
R-squared	0.277	0.300	0.301	0.336	0.221	0.123	0.128	0.140	0.133	0.113
F-test p-value		0.457		0.384			0.549		0.362	

Only NINO3 shown; other NINO indices yield similar results. Heteroscedastic robust errors in brackets. ** $p<0.05$, * $p<0.1$. Coefficients are percent probability responses in units of $\%1/°C$, 1 means the probability of conflict in a given year rises 0.01 for each 1°C increase in NINO3 sea surface temperature averaged May-Dec. Models contain a linear trend and a post Cold War dummy. 1989 obs. dropped. F-stat tests the null hypothesis that all ENSO associated conflicts are displaced in time and the null is not rejected.

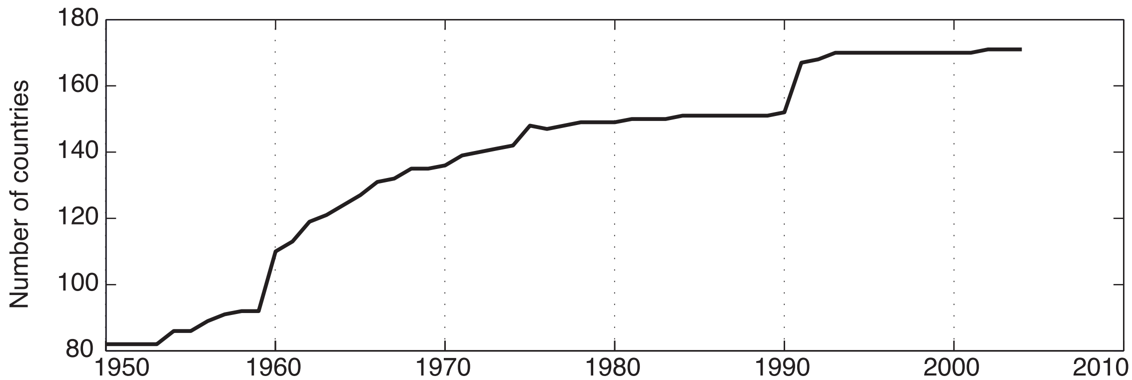


Figure 3.4: The number of countries in the dataset is growing over time, more than doubling over the period of observation. Because *conflict onset* is coded as a binary variable for each country-year observation, it is necessary to normalize the total number of observed *conflict onsets* by the number of distinct countries being observed. To check that this trend is not driving any of our results, we re-estimate the model while restricting the sample to the period following 1975 (inclusive) when the sample of teleconnected countries was stable; we also estimate a model with the raw panel data using country-specific constants in the regression (country fixed-effects).

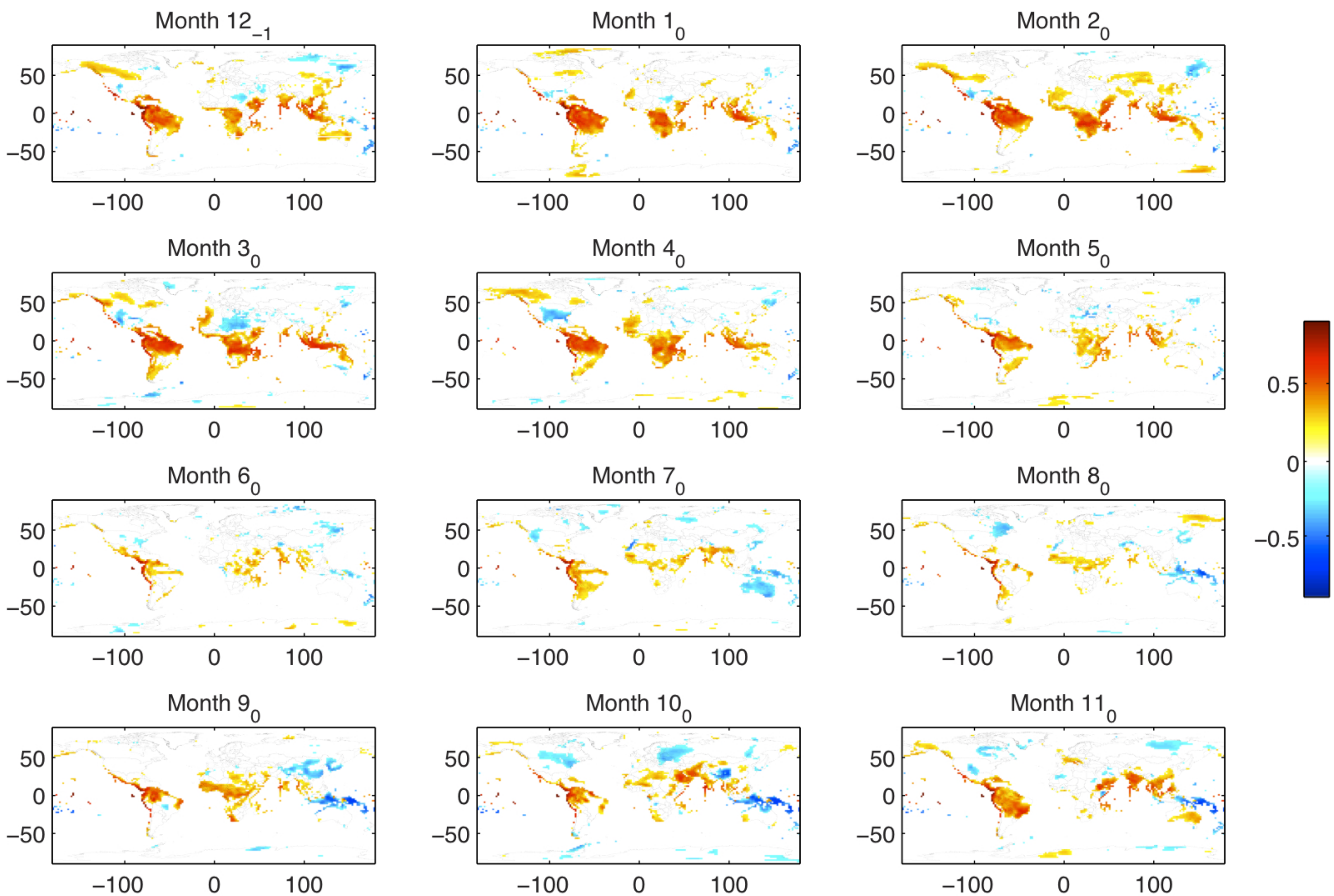


Figure 3.5: The pixel-level correlation between surface temperatures and NINO3 two months earlier. Only statistically significant ($\alpha = 0.1$) correlations over land are colored.

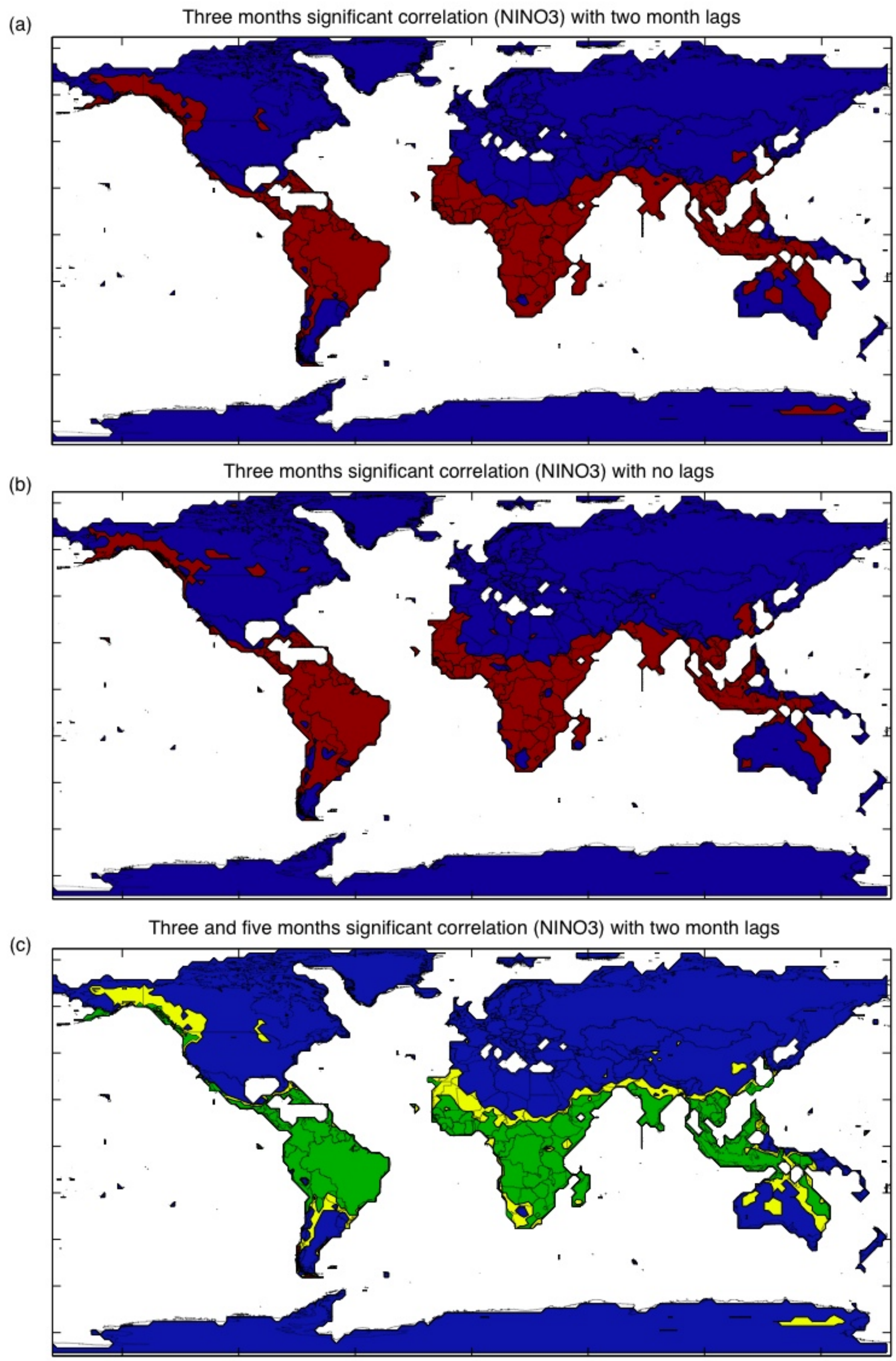


Figure 3.6: (A) Global ENSO teleconnection partition used in main analysis. Red: pixels coded as teleconnected when surface temperatures are positively correlated with NINO3 two months earlier ($L = 2$) for at least three months ($R = 3$). Blue: weakly-affected pixels failing this criteria. (B) Same, but $L = 0$. (C) Green: teleconnected pixels when $R = 5$ and $R = 3$ (and $L = 2$). Yellow: teleconnected pixels when $R = 3$ but not when $R = 5$. Blue: weakly-affected pixels when $R = 3$ and $R = 5$.

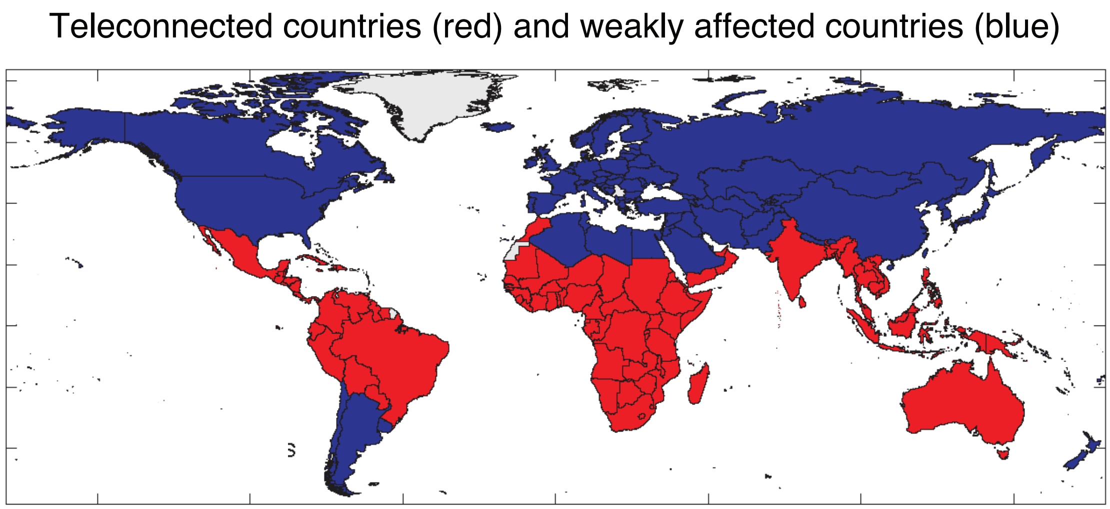


Figure 3.7: Countries assigned to be teleconnected when pixels are weighted by population ($w_x = population_{x,t=2000}$) are red, weakly-affected countries are dark blue. Grey countries have no conflict data.

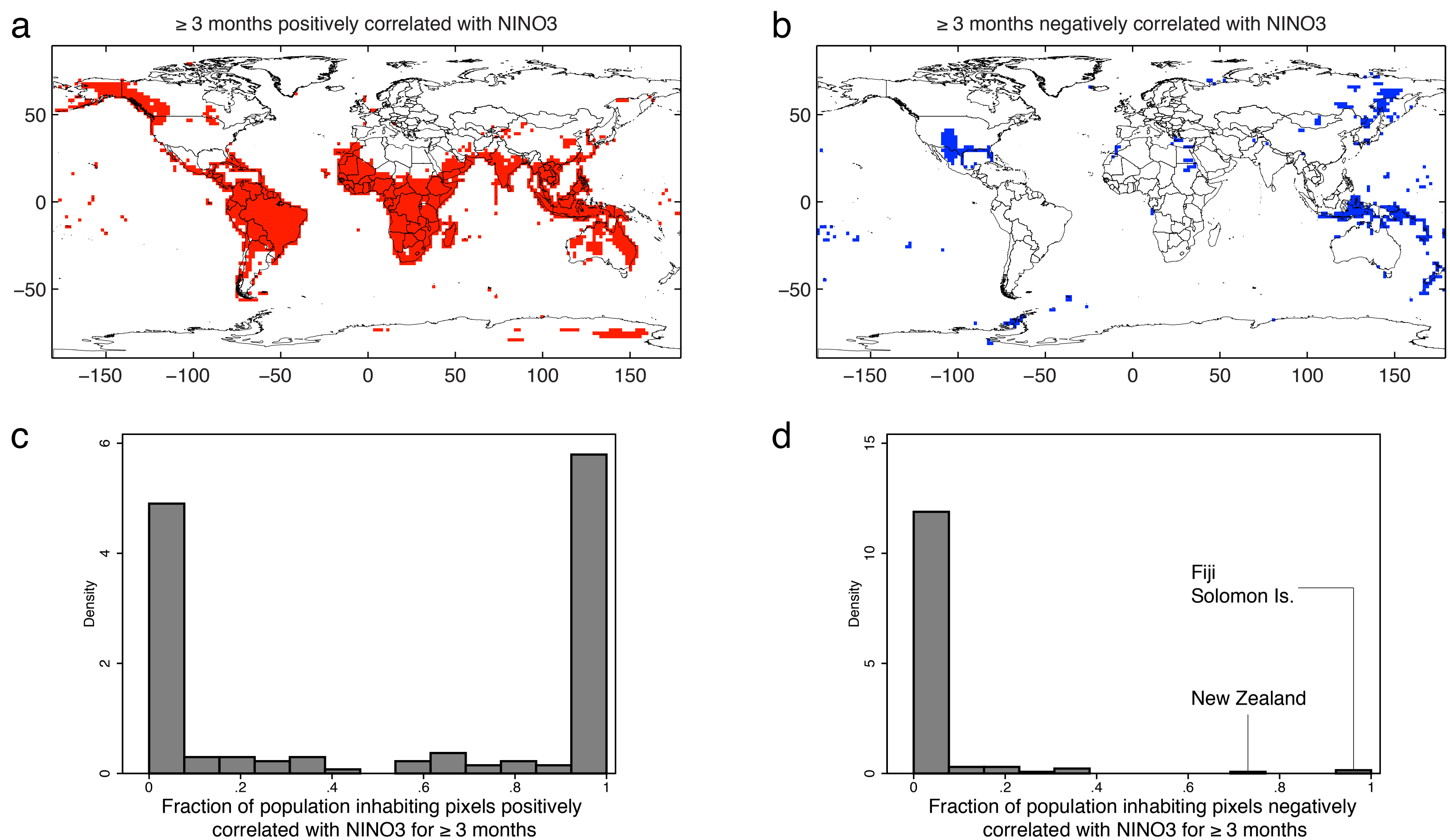


Figure 3.8: Few continental locations have temperates negatively correlated with NINO3, i.e. few locations experience cooling when the NINO3 region warms. (a) Pixels with surface temperature significantly ($\alpha = 0.1$) and positively correlated with NINO3 for at least 3 months are red ($L = 2$). (b) Pixels with surface temperature significantly and negatively correlated with NINO3 for at least 3 months are blue ($L = 2$). As established in previous literature, cooling in the western United States, Mexico, Indonesia and Russia is apparent, but not enough individuals live in "negatively teleconnected" pixels to justify coding these countries differently. (c) The distribution of countries in 2000 by their population fractions that inhabit positively teleconnected pixels from Panel (a); in the main analysis, countries were coded as teleconnected if > 0.5 of the population lived in teleconnected pixels. (d) Same, but for the negatively teleconnected pixels from Panel (b). Only in Fiji, the Solomon Islands and New Zealand do a majority of individuals live in negatively teleconnected pixels, although none of these countries have experienced civil conflict during the period of observation.

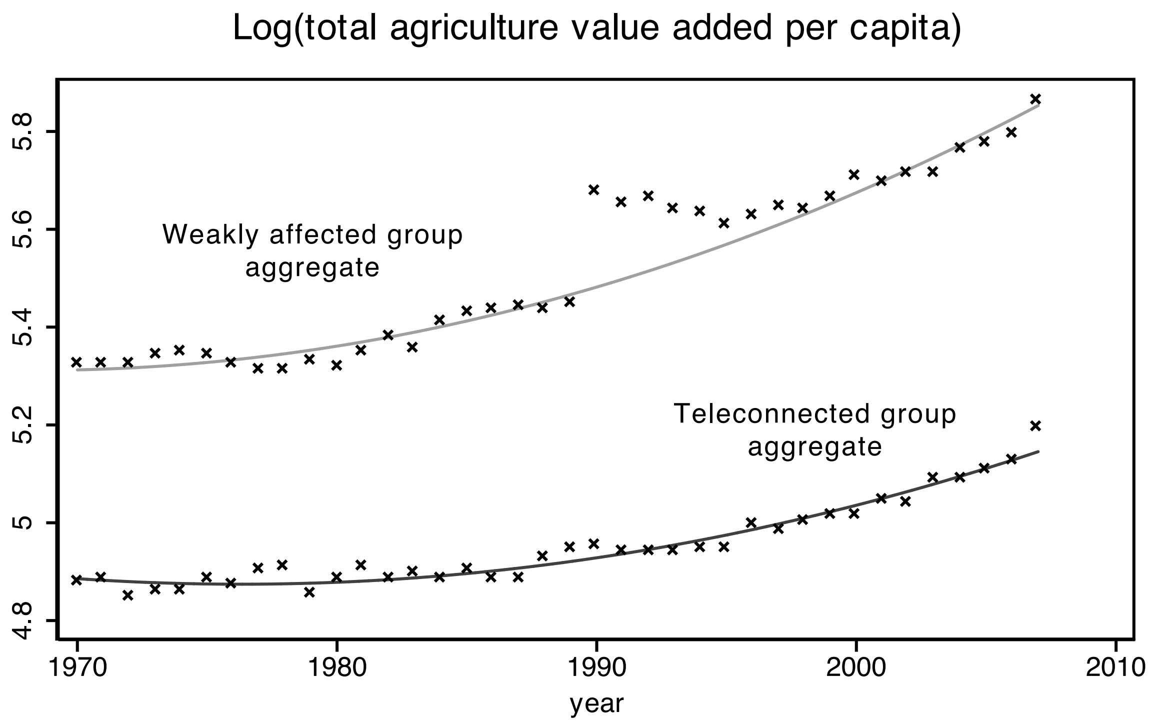


Figure 3.9: Total agricultural revenue for the weakly affected group (top) and teleconnected group (bottom), both with a quadratic fit. During 1990-1994 values for the weakly affected group are unreliable and are omitted from the analysis.

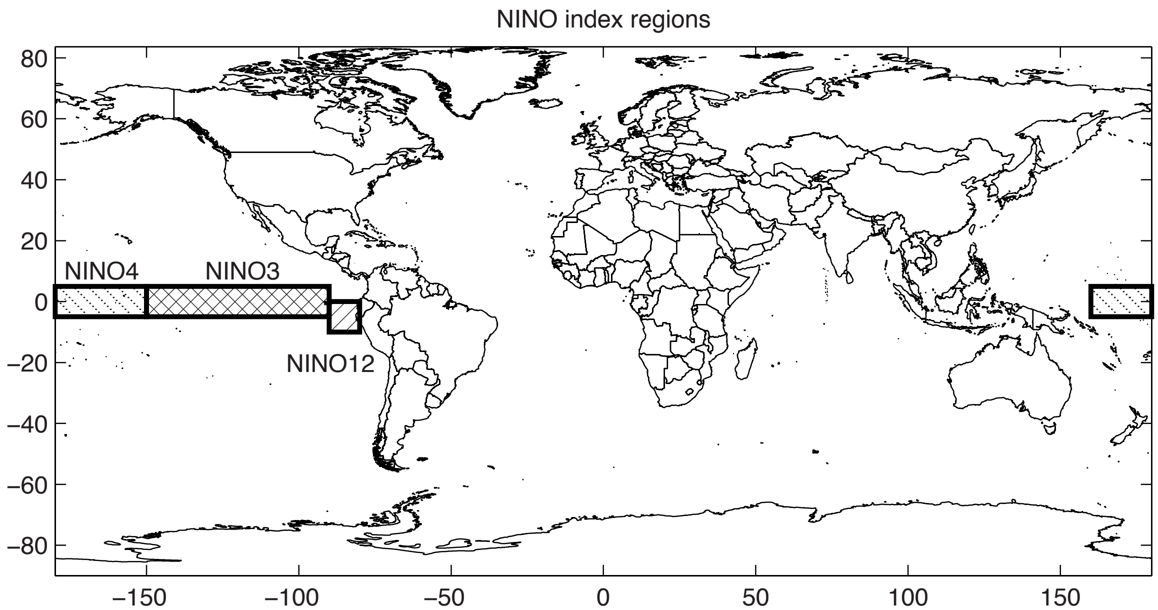


Figure 3.10: The NINO12, NINO3 and NINO4 regions in the equatorial Pacific Ocean. NINO index values are defined as the average sea surface temperature over a NINO region minus the long-term mean sea surface temperature in that region.

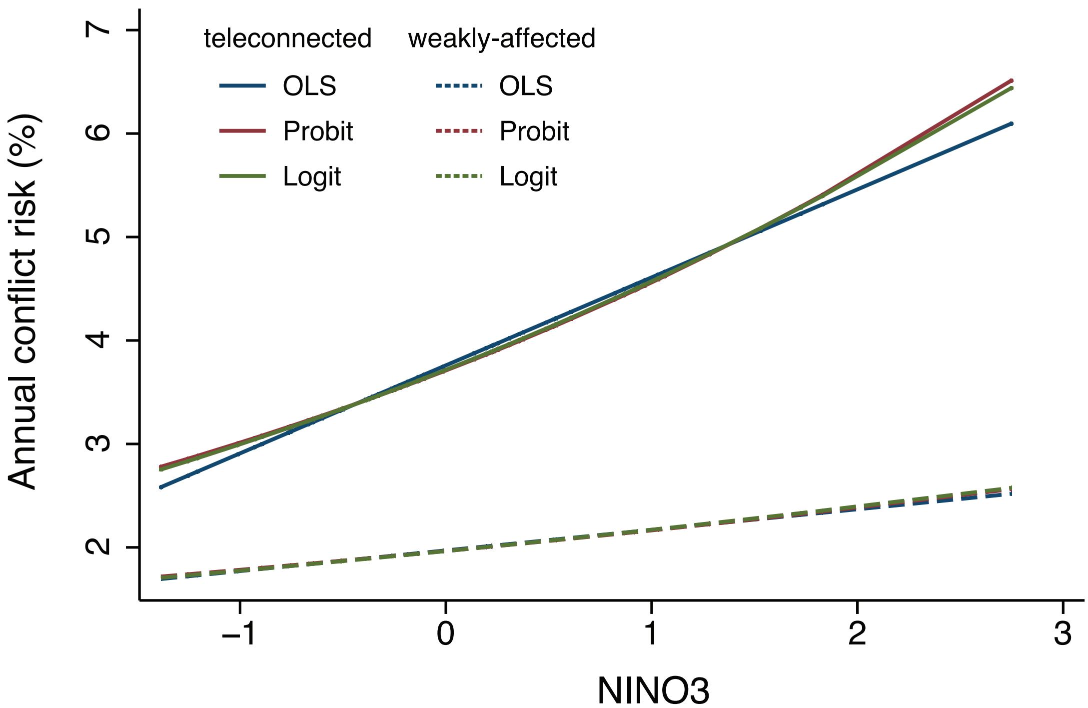


Figure 3.11: The linear probability model used for our country-level analysis (see main text Table 3.1 row 5) is virtually indistinguishable from non-linear probability models. For both regions, logit and probit models produce almost identical results to the linear probability model used in the main analysis. We prefer (and present) the linear probability model because it is simpler.

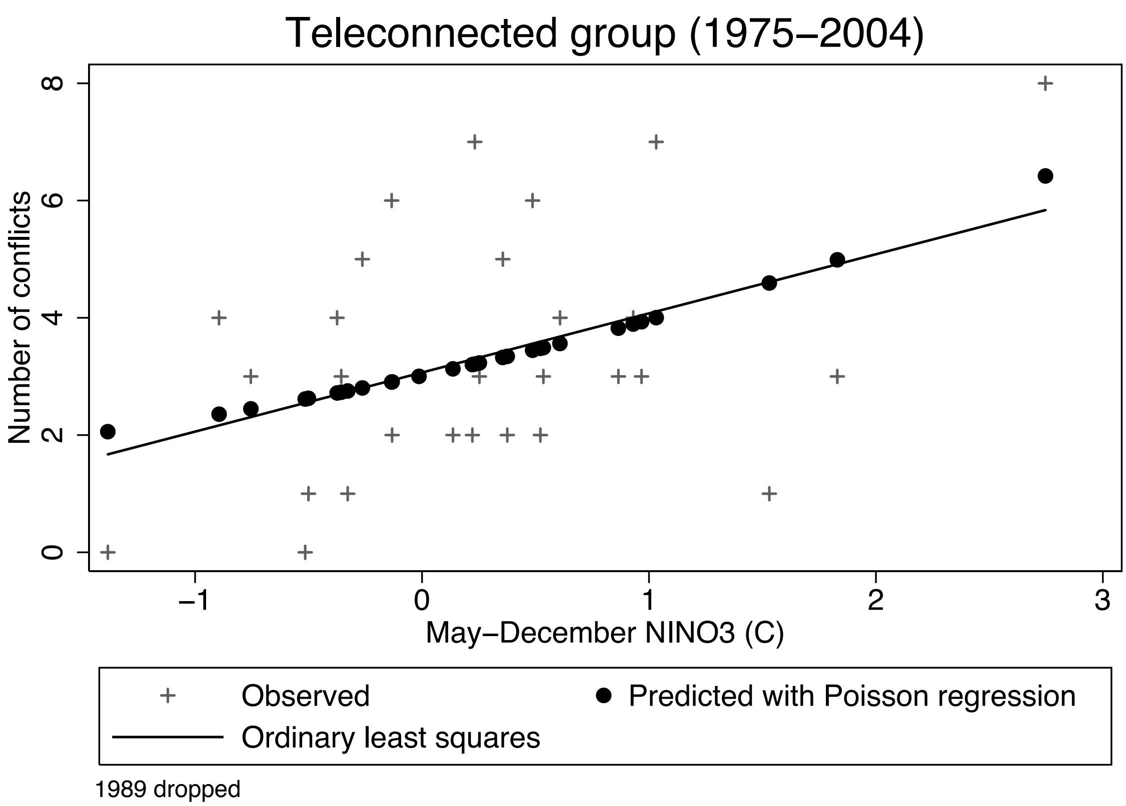


Figure 3.12: The linear probability model used for our country-level analysis (see main text Table 3.1 row 4) could instead be modeled with standard statistical techniques for "count data" such as a Poisson regression. Unfortunately, such an approach is difficult to interpret when the sample size of countries is changing over time (See Fig. 3.4). Nonetheless, we can use a Poisson regression to model the number of conflicts for the period 1975-2004, when the sample of countries is almost constant. However, we find there is no obvious gain in prediction over ordinary least squares.

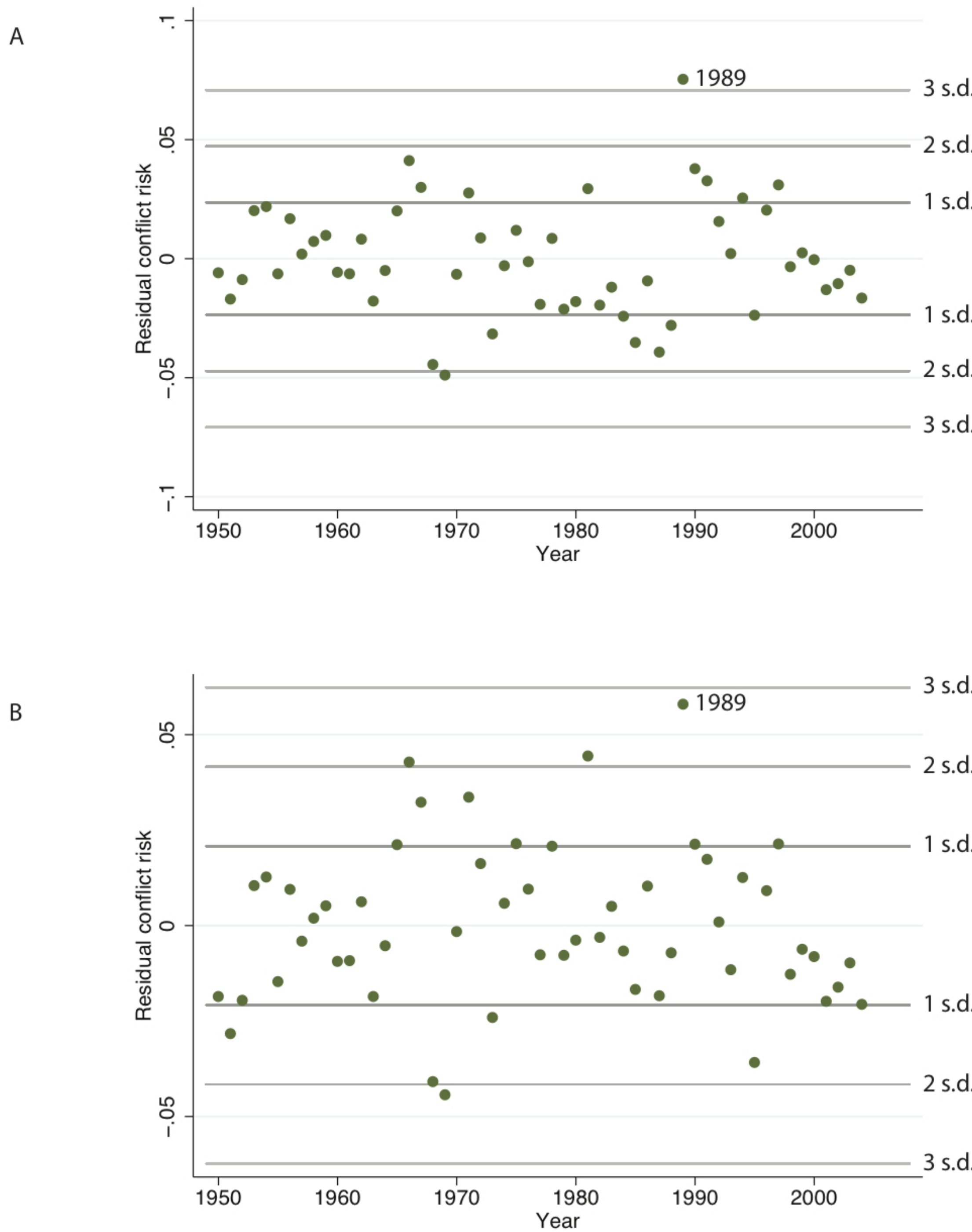


Figure 3.13: (A) Residuals (ϵ_{it}) estimated with a linear trend (see main text Table 3.1 row 2 and Equation 3.4). 1989 is a 3 standard deviation outlier and therefore has been dropped from all models, for both the teleconnected and weakly-affected groups. (B) When a post-1989 (inclusive) constant term is added to the regression (see Table 3.1 panel d and Equation 3.4), 1989 is less of an outlier. However, for consistency in models, it is still dropped from the estimation. We re-introduce the 1989 observation in Table 3.1 Panel e using this specification and find our results are largely unchanged.

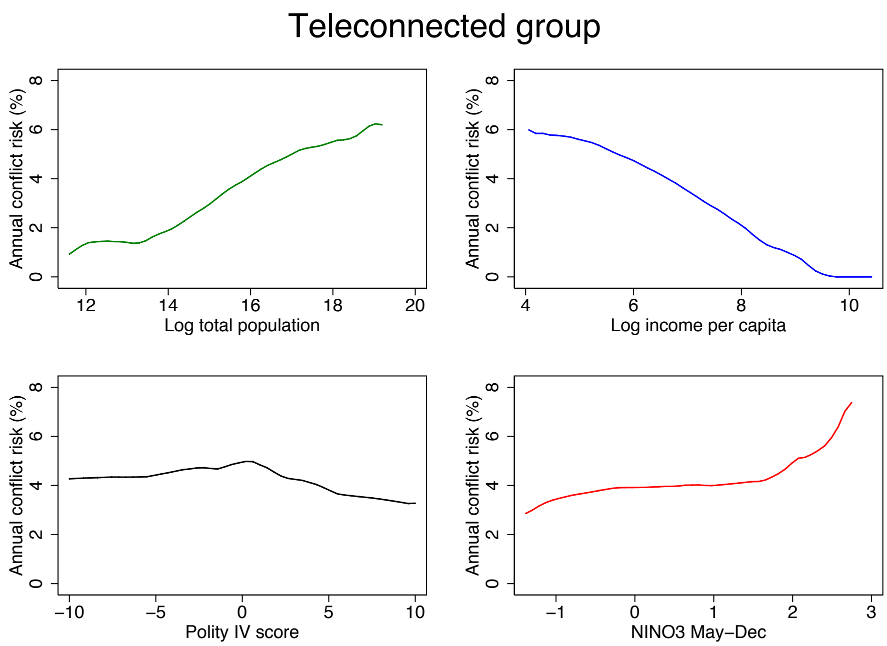


Figure 3.14: Bivariate non-linear fits of ACR against three standard correlates and NINO3. While population and income are correlated with conflict risk across countries, when country means (fixed-effects) are included, the correlation is not significantly different than zero (Table 3.12). Only Polity IV (a measure of democratic institutions) remains statistically significant, however it explains very little variation in conflict risk over time when compared to NINO3.

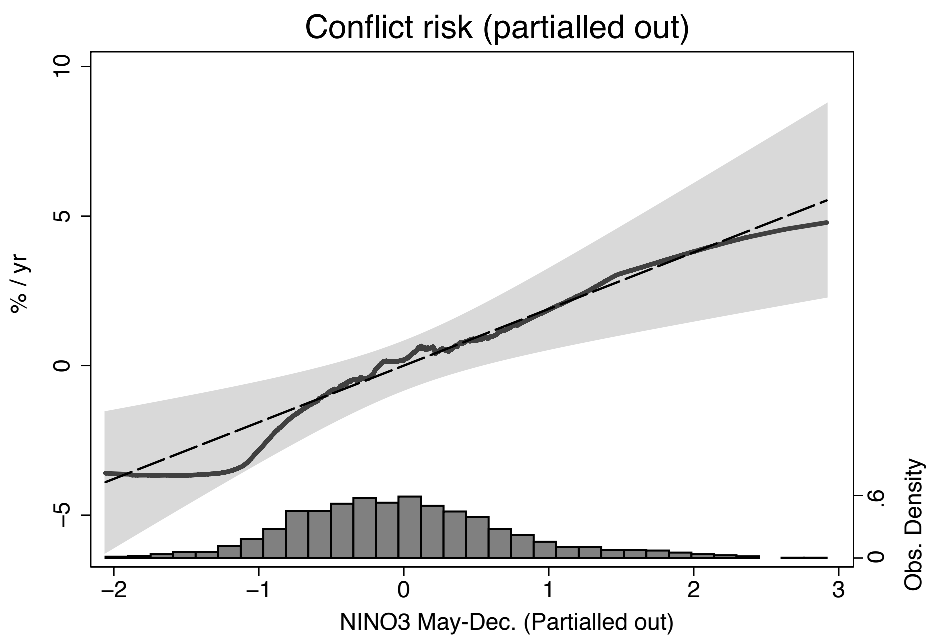


Figure 3.15: Linearity of ACR regression on NINO3 when both are partialled-out on 35 time-varying controls, country fixed-effects and country-specific time trends. Dashed line is the OLS fit (with 95% confidence interval), and solid line is a non-linear fit. The density of observations following this transformation is the histogram at the bottom.

Chapter 4

Global Losses and Declining Vulnerability to Tropical Cyclones

Solomon M. Hsiang & Daiju Narita[1]

[1]This chapter was funded in part by a research grant from the Center for International Business Education and Research at Columbia University Business School.

Abstract

An extreme environmental event may generate different losses for different societies. If the physical exposure to an event is held fixed, then the magnitude of a society's loss defines its vulnerability to that event. Competing hypotheses suggest that social and economic developments could make vulnerability rise or fall over time, but previous studies have been unable to reject either hypothesis because they lacked accurate data on societies' physical exposure to extreme events. We address this problem for a specific type of event by reconstructing the exposure of 233 countries to every tropical cyclone (TC) on the planet between 1950 and 2008. By filling a critical data gap, this reconstruction enables us to compare how revenue losses, damages, and deaths from physically similar events change over time. On a global scale, we find that populations rapidly mitigate certain TC risks, reducing their reported damages from a TC of fixed intensity by a remarkable 10% yr^{-1} and death rates by 5% yr^{-1}. However, these rapid reductions in vulnerability are not evident for the highest intensity TCs and lost agricultural revenues, which are more difficult to observe than deaths or damages, exhibit non-declining vulnerability for events of all intensities. Because the vulnerability of agriculture has remained high while vulnerability to damages has declined rapidly, our results indicate that lost agricultural revenues have dominated TC losses ever since $\sim$1990.

4.1 Introduction

A general trend common throughout human history is a declining dependance of societies on their environment [Diamond, 1997, McNeil, 2000, Richards, 2005], however the universality of this trend is contested. In particular, it has been argued that the vulnerability of societies to extreme environmental events is not declining and may even be increasing [ISDR, 2009, Bank and the United Nations, 2010] because societies plan for extreme events in emotional, political and financially inefficient ways [Taleb, 2007, Smil, 2008, Weitzman, 2009, Kunreuther et al., 2009]. To date, this idea has remained largely anecdotal and theoretical because it has been difficult to test with data – primarily because objective data on societies' exposure to extreme events is difficult to obtain. By developing a new global dataset, we are able to examine this question for a specific type of extreme event: tropical cyclones (TCs), the family of phenomena that includes hurricanes, typhoons, tropical storms and cyclones. We document that on a global scale, over the last half century, vulnerability to TCs has not only declined but it has fallen rapidly.

The "vulnerability" of a population is a measure of how effectively environmental hazards are translated into social losses [Mutter, 2005], where the magnitude of a hazard (eg. TC) is measured by strictly physical processes. In some cases, vulnerability may decline as an unintentional but beneficial side effect of technological and social changes or economic investments that would still occur in the absence of TCs. For example, sturdier houses may be built because they are more comfortable and they happen to be more robust to high winds. In other cases, individuals intentionally invest in infrastructure or alter their behavior in ways that protect them from a hazard [ISDR, 2009, Bank and the United Nations, 2010, Pielke Jr. and Sr., 1997, Smith et al., 2006, IPCC, 2007, Deschenes and Greenstone, 2007, Patt et al., 2010]. This active response of agents, referred to as "adaptation," is known to occur in response to numerous environmental hazards and has been observed in different contexts around the world [ISDR, 2009, Bank and the United Nations, 2010, IPCC, 2007]. In general, both unintentional and intentional actions that influence vulnerability are implemented at the level of individuals, households, communities, firms or governments and involve a large number of small investments or behavioral changes. This makes it difficult to observe and understand how these large number of actions interact and aggregate, gradually altering the ways in which a large society interacts with its environment.

A fundamental question in the study of coupled human-natural systems is how quickly and effectively societies can limit their vulnerability to environmental fluctuations [Patt et al., 2010, Dell et al., 2009b]. For different environmental stressors it is possible that the vulnerability of societies falls slowly, quickly or not at all. Understanding the rates of these changes is important, for example, in the evaluation of future climate changes [IPCC, 2007, Patt et al., 2010, Schlenker et al., 2005, Narita et al., 2009] where it is expected that populations will adjust to environmental changes but it is unknown if these adjustments will take days or centuries. Furthermore, vulnerability may vary by society or by environmental stressor. For example, poor populations may be less able to adapt to certain stressors or there may be certain types of extreme hazards that no society can adapt to with existing technologies.

4.2 Approach

In this study, we use a physical model [Hsiang, 2010] to reconstruct every tropical cyclone (TC) between 1950-2008. We then systematically evaluate how the effects of TCs on societies have changed over time. If the social impact of TCs diminishes with time, we interpret this as evidence that a population has become less vulnerable to their current TC-climatology.

By objectively measuring TC events as populations on the ground would have experienced them, we are able to compare social responses to physically similar events that occur at different points in time. This allows us to disentangle changes in vulnerability from changes in TC exposure and changes in TC reporting. Our approach contrasts with a large literature, summarized in recent assessments by the United Nations and the World Bank [ISDR, 2009, Bank and the United Nations, 2010], that relies on rapidly evolving systems of disaster reporting [OFDA/CRED, 2009]. We demonstrate that institutional changes in how events are reported seriously confound any effort to measure rates of change in vulnerability without reconstructing objective measures of events' physical properties.

Previous global-scale studies have relied almost exclusively on the Emergency Events Database (EM-DAT) [OFDA/CRED, 2009] to measure the physical properties of TCs [ISDR, 2009, Bank and the United Nations, 2010, Narita et al., 2009, Kahn, 2005, Toya and Skidmore, 2007, Kellenberg and Mobarak, 2008, Loayza et al., 2009, Cavallo and Noy, 2009, Noy, 2009, Mendelsohn et al., 2010]. However, TCs are not recorded in EM-DAT unless the TC's social impact is sufficiently large or unless a social institution (eg. a national government, international organization or reinsurance company) reports the event [OFDA/CRED, 2009]. This means that parameters reported in EM-DAT are unreliable measures of physical processes because they are strongly influenced by changes in social systems that may also affect the vulnerability of societies. Yet, summarizing patterns reported in EM-DAT without accounting for the physical incidence of TCs at all [ISDR, 2009, Bank and the United Nations, 2010] cannot accurately describe trends in vulnerability because the physical properties of TC may themselves be changing over time [Knutson et al., 2010a, Knutson et al., 2010b]. Thus, in order to estimate trends in vulnerability with EM-DAT, the data must be combined with physical measures of TC incidence from unbiased (and therefor non-EM-DAT) sources.

We generate objective measures of TC incidence by reconstructing every TC in the International Best Track Archive for Climate Stewardship (IBTrACS) database [Knapp, 2009] as a translating vortex [Mallen et al., 2005, Kossin et al., 2007] using the Limited Information Cyclone Reconstruction and Integration for Climate and Economics (LICRICE) model [Hsiang, 2010] (see Methods). LICRICE reconstructs the wind field for all 6712 storms (interpolating among 191822 6-hr observations) over every $0.1° \times 0.1°$ cell between 48°N-48°S latitude (See Fig. 4.5 and 4.6). We measure storm exposure using both (1) the energy dissipated by a storm at a location over its lifetime [Hsiang, 2010] and (2) the maximum wind speed achieved at a given location during a storm's lifetime. Fig. 4.1A shows the maximum wind speed achieved at each location in an average year (see Fig. 4.7 for more summary statistics) and Fig. 4.1B shows the estimated distribution of the highest wind speeds experienced by the global population [CIESIN, 2009]. One-third of the world population would have experienced TC winds of at least tropical-storm intensity over 1950-2008.

To match TC exposure with socio-economic outcomes, cyclone measures are aggregated and spatially averaged so there is a single observation for each of 233 countries in every year (n = 13688, see Fig. 4.8). We focus here on the wind speed measure (mean = 3.4 ms^{-1}, s.d. = 7.7, min. = 0, max = 78.3) for succinctness, however wind speed and energy are highly correlated (Fig. 4.9) and generally produce similar results (estimates using energy are presented in the Appendix). Fig. 4.1C shows the distribution of country-year wind speeds for each continent (country-level distributions are shown in Figs. 4.10-4.14). Figs. 4.1D plots LICRICE output when events are and are not recorded in EM-DAT, revealing that over time smaller scale TC events have been reported with increasing frequency in EM-DAT (also see Fig. 4.15). This has lead to a dramatic increase in the number of TCs reported in EM-DAT, a trend that does not reflect the physical incidence of TC's on society (Fig. 4.1E). This reporting bias in EM-DAT is driven by an increase in the number of countries reporting TCs and the number of TC's reported per country (Fig. 4.16), probably reflecting improvements in disaster monitoring.

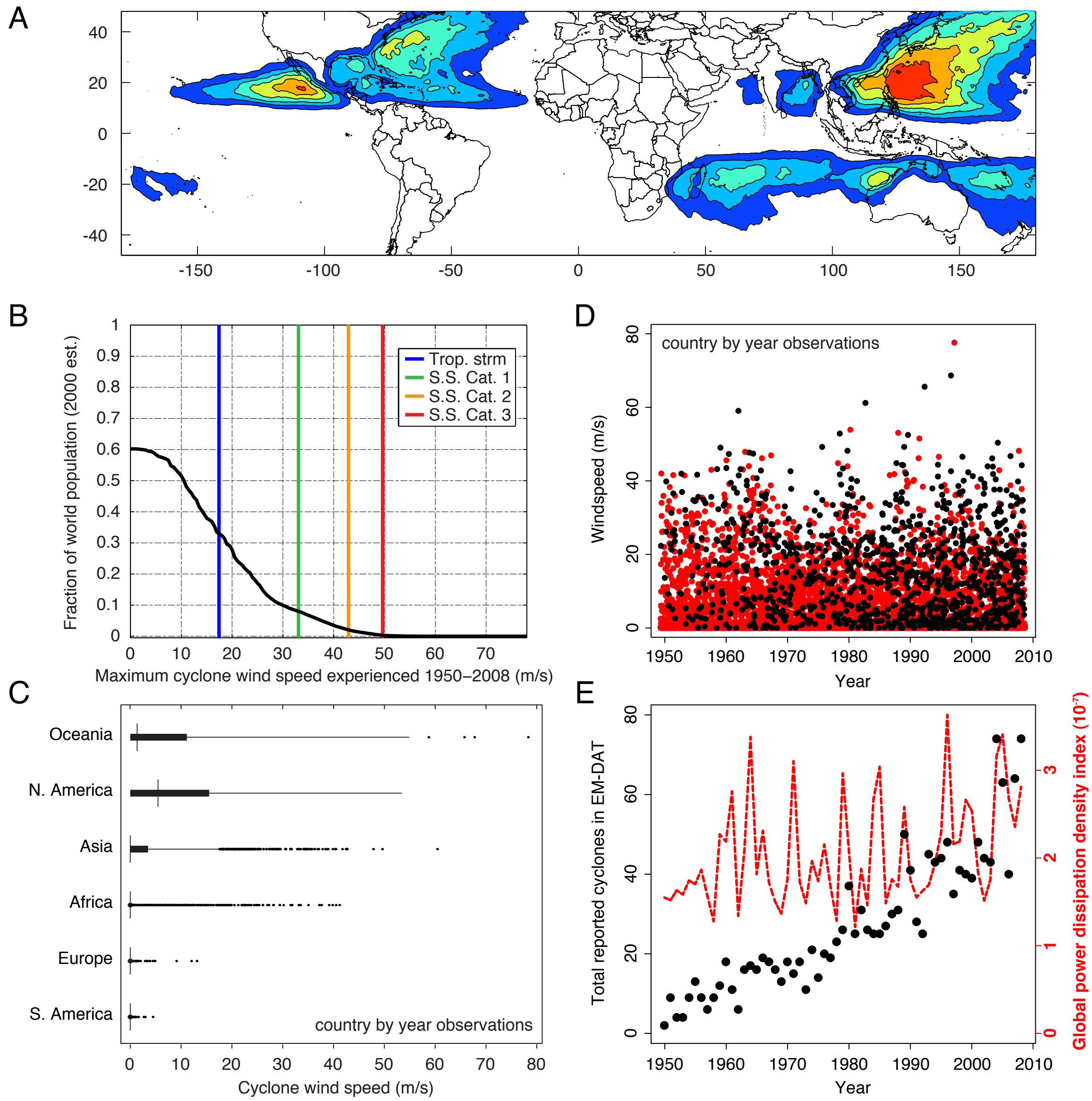


Figure 4.1: **Global TC exposure.** (A) Annual average maximum wind speed achieved by TCs at each location (1950-2008). Contours are 5 ms^{-1}. (B) The number of individuals who experience TC wind speeds above a given value (inverse cumulative distribution function) for the maximum TC wind speed experienced (1950-2008) at an individuals' locations. The spatial distribution of the global population is held fixed (2000 estimate [CIESIN, 2009]). Vertical lines are cutoff wind speeds for the Saffir-Simpson (S.S.) scale. (C) Distributions of country-by-year TC observations after TC exposure is spatially averaged. Boxes are the interquartile range and vertical lines are medians. (D) Country-by-year TC exposure when a TC is reported in EM-DAT (black) and when no TC is reported in EM-DAT (red). (E) The total number of TCs reported annually in EM-DAT (black) and the total energy dissipated by TCs [spatial average] over countries in the sample (red).

4.3 Results

To minimize the impact of EM-DAT's reporting bias on our estimates, we estimate TC losses conditional on the intensity of physical exposure estimated by LICRICE for the 91 countries in EM-DAT (see Fig. 4.17 for a graphical explanation of why this corrects the bias). Normalizing the number of individuals killed in a country by its population and the economic damages in a country by its gross domestic product [Pielke Jr. et al., 2008], we find that that the former increases by 7.7% (±0.7%) and the latter increases by 10.2% (±1.2%) for every additional 1 ms^{-1} in TC wind speed (see Figs. 4.2A-B, also Fig. 4.18). These average relationships hold for a large number of alternative statistical models (Table 4.2) with only moderate variation across continents (Table 4.3). Furthermore, for the pooled sample (Fig. 4.19) and for individual countries (Figs. 4.20-4.23) we verify that this relationship is well approximated by our exponential model (see Methods), which seems to be a more reasonable approximation than the power function used in previous analyses [Mendelsohn et al., 2010, Nordhaus, 2006a] (see Fig. 4.19).

The economic damages reported by EM-DAT are an estimate of economic losses, which may include lost consumption goods (eg. vacation homes), lost productive capital (eg. factories) or costs of business interruption, depending on the protocols of the reporting institution [OFDA/CRED, 2009]. In general, these estimates are probably dominated by physical damages, as many researchers have assumed [Cavallo and Noy, 2009, Noy, 2009], and some of the value reflected in capital losses may reflect lost future revenues [Bank and the United Nations, 2010, Mendelsohn et al., 2010]. However, it seems likely that many income streams lost to a TC are not reported because income that is never earned is difficult to observe, report and verify. Thus, we examine how economic growth scales with TC incidence in 200 countries reporting national income statistics [UN, 2009]; although we note that some of these lost income streams may overlap with the damages reported by EM-DAT.

Globally, we find robust and consistent evidence that the growth rate in *agriculture, hunting & fishing* (mean = 3.07 percentage points, n = 6912) falls by 1.4 ± 0.3 percentage points for every additional 10 ms^{-1} in TC wind speed, with growth rates in following years recovering (Fig. 4.2C). This average response is robust across statistical models (Table 4.4), is evident when annual changes in rainfall and temperature are controlled for (Table 4.4 and Fig. 4.24), is broadly consistent across continents (Table 4.5) and leads to persistent reductions in income over many years (Table 4.4). Analysis of yield data reveals that TCs impact a variety of crops, with fiber crops exhibiting the largest response (Fig. 4.2D-E). In contrast, non-agricultural industries do not reveal systematic TC responses

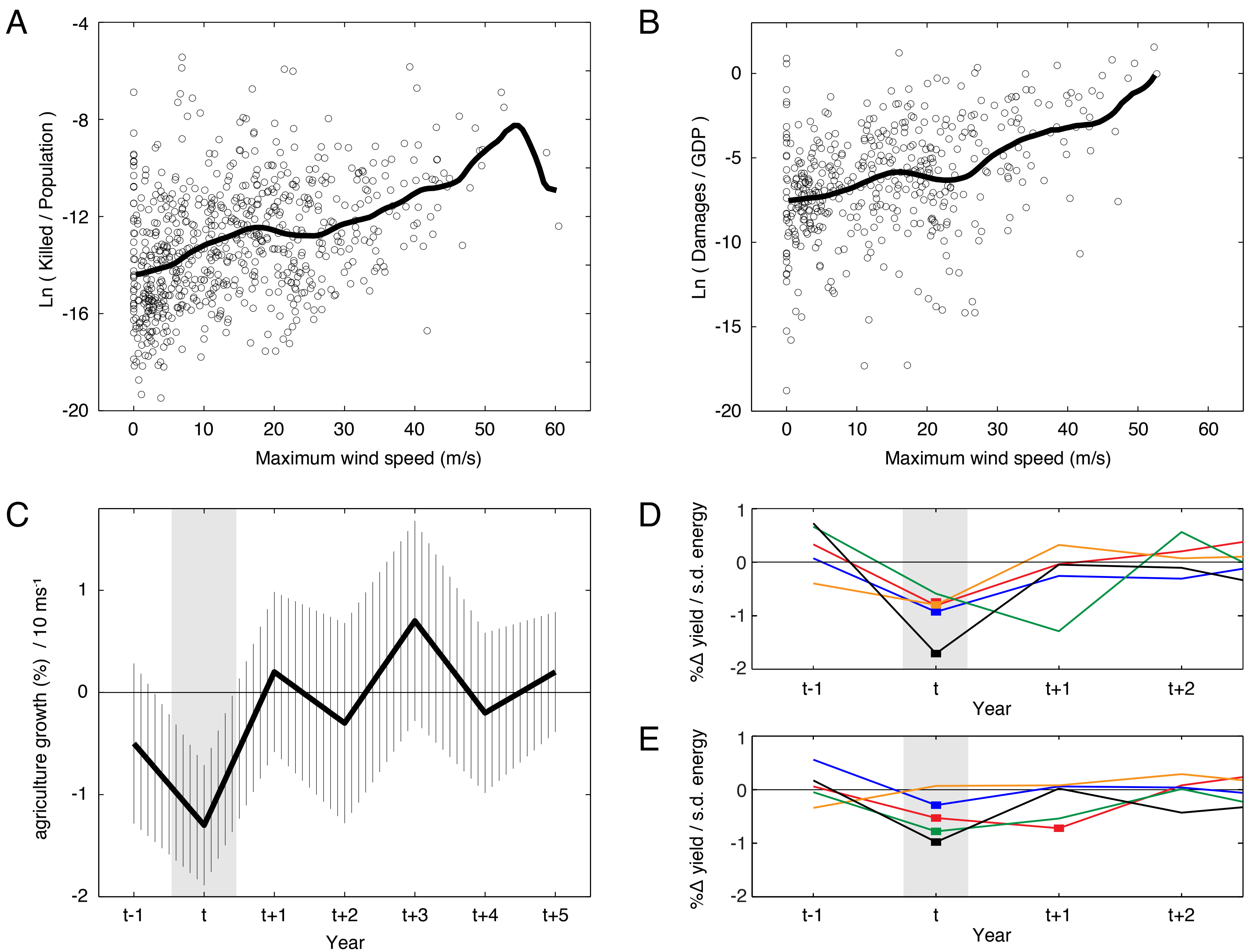


Figure 4.2: **Global TC impacts.** (A) Observations of normalized TC deaths and a weighted moving average (B) Same, but normalized damages [also see Fig. 4.18]. (C) Response of agricultural income growth for a 10 ms^{-1} TC event occuring in year t (95% C.I. hatched). (D) Response of yields (square denotes statistical significance at $\alpha = 0.1$) for maize (red, N=4242), sugarcane (blue, N=2845), oranges (green, N=2840), bananas (yellow, N=3337) and seed cotton (black, N=2514). (E) Same, but aggregated over crop groups: cereals (red, N=4723), vegetables & melons (blue, N=5167), citrus (green, N=3351), fruit (yellow, N=5087) and fiber (black, N=3109).

in the global dataset (Fig. 4.25 and Tables 4.6-4.7); results that differ from a similar analysis restricted to the Caribbean and Central America [Hsiang, 2010] because some non-agricultural industries do not respond to TCs in a consistent way inside and outside of North America (Tables 4.6-4.7).

Focusing on deaths, damages, and agricultural growth, we examine how TC losses change over time to estimate the rate at which societies become less vulnerable to their TC climatology. To ensure that we only compare the impacts of equivelently-sized TC events, we use ordinary least squares to estimate the linear equation

$$Z_{it} = \alpha_Z(T) + \beta_Z(T) \times wind\_speed_{it} + \epsilon_{it} \tag{4.1}$$

where Z is one of the outcomes from Fig. 4.2A-C and ϵ is a disturbance. For each outcome we estimate the intercept α and the slope β for a moving window of fifteen years centered on year T. We find that none of the slopes β have neared zero over time (Figs. 4.3A-C) however we observe that the intercept terms α have been declining rapidly for both deaths and damages (Figs. 4.3D-E). Holding windspeed fixed, per capita deaths from TCs have been steadily declining by $\sim 5\%$ yr^{-1} and normalized damages fell $\sim 10\%$ yr^{-1}. However, it is important to note that $\beta_{damages}$ has risen gradually (Fig. 4.3C), indicating that vulnerability to large TC events has remained stationary or declined more slowly than the falling vulnerability to small and moderate TC events (we estimate that zero change occurs at ~ 37 ms^{-1}).

Declining vulnerability to TCs may be driven by improvements in risk-mitigating technology, such as TC forecasting [Heming and Goerss, 2010], by rising incomes that enable populations to invest in existing technologies [Kahn, 2005, Noy, 2009], or by institutional developments that help societies prepare for disasters better, such as improvements in a government's capacity to enforce building codes [Kahn, 2005, Toya and Skidmore, 2007] – although, the gradualness of the trends in Fig. 4.3D-E suggest these changes are not determined by the discrete effect of a single technology or global event. We find suggestive evidence that rising incomes may influence this trend when we compute β_{damage} for individual countries (Figs. 4.22-4.23) and plot their values against the incomes of those countries in 1970 (Fig. 4.3F). It is clear that countries with higher initial incomes suffer smaller normalized damages when exposed to similar TCs. (Note that in Fig. 4.3F the United States is a clear outlier, so it is omitted from the following analysis. This also suggests that the American experience with TCs should not be extrapolated to other countries [Mendelsohn et al., 2010].) However, when we simultaneously estimate the effect of income on TC losses and global trends in TC losses, we find evidence that rising

Table 4.1: Rapid reduction of Tropical Cyclone vulnerability (1971-2007)

dependent variable:	$damage_t/GDP_{t-1}$		$killed_t/pop._{t-1}$	
model contains country constants:	no	yes	no	yes
slope variables				
$wind\_speed_t$ (ms^{-1})	13.0***	10.2***	10.6***	6.4***
	[1.2]	[1.7]	[0.9]	[1.0]
$year_t \times wind\_speed_t$	0.4***	0.3***	0.1	0.1
	[0.1]	[0.1]	[0.1]	[0.1]
$GDP_{t-1} \times wind\_speed_t$	-0.022**	-0.025	-0.028***	-0.015**
	[0.010]	[0.015]	[0.006]	[0.007]
intercept variables				
$year_t$	-11.2***	-11.0***	-4.6***	-5.7***
	[2.2]	[2.7]	[1.7]	[1.4]
GDP_{t-1}	-0.39**	0.36	-0.03	0.07
	[0.18]	[0.62]	[0.10]	[0.32]
$year_t \times GDP_{t-1}$	0.020**	0.012	-0.002	-0.005
	[0.009]	[0.009]	[0.005]	[0.004]
Observations	420	420	545	545
R^2	0.3	0.6	0.3	0.7

Each column is a separate multiple regression and the United States is omitted from all four models. Heteroscedasticity-robust standard errors [White, 1980] in brackets: *** p<0.01, ** p<0.05, * p<0.1. Coefficients are percentage changes. 1 unit of $wind\_speed$ is 1 ms^{-1} and 1 unit of GDP is a 1% change. A coefficient of 10 for $wind\_speed$ means losses increase 10% for every 1 ms^{-1} increase in $wind\_speed$. A coefficient of 0.1 for $year \times wind\_speed$ means that after one year, losses rise an addition 0.1% for every 1 ms^{-1} increase in $wind\_speed$. A coefficient of 0.01 for $GDP \times wind\_speed$ means that after a 1% rise in GDP, losses rise an addition 0.01% for every 1 ms^{-1} increase in $wind\_speed$. A coefficient of -1 for $year$ implies that losses fall 1% every year at all values of $wind\_speed$.

incomes reduce slopes $\beta_{damages}$ and β_{killed} (consistent with Fig. 4.3F) but we fail to find evidence that the dramatic declines in intercepts $\alpha_{damages}$ or α_{killed} are driven by rising incomes (Table 4.1). Moreover, the effect of rising incomes on the slope terms is small compared to the secular trend in the slopes: in order for income growth to offset the positive secular trends, countries would need to grow an impressive 12% (6.7%) annually to keep the slope $\beta_{damages}$ (β_{killed}) constant. Taken together, these findings suggest that rising incomes may be dramatically less important for declining vulnerability than other global processes, such as technological innovations or institutional developements. This result contrasts with previous studies, based exclusively on EM-DAT, which find that income is a central determinant of disaster vulnerability [Kahn, 2005, Toya and Skidmore, 2007, Noy, 2009].

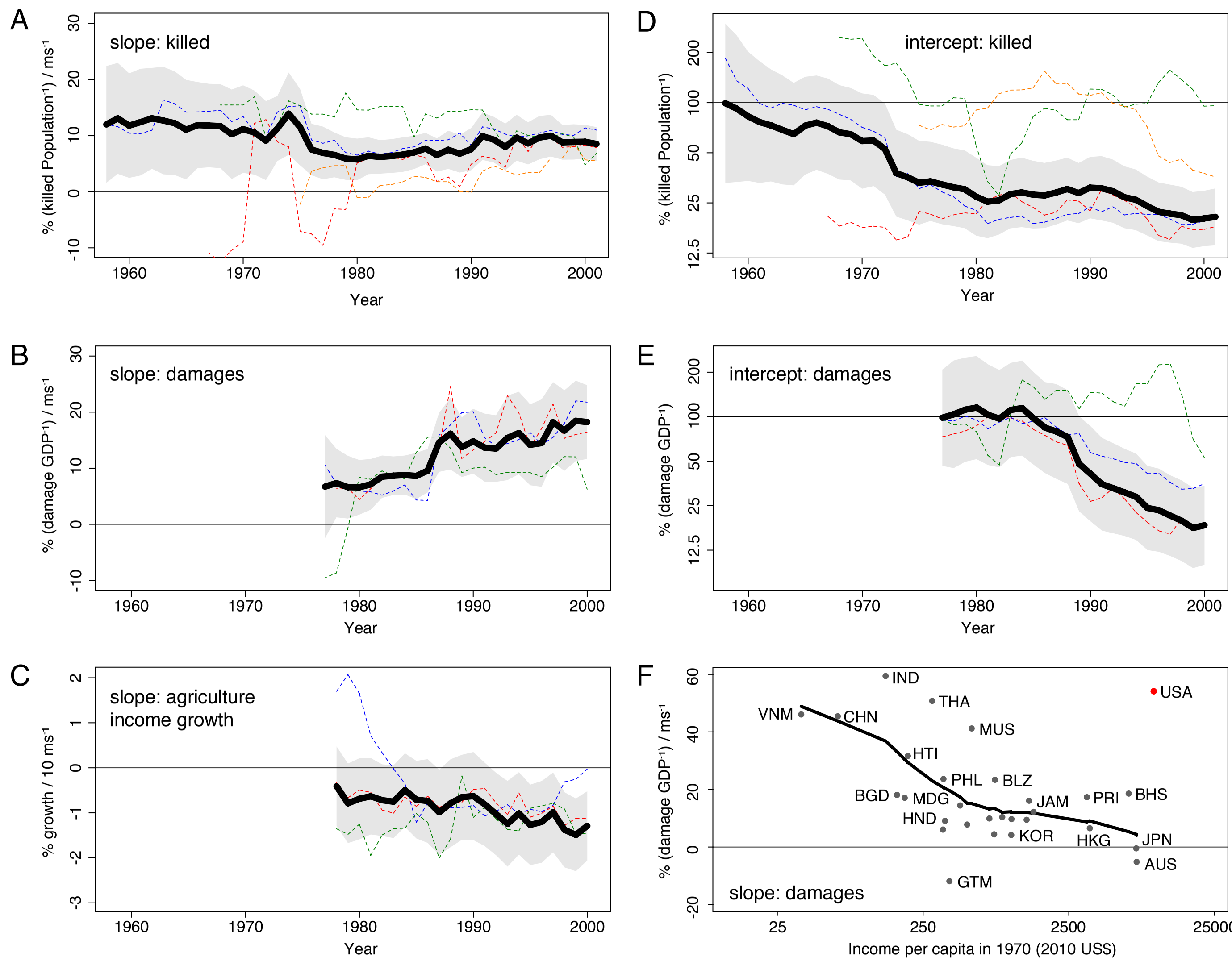


Figure 4.3: **Evidence of falling global vulnerability to TCs.** Equation 4.1 is estimated for 15 yr moving windows, values are plotted in the middle year of each window. (A) Slope β_{killed}. The global estimate (black, 95% C.I. grey) and continent-specific estimates for Asia (blue), North America [including Caribbean and Central America] (red), Oceania (green) and Africa (orange). Slope estimates are from a model with country-specific constants and year-specific constants. (B) Same, for slope $\beta_{damages}$. (C) Same, for slope $\beta_{agr\_income\_growth}$. (D) Same, for intercept α_{killed}. (E) Same, for intercept $\alpha_{damages}$. (F) Country-specific regressions estimate slope coefficients that are plotted against countries' income in 1970. The local linear regression curve is fit without the USA observation.

Globally, average deaths and damages from TCs have fallen rapidly over the last half-century. For a country with a GDP growth rate of 5% yr^{-1}, the death rate for a 10 ms^{-1} TC fell by half every 12.7 years and normalized damages for that event fell by half every 7.5 years. These rapid declines contrast starkly with agricultural income growth, which persistently suffered declines of 1-1.4% for the same 10 ms^{-1} event with no fall in vulnerability (Fig. 4.3C). As mentioned earlier, we cannot know for certain whether these observed declines in vulnerability are due to intentional "adaptation" or are simply unintentional but beneficial gains from investments and changes that would have occurred even in the absence of TCs. Yet, we observe that countries experiencing frequent and intense TCs do not suffer the same losses as countries experiencing TCs less frequently when both countries are exposed to events of the same intensity (Fig. 4.26). This evidence suggests that populations may be intentionally adapting to their TC climates [Deschenes and Greenstone, 2007], although it is hardly conclusive.

We use our statistical models to hindcast damages and agricultural income lost to TCs since 1970 (see Figure 4.4). We estimate that EM-DAT severely underreported damages in the 1970's and only approached the distribution of true damages in the 1990's. Moreover, we estimate that total damages from TCs declined dramatically and rapidly (in terms of total US dollars) between 1970 and the present. However, because loses to agricultural incomes did not decline but grew gradually with growth in agriculture, they began to generally exceed direct damages sometime in the 1980's.

4.4 Discussion

These results contrast with previous global assessments that strictly rely on self-reported EM-DAT data to understand trends in human vulnerability to TCs and other disasters [ISDR, 2009, Bank and the United Nations, 2010]. Analyses that do not compare physical events of the same magnitude over time but instead summarize the universe of all reported TC losses conclude that deaths and damages from TCs are stationary or rising (orange line in Fig 4.4A) because expansions in reporting networks have increased the total number of events that are accounted for. With the exception of a few exceptionally costly outlying events, we find that both normalized and total deaths and damages have declined continuously and rapidly over recent history, on a global scale. These results suggest that modern societies have become decreasingly vulnerable to their TC climates, probably through technological advances since rising incomes appear to have had only secondary impacts. However, losses in agricultural income and damages from extreme TCs have not declined in recent history and may even have grown gradually. This suggests that existing patterns of adaptation or investments

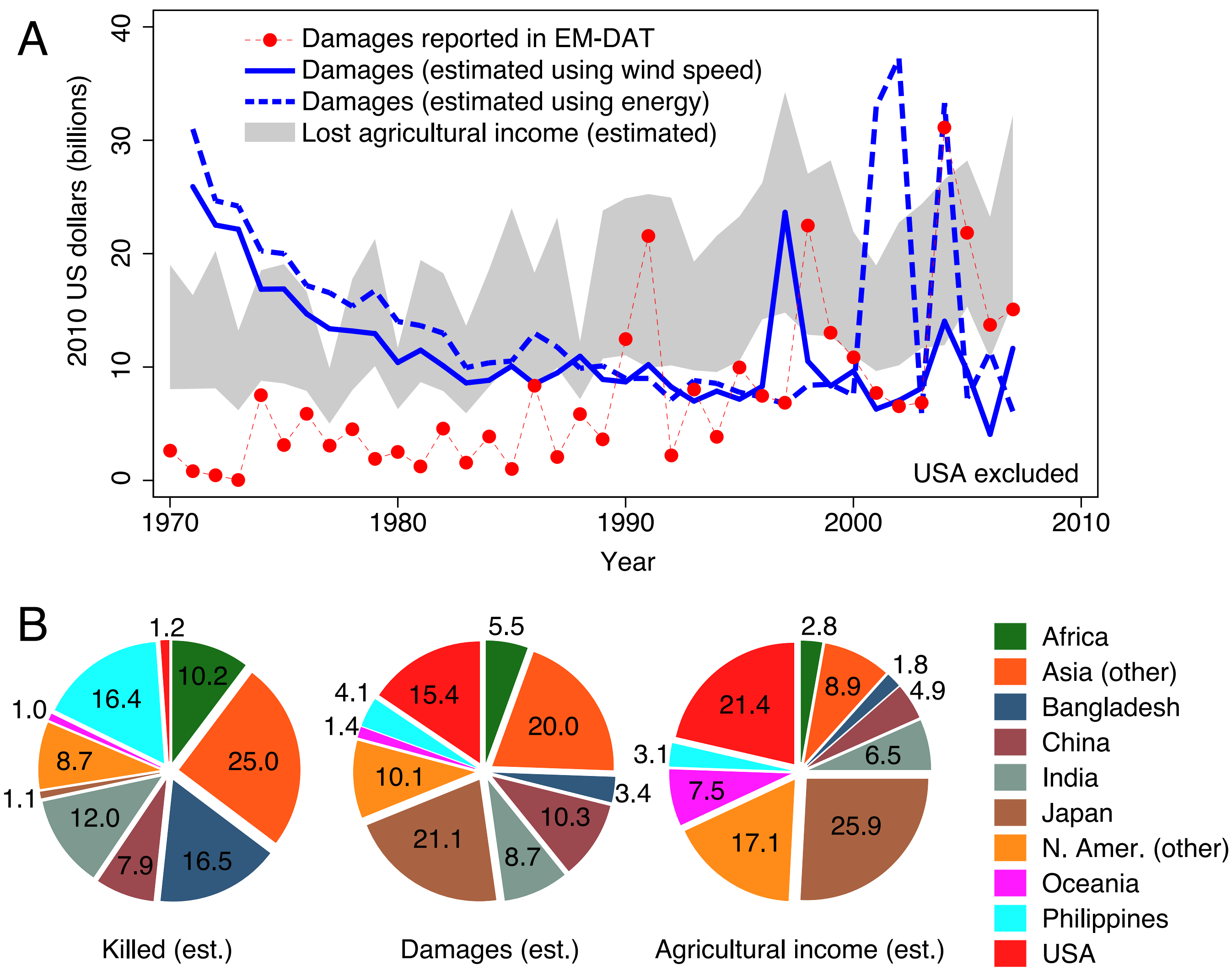


Figure 4.4: **Hindcast of global TC losses.** (A) Regression models are used to estimate historical TC losses. Global agricultural income losses are depicted as a band between a "high" estimate (using a single global coeffieicnt) and a "low" estimate (using continent specific coefficients). High frequency variation is less reliable than moments of the time series. Hindcasts of lost income account for serial correlation in income which increases losses by a factor $\frac{1}{1-\rho} = 4$. (B) The global distribution of hindcast losses as a percentage of global losses.

have not successfully reduced all types of TC vulnerability. For example, it is possible that lost agricultural income is difficult to observe (compared to damaged infrastructure, for example) so societies underinvest in its protection; or it may not be cost-effective to protect agricultural production that is widely dispersed over large areas. Further, it is possible that damages from extreme TCs persist because their intensity overwhelms otherwise effective risk-mitigating systems. These results suggest that future research, policies and investment in risk-mitigation may be most effective if they focus on agriculture and high-intensity TCs.

Understanding how societies adapt to large-scale environmental conditions is a central issue in the assessment of future climate changes [IPCC, 2007, Patt et al., 2010]. In particular, many studies suggest that total TC counts might decline while the number of extreme TCs may rise (see [Knutson et al., 2010a, Knutson et al., 2010b] for reviews), this is concerning if the observed failure to adapt to extreme TCs persists. Insofar as adaptation to other climatic variables resembles historical adaptation to TCs, we might expect adaptation to small and moderate-scale changes that are easily observable to be relatively rapid. However, losses to extreme events or losses that are difficult to observe, such as reductions in productivity [Dell et al., 2009b, Hsiang, 2010], might persist in the absence of explicit measures to promote adaptation.

4.5 Methods

Data TC *wind speed* is measured as the maximum wind speed achieved at a location during the lifetime of a storm. If a location experiences multiple storms, the annual maximum is used as the *wind speed* measure for that year. Location-specific annual *wind speed* estimates are spatially averaged over a country to aggregate exposure into country-by-year observations. TC *energy* is measured using a "power dissipation density index" following Hsiang (2010) [Hsiang, 2010] (mean = 0.22, s.d. = 1, min = 0, max = 19.4). Income data is from the United Nations National Accounts files [UN, 2009], population data is from the World Development Indicator files [World Bank, 2008], yield data is from the Food and Agriculture Administration files [Food and Agriculture Organization, 2009], temperature data is from the National Center for Environmental Prediction reanalysis [Kalnay et al., 1996], and rainfall data is from the Climate Prediction Center Merged Analysis of Precipitation [Xie and Arkin, 1996].

Analysis Table 4.1 contains coefficients from the model

$$\begin{aligned}\ln(Z_{it}) =& \alpha_i + \alpha_1 \cdot year_t + \alpha_2 \cdot \ln GDP_{it-1} + \alpha_3 \cdot year_t \cdot \ln GDP_{it-1} \\ &+ [\beta_0 + \beta_1 \cdot year_t + \beta_2 \cdot \ln GDP_{it-1}] \cdot wind\_speed_{it} + \epsilon_{it}\end{aligned} \tag{4.2}$$

where Z_{it} is normalized deaths or damages for country i in year t and α_i is a country specific constant. Income impacts (Figs. 4.2C and 4.3C and Tables 4.4-4.7) are estimated as

$$\begin{aligned}\Delta \ln(Z_{it}) =& \sum_{L=0}^{\Lambda} \beta^L \cdot wind\_speed_{it-L} \\ &+ \sum_{L=0}^{\Lambda} \gamma_1^L \cdot temperature_{it-L} + \sum_{L=0}^{\Lambda} \gamma_2^L \cdot precipitation_{it-L} \\ &+ \alpha_i + \alpha_t + \delta_i \cdot year_t + \epsilon_{it}\end{aligned} \tag{4.3}$$

where Z_{it} is industry value added per capita (inflation adjusted) α_t are year specific constants and δ_i are country specific trends. Yield impacts (Figs. 4.2D-E) are estimated as

$$\begin{aligned}\ln(Z_{it}) =& \sum_{L=0}^{\Lambda} \beta^L \cdot wind\_speed_{it-L} \\ &+ \sum_{L=0}^{\Lambda} \gamma_1^L \cdot temperature_{it-L} + \sum_{L=0}^{\Lambda} \gamma_2^L \cdot precipitation_{it-L} \\ &+ \alpha_i + \alpha_t + \rho_1 \cdot \ln(Z_{it-1}) + \rho_2 \cdot \ln(Z_{it-2}) + \epsilon_{it}\end{aligned} \tag{4.4}$$

where Z_{it} is average yields (kg/ha) and ρ_{1-2} are autoregressive coefficients. In Equations 4.3-4.4, the disturbance term ϵ is assumed to have arbitrary forms of spatial correlation up to distances of 500 km and serial correlation over five years [Hsiang, 2010, Conley, 1999]. All models are assumed to be heteroscedastic.

Appendix

4.A Supplementary Tables and Figures

Table 4.2: Global tropical cyclone damages and deaths (1950-2008)

Model:	(1)	(2)	(3)	(4)	(5)	(6)
Controls:	-	FE	FE	FE	FE	FE
	-	-	YE	YE	YE	YE
	-	-	-	WEA	WEA	WEA
	-	-	-	-	Yi	-
	-	-	-	-	-	PO
			Panel (a) Dependent Variable: log(damage/GDP)			
Wind Speed (m/s)	0.1018***	0.0989***	0.0904***	0.0931***	0.1020***	0.1357***
	[0.0123]	[0.0158]	[0.0129]	[0.0148]	[0.0145]	[0.0256]
Observations	447	447	447	385	385	207
			Panel (b) Dependent Variable: log(damage/GDP)			
Energy (s.d.)	0.5447***	0.4050***	0.4125***	0.4893***	0.5977***	0.7907***
	[0.0742]	[0.0884]	[0.0725]	[0.0817]	[0.0877]	[0.1123]
Observations	447	447	447	385	385	207
			Panel (c) Dependent Variable: log(killed/population)			
Wind Speed (m/s)	0.0771***	0.0706***	0.0577***	0.0553***	0.0649***	0.0855***
	[0.0054]	[0.0087]	[0.0072]	[0.0086]	[0.0096]	[0.0155]
Observations	701	701	701	495	495	310
			Panel (d) Dependent Variable: log(killed/population)			
Energy (s.d.)	0.3378***	0.2809***	0.2448***	0.2926***	0.3506***	0.5234***
	[0.0317]	[0.0400]	[0.0365]	[0.0506]	[0.0559]	[0.1236]
Observations	701	701	701	495	495	310

*** p<0.01, ** p<0.05, * p<0.1. Heteroscedasticity, serial correlation (5 years) and spatial correlation (500 km) robust standard errors in brackets. Abbreviations for control variables: FE - "fixed effects" (country-specific constants); YE - "year effects" (year-specific constants); WEA - "weather controls" (annual temperature and precipitation); Yi - country-specific time trends; PO - "previous observations" (the sample is restricted to countries reporting losses one or two years prior).

Table 4.3: Global tropical cyclone damages and deaths by continent (1950-2008)

	(1)	(2)	(3)	(4)	(5)
	Global	Africa	Asia	N. America	Oceania
			Panel (a) Dependent Variable: log(damage/GDP)		
Wind Speed (m/s)	0.0904***	0.1883**	0.1245***	0.0829***	0.1195***
	[0.0129]	[0.0598]	[0.0327]	[0.0205]	[0.0204]
Observations	447	35	175	169	53
			Panel (b) Dependent Variable: log(damage/GDP)		
Energy (s.d.)	0.4125***	0.9252***	0.4125***	0.3950***	1.1206***
	[0.0725]	[0.1417]	[0.1545]	[0.1217]	[0.1078]
Observations	447	35	175	169	53
			Panel (c) Dependent Variable: log(killed/population)		
Wind Speed (m/s)	0.0577***	-0.0275	0.0769***	0.0545***	0.0418**
	[0.0072]	[0.0234]	[0.0163]	[0.0111]	[0.0176]
Observations	701	57	341	211	76
			Panel (d) Dependent Variable: log(killed/population)		
Energy (s.d.)	0.2448***	-0.0448	0.1708***	0.3536***	0.1143
	[0.0365]	[0.0969]	[0.0446]	[0.0843]	[0.0971]
Observations	701	57	341	211	76

*** p<0.01, ** p<0.05, * p<0.1. Heteroscedasticity, serial correlation (5 years) and spatial correlation (500 km) robust standard errors in brackets. All models include country-specific constants (fixed-effects) and year specific constants (year-effects).

Table 4.4: Tropical cyclone impact on agricultural growth (1970-2007)

	Direct effect							Cumulative effect	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Independent variable: Wind Speed (m/s)								
	FE	-	FE	FE	FE	FE	FE	FE	FE
	-	YE	YE	YE	YE	YE	YE	YE	YE
	-	-	-	Yi	Yi	Yi	Yi	-	Yi
	-	-	-	-	T	TP	TP	-	TP
$t+1$							-0.0005		
							[0.0004]		
t	-0.0010***	-0.0009***	-0.0011***	-0.0010***	-0.0010***	-0.0014***	-0.0013***	-0.0011***	-0.0014***
	[0.0003]	[0.0002]	[0.0003]	[0.0003]	[0.0003]	[0.0003]	[0.0003]	[0.0003]	[0.0003]
$t-1$	-0.0001	0.0001	-0.0001	0.0000	0.0000	0.0001	0.0001	-0.0012***	-0.0012***
	[0.0003]	[0.0003]	[0.0003]	[0.0003]	[0.0003]	[0.0003]	[0.0003]	[0.0004]	[0.0005]
$t-2$	-0.0001	0.0001	-0.0000	0.0000	0.0001	-0.0003	-0.0003	-0.0012**	-0.0015**
	[0.0004]	[0.0003]	[0.0004]	[0.0004]	[0.0004]	[0.0005]	[0.0004]	[0.0006]	[0.0006]
$t-3$	0.0006	0.0006*	0.0005	0.0006	0.0006*	0.0007	0.0006	-0.0007	-0.0009
	[0.0004]	[0.0003]	[0.0004]	[0.0004]	[0.0004]	[0.0005]	[0.0005]	[0.0006]	[0.0008]
$t-4$	-0.0003	-0.0001	-0.0002	-0.0002	-0.0002	-0.0003	-0.0003	-0.0010	-0.0011
	[0.0003]	[0.0003]	[0.0003]	[0.0003]	[0.0003]	[0.0004]	[0.0004]	[0.0008]	[0.0009]
$t-5$	-0.0000	0.0001	-0.0000	0.0000	0.0000	0.0001	0.0001	-0.0010	-0.0010
	[0.0003]	[0.0003]	[0.0003]	[0.0003]	[0.0003]	[0.0003]	[0.0003]	[0.0008]	[0.0009]
Obs.	6,895	6,895	6,895	6,895	6,895	4,607	4,607	6,895	4,607
	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
	Independent variable: Energy (s.d.)								
$t-1$							-0.0018		
							[0.0024]		
t	-0.0077***	-0.0070***	-0.0081***	-0.0079***	-0.0078***	-0.0085***	-0.0085***	-0.0081***	-0.0085***
	[0.0020]	[0.0018]	[0.0019]	[0.0020]	[0.0019]	[0.0018]	[0.0018]	[0.0019]	[0.0018]
$t-1$	-0.0006	0.0007	-0.0003	-0.0000	0.0001	-0.0001	-0.0003	-0.0084***	-0.0086***
	[0.0021]	[0.0021]	[0.0022]	[0.0022]	[0.0022]	[0.0022]	[0.0022]	[0.0030]	[0.0029]
$t-2$	-0.0023	-0.0006	-0.0017	-0.0013	-0.0012	-0.0047	-0.0048	-0.0101**	-0.0133***
	[0.0033]	[0.0030]	[0.0032]	[0.0033]	[0.0033]	[0.0034]	[0.0033]	[0.0045]	[0.0046]
$t-3$	0.0036	0.0049*	0.0037	0.0042	0.0044	0.0043	0.0045	-0.0064	-0.0089
	[0.0028]	[0.0029]	[0.0029]	[0.0030]	[0.0030]	[0.0035]	[0.0033]	[0.0055]	[0.0064]
$t-4$	-0.0017	-0.0003	-0.0012	-0.0011	-0.0011	0.0001	0.0000	-0.0076	-0.0088
	[0.0022]	[0.0020]	[0.0021]	[0.0020]	[0.0020]	[0.0020]	[0.0019]	[0.0060]	[0.0069]
$t-5$	-0.0020	-0.0012	-0.0022	-0.0020	-0.0020	-0.0007	-0.0006	-0.0098*	-0.0095
	[0.0016]	[0.0018]	[0.0017]	[0.0016]	[0.0016]	[0.0016]	[0.0016]	[0.0059]	[0.0068]
Obs.	6,889	6,889	6,889	6,889	6,889	4,601	4,600	6,889	4,601

*** p<0.01, ** p<0.05, * p<0.1. Heteroscedasticity, serial correlation (5 years) and spatial correlation (500 km) robust standard errors in brackets. Abbreviations for control variables: FE - "fixed effects" (country-specific constants); YE - "year effects" (year-specific constants); Yi - country-specific time trends; T - temperature; TP - temperature and preciptiation.

Table 4.5: Tropical cyclone impact on agricultural growth by continent (1970-2007)

	(1)	(2)	(3)	(4)	(5)
	Global	Africa	Asia	N. America	Oceania
Wind Speed (m/s)	-0.0014***	-0.0023*	-0.0005	-0.0014***	-0.0014*
	[0.0003]	[0.0012]	[0.0006]	[0.0004]	[0.0008]
$t-1$	0.0001	0.0021*	-0.0005	-0.0002	0.0000
	[0.0003]	[0.0012]	[0.0007]	[0.0005]	[0.0008]
$t-2$	-0.0003	0.0001	0.0008	-0.0002	-0.0017*
	[0.0005]	[0.0011]	[0.0005]	[0.0007]	[0.0010]
$t-3$	0.0007	0.0006	-0.0002	0.0012**	-0.0009
	[0.0005]	[0.0011]	[0.0006]	[0.0006]	[0.0011]
$t-4$	-0.0003	0.0004	-0.0005	-0.0001	-0.0012
	[0.0004]	[0.0010]	[0.0005]	[0.0006]	[0.0007]
$t-5$	0.0001	0.0000	0.0010*	0.0003	-0.0011
	[0.0003]	[0.0011]	[0.0006]	[0.0005]	[0.0007]
Observations	4,607	1,234	1,038	792	403
	(6)	(7)	(8)	(9)	(10)
	Global	Africa	Asia	N. America	Oceania
Energy (s.d.)	-0.0085***	-0.0165***	-0.0023	-0.0090***	-0.0087
	[0.0018]	[0.0055]	[0.0064]	[0.0017]	[0.0054]
$t-1$	-0.0001	0.0096	-0.0005	-0.0032	-0.0028
	[0.0022]	[0.0062]	[0.0061]	[0.0024]	[0.0044]
$t-2$	-0.0047	0.0026	0.0085	-0.0037	-0.0099
	[0.0034]	[0.0077]	[0.0066]	[0.0033]	[0.0067]
$t-3$	0.0043	-0.0006	-0.0008	0.0078**	-0.0104
	[0.0035]	[0.0048]	[0.0062]	[0.0033]	[0.0098]
$t-4$	0.0001	0.0021	-0.0063	0.0013	-0.0058
	[0.0020]	[0.0047]	[0.0070]	[0.0023]	[0.0046]
$t-5$	-0.0007	0.0000	0.0035	0.0013	-0.0046
	[0.0016]	[0.0045]	[0.0073]	[0.0017]	[0.0046]
Observations	4,601	1,234	1,038	792	397

*** p<0.01, ** p<0.05, * p<0.1. Heteroscedasticity, serial correlation (5 years) and spatial correlation (500 km) robust standard errors in brackets. All models include country fixed-effects, year dummies, country-specific trends, and temperature and precipitation controls.

Table 4.6: Tropical cyclone windspeed impact on industry growth (1970-2007)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Total production		Agriculture, Hunting & Fishing		Manufacturing		Other Services	
Controls:	FE	FE	FE	FE	FE	FE	FE	FE
	YE	YE	YE	YE	YE	YE	YE	YE
	-	Yi	-	Yi	-	Yi	-	Yi
	-	TP	-	TP	-	TP	-	TP
Wind Speed (m/s)	-0.0001	-0.0000	-0.0011***	-0.0014***	-0.0003	-0.0003	-0.0001	0.0001
	[0.0001]	[0.0001]	[0.0003]	[0.0003]	[0.0004]	[0.0005]	[0.0002]	[0.0002]
$t-1$	0.0001	0.0000	-0.0001	0.0001	-0.0002	-0.0003	0.0001	0.0001
	[0.0002]	[0.0002]	[0.0003]	[0.0003]	[0.0003]	[0.0003]	[0.0002]	[0.0002]
$t-2$	-0.0002	-0.0002	-0.0000	-0.0003	-0.0003	-0.0009**	-0.0001	-0.0000
	[0.0001]	[0.0002]	[0.0004]	[0.0005]	[0.0003]	[0.0004]	[0.0002]	[0.0002]
$t-3$	-0.0001	0.0000	0.0005	0.0007	0.0002	0.0006	0.0000	0.0001
	[0.0002]	[0.0001]	[0.0004]	[0.0005]	[0.0004]	[0.0006]	[0.0002]	[0.0002]
$t-4$	0.0000	-0.0001	-0.0002	-0.0003	0.0005	-0.0000	0.0000	-0.0000
	[0.0002]	[0.0001]	[0.0003]	[0.0004]	[0.0004]	[0.0005]	[0.0002]	[0.0002]
$t-5$	-0.0001	-0.0001	-0.0000	0.0001	-0.0001	-0.0001	0.0001	0.0001
	[0.0001]	[0.0002]	[0.0003]	[0.0003]	[0.0003]	[0.0004]	[0.0002]	[0.0002]
Observations	6,968	4,612	6,895	4,607	6,770	4,538	6,863	4,588

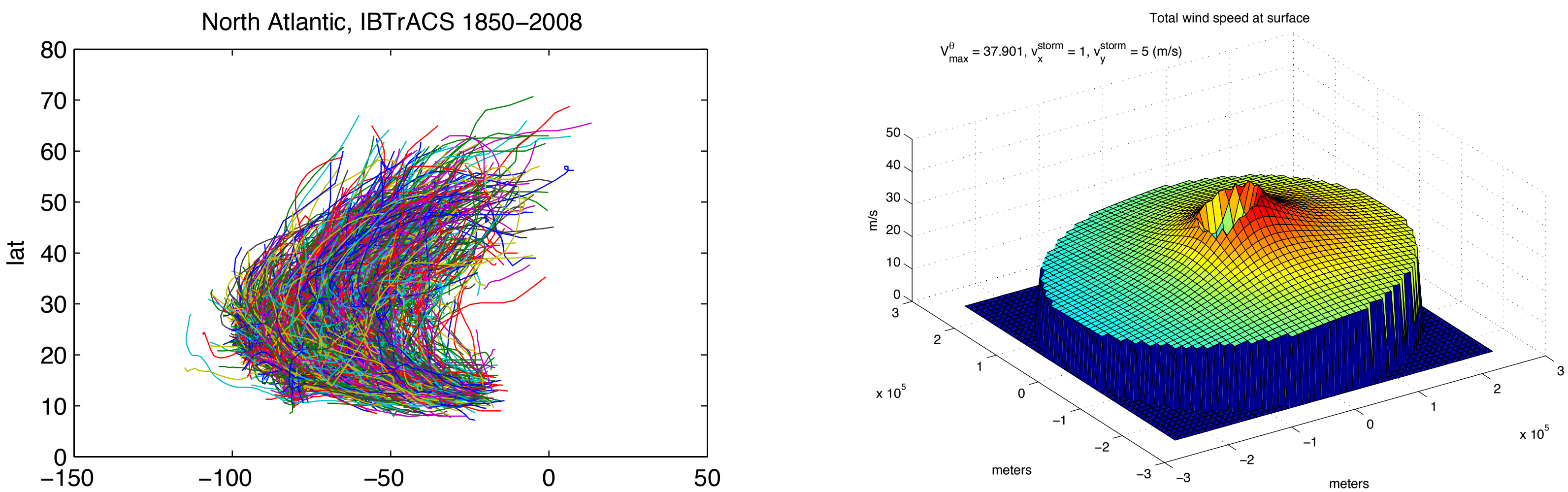
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	Total production		Agriculture, Hunting & Fishing		Manufacturing		Other Services	
	N. Am.	Rest	N. Am.	Rest	N. Am.	Rest	N. Am.	Rest
Controls	FE	FE	FE	FE	FE	FE	FE	FE
	YE	YE	YE	YE	YE	YE	YE	YE
	Yi	Yi	Yi	Yi	Yi	Yi	Yi	Yi
	TP	TP	TP	TP	TP	TP	TP	TP
Wind Speed (m/s)	0.0000	-0.0000	-0.0014***	-0.0012**	-0.0013**	0.0012*	0.0001	0.0000
	[0.0002]	[0.0002]	[0.0004]	[0.0005]	[0.0006]	[0.0007]	[0.0002]	[0.0003]
$t-1$	0.0001	0.0000	-0.0002	0.0005	0.0001	-0.0001	-0.0001	0.0004
	[0.0002]	[0.0002]	[0.0005]	[0.0005]	[0.0003]	[0.0007]	[0.0002]	[0.0004]
$t-2$	-0.0002	-0.0004	-0.0002	-0.0008	-0.0011***	0.0003	0.0001	-0.0002
	[0.0002]	[0.0002]	[0.0007]	[0.0006]	[0.0004]	[0.0007]	[0.0002]	[0.0004]
$t-3$	0.0000	-0.0002	0.0012**	-0.0006	0.0004	0.0016**	0.0002	-0.0004
	[0.0001]	[0.0003]	[0.0006]	[0.0006]	[0.0007]	[0.0007]	[0.0002]	[0.0004]
$t-4$	-0.0001	-0.0003	-0.0001	-0.0011***	-0.0001	0.0001	0.0001	-0.0003
	[0.0001]	[0.0002]	[0.0006]	[0.0004]	[0.0006]	[0.0009]	[0.0001]	[0.0004]
$t-5$	-0.0000	-0.0002	0.0003	-0.0006	-0.0001	0.0002	0.0001	0.0001
	[0.0002]	[0.0003]	[0.0005]	[0.0004]	[0.0004]	[0.0008]	[0.0002]	[0.0003]
Observations	792	3,820	792	3,815	790	3,748	792	3,796

Top panel displays the effect of TC wind speed on different industries. Bottom panel displays the effect on these industries for North America only ("N. Am.") and for the rest of the world ("Rest"). *** p<0.01, ** p<0.05, * p<0.1. Heteroscedasticity, serial correlation (5 years) and spatial correlation (500 km) robust standard errors in brackets. Abbreviations for control variables: FE - "fixed effects" (country-specific constants); YE - "year effects" (year-specific constants); Yi - country-specific time trends; T - temperature; TP - temperature and precipitation.

Table 4.7: Tropical cyclone energy impact on industry growth (1970-2007)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Total production		Agriculture, Hunting & Fishing		Manufacturing		Other Services	
Controls:	FE	FE	FE	FE	FE	FE	FE	FE
	YE	YE	YE	YE	YE	YE	YE	YE
	-	Yi	-	Yi	-	Yi	-	Yi
	-	TP	-	TP	-	TP	-	TP
Energy (s.d.)	-0.0005	-0.0003	-0.0081***	-0.0085***	-0.0006	0.0002	0.0002	0.0001
	[0.0010]	[0.0012]	[0.0019]	[0.0018]	[0.0024]	[0.0029]	[0.0010]	[0.0011]
$t-1$	0.0005	-0.0004	-0.0003	-0.0001	0.0026	0.0021	0.0019	0.0016
	[0.0013]	[0.0015]	[0.0022]	[0.0022]	[0.0018]	[0.0018]	[0.0015]	[0.0016]
$t-2$	-0.0012	-0.0022**	-0.0017	-0.0047	-0.0061***	-0.0093***	-0.0001	-0.0010
	[0.0009]	[0.0010]	[0.0032]	[0.0034]	[0.0019]	[0.0027]	[0.0014]	[0.0013]
$t-3$	-0.0011	-0.0006	0.0037	0.0043	-0.0004	-0.0003	-0.0003	0.0004
	[0.0012]	[0.0011]	[0.0029]	[0.0035]	[0.0048]	[0.0058]	[0.0012]	[0.0011]
$t-4$	-0.0009	-0.0013	-0.0012	0.0001	0.0014	-0.0004	0.0002	-0.0000
	[0.0015]	[0.0013]	[0.0021]	[0.0020]	[0.0027]	[0.0034]	[0.0016]	[0.0013]
$t-5$	-0.0004	-0.0002	-0.0022	-0.0007	-0.0020	-0.0023	0.0005	0.0012
	[0.0011]	[0.0011]	[0.0017]	[0.0016]	[0.0025]	[0.0028]	[0.0012]	[0.0010]
Observations	6,962	4,606	6,889	4,601	6,764	4,532	6,857	4,582
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	Total production		Agriculture, Hunting & Fishing		Manufacturing		Other Services	
VARIABLES	N. Am.	Rest	N. Am.	Rest	N. Am.	Rest	N. Am.	Rest
Controls:	FE	FE	FE	FE	FE	FE	FE	FE
	YE	YE	YE	YE	YE	YE	YE	YE
	Yi	Yi	Yi	Yi	Yi	Yi	Yi	Yi
	TP	TP	TP	TP	TP	TP	TP	TP
Energy (s.d.)	0.0001	-0.0023	-0.0090***	-0.0097**	-0.0026	0.0024	0.0005	-0.0012
	[0.0014]	[0.0015]	[0.0017]	[0.0041]	[0.0032]	[0.0040]	[0.0013]	[0.0020]
$t-1$	-0.0003	-0.0011	-0.0032	0.0032	0.0016	0.0053	0.0001	0.0046
	[0.0015]	[0.0017]	[0.0024]	[0.0030]	[0.0022]	[0.0050]	[0.0015]	[0.0033]
$t-2$	-0.0015	-0.0035**	-0.0037	-0.0067	-0.0091***	-0.0016	0.0003	-0.0027
	[0.0010]	[0.0017]	[0.0033]	[0.0052]	[0.0028]	[0.0044]	[0.0013]	[0.0026]
$t-3$	-0.0005	-0.0024	0.0078**	-0.0079	-0.0030	0.0076*	0.0003	-0.0016
	[0.0008]	[0.0025]	[0.0033]	[0.0062]	[0.0058]	[0.0045]	[0.0011]	[0.0025]
$t-4$	-0.0009	-0.0034**	0.0013	-0.0048*	0.0027	-0.0057	0.0004	-0.0019
	[0.0013]	[0.0016]	[0.0023]	[0.0027]	[0.0036]	[0.0049]	[0.0013]	[0.0029]
$t-5$	0.0006	-0.0010	0.0013	-0.0042	-0.0039	0.0026	0.0025**	0.0004
	[0.0014]	[0.0016]	[0.0017]	[0.0028]	[0.0034]	[0.0050]	[0.0012]	[0.0016]
Observations	792	3,814	792	3,809	790	3,742	792	3,790

Top panel displays the effect of TC energy on different industries. Bottom panel displays the effect on these industries for North America only ("N. Am.") and for the rest of the world ("Rest"). *** p<0.01, ** p<0.05, * p<0.1. Heteroscedasticity, serial correlation (5 years) and spatial correlation (500 km) robust standard errors in brackets. Abbreviations for control variables: FE - "fixed effects" (country-specific constants); YE - "year effects" (year-specific constants); Yi - country-specific time trends; T - temperature; TP - temperature and precipitation.



A **B**

Figure 4.5: **Elements of the LICRICE model.** (A) The global IBTrACS data dataset [Knapp, 2009] records TC track data along with maximum sustained winds and central presssure. The panel displays all the track records for the Atlantic Ocean. (B) TC wind-fields are appoximated as translating Renkine votices and are projected onto each track and integrated through the life of each storm. Radii of maximum winds (RMW) are estimated using maximum windspeeds and latitude following Kossin et al. (2007) [Kossin et al., 2007], Renkine parameters are estimated following Mallen et al. (2005) [Mallen et al., 2005].

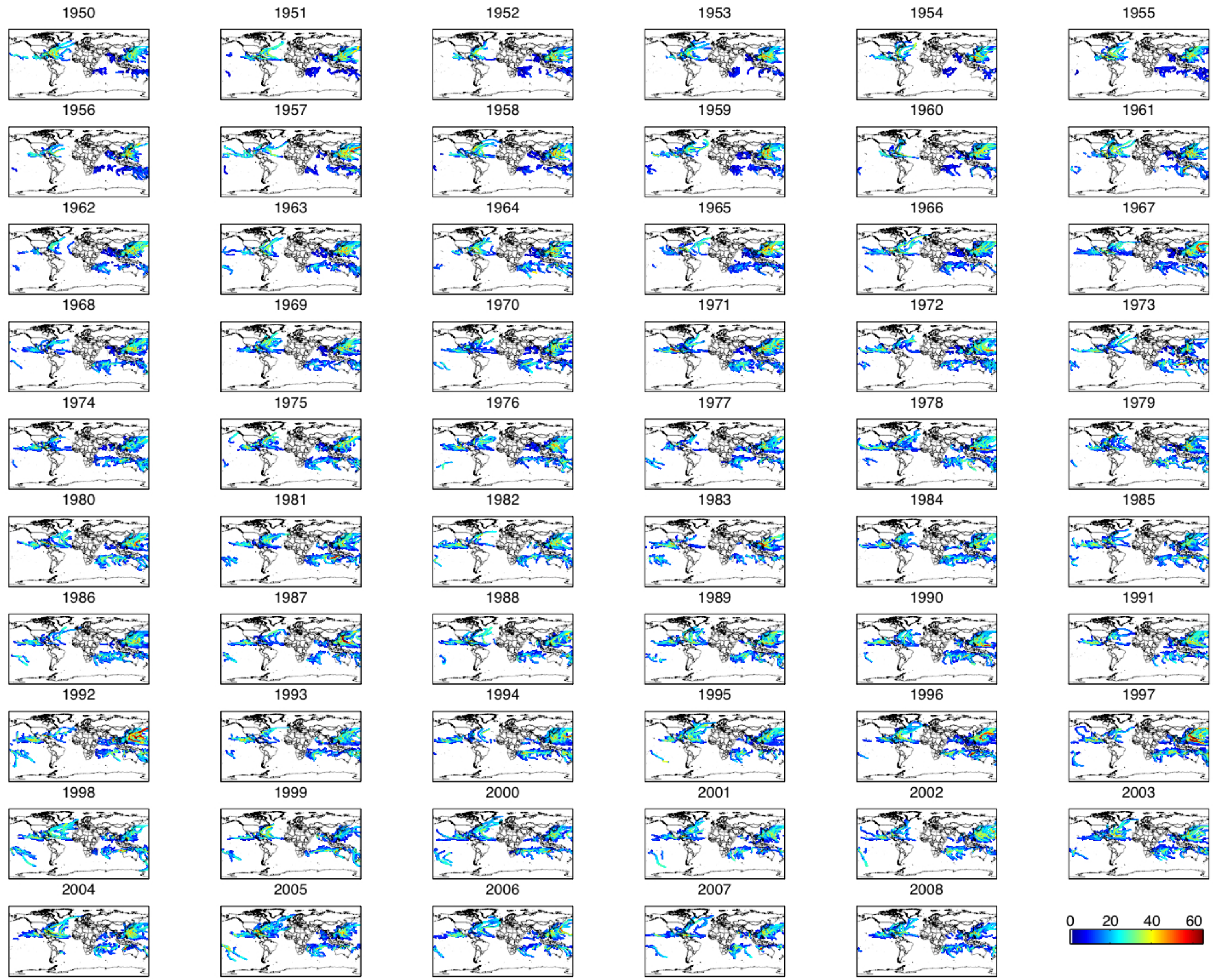


Figure 4.6: **Annualized LICRICE estimates.** Maximum TC surface winds (1950-2008) in ms^{-1}

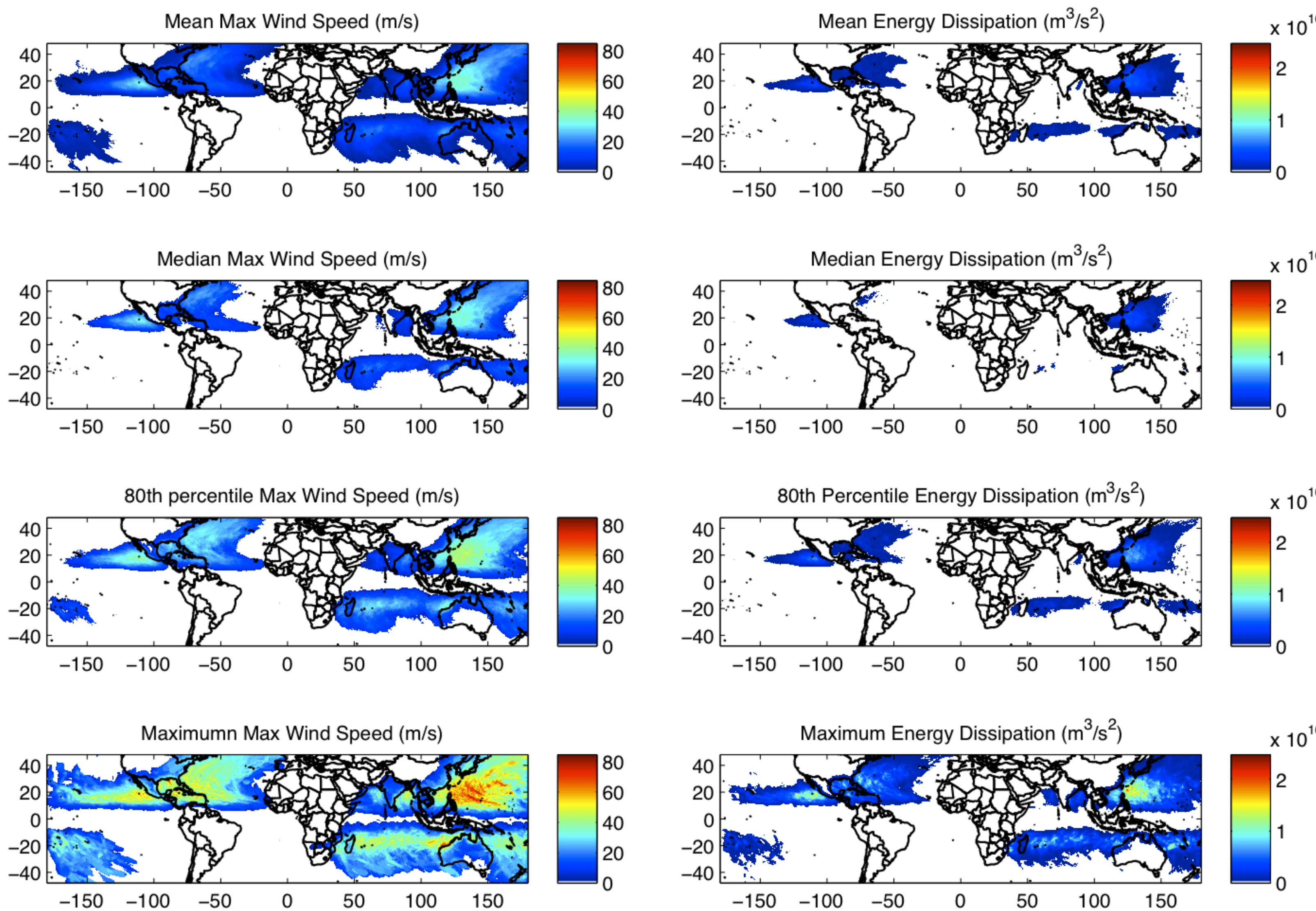


Figure 4.7: **Field summary statistics.** Point-wise summaries of maximum wind speed (left) and power dissipation density index (right). The TC time series for any given pixel is approximately gamma distributed.

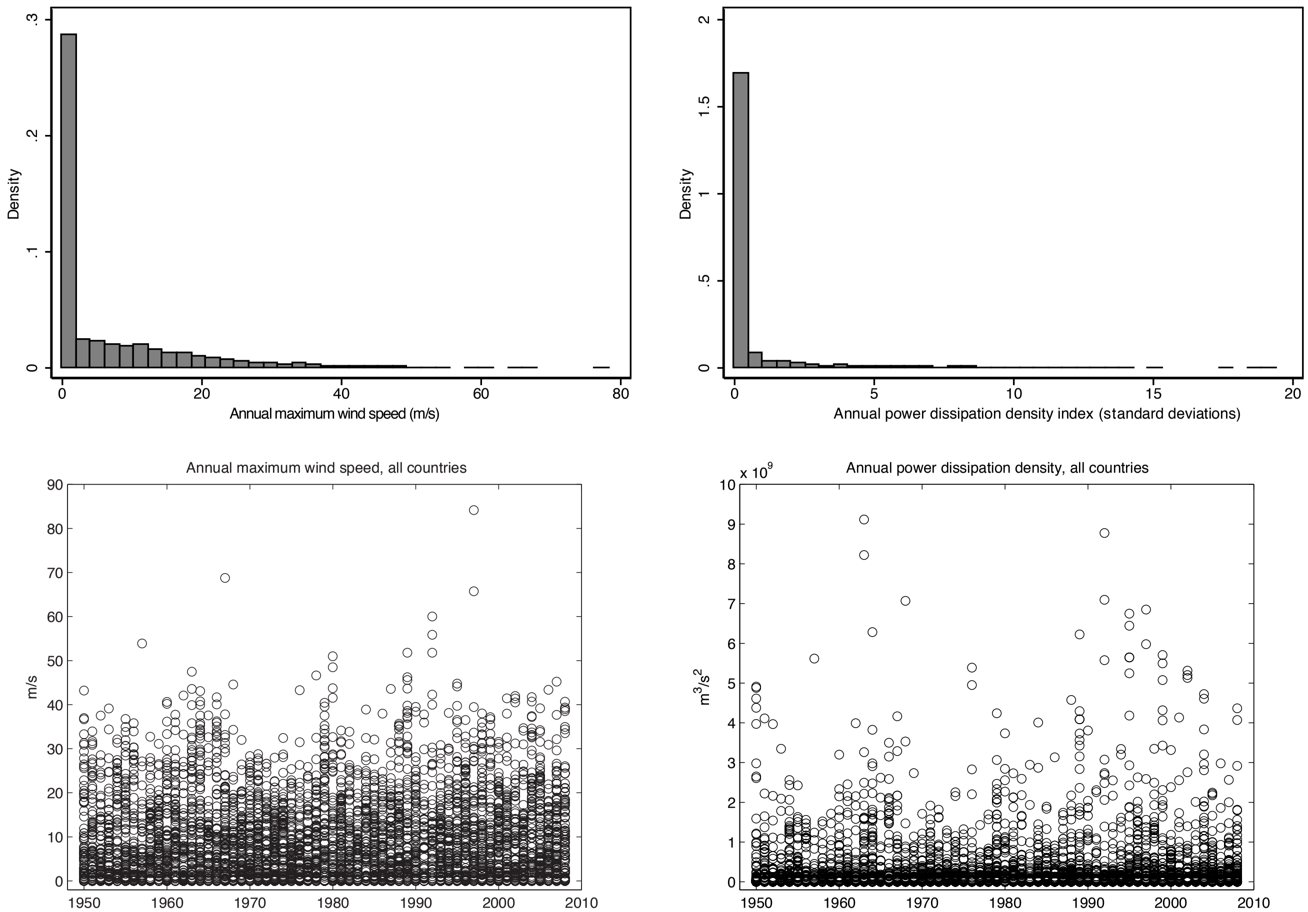


Figure 4.8: **TC exposure aggregated to country-by-year observations.** The histogram of all observations (top) and the distribution of observations over time (bottom).

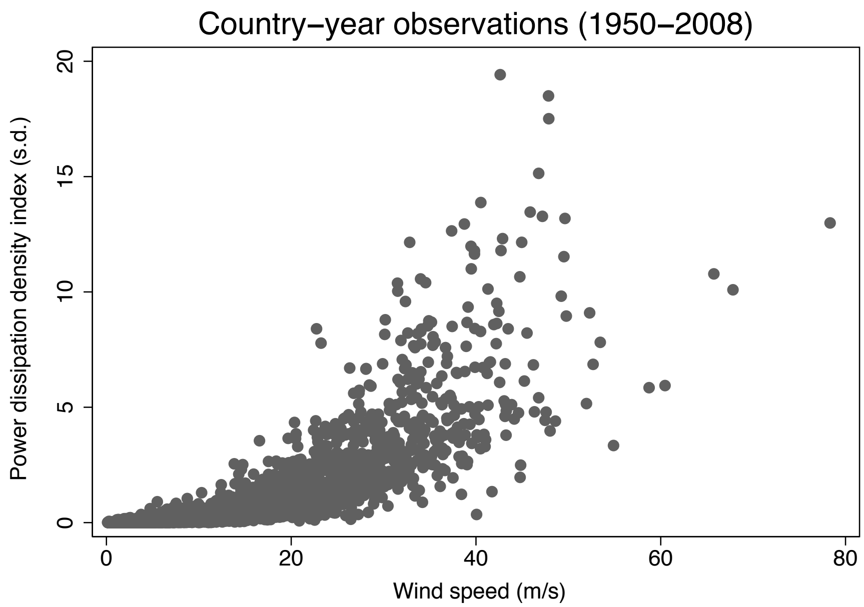


Figure 4.9: **Comparing energy and wind speed measures.** Country-by-year observations of annual TC energy and wind speed measures. Energy differs from the simple cube of wind speed because (1) the wind speed measure is only the maximum wind speed achieved over a storm's lifetime, while the energy measure integrates power dissipation over the storm's entire lifetime; (2) energy rises if storms move more slowly, doing greater work at the surface; (3) wind speed measures are aggregated by taking the maximum value at each location within each year, while energy is summed across storms.

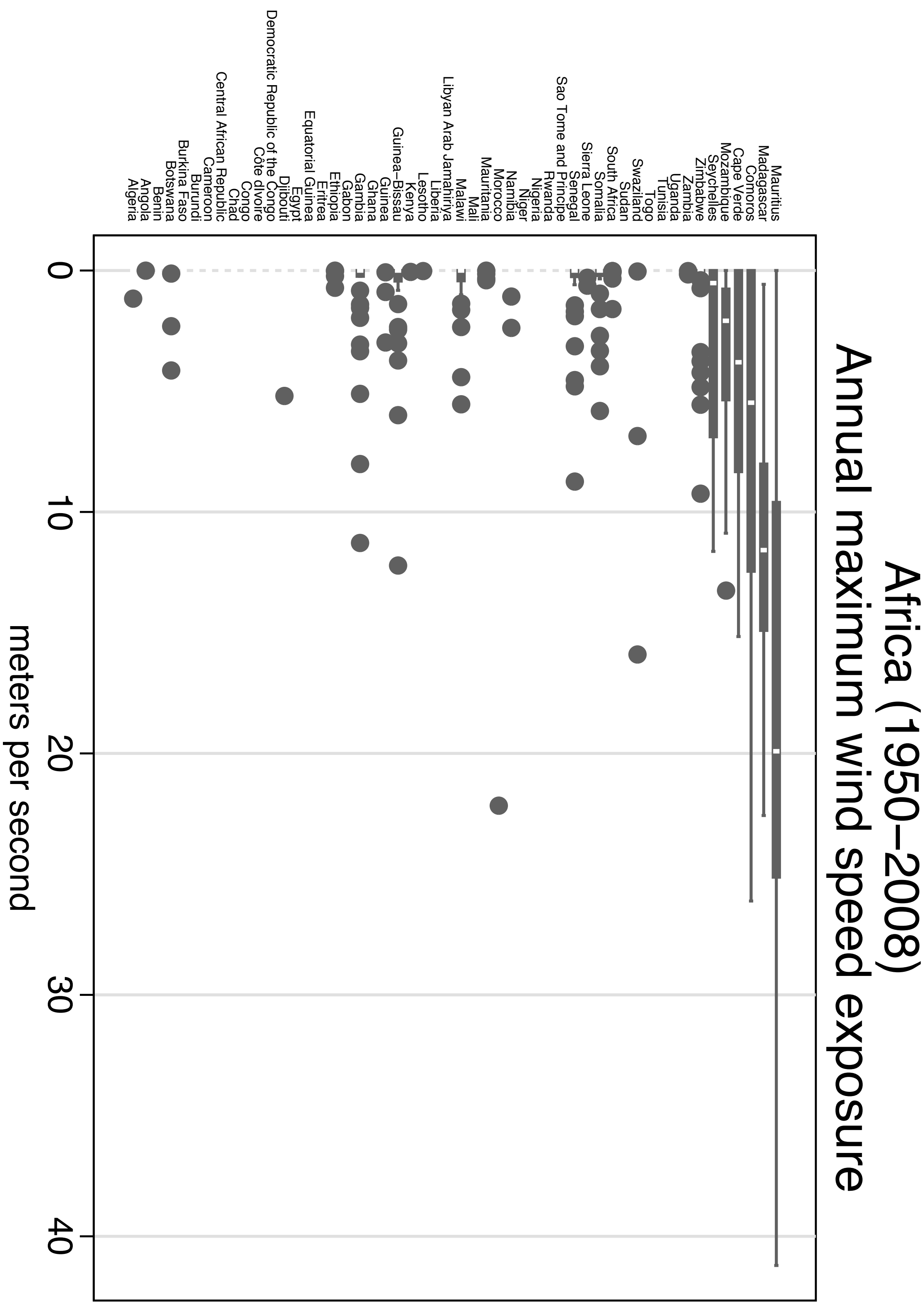


Figure 4.10: The distributions of country-by-year TC observations for African countries. Boxes mark 25th-75th centile ranges and white bands mark medians.

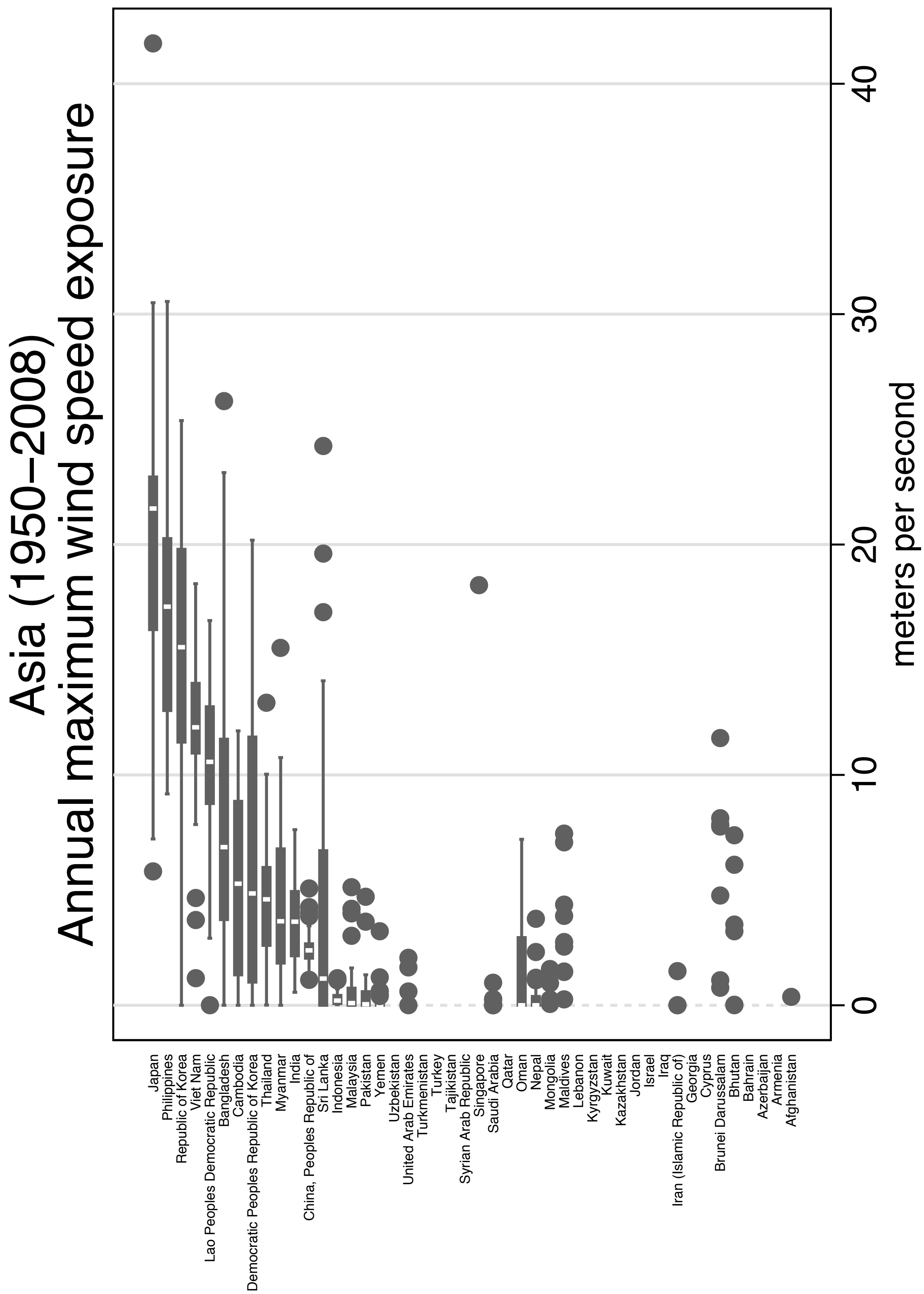


Figure 4.11: The distributions of country-by-year TC observations for Asian countries. Boxes mark 25th-75th centile ranges and white bands mark medians.

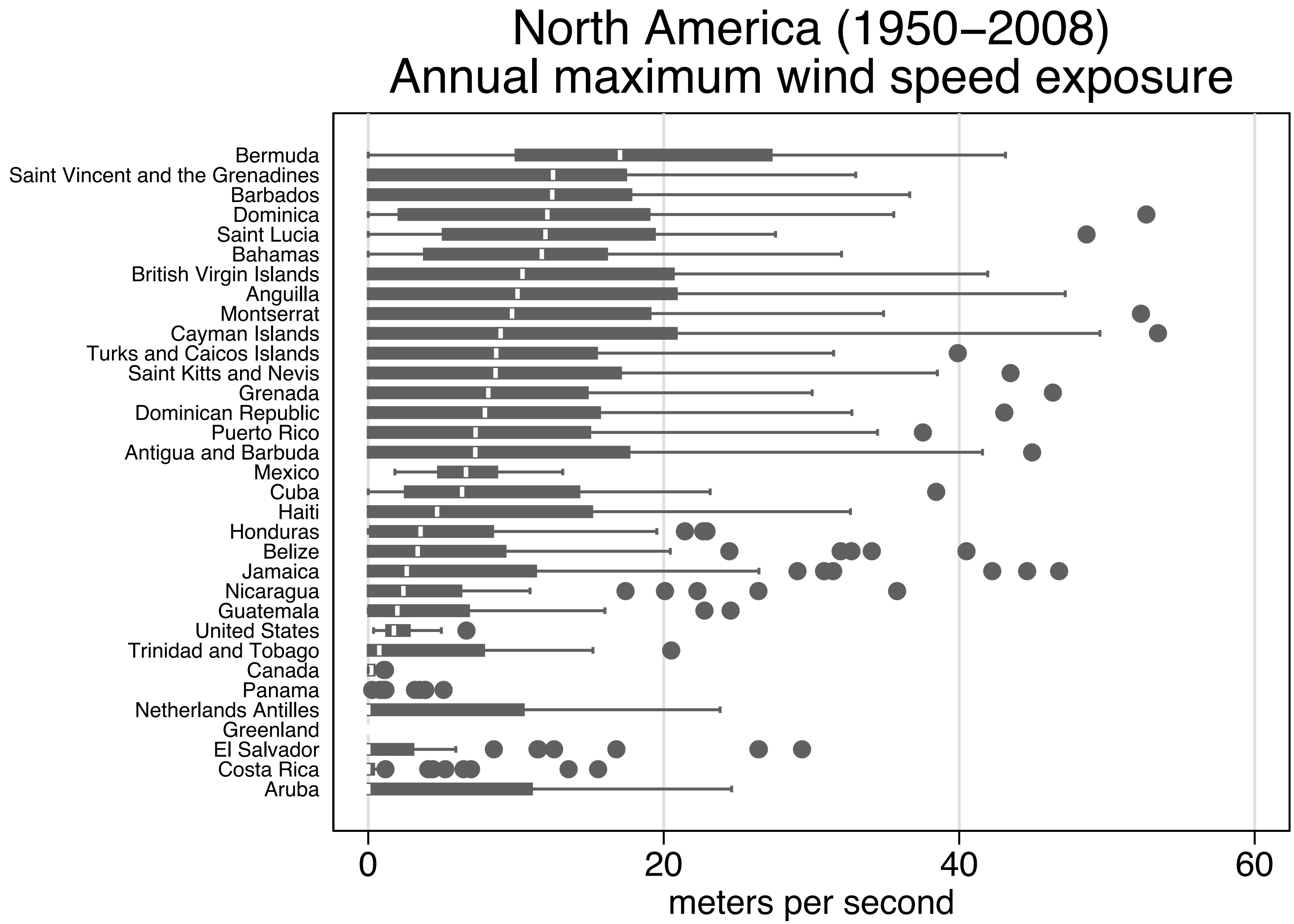


Figure 4.12: The distributions of country-by-year TC observations for North American countries. Boxes mark 25th-75th centile ranges and white bands mark medians.

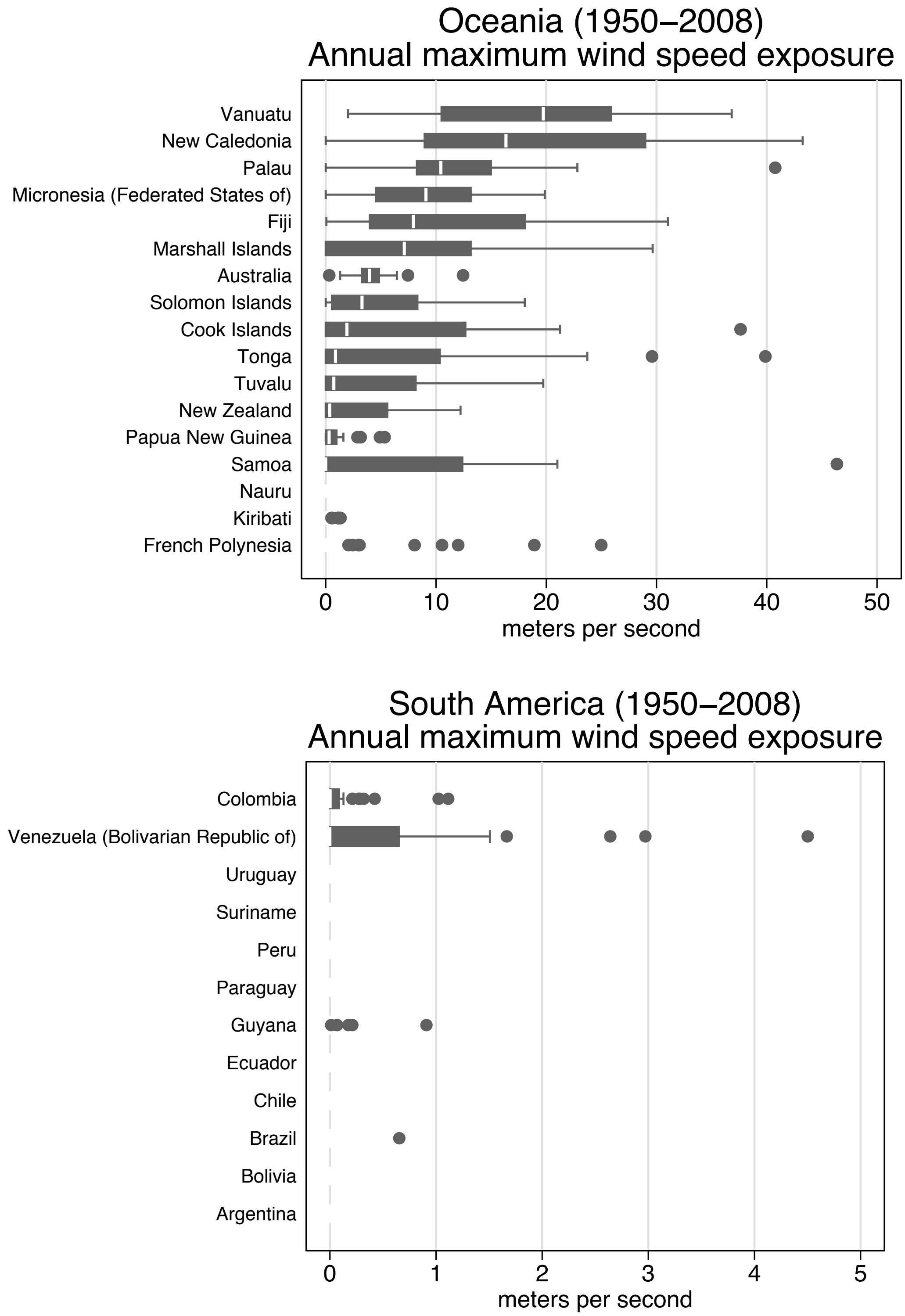


Figure 4.13: The distributions of country-by-year TC observations for Oceanian (top) and South American (bottom) countries. Boxes mark 25th-75th centile ranges and white bands mark medians.

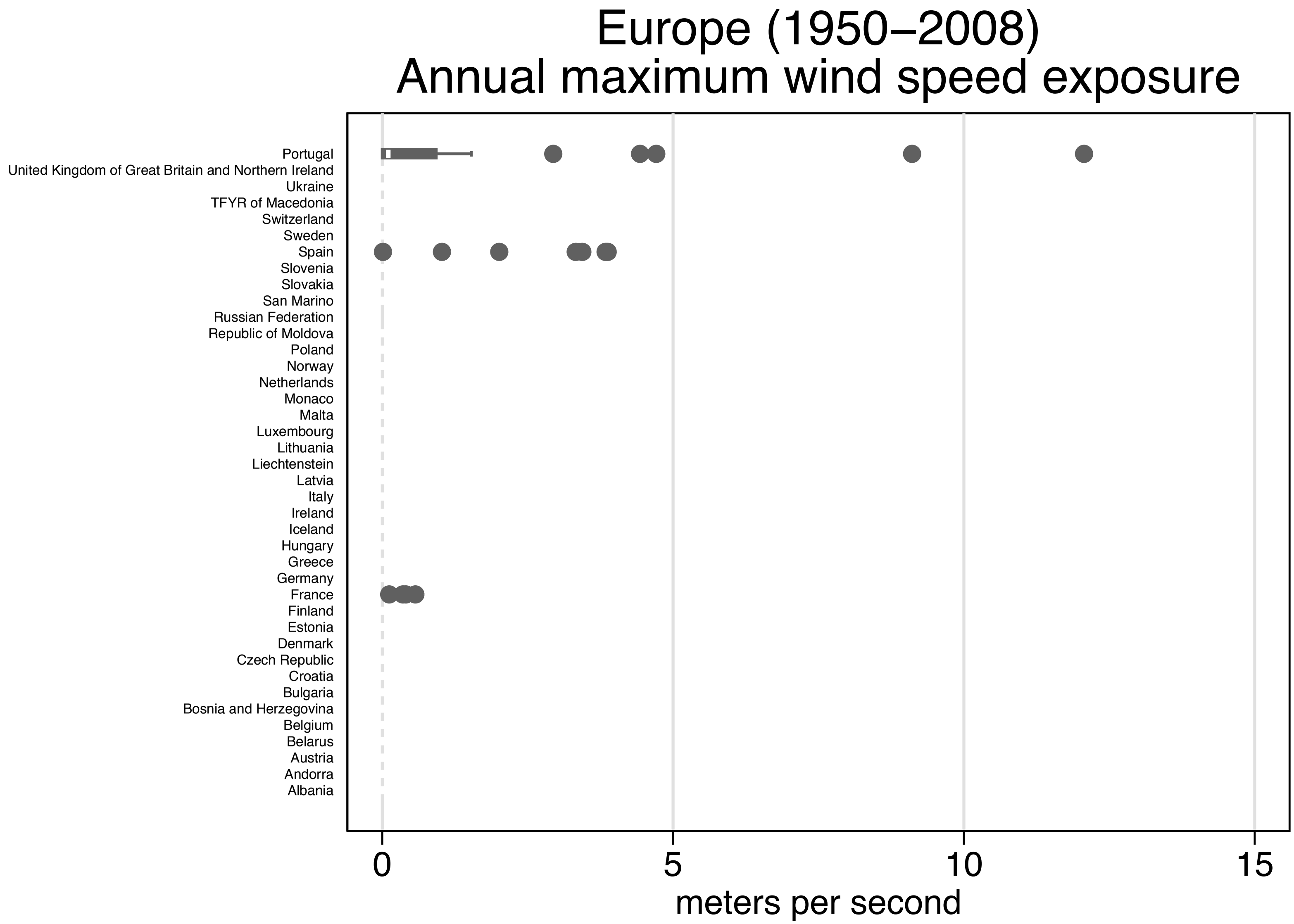


Figure 4.14: The distributions of country-by-year TC observations for European countries. Boxes mark 25th-75th centile ranges and white bands mark medians.

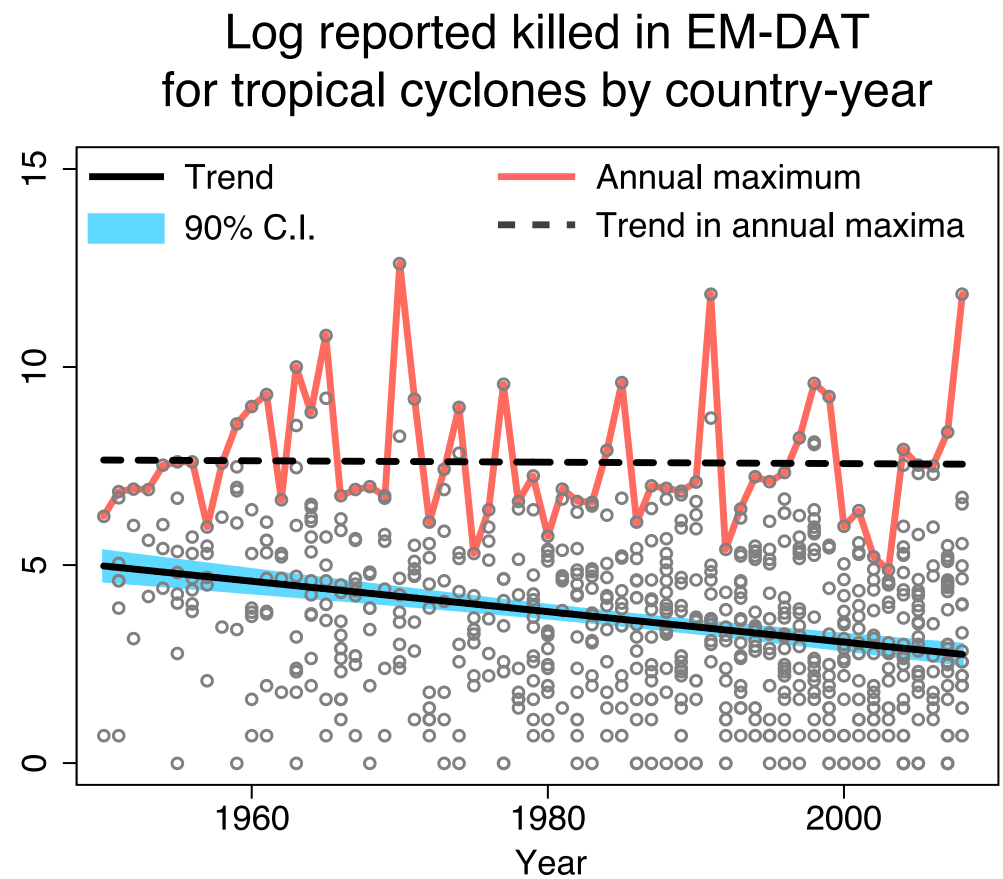


Figure 4.15: **Trends in EM-DAT deaths data.** The raw EM-DAT data on deaths from TCs show a strong trend (black line). However, without using data on physical measures of TCs, it is impossible to know whether this is due to adaptation to TCs, trends in TC exposure due to climatological changes or trends in reporting practices. The absence of a trend in the annual maximum (orange line) suggests that reporting biases may be important or that adaptation to extreme TCs is not effective (we find evidence for both in the main analysis).

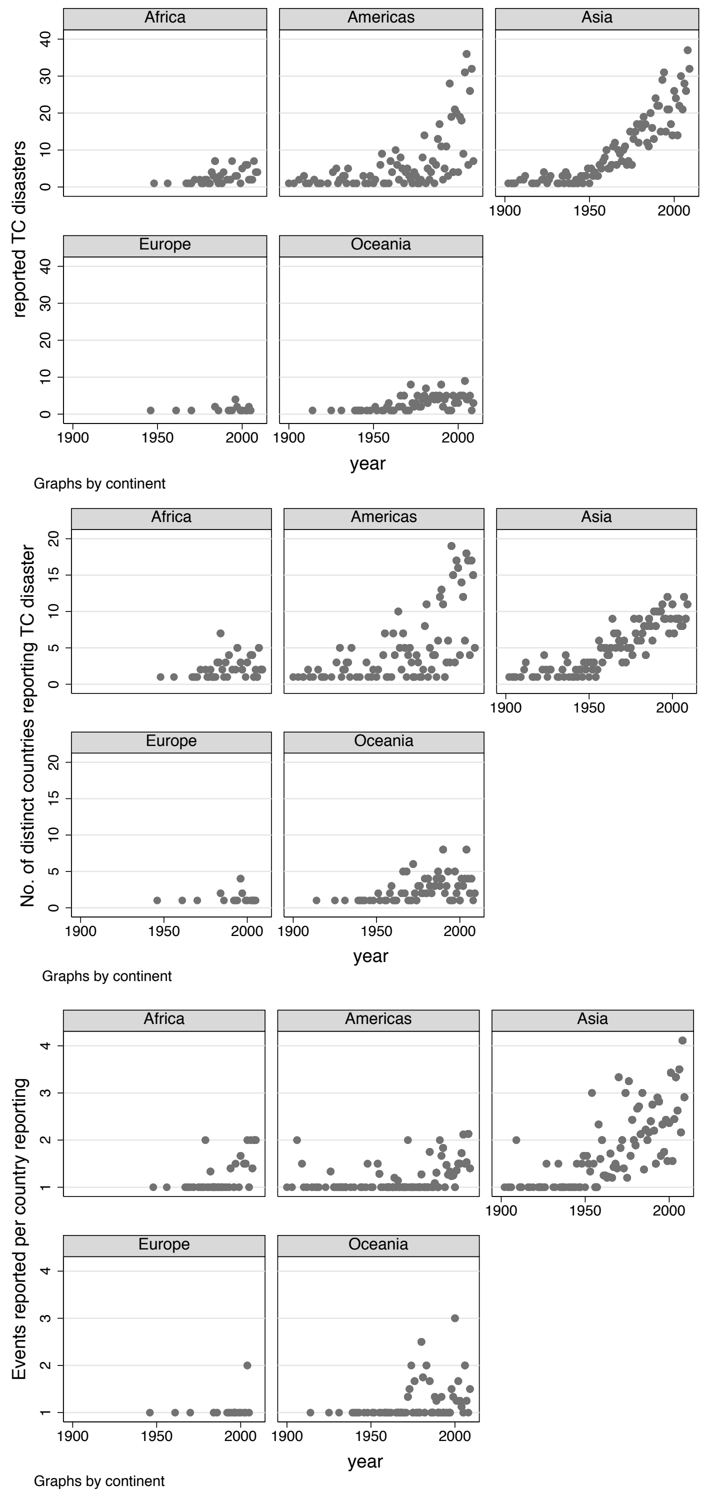


Figure 4.16: **Reporting biases in EM-DAT.** The reporting bias in EM-DAT (see Fig. 4.1D-E) is driven by trends in all continents (top). This is driven both by (1) trends in the number of countries reporting TCs (middle) and (2) trends in the number of TCs reported per reporting country (bottom).

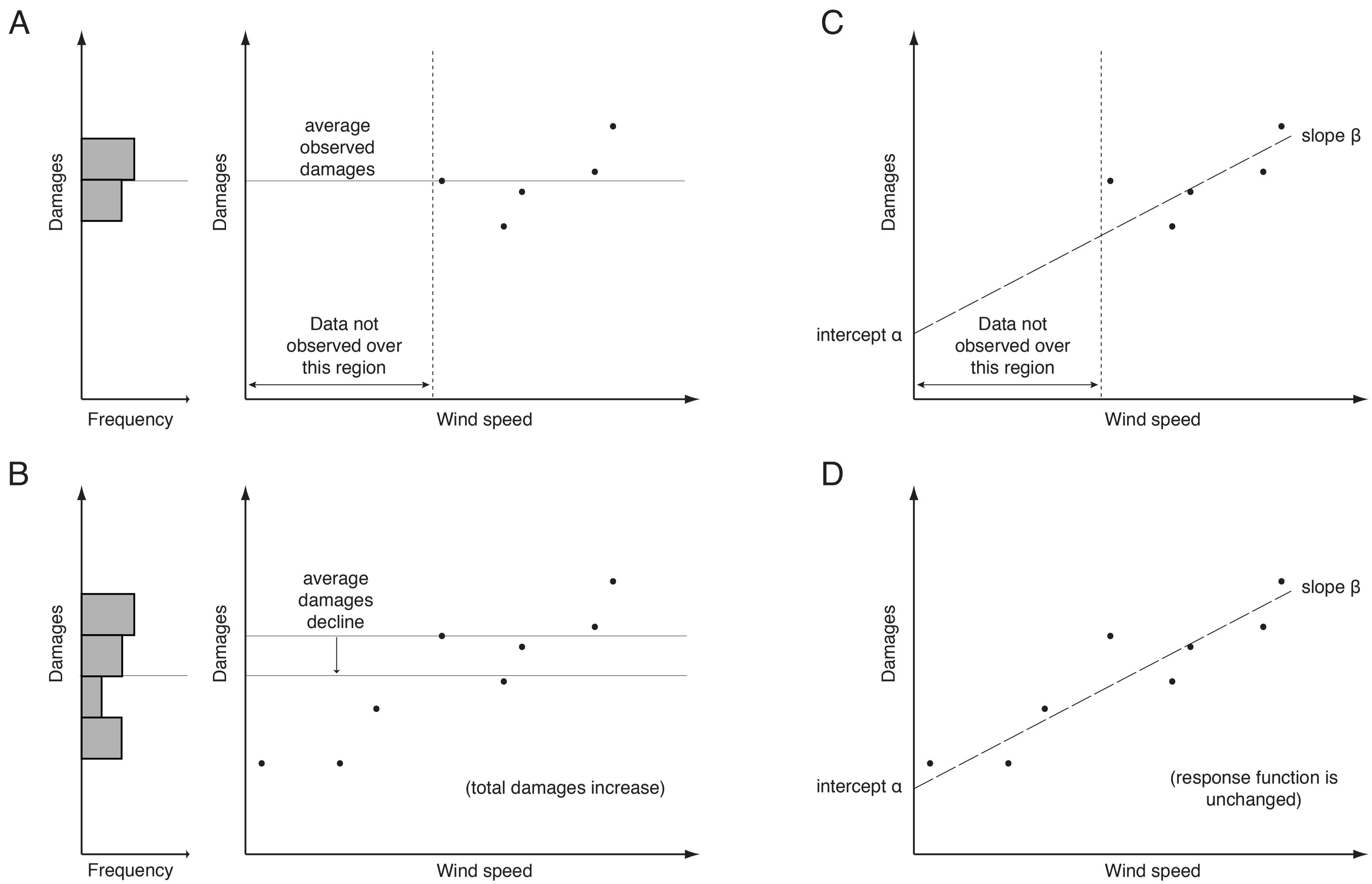


Figure 4.17: **Why does combining LICRICE to EM-DAT data allows us to estimate adaptation rates?** Fig. 4.1D shows that low intensity TC events have been reported in EM-DAT with increasing reliability. This counfounds estimates of adaptation if EM-DAT data is used alone but does not confound analysis if physical TC exposure is accounted for. Histograms display the marginal distribution of TC events described by EM-DAT when no information on windspeed is utilized. (A) If low wind speed events are not reliably reported, this raises the average TC damage recorded. (B) If all TC events are observed, average TC damages fall and total TC damage rises. (C) However, if we use information about TC intensity (eg. wind speed) the response of damages to exposure should not be affected by missing observations. (D) If vulnerability changes, we can observe it by estimating changes in intercept α and slope β over time.

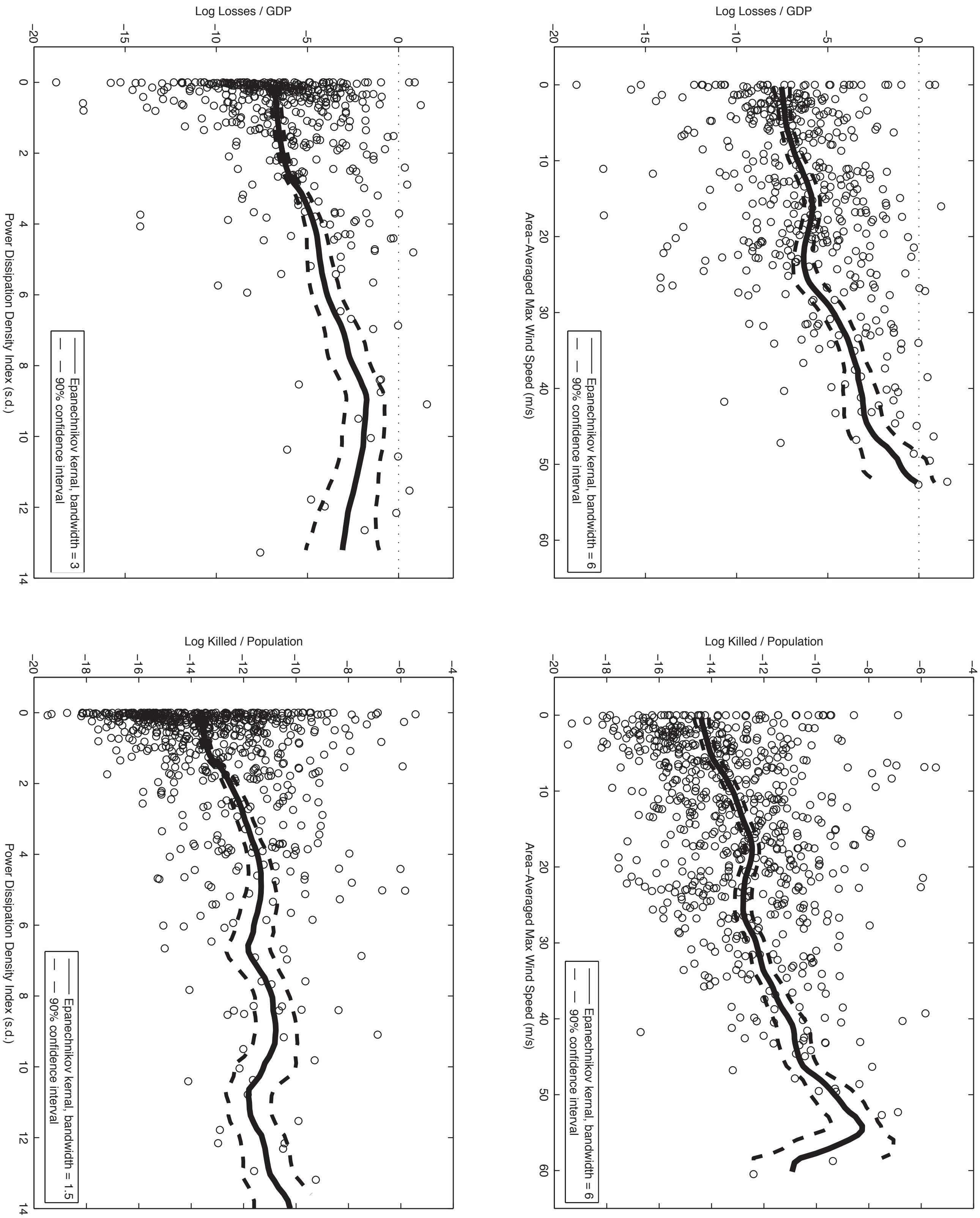


Figure 4.18: **Average deaths and damages from TCs.** Moving locally-weighted averages of normalized deaths and damages to TC wind speed and energy.

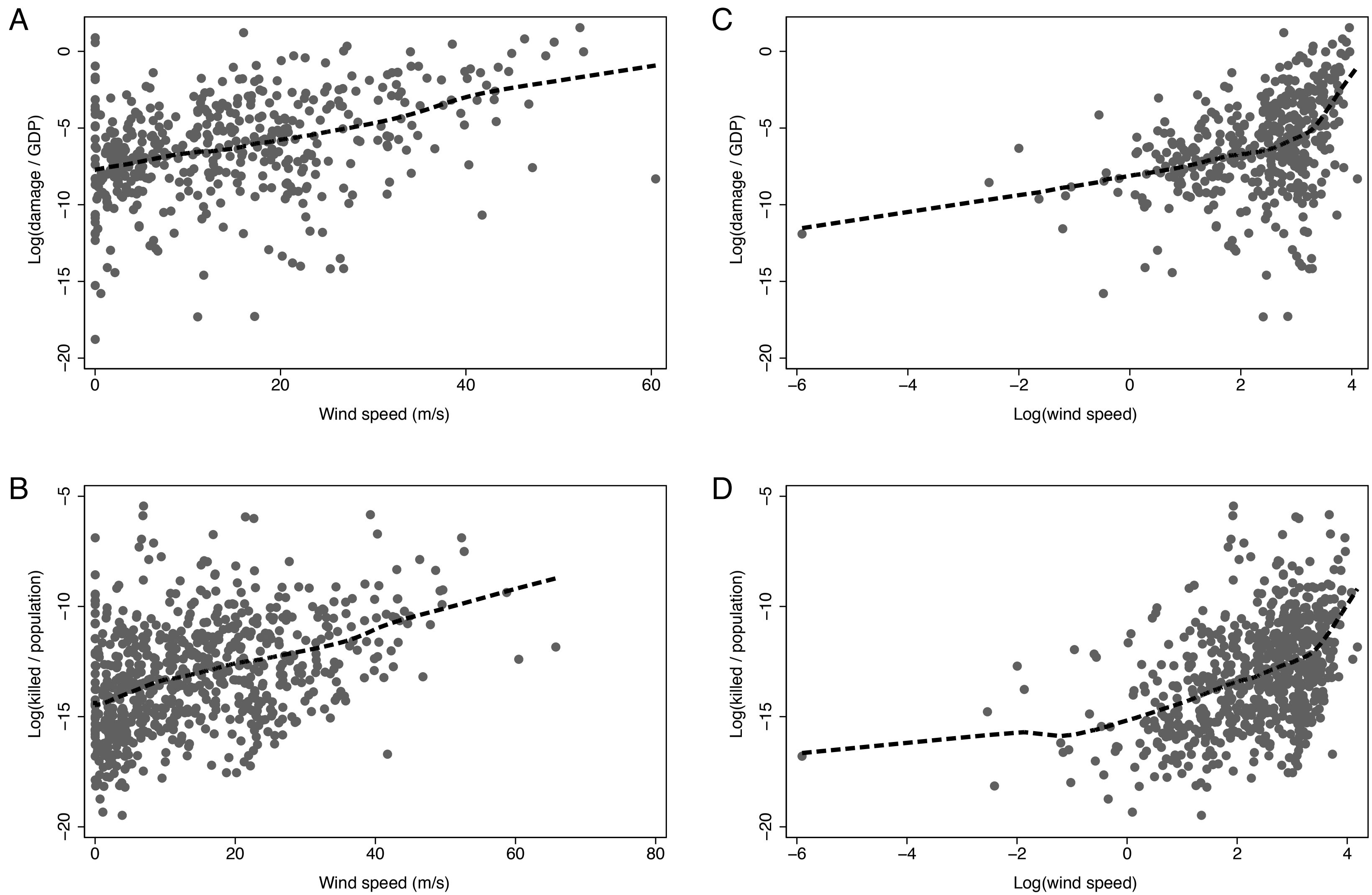


Figure 4.19: **Fitting a log-linear model instead of a log-log model.** Local linear regressions suggest that when using a linear fit, a log-linear model is probably more appropriate. (A) and (B) display fits of normalized damages and deaths against *wind_speed*. (C) and (D) display fits against $log(wind\_speed)$. Using $log(wind\_speed)$, as has been done in previous analysis [Mendelsohn et al., 2010], stretches the independant variable at very low values so that small cyclone events exert the most influence on regression coefficients.

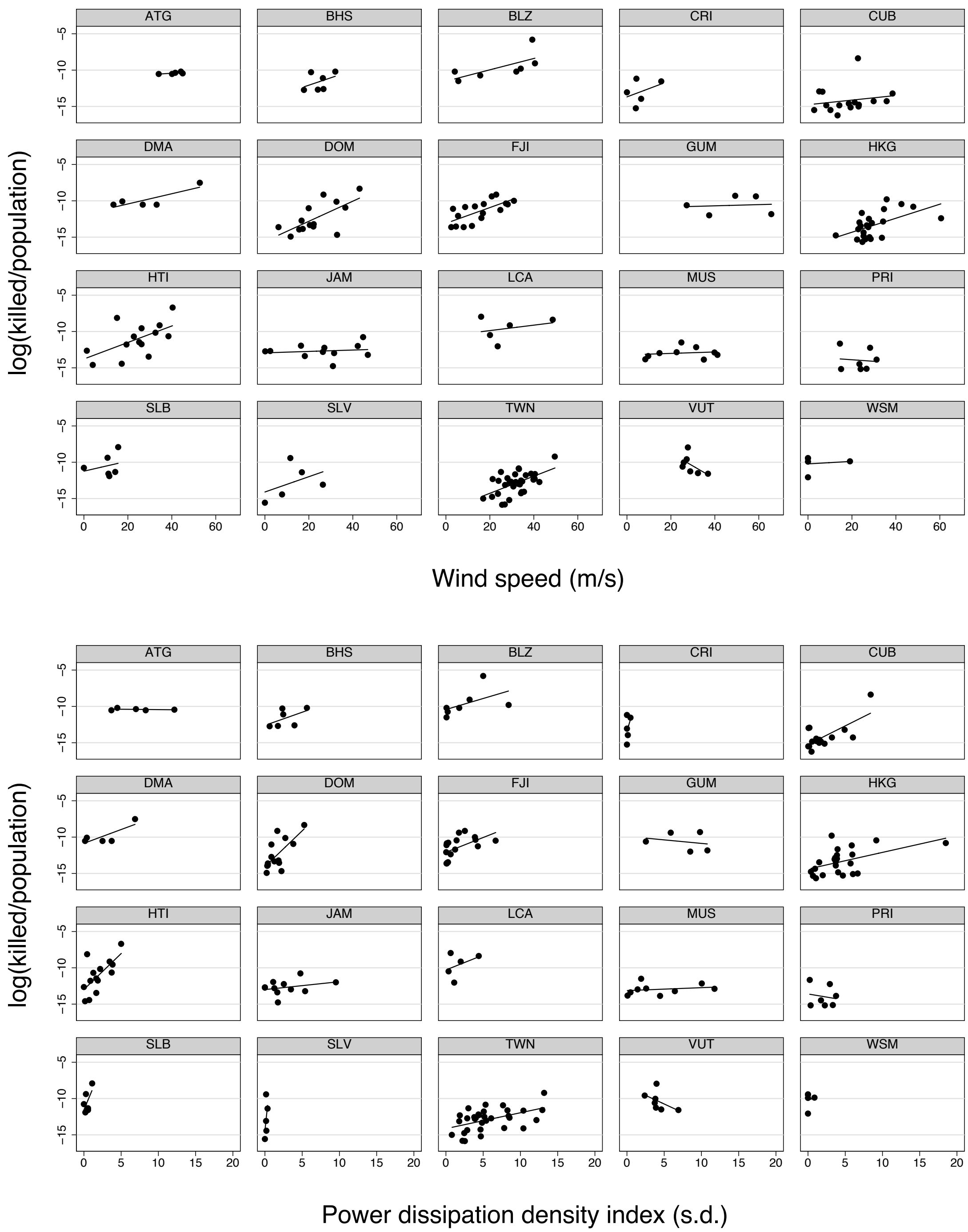


Figure 4.20: Country-level correlations between TC exposure and normalized deaths for small countries with at least 5 observations.

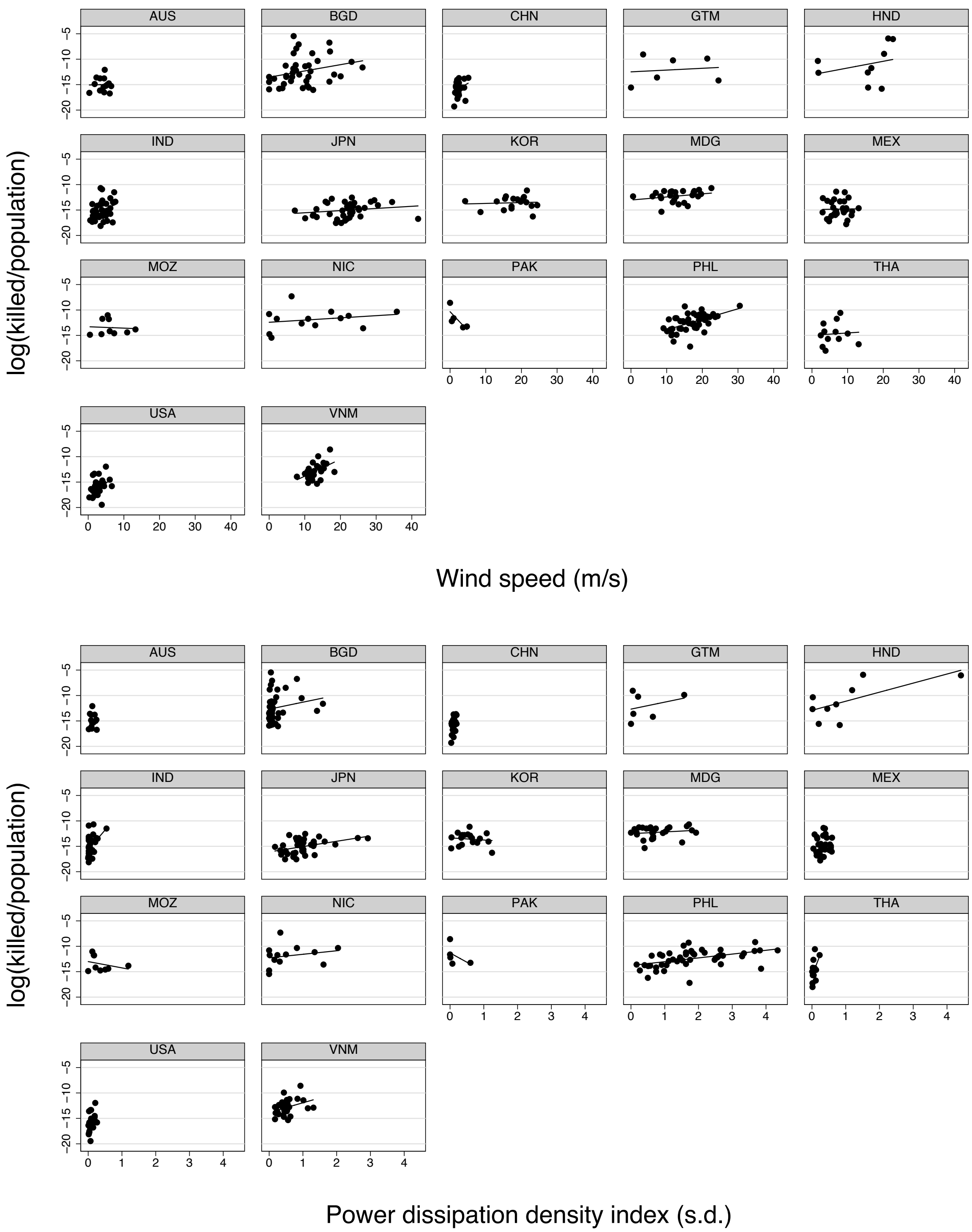


Figure 4.21: Country-level correlations between TC exposure and normalized deaths for large countries with at least 5 observations.

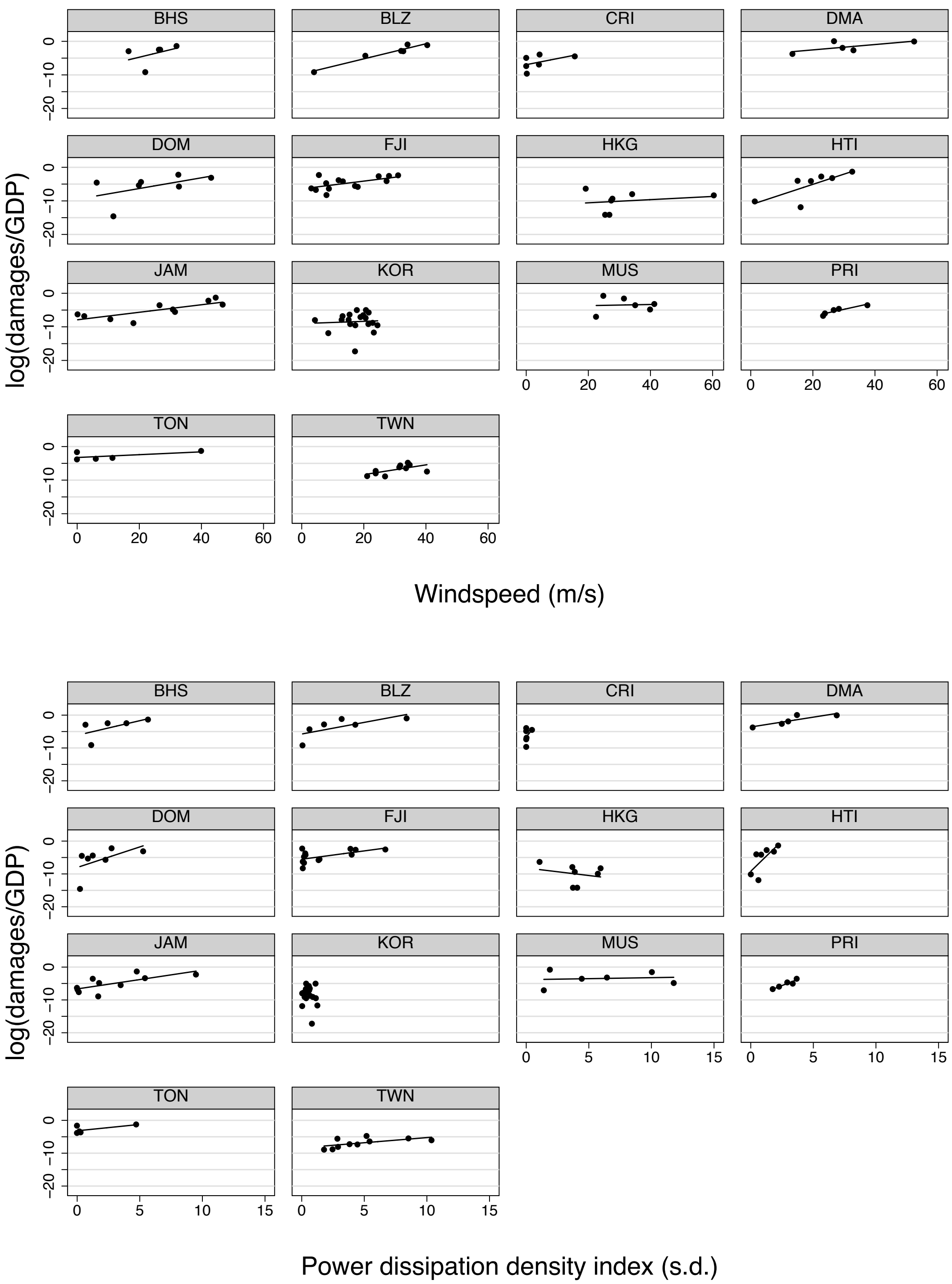
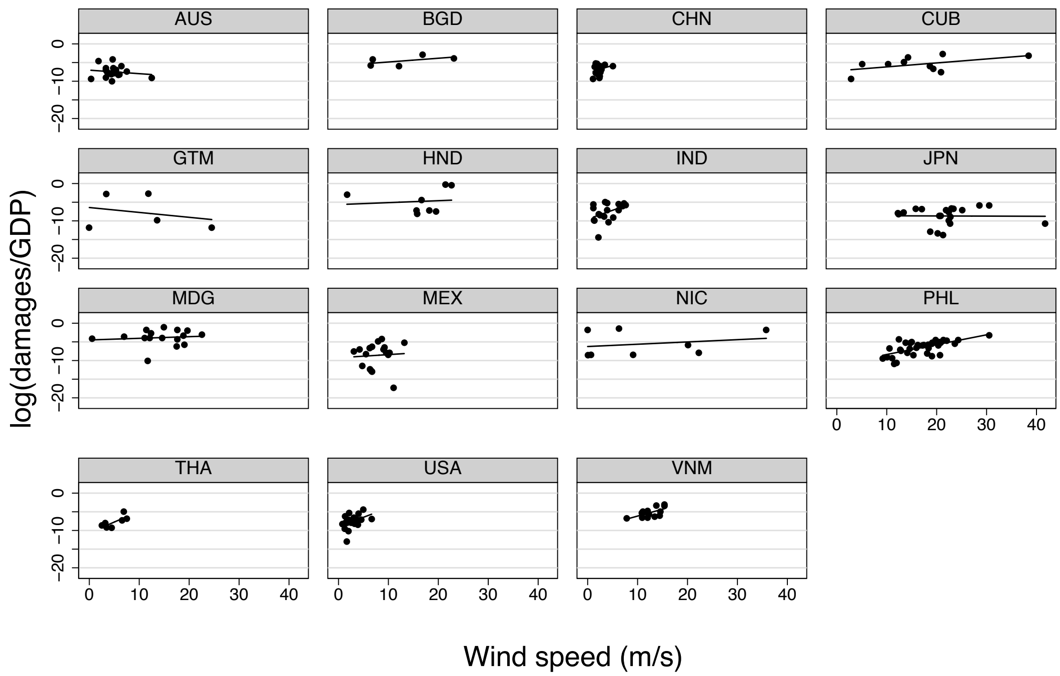


Figure 4.22: Country-level correlations between TC exposure and normalized damages for small countries with at least 5 observations.



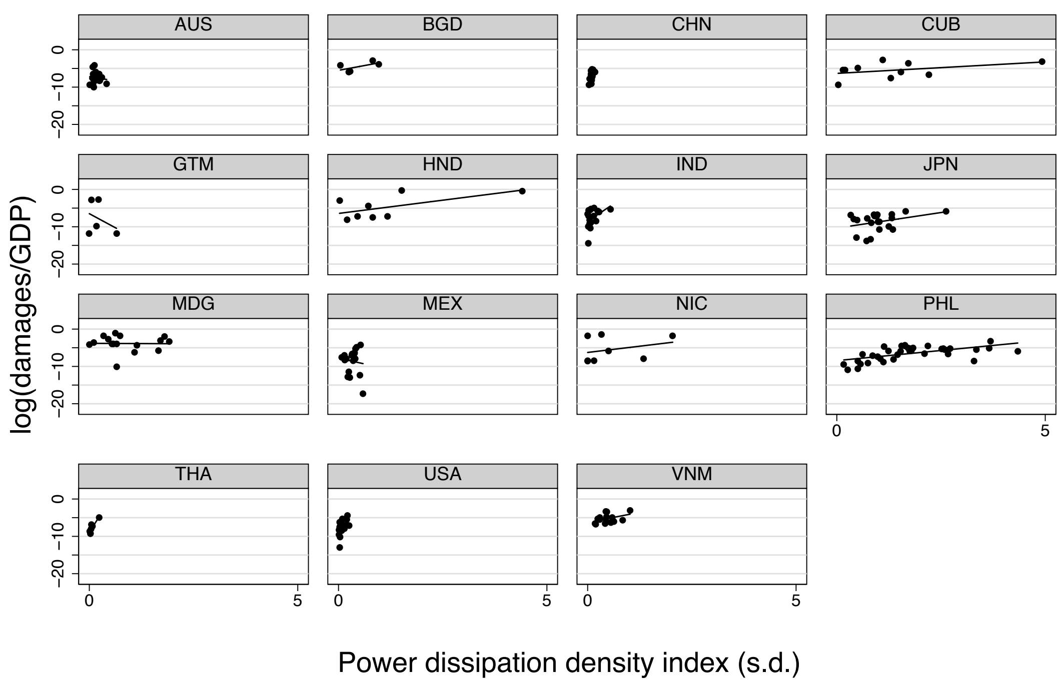


Figure 4.23: Country-level correlations between TC exposure and normalized damages for large countries with at least 5 observations.

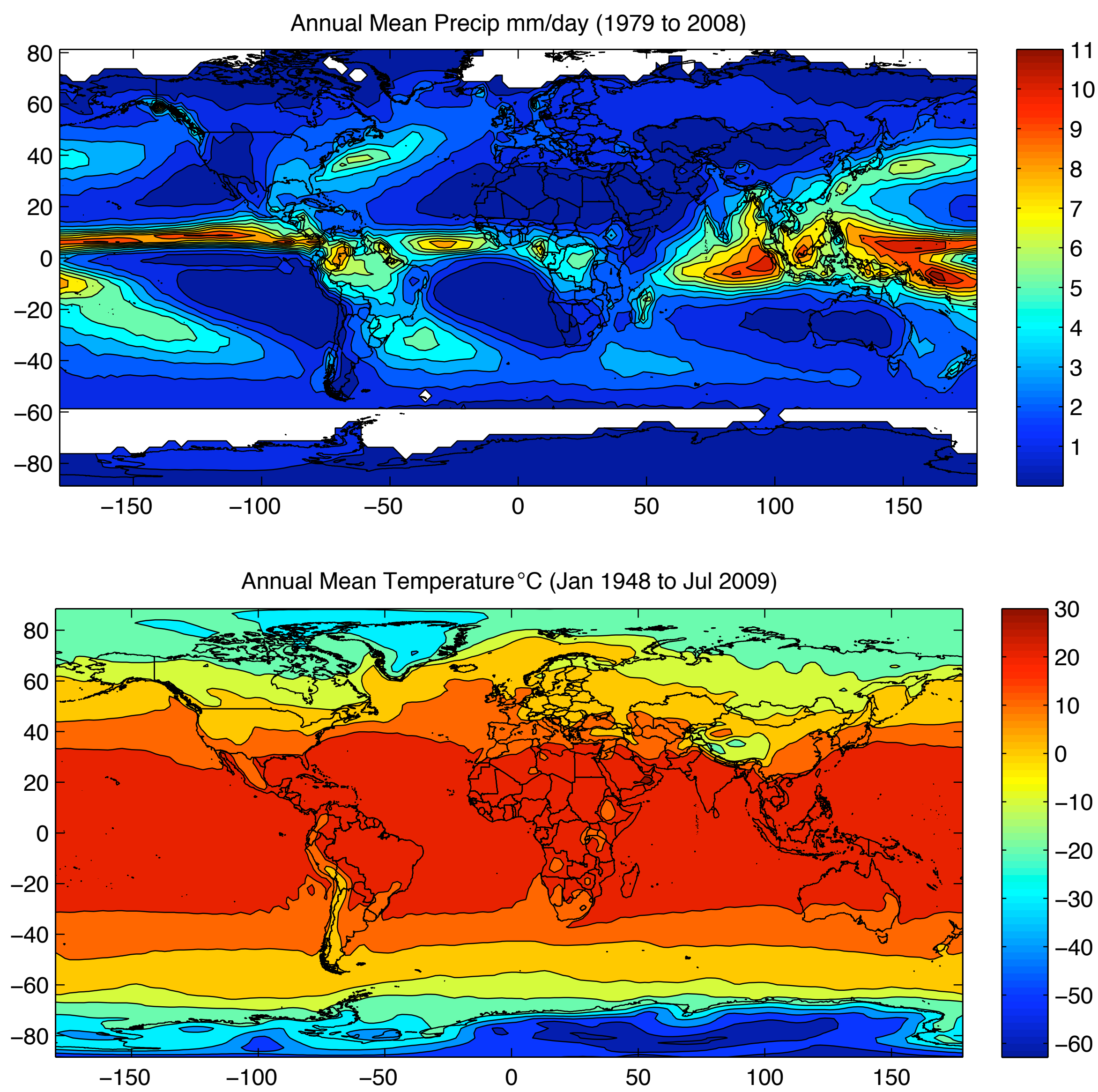


Figure 4.24: Average precipitation and temperature fields for the datasets that are used to generate control variables. Temperature and rainfall are spatially averaged over countries for each year.

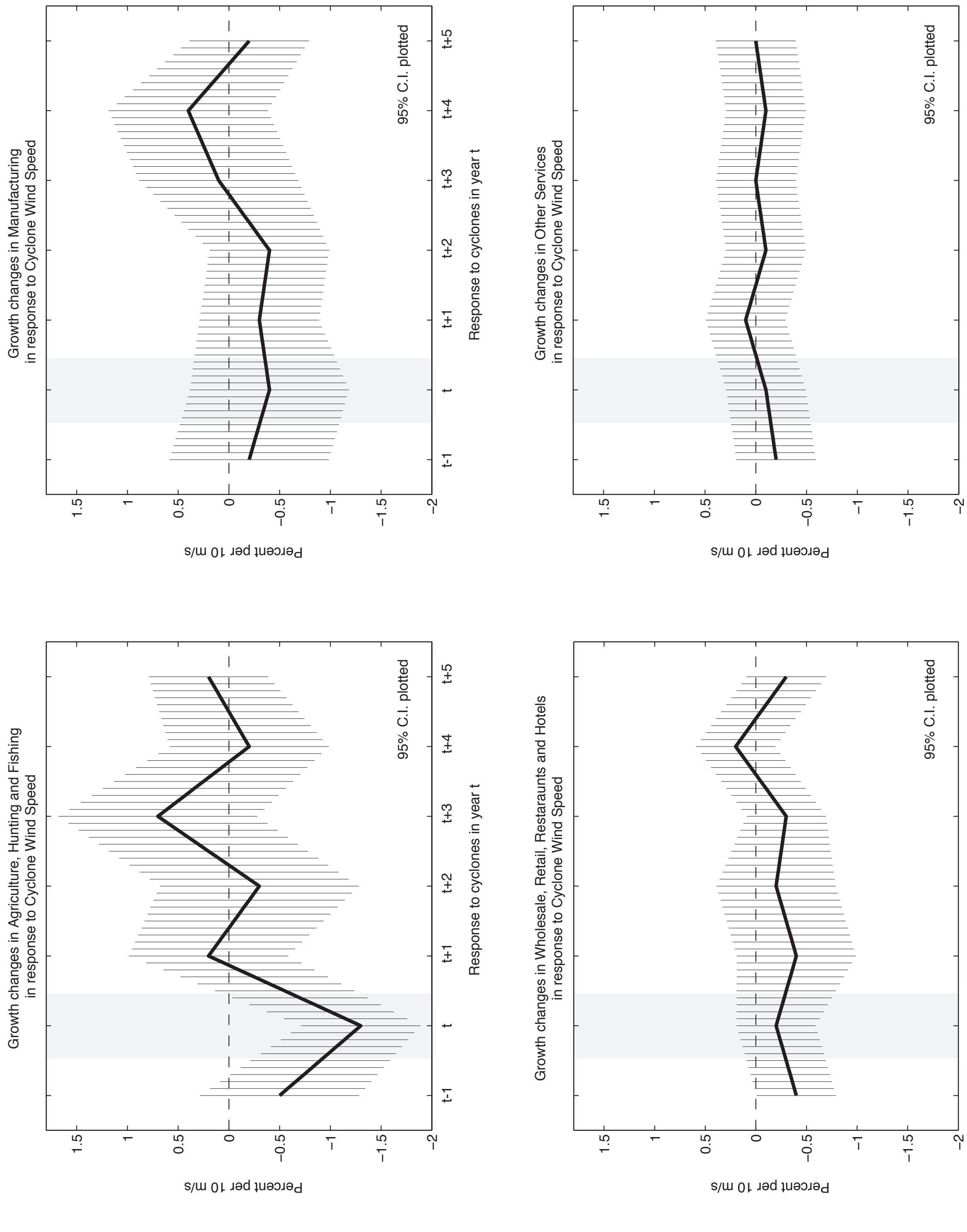


Figure 4.25: **Industry income growth in response to TC event in year** ***t*****.** Only agricultural income growth displays a large, statistically significant and globally pervasive response to TCs.

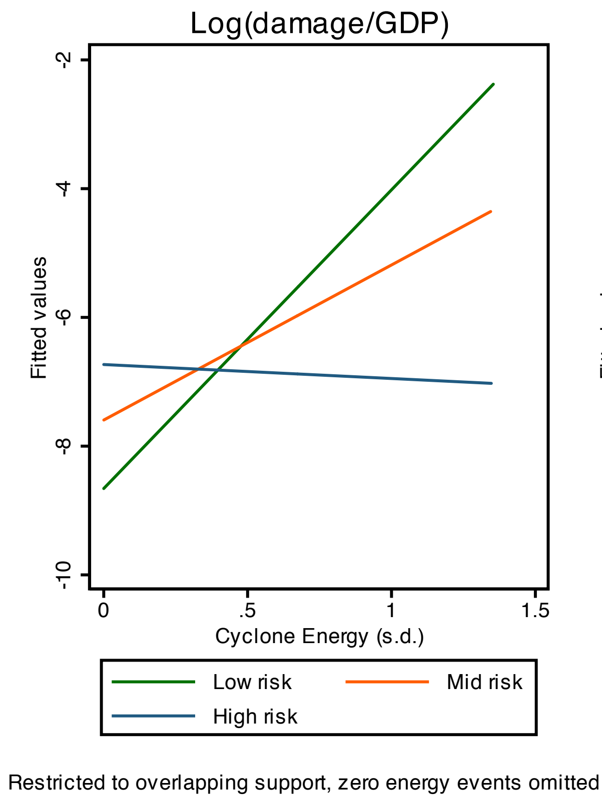


Figure 4.26: **Suggestive evidence that populations "adapt" to TCs.** We estimate the response of countries when they are stratified according to their average annual TC exposure. "High risk" countries are the third of countries reporting in EM-DAT with highest average TC exposure, "Low risk" countries are the third with lowest avarage TC exposure. Linear regressions are fit for only the range of TC exposures that are observed across all three groups. For countries with higher average exposure, the slope of the response functions are generally lower. We take this as suggestive evidence that populations facing more intense TC climates take steps to lower their risk through adaptation [Deschenes and Greenstone, 2007]. Note that we do not feel this plot provides conclusive evidence of this idea because high and low risk countries may differ in many other important ways that we may be unable to observe or measure.

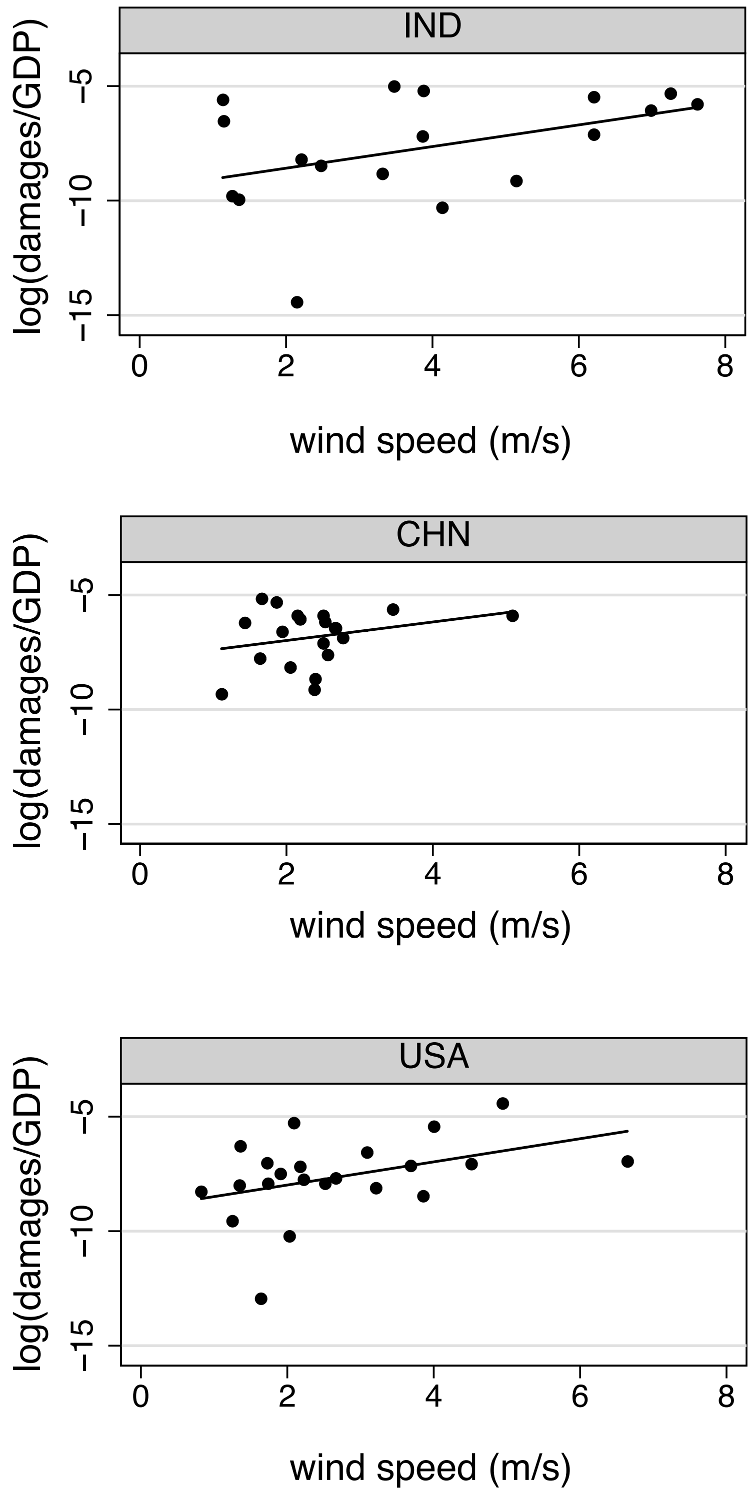


Figure 4.27: **Comparing the normalized damages of the USA with India and China.** In contrast to other wealthy nations (see Fig. 4.3F) The USA has a large response to TC exposure that more closely resembles the response of China and India.

Chapter 5

Global Economic Exposure to Future Temperature Changes

Solomon M. Hsiang[1]

[1]This chapter emerged from discussions and preliminary analyses with Lily Parshall, who I thank for her insight and support.

Abstract

In global-scale analyses of future climate change, "global average temperature change" is a commonly used summary statistic. Unfortunately, this statistic may not be useful for many types of economic analyses because it is an average over the planet's entire surface and is therefore dominated by changes over oceans and other uninhabited regions. Here, we attempt to summarize projected temperature changes in a manner that is more useful for economic analyses: we construct the distributions of future temperature exposure for a randomly selected person, a random hectare of cropland, and a random dollar of value-added. Our results streamline global cost analyses, enabling future studies to estimate global losses by combining their locally derived loss-functions with our estimates of global exposure. We demonstrate this application by estimating that low and middle income populations may suffer income losses of 9% annually due only to the effects of thermal stress on workers, a mechanism previously omitted from global cost estimates. In ancillary findings, we also document that (1) when exposure distributions are substituted for global average temperature change in standard models of economic costs, projected annual losses increase by trillions of dollars; (2) low and middle income populations will be twice as exposed to harmful temperatures as high income populations, based only on their locations; and (3) it is unlikely the direct effects of warming can have a positive net impact on the global economy.

5.1 Introduction

"Change in global average surface temperature" is a summary statistic that emerges naturally from simple and elegant theoretical models of the Earth's climate. Following these theoretical models, the more complex and less elegant computational models of the climate are made to produce the same summary statistic in an an effort to inform global climate policies. While this statistic may be a useful summary for climate modelers, it is less useful for economic and policy analysts. The objective of this analysis is to repackage the temperature changes predicted by 20 modern climate models in a simple way that can be immediately applied to policy analysis.

At the core of all climate policy analysis is the idea the climate changes may incur costs (or benefits) to society. However the global impacts of climate changes are still poorly understood. While many recent empirical studies have begun to estimate the direct impact that temperatures have on particular social outcomes, it has remained difficult to conceptualize the magnitude of these impacts at the planetary scale. For example, though recent studies indicate that workers exposed to high temperatures are less productive [Graff Zivin and Neidell, 2010, Hsiang, 2010], it is not clear whether this impact should be large or trivial on a global scale [Tol, 2009], in part because we lack global estimates for the future exposure of workers to high temperatures. It is difficult to estimate the magnitude of this and other effects because the climate change statistics that climate modelers "hand off" to economic analysts are not structured to describe economic exposure.

Climate models report average temperature changes over space: temperature changes are estimated for every square kilometer of the planet and the global average is taken. If workers, croplands and capital were uniformly distributed over the planet, then this global average would correspond well with the average exposure of the global economy. However, most of the planet is covered by oceans, ice caps, mountains and deserts; regions that strongly influence climate change statistics but contain few or no inhabitants. Thus, to construct global summary statistics more useful for economic analysis, we use detailed data on the spatial distribution of people, croplands and output to estimate the direct exposure of economic activity to temperature changes.

Estimating economic exposure to climate changes is only one step in a long sequence that is needed to understand how these global changes will impact societies around the world. A massive number of climate scientists have constructed detailed and complex models that predict future temperature changes [IPCC, 2007, Meehl et al., 2007] and a growing number of econometricians have analyzed how local temperature changes have impacted economic outcomes at a national or subnational scale

[Deschenes and Moretti, 2009, Schlenker and Roberts, 2009, Deschenes et al., 2009, Dell et al., 2009a, Albouy et al., 2010, Schlenker and Lobell, 2010, Welch et al., 2010, Hsiang, 2010, Graff Zivin and Neidell, 2010, Deschenes et al., 2011]. This study links these two research groups by transforming output from the climate projections into useful input for econometric estimates. By enabling economists to project their local estimates onto the global scale we hope to streamline much needed research on the global costs of climate change.

For planetary-scale estimates, our understanding of the cost of climate change is dominated by "integrated assessments" [Tol, 2009]. Yet, these studies continue to have difficulty describing how climate changes translate into economic losses. In their seminal book, [Nordhaus and Boyer, 2000] described the challenge:

> It must be emphasized that attempts to estimate the impacts of climate change continue to be highly speculative. Outside of agriculture and sea-level rise for a small number of countries, the number of scholarly studies on the economic impacts of climate change remains small. Estimates of the regional climatic impacts of global warming are still inconsistent across different climate models, and economic studies have made little progress in estimating impacts, particularly in low-income countries. Much more work is needed to improve understanding of the impacts of climate change. (p. 98)

Despite these challenges, the desire to produce a precise number forced the authors to postulate a relationship between the climate and warming:

> For the purpose of this book, it is assumed that there is a relationship between the damage from greenhouse warming and the extent of warming. More specifically, the relationship between global-temperature increase [ΔT] and income loss [D] is given by:
>
> $$D = \theta_1 \Delta T + \theta_2 \Delta T^2$$
>
> (p. 23)

After almost another decade of research, [Nordhaus, 2008] revisited this issue, expressing little confidence in research advances made since his earlier evaluation

> It is clear that this [damage function] is extremely conjectural, given the thin base of empirical studies on which it rests. (p. 42)

In an attempt to address these concerns, we have designed a characterization of economic exposure that is easy and practical for other researchers to use. It is our hope that when econometricians discover new mechanisms through which temperature affects economic activity (eg. labor productivity, [Graff Zivin and Neidell, 2010, Hsiang, 2010]), they can use our characterization to quickly update these highly uncertain global damage functions.

We feel that a practical summary of future temperature changes (that is designed for global economic analysis) should satisfy the following criteria.

1. It should be global in scale.
2. It should be as simple as possible.
3. It should summarize output from all of our climate simulations.
4. It should respect our understanding that temperature impacts economies through multiple mechanisms (eg. health, agriculture or labor).
5. It should respect our understanding that different populations may be better able to adapt to temperature changes (eg. use air conditioning or irrigate crops).
6. It should respect the notion that changes in temperature and the level of temperature exposure may both impact economic outcomes.
7. It should describe changes that we expect to observe before 2100, rather than focusing on the extremely distant future.

This study attempts to meet all these criteria when summarizing future temperature changes. Though it is clearly limited in scope and simplified, we only attempt to estimate direct exposure to temperature changes and omit indirect impacts. For example, temperature changes will influence ecosystems in ways that will affect economic outcomes; however these pathways are not accounted for in this analysis. Furthermore, there are many environmental variables other than temperature whose distributions will change with the global climate (eg. precipitation, humidity, clouds, winds, etc.) and none of these variables are accounted for in this study. Rather than a comprehensive analysis of all climate changes, this study is a first attempt to translate a single output from the physical sciences into a useful input for the social sciences[2].

[2] Of course, if this analysis proves useful, we hope that additional analyses will follow and improve on this simple methodology.

In the remainder of this paper, we describe our method and data and then present changes in exposure based on temperature changes and absolute temperature levels. We conclude with an example of how these results can be used to extend local analyses to the planetary scale (we estimate global economic losses resulting from reduced worker productivity [Hsiang, 2010]) and some important caveats.

5.2 Approach

The approach of this analysis is to estimate how future temperature changes project onto the distribution of three types of "economic units": people, croplands and economic output (dollars of value added). To do this, we first fix the locations of these economic units in the year 2000. We then imagine that we randomly select an economic unit at random (eg. a random person our of the 6-billion alive in 2000). Holding the location of that economic unit fixed, we then record the temperature changes that would occur at that location. By repeating this for all economic units (eg. all 6-billion people), this procedure generates a distribution of exposure for all economic units of a certain type. We then normalize this distribution by the total number of economic units in 2000 so that it integrates to unity. The resulting distribution is a probability density function (PDF) that describes the distribution of exposure one would expect to observe if a random person, a random hectare of cropland or a random dollar of output was drawn randomly from the universe of units in 2000. We elect not to use projections of future economic units because this would introduce another dimension of unquantifiable uncertainty, because projections of croplands and economic activity are not readily available, and because our PDF is a reasonable approximation for future exposure if growth in these economic units is not spatially correlated with changes in temperature[3].

[3] In a formal sense, if one thinks of human exposure (H) to temperature (T) as $H \times T$ (for a specific location), then changes in this quantity can be approximated by a Taylor series

$$\Delta[HT] = H\Delta T + T\Delta H + \Delta T\Delta H + ...$$

We choose to focus only on this first term, the change in temperature holding the distribution of humans (or other economic units) fixed. The second term is the change in population projected on the modern temperature distribution and the third term is the change in temperature projected on changes in population. Because the second term does not relate directly to climate changes and the third term is "second order", the first term is the focus of our analysis. However, to further prevent this approximation from distorting our summary statistics, we normalize by population

$$\begin{aligned}\frac{\Delta[HT]}{H} &= \frac{H\Delta T}{H} + \frac{T\Delta H}{H} + \frac{\Delta T\Delta H}{H} + ... \\ &\approx \Delta T\end{aligned}$$

where the second equality holds if $\frac{\Delta H}{H}$ is small. This approximation (for climate-driven changes) behaves poorly only when locations' temperature changes are correlated with their population growth rates, causing the term $\frac{\Delta T\Delta H}{H}$ to be large. However, if population growth is relatively uniform over regions with different temperature changes, than our

We consider the A1B climate change scenario that has been simulated by many modeling groups and describes climate changes when greenhouse gas emissions are only mitigated slightly. We focus on changes in temperature experienced during the transition between stable climate states, taking the difference between average climates in the distant future (2080-2099) and the immediate future (2011-2030). We do not use historical climatologies as our baseline because we wish to focus on patterns associated with tansitions in the global climate where mean temperature is increasing approximately linearly, since our results may then be easier to generalize across different scenarios.

We evaluate annual and monthly climatologies for the two averaging periods, using data from 20 general circulation models (GCMs). We treat the models as each having an equal probability that it is "correct" because this approach has been shown to outperform any individual model [Reichler and Kim, 2008, Auffhammer et al., 2010]. Predictions from each model are overlaid onto the global distribution of economic units and the distribution of temperature changes are separately computed for people (ΔT_p), croplands (ΔT_c) and output (ΔT_y). These distributions are then averaged across models.

The A1B scenario leads to a 2.0°C increase in average surface temperature (ΔT_a) between 2011-2030 and 2080-2099. Because we focus only on transient climate states, it might be reasonable to interpolate or extrapolate our results to slightly smaller or larger changes in global average temperature, however this should be done with caution and with the recognition that it is an approximation.

5.3 Data

Temperature Twenty temperature projections for the A1B scenario are obtained from the Fourth Assessment Report of the International Panel on Climate Change [IPCC, 2007, Meehl et al., 2007]. Each projection is the mean reconstruction using multiple ensemble members and model outputs vary in spatial resolution (see [Meehl et al., 2007] for details). The annual mean temperature change averaged across all models is shown in Fig. 5.1A.

summary statistics will be a fair approximation for climate-driven changes in temperature exposure.

Note that if there are large migrations induced by climate, this may also cause our approximation to behave poorly. We discuss this issue in Section 5.6.

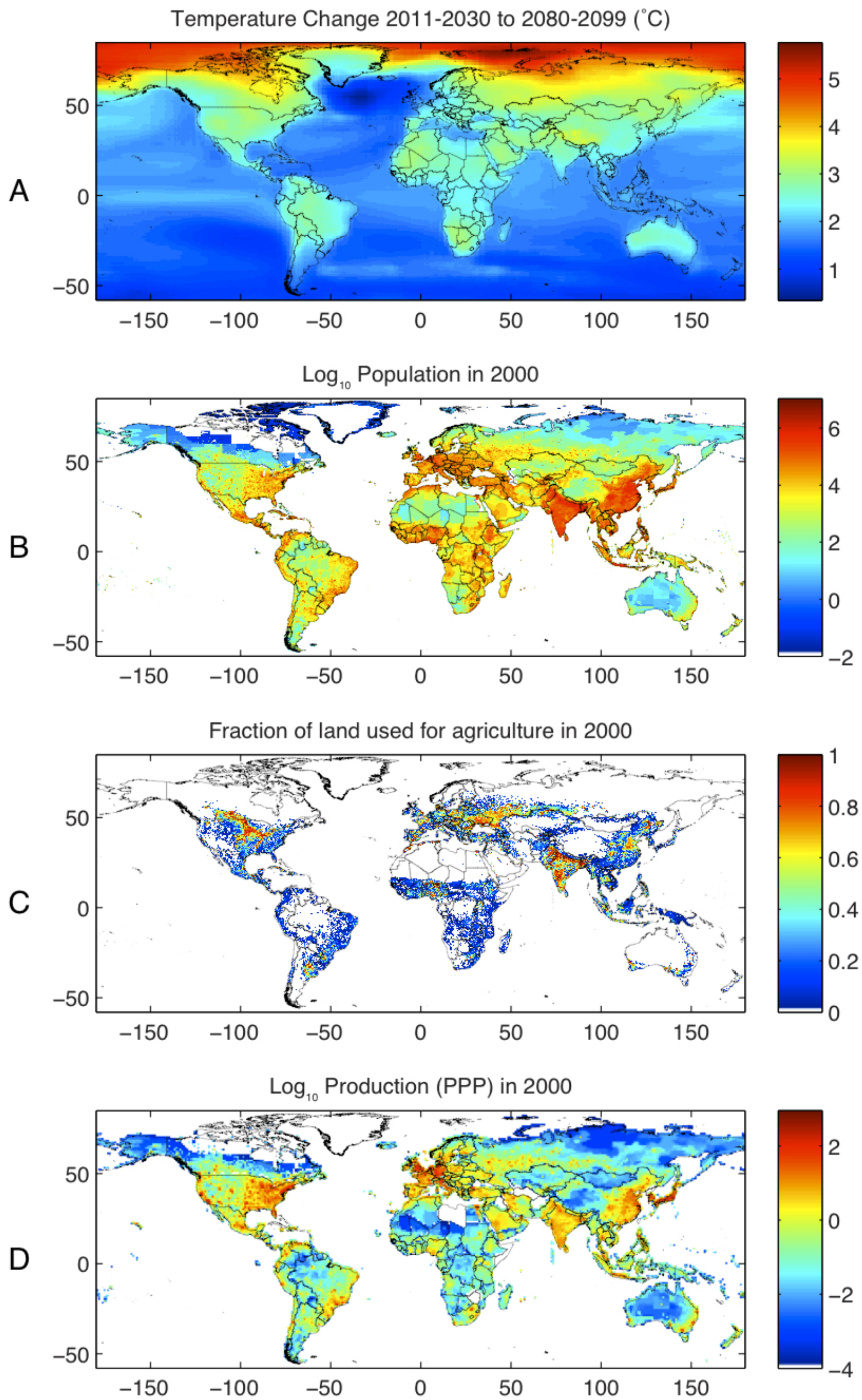


Figure 5.1: **The global distributions of temperature changes and economic units.** (A) Changes in annual mean surface temperature [°C] between 2011-2030 and 2080-2099 averaged across 20 GCMS in the A1B scenario. (B) The distribution of the global population in 2000. (C) Same, for croplands. (D) Same, for economic output (value added).

Population We obtain the distribution of the global population in 2000 from the Gridded Population of the World (GPW) files (version 3) produced by the Center for International Earth Science Information Network at Columbia University [CIESIN, 2009]. Subnational census data are georeferenced and adjusted to match United Nations estimates. The distribution of the global population is plotted in Fig. 5.1B.

Croplands The global distribution of croplands in 2000 are obtained from the high resolution global land use files produced by the Center for Sustainability and the Global Environment at University of Wisconsin-Madison [Ramankutty et al., 2008]. This dataset integrates satellite observations from two satellite missions and subnational agricultural census data. The fraction of land dedicated to croplands are displayed in Fig. 5.1C.

Production The distribution of economic output in 2000 is obtained from the G-Econ (version 3.4) files produced by William Nordhaus's research group at Yale University [Nordhaus, 2006b]. Subnational production statistics are georeferenced and converted to purchasing power parity (PPP). In some cases, the GPW files are used to scale production within countries, so the construction of this dataset is not entirely independent from the data described above. The distribution of total economic output is shown in Fig. 5.1D.

Income distribution Because low income populations may have greater difficulty adapting to temperature changes, it is important to consider whether populations with lower income are differentially exposed to larger or smaller changes. We know of no global dataset that disaggregates the global population by income and location at the subnational level, so we construct one by combining the GPW files with the income distributions of each country in 2000, as estimated by Sala-i-Martin [Sala-i Martin, 2006] (see Fig. 5.10 for the global distribution of income). For a population at a given location within a country, the distribution of incomes are assumed to mirror the country's income distribution. The global population is then stratified into thirds according to income[4]. The resulting distribution of high, middle and low income individuals are shown in Figs. 5.2A-C respectively.

[4] We only separate the global population at two income cutoffs (low-middle and middle-top). Therefore, if we generate errors in our assignment of individuals to income groups, it should only affect the few individuals in the vicinity of those cutoffs.

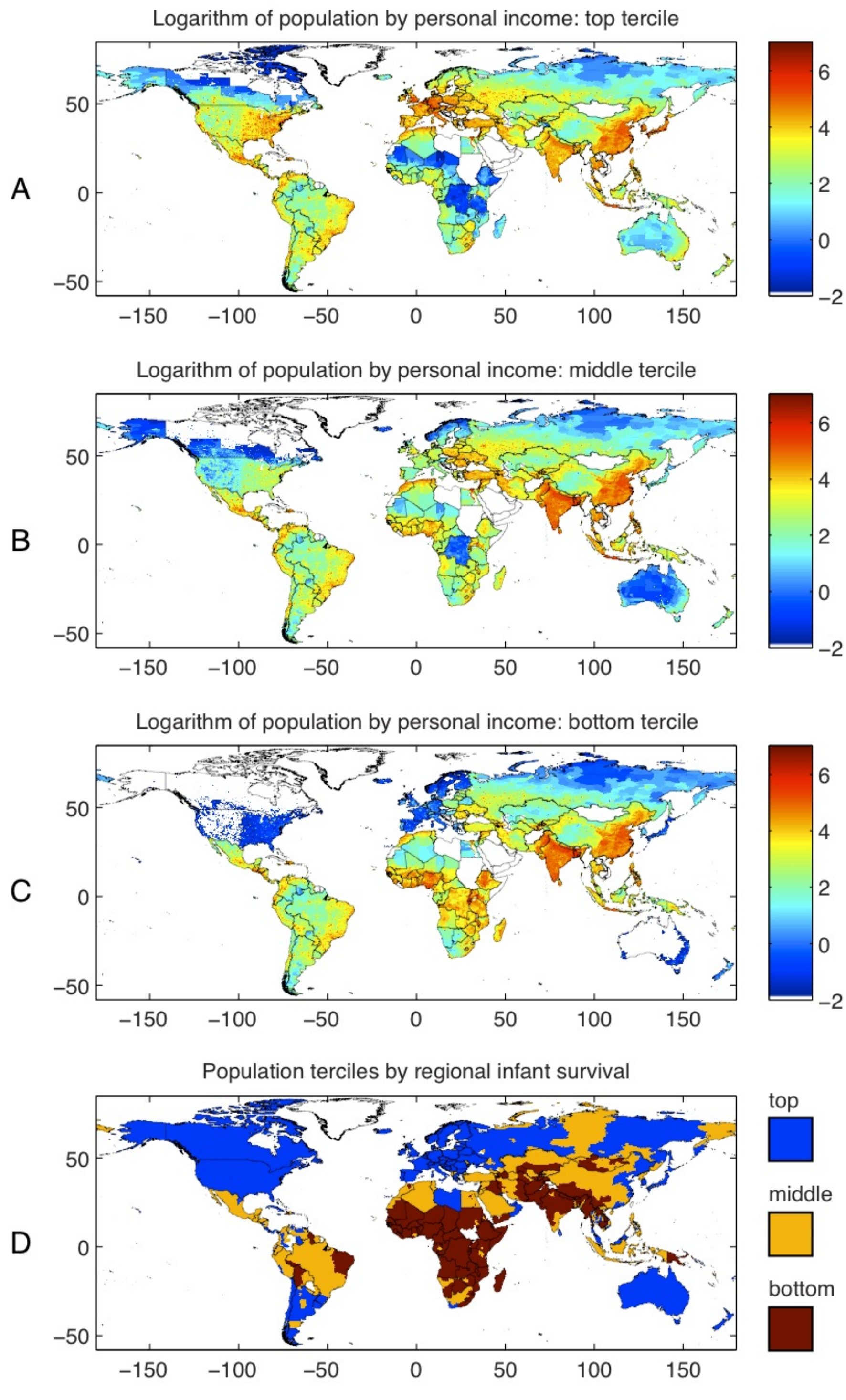


Figure 5.2: **The global distribution of income terciles and infant survival terciles.** (A) Distribution of the wealthiest third of the world by personal income in 2000. (B) Same, but middle third by personal income. (C) Same, but poorest third by personal income. (D) Distribution of population thirds according to infant survival rates.

Infant survival Because the extent of public infrastructure and governance capacity may also affect the ability of populations to adapt to temperature changes, we use infant survival rates[5] as a proxy measure for these variables. We obtain infant survival rates from the World Development Indicators files [World Bank, 2008], which integrate subnational health surveys and census data. We partition the population distribution from the GPW files into thirds according to their district's infant survival rate[6]. The distribution of infant survival rates are displayed in Fig. 5.2D.

5.4 Results

Economic damages from climate change (D) are often modeled as independent of the initial temperature at a location and scaling only with the magnitude of changes in mean temperature ($\bar{T}$) [Stern, 2006, Tol, 2009, Dell et al., 2009b]:

$$D = g(\Delta\bar{T}). \tag{5.1}$$

The simplicity of this approach is appealing, however, recent studies suggest that some impacts may depend strongly on the initial temperature of a location, with output increasing or constant up to some optimal temperature and then declining [Schlenker and Roberts, 2009, Schlenker and Lobell, 2010, Welch et al., 2010, Deschenes et al., 2011, Hsiang, 2010, Albouy et al., 2010]. Total value generated by an economy (Y) is then the sum of all output produced over a temperature schedule (T_t):

$$Y = \int_t f(T_t)dt$$

Under this approach, damages are the difference between output under a climate change temperature schedule (T_t^c) and a counterfactual schedule in the absence of climate change (T_t^0):

$$D = -\int_t f(T_t^c) - f(T_t^0)dt \tag{5.2}$$

Thus, in order to support both of these modeling approaches, we first construct simple summaries of economic exposure using both changes in annual mean temperature ($\Delta\bar{T}$ for use in Eq. 5.1) and

[5] Infant survival rates are one minus infant mortality rates. Survival rates are used so that the top tercile in infant survival corresponds roughly with the top tercile in income.

[6] Different regions within the same country can have different infant survival rates. This contrasts with the construction of income terciles, which assumes that the income distribution is uniform across all locations within a country. However, it is assumed that infant survival rates are uniform across all individuals within a district. Clearly neither of these assumptions is correct, however we will show that they produce results that are very similar to one another.

Table 5.1: Global distribution of ΔT

	Population		Croplands		Production	
	°C	°F	°C	°F	°C	°F
Mean:	2.4	4.3	2.6	4.6	2.4	4.3
Centiles						
1	1.0	1.8	1.1	1.9	0.7	1.3
20	1.7	3.1	1.9	3.3	1.7	3.0
25	1.9	3.3	1.9	3.5	1.8	3.2
33	2.0	3.6	2.1	3.8	1.9	3.5
50	2.3	4.1	2.4	4.3	2.3	4.1
66	2.7	4.8	2.8	5.0	2.7	4.8
75	2.9	5.2	3.1	5.5	2.9	5.3
90	3.5	6.2	3.7	6.6	3.4	6.2
99	4.3	7.7	4.7	8.5	4.4	7.9

then construct changes in the amount of time economic units are exposed to a specific temperature ($\int_t \mathbf{1}[T_t^c = T] - \mathbf{1}[T_t^0 = T]dt$ for use in approximations of Eq. 5.2).

5.4.1 Changes in annual mean temperature

There are two reasons to summarize changes in average temperature: (1) as mentioned, economic impacts may be a function only of changes in temperature and (2) average changes are probably the most widely cited statistics in policy discussions [IPCC, 2007, Stern, 2006, Nordhaus, 2008], perhaps because it is so simple to articulate a shift in a mean.

Unfortunately the common use of "global average changes" in policy is misleading because climate scientists use an area-weighted average and most of the planet's surface is covered by oceans that warm more slowly than land (see Fig. 5.1A). Since the oceans dominate global area-weighted changes, globally averaged temperature changes are substantially smaller than predicted changes over the continents, where most economic activity is located. When the oceans and Antarctica are dropped from the area-weighted average, the global average temperature change ($\overline{\Delta T_l}$) increases 35% from 2.0°C to 2.7°C in the A1B scenario.

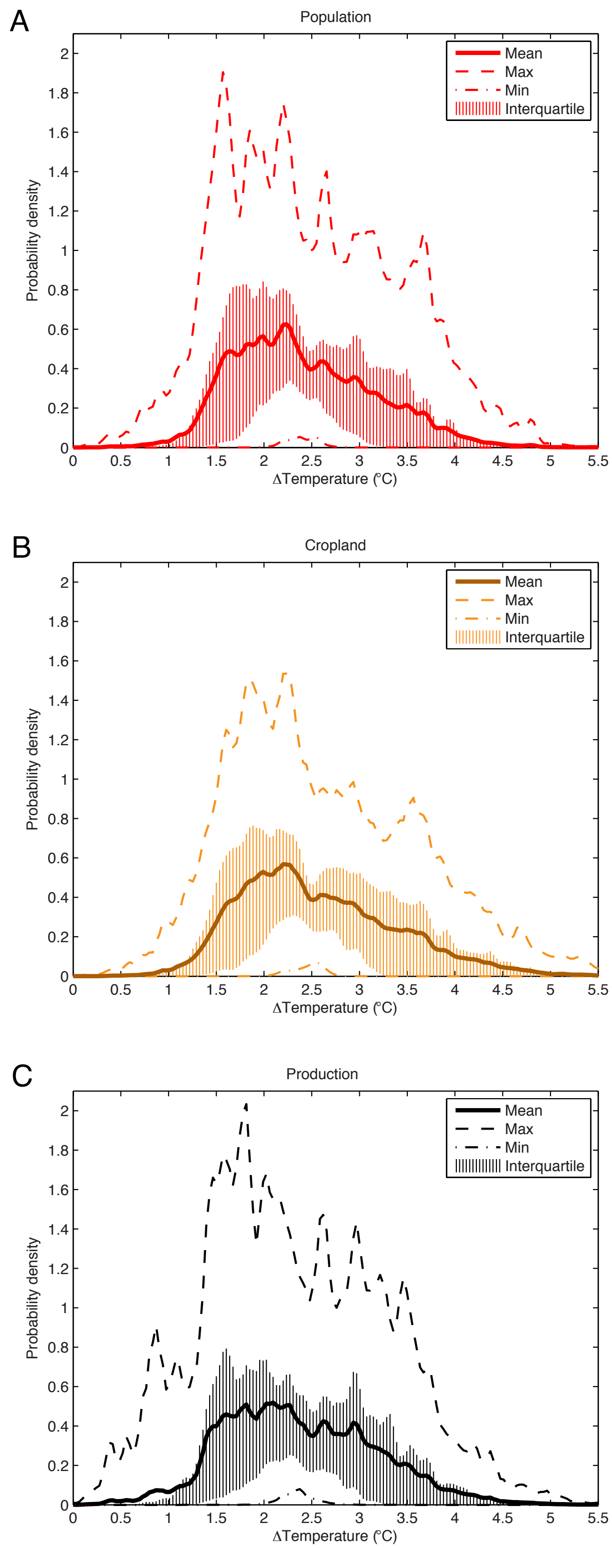


Figure 5.3: **The distribution of temperature changes experienced by randomly selected economic units.** (A) The change in temperature experienced by a randomly selected person. The thick solid line is the average distribution across 20 climate models. The dashed lines are the outer envelopes for the set of 20 distributions and the hatched region is the interquartile range computed for each temperature value. (B) Same, but croplands. (C) Same, but economic output.

While illustrative of the oceans' influence on global temperature statistics, the land-only annual average temperature increase of 2.7°C is an overestimate of economic exposure. Populations and economic activity cluster near temperate and tropical coastlines while temperature gains are largest in the mountains and Arctic regions (see Fig. 5.1A). The change in annual mean temperature experienced by an average person is 2.4°C (4.3°F). Somewhat coincidentally, this is also the average change experienced by an average dollar in economic output. An average hectare of cropland warms slightly more, 2.6°C (4.6°F), close to the land-only average change. While these means are useful, they may oversimplify exposure levels. For people, croplands and output, the inter-quartile ranges[7] in exposure are all about 1°C (1.8°F, or 40% of the person-weighted average change of 2.4°C), indicating that the variation in exposure around the world is substantial compared to the global average shifts. The thick lines in Figs. 5.3A-C plot the distributions of annual mean temperature changes for people, croplands and economic output (Table 5.1 tabulates the centiles of these distributions so other researchers may use them). All three of these distributions look qualitatively similar, but the distribution for croplands has a slightly thicker right tail which increases its mean. These distributions are all positively skewed, so their medians (∼2.3°C) are all slightly below their means. In general, about 70-75% of their mass is above 2°C, the global area-weighted average change of 2°C (3.6°F), and at least 25% of their mass is above 2.9°C (5.2°F). Virtually no mass falls below 1°C (1.8°F) and about 10% of their mass lies above 3.5°C (6.2°F), a massive shift in annual mean temperature.

The distributions of annual mean temperature changes across climate models exhibits substantial variation. Figs. 5.3A-C display the point-wise distribution of PDF values across all 20 GCMs. For any given temperature, the inter-quartile range of densities is about as large as the average value itself. Further, maximum density values are extremely high for temperature changes in the range of 1.5-3.5°C. If policy-makers or economic agents are only concerned with average outcomes (i.e. they wish to maximize "expected utility") then this inter-model uncertainty is unimportant. However, if these agents are "ambiguity averse" with respect to climate changes [Millner et al., 2010], then this inter-model uncertainty over the distribution of future outcomes is itself costly.

The solid curve in Fig. 5.3A seems to be a simple, general and robust description of economic exposure to future mean temperature changes in a scenario where area-average global temperature increases by 2°C. Not only do the distributions of cropland and output exposure closely mirror this distribution of human exposure, but it also describes exposure across months, income terciles and

[7] The difference between the 25th and 75th percentiles in exposure.

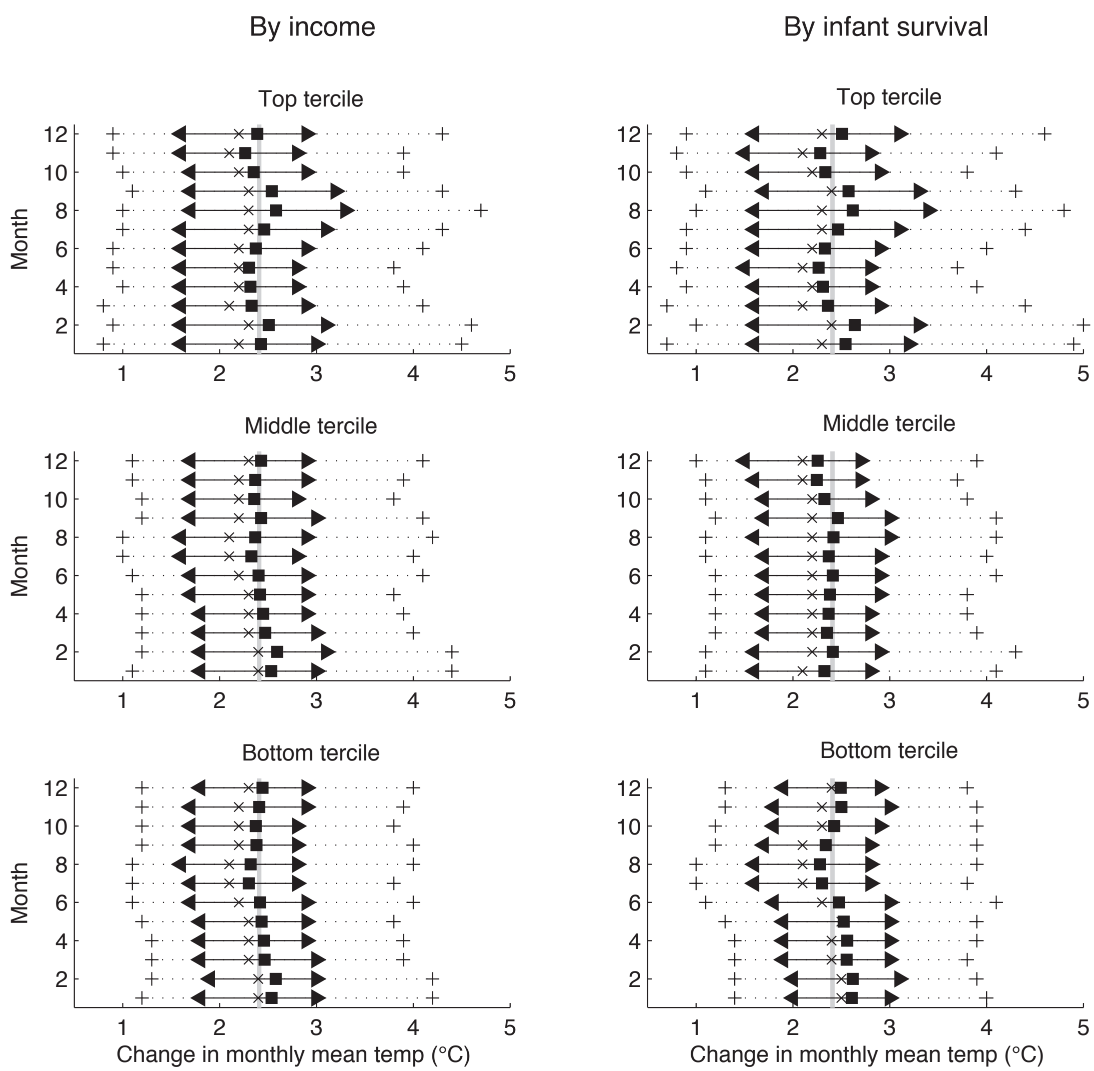


Figure 5.4: **The generality of Fig. 5.3A.** The distribution in Fig. 5.3A. is estimated for each income tercile and each infant survival tercile for every month. Squares mark the mean, 'x' marks the median, triangles mark the interquartile range and crosses mark the 5th and 95th centiles. The grey line marks the unconditional mean of 2.4°C. Across all subsamples, the overall structure of the distribution is relatively unchanged.

Table 5.2: Global damages from global temperature changes using different temperature statistics

Global change summary statistic	ΔT (°C)	Global economic losses: Percent of Global GDP	Relative to ΔT_a	Scaled to $\mathrm{GGDP}^{\star}_{2009}$
		DICE damage function[‡] [Nordhaus (2008)]		
$\overline{\Delta T_a}$ (Global area weighted average)	2.0	1.14	100%	$657 billion
$\overline{\Delta T_l}$ (Exclude oceans & Antarctica)	2.7	2.07	182%	$1197 billion
$\overline{\Delta T_p}$ (Person weighted average)	2.4	1.64	144%	$946 billion
Distribution of ΔT_p	See Table 5.1	1.80	159%	$1043 billion
$\overline{\Delta T_c}$ (Crop weighted average)	2.6	1.92	169%	$1110 billion
Distribution of ΔT_c	See Table 5.1	2.05	181%	$1187 billion
		PAGE damage function[†] [Stern Report (2006)]		
$\overline{\Delta T_a}$ (Global area weighted average)	2.0	0.67	100%	$390 billion
$\overline{\Delta T_l}$ (Exclude oceans & Antarctica)	2.7	1.15	170%	$663 billion
$\overline{\Delta T_p}$ (Person weighted average)	2.4	0.93	138%	$538 billion
Distribution of ΔT_p	See Table 5.1	1.00	148%	$577 billion
$\overline{\Delta T_c}$ (Crop weighted average)	2.6	1.07	159%	$620 billion
Distribution of ΔT_c	See Table 5.1	1.12	166%	$646 billion

* At 3% (5%) growth GGDP increases by a factor of 14 (81) between 2009 and 2099.
$^{\ddagger}Percent\_damages(\Delta T) = 0.28388 \times \Delta T^2$
$^{\dagger}Percent\_damages(\Delta T) = \left(\frac{\Delta T}{2.5}\right)^{1.77}$

infant survival terciles. Fig. 5.4 displays this distribution for each income group and infant survival group, across all twelve months. While there are some small variations, the overall structure of the distribution is persistent across all subcategories.

How much does it matter if global economic exposure is summarized by Fig. 5.3A rather than by the global area-average of 2°C? Consider how they map onto simple global models of economic impacts. For this comparison, we apply different measures of exposure to the "damage functions" described in two well know global assessments of climate change, the Dynamic Integrated Climate-Economy (DICE) model [Nordhaus, 2008] and the Policy Analysis for the Greenhouse Effect (PAGE) model used in the Stern Review [Stern, 2006]. Both models are variations on Eq. 5.1 and transform an average global temperature statistic into an estimate for global economic losses. A benefit of using these models is that they monetize measures of global exposure, converting global average temperature changes into dollars, a unit that is familiar. However, these models are not designed for this particular exercise[8], so the following comparisons should be viewed as suggestive and should not be interpreted

[8] The damage function in DICE is

$$D(\Delta T)_{DICE} = 0.283888 \times \Delta T^2$$

where D is a percentage change in global economic output (global gross domestic output) [Nordhaus, 2008]. The damage literally. The purpose of this comparison is get a general sense of how significant or innocuous it is to approximate global economic exposure with the traditionally reported area-weighted averages; it is *not* a re-estimation of the true global cost of climate changes.

When the economic exposure to temperature changes are loosely translated in economic losses, the traditionally reported area-weighted averages produce loss estimates that are much lower than those derived using the summary statistics we have constructed (see Table 5.2). The area-weighted average change of 2°C generates losses in DICE (PAGE) of 1.14% (0.67%) of global output. When oceans and Antarctica are dropped from this average, losses rise to 2.07% (1.15%) and when person-weighted averages are used then losses are 1.64% (0.93%). (Recall that the crop-weighted average is very near the land-only average and the output-weighted average is the same as the person-weighed average.) These adjustments are large, amounting to changes that are 38-82% of the original estimate. If the total distribution of exposure (shown in Fig. 5.3 and in Table 5.1) is used to compute the average loss per person or per hectare of cropland, then economic losses rise a further 5-10% due to the convexity of these damage functions (see Fig. 5.5).

function in PAGE is

$$D(\Delta T)_{PAGE} = \frac{\Delta T^{\gamma}}{2.4}$$

where γ is a stochastic variable. For this exercise, we use the average value $\bar{\gamma} = 1.77$ taken from the stochastic distribution used in the Stern Review [Stern, 2006].

Several points are worth noting about these two functions.

First, $D_{DICE} < D_{PAGE}$ for $\Delta T < 2.5$°C, but $D_{DICE} > D_{PAGE}$ for $\Delta T > 2.5$°C since D_{DICE} is more convex. This point is not always appreciated because Stern (PAGE) argues that the costs of climate change are higher than Nordhaus (DICE) claims. This difference comes from the ways in which they discount future earnings, not from the differences in their damage functions. If everything in a model was held fixed, except the two damage functions were interchanged, than D_{DICE} would likely generate larger overall losses.

Second, the interpretation of these functions is very different. D_{DICE} is constructed by mapping global average temperature onto regional average temperatures, computing regional damages using region specific damages functions and then combining those averages to produce a global estimate. In contrast, D_{PAGE} is a general "law" for how output scales with temperature changes and is applied to each region, given regional average temperature changes. Recognizing this, the use of D_{PAGE} in this exercise is at least partially valid, although it is clearly not a correct interpretation of D_{DICE}.

Third, the damages included in the estimation of these damage functions includes non-market damages (eg. biodiversity loss) and theoretical welfare losses (eg. catastrophe risk) that may scale with environmental variables other than temperature (eg. precipitation or hurricane intensity). Thus, global temperature is used in these damage functions as a summary statistic for many environmental variables that may affect economic impacts both directly and indirectly. This contrasts with the purpose of this study, which is to characterize the magnitude of economies' direct exposure to temperature changes themselves. For this reason, it is unclear exactly how this exercise should be interpreted, but it is clear that it should not be interpreted literally.

Finally, it is worth noting that neither author who uses these functions takes them extremely seriously themselves. Both authors have been open to criticisms that the damage functions they use are incomplete. As will be demonstrated at the end of this paper, direct economic losses due to labor productivity [Graff Zivin and Neidell, 2010, Hsiang, 2010] are on the scale of the total losses described by these functions, however losses to labor productivity have never been included in the construction of these damage functions. Thus, there remains dramatic uncertainties in the "true" form of these functions.

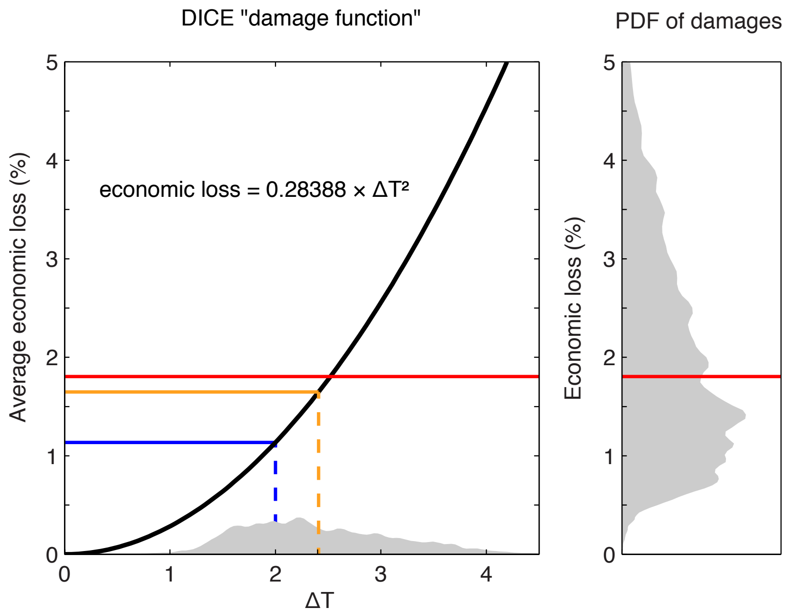


Figure 5.5: **The costs of average temperature change vs. the average costs of temperature change.** The damage function used in DICE (black) [Nordhaus, 2008]. Global economic losses computed with global area-weighted mean temperature change (2°C, blue) and population-weighted mean temperature change (2.4°C, orange). The distribution of human exposure is plotted along the bottom as a gray distribution, and the distribution of economic losses (if each individual's damage function is identical to the global damage function) is in the right panel. The economic loss to an average individual is then displayed as the red line (both panels). The average losses (red) are greater than losses at the average temperture change (orange) because the damage function is convex.

Even if one takes the above exercise only moderately seriously, the error introduced to by approximating economic exposure with global average temperature is large. Using the DICE damage function, changing from the area-average temperature to the distribution of human exposure raises economic losses by 0.66% of global output. Scaled to production values in 2009, this amounts to a difference of \$386 billion[9]. If one then considers that future output in 2099 will be larger, growing by 3-5% annually between now and 2099, then the annual error introduced by this single approximation amounts to 10-54% of modern global output! Of course, there are many other "thought experiments" that, if extrapolated exponentially, can produce similarly dramatic errors. However this particular adjustment is notable for the fact that it results solely from how global temperature changes are measured. Nothing about our understanding of climate change physics or global economics is changed.

[9]This is approximately the outputs of Austria, Norway, Taiwan or Saudi Arabia.

5.4.2 Changes in the quantity of time economic units are exposed to specific temperatures

Several recent econometric analyses suggest that temperature exposure generates nonlinear impacts on economic variables [Schlenker and Roberts, 2009, Albouy et al., 2010, Schlenker and Lobell, 2010, Welch et al., 2010, Hsiang, 2010, Deschenes et al., 2011] and thus it is important to consider the actual temperature that a productive unit is exposed to, not just *changes* in its local temperature. For these types of impacts, we must know for how much time economic units are exposed to a particular temperature. We can then compute how this distribution of $time \times temperature \times economic\ units$ changes in the future (recall Eq. 5.2).

We begin by estimating the distribution of temperatures one would observe if we randomly selected a random person (or hectare of cropland or dollar of output) during a random month over 2011-2030. We then estimate the same distribution for 2080-2099 and take the difference between these two distributions. The result is shown in Figs. 5.6. These plots show changes in the quantity of time in months that a randomly selected unit would spend at each temperature. Positive values indicate that more time is spent at a given temperature, negative values indicate that less time is spent at a given temperature, and each curve must integrate to zero.

The most striking feature of Figs. 5.6A-B are the spikes around 30°C (86°F). These spikes show that all types of economic units will spend substantially more time at temperatures above 27°C (81°F), balanced by reductions in the amount of time spent below 27°C.

The second important feature of these figures is the difference in exposure between high income individuals and the lower income groups. Conditional on individuals being middle or low income, the quantity of additional time they spend at any temperature above 27°C is approximately double the additional time spent by a high income individual at the same temperature. If high temperatures are economically costly, as the literature indicates, this suggests that the economic exposure to costly temperatures will be greatest for middle and low income populations. When we stratify the global population by infant survival, then the result is similar except low survival populations spend more time at extremely high temperatures (> 32°C) and middle survival populations spend more time near 30°C.

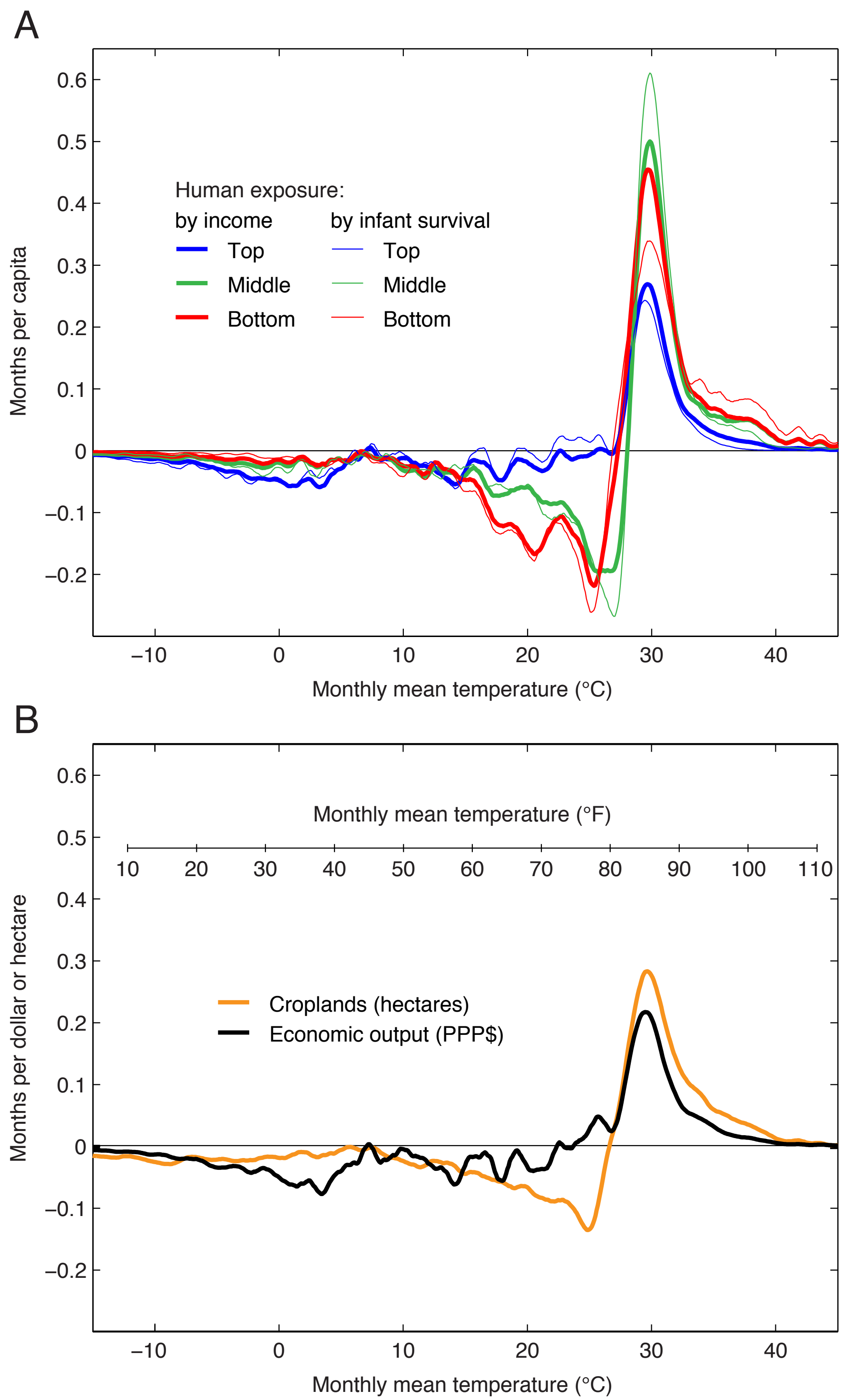


Figure 5.6: **Change in the quantity of time economic units are exposed to different temperatures.** (A) Change [2080-2099 less 2011-2030] in the number of months a randomly selected person is exposed to each temperature. Positive values indicate that more time is spent at the corresponding temperature. These curves are integrated in Table 5.3. (B) Same, but for croplands and economic output.

Table 5.3: Additional months exceeding each cutoff temperature per unit

Exposure to: (unit)	Population (capita)				Croplands (area)	Production ($PPP)
Cutoff temp. (°C)	All	Global income tercile Bottom	Middle	Top	All	All
40	0.06	0.08	0.08	0.02	0.04	0.02
39	0.08	0.12	0.11	0.03	0.07	0.03
38	0.11	0.16	0.15	0.04	0.09	0.04
37	0.15	0.21	0.20	0.05	0.13	0.06
36	0.19	0.26	0.25	0.07	0.18	0.08
35	0.24	0.34	0.31	0.10	0.24	0.10
34	0.30	0.40	0.37	0.13	0.31	0.14
33	0.37	0.49	0.44	0.18	0.40	0.20
32	0.49	0.63	0.57	0.26	0.52	0.26
31	0.70	0.89	0.82	0.39	0.69	0.37
30	1.08	1.30	1.28	0.63	0.95	0.55
29	1.50	1.75	1.77	0.90	1.24	0.78
28	1.68	1.98	1.88	1.06	1.44	0.94
27	1.63	1.99	1.72	1.08	1.50	1.00
26	1.51	1.88	1.53	1.07	1.49	1.02
25	1.36	1.65	1.33	1.07	1.37	1.07
20	0.93	0.96	0.88	0.99	0.91	1.01
15	0.64	0.47	0.59	0.86	0.64	0.89
10	0.47	0.31	0.41	0.70	0.49	0.73
5	0.41	0.25	0.34	0.64	0.46	0.65
0	0.27	0.17	0.25	0.39	0.39	0.35
-5	0.14	0.09	0.14	0.19	0.29	0.17
$\underline{T}$ (°C)	Heating "degree-months" above $\underline{T}$					
> 30	3.88	5.04	4.74	1.93	3.69	1.89
> 27	8.69	10.76	10.11	4.97	7.87	4.61

Figure 5.6 displays differences between pairs of continuous PDFs, so the units are a *density of time* that is hard to interpret. To ease interpretation, we integrate these curves from a cutoff temperature to positive infinity. These integrals describe the amount of additional time (in the future) that a unit is expected to spend above a certain temperature cutoff. Integrals for integer-valued temperature cutoffs between 25-40°C (and by 5°C steps below 25°C) are shown in Table 5.3. These values are tabulated, instead of graphed, because they are the results we expect other researchers will find useful in their own work.

We find that a randomly selected person will experience 1.6 more months above 27°C (81°F), a randomly selected hectare of cropland will spend 1.5 more months above that cutoff and a randomly selected dollar of value will be produced at a location spending 1 additional month above that cutoff. We note that low, middle and high income groups will respectively spend 2.0, 1.9 and 1.1 additional months above that cutoff, indicating that the burden of high temperature exposure is almost twice as large for low and middle income populations. This differential exposure of the middle and low income groups is even stronger for more extreme temperatures. For example, low and middle income populations will spend an additional 0.25 months above 36°C (97°F), 3.5 times the additional 0.07 months that high income populations will spend above that cutoff.

This increased quantity of time that individuals will be exposed to high temperatures is accounted for by reductions in their exposure to lower temperatures. Because exposure to low temperatures may also have adverse economic impacts, it is sometimes suggested that this reduction in exposure to low temperatures may substantially (or completely) offset the increased exposure to high temperatures [Tol, 2009]. This idea is somewhat supported by recent econometric studies which indicate that economic production increases with respect to temperature up to some critical point, beyond which it declines [Nordhaus, 2006b, Deschenes et al., 2009, Schlenker and Roberts, 2009, Albouy et al., 2010, Schlenker and Lobell, 2010, Welch et al., 2010].

By using our measure of global exposure to the entire range of temperatures, we can ask how large the gains from warming must be in order to offset the losses it generates. For this exercise, we consider the aggregate losses that would be incurred if the distribution of human exposure (Fig. 5.7A) were projected onto different response functions (Fig. 5.7B). In our view, a "true" response function that describes all economic impacts is still unknown, however we build caricature response functions that share some properties of those derived in the previous analyses mentioned. First, we define the temperature band of 20-27°C (68-81°F) as "economically optimal." While these cutoff

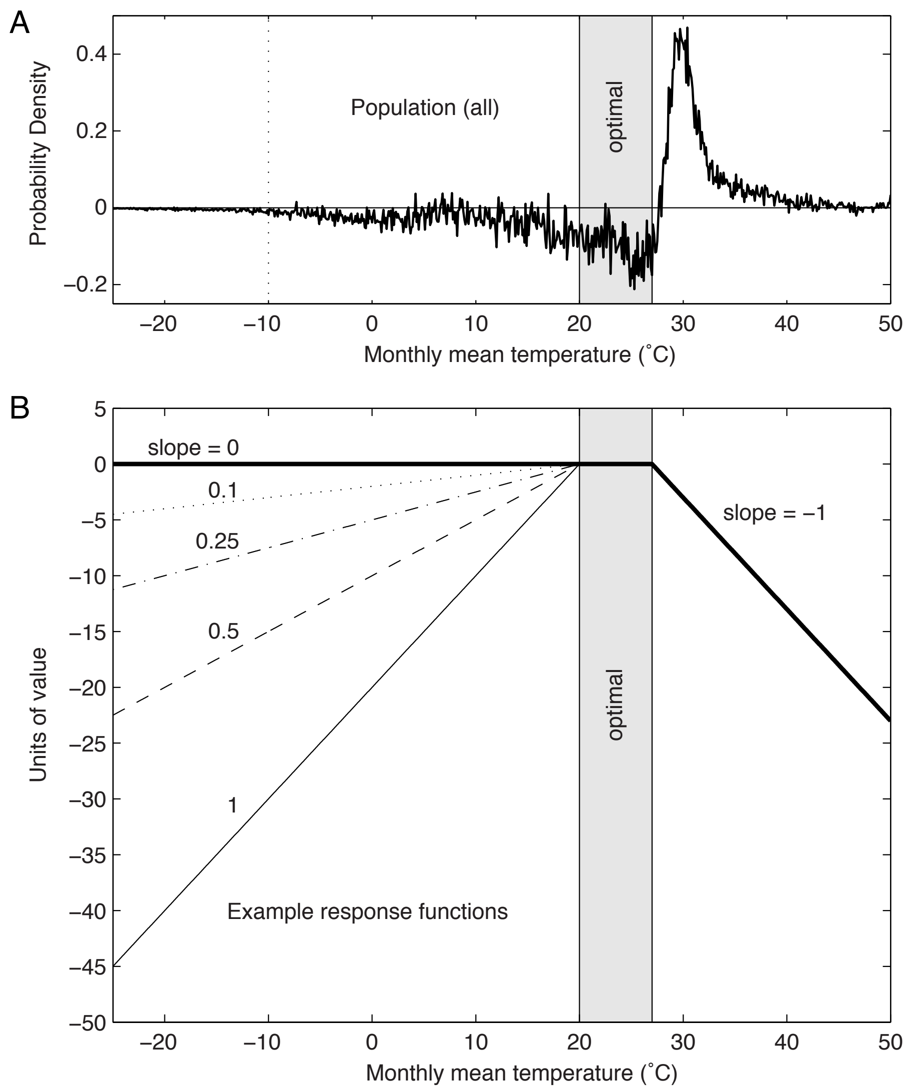


Figure 5.7: **Examples of nonlinear response functions.** (A) The distribution of months spent at each temperature for a randomly selected person [same as 5.6A except the curve represents all income groups and is not smoothed]. (B) Five example response functions that are qualitatively similar to those derived empirically in the econometrics literature. Temperatures in the range 20-27°C are assumed to be "optimal". Temperatures above 27°C generate marginal losses of one unit in value per 1°C. Temperatures below 20°C have marginal gains of 1, 0.5, 0.25, 0.1 and 0 units of value per 1°C. When the distribution in (A) is projected on each of these response functions, the total change in value is tabulated in Table 5.4.

Table 5.4: Value lost for example response functions

Slope	Lost value (all T)	Lost value ($T > -10°$C)
0.0	-78.7	-78.7
0.1	-66.3	-68.9
0.25	-47.7	-54.1
0.5	-16.8	-29.6
0.636	0.0	16.3
0.802	20.5	0.0
1.0	45.0	19.4

temperatures are uncertain, they are sufficiently close to those observed in several studies that this is a good approximation. Second, we constrain the response function to decline linearly above 27°C , and scale the decline to 1 unit of value per 1°C. We also constrain the slope of the response function below 20°C to be constant, but to vary between 0 and +1 unit of value per 1°C. (These units are unimportant and can be arbitrarily rescaled; the only thing that matters to our analysis is the ratio of the slopes in the regions above and below the optimal temperature band.) We allow this slope to vary because there remains uncertainty in the gains from warming cold locations. Some studies suggest that certain types of economic output do not vary substantially below the optimal temperature band [Schlenker and Roberts, 2009, Albouy et al., 2010, Graff Zivin and Neidell, 2010] while some studies suggest that it it increases with temperature [Deschenes et al., 2009, Welch et al., 2010]. In either case, the rate of increase generally appears to be substantially lower than the rate of decline at high temperatures, which is why the slope is constrained to remain weakly below 1. Fig. 5.7B illustrates the range of response functions considered.

We find that in order for the gains in warming to offset its costs, we must postulate relatively strong gains from warming. The middle column of Table 5.4 tabulates the global economic impact of warming when the distribution in Fig. 5.7A is projected onto the response functions in Fig. 5.7B. The third column tabulates analogous values when the distribution in Fig. 5.7A is truncated at $-10°$C (dotted line) because the very small number of individuals at very cold temperatures strongly affects the global aggregate when gains from warming become large. For functions with no or little slope below the optimal temperature, global aggregate losses are large. When we use a slope of 0.5, half the slope at high temperatures, we find that the global impact remains negative and a large fraction of the gains we observe are generated by an extremely small number of individuals at very low temperatures. The gains from warming exactly offset the losses if a slope of 0.64 is used for the whole distribution of exposure. The same occurs at a slope of 0.80 for the exposure distribution that is truncated at $-10°$C.

When a slope of 1 is used, i.e. the marginal gains from warming cold locations is exactly equal to the marginal losses from warming hot locations, then global output increases but is strongly driven by the few individuals at very low temperatures.

To see why gains are limited and strongly affected by the few individuals at very low temperatures, consider Fig. 5.8 which displays the joint distribution of population's initial temperatures and the temperature changes they experience in the future. For initial temperatures between 10-30°C, the distribution of temperature changes are similar and near the population-weighted mean of 2.4°C. This means that with climate change, the distribution of experienced temperatures simply shifts by an approximately fixed value for all individuals. Individuals who had been just below the optimal temperature range shift into this temperature band, but individuals who had previously been in the optimal temperature range shift out of it to the higher sub-optimal temperatures. In aggregate, there is no accumulation of individuals within this optimal range because more individuals shift out of the optimal range than shift into it[10]. However, individuals at very low temperatures exhibit very large temperature gains (recall Fig. 5.1A), exerting strong influence on the global outcome when we considered response functions with large slopes[11].

While we lack definitive estimates for the economic benefits of warming, it seems unlikely that direct warming will benefit the global economy. In order to achieve global gains from warming, we must postulate a response function where the gains from warming cold locations generate benefits larger than most empirical studies would imply. Moreover, when we do this, the global gains from warming are strongly driven by a very small number of individuals in Arctic environments.

[10]This discussion only considers the current location of economic units, however it is possible that currently uninhabited regions become relatively more optimal and that populations can "win" by migrating into those regions. However this migration may be costly and it is unclear that voluntary migration can offset what are otherwise large global losses.

[11]These populations come almost entirely from the Arctic and it seems ambiguous to us whether dramatic temperature changes in these regions are economically beneficial.

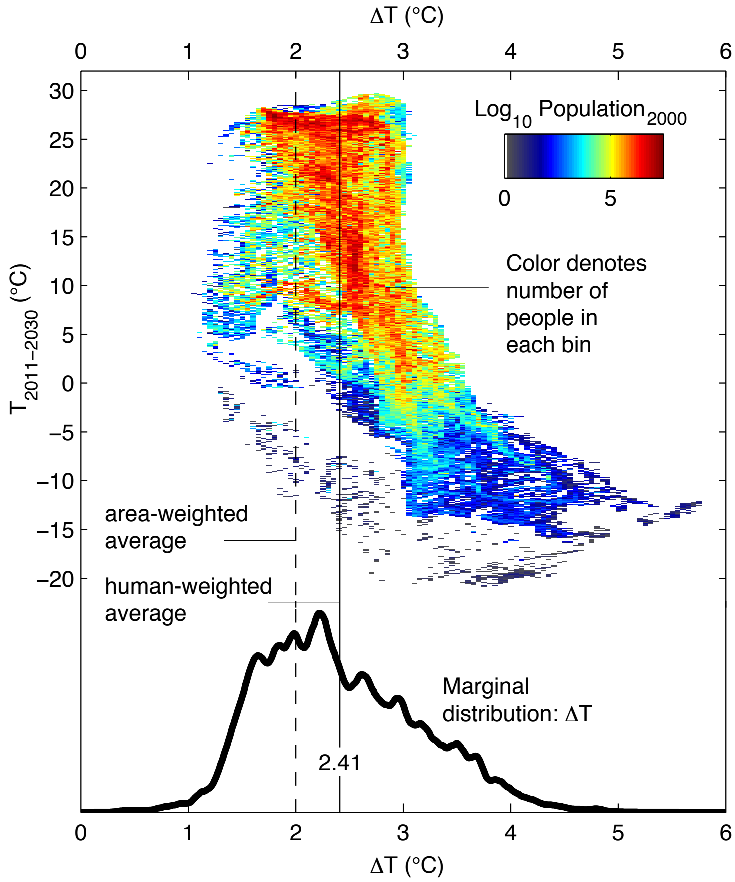


Figure 5.8: **The joint distribution of temperature changes and initial temperatures.** Top: the joint distribution of log population by $\Delta\bar{T}$ (abscissa) and average temperatures over 2011-2030 (ordinate). Bottom: marginal distribution of $\Delta\bar{T}$ (compare to Fig.5.3A).

5.5 An example application: workers exposed to thermal stress

Figure 5.6 and Table 5.3 are sufficient to estimate global economic losses from a non-linear response function if we believe that the mechanism underlying the response is sufficiently general that it can be extrapolated globally. For many mechanisms, such as the physiological responses of crops or workers to extreme temperatures, this might be a reasonable assumption. However, even if mechanisms around the world are the same, the ability of populations to adapt to them may not be. Thus, we can use our breakdown of the global income distribution to separately consider impacts for sub-populations that may have different capacities for adaptation.

To illustrate how these estimates can be applied, we consider the impact of high temperatures on the productivity of workers around the world [Hsiang, 2010], a mechanism that is omitted from all previous analyses of global economic costs [Tol, 2009]. The following calculations are simple "back of the envelope" estimates. Yet, there is value in illustrating how the results of this analysis can be used to quickly estimate global cost estimates from smaller scale analyses. Moreover, our example also illustrates why such a streamlined approach to global estimates may be important: in this case we demonstrate that a physiological mechanism previously ignored may have first-order significance.

The impact of high temperatures on worker productivity has never been seriously considered in economic models of global warming, despite extensive literatures in ergonomics and engineering that document large reductions in worker productivity at high temperatures [Ramsey and Morrissey, 1978, NIOSH, 1986, Wyon, 2001, Pilcher et al., 2002, Hancock and Vasmatzidis, 2003, Seppänen et al., 2003, Hancock et al., 2007]. Recent work indicates the effect of high temperatures on workers is apparent in macro-economic fluctuations of some low and middle income countries [Hsiang, 2010]. Though high income populations appear to be less affected by temperature when working environments can be controlled [Graff Zivin and Neidell, 2010]. It is possible that this dichotomy explains why output in poor populations around the world is strongly correlated with temperature while output in wealthier countries is not [Dell et al., 2009a].

To estimate future loses from reduction in worker performance, we begin with the estimated rate at which output is lost when temperatures rise above 27°C. Hsiang (2010) estimates that annual output falls 2.65% for a 1°C increase in temperature over a three month period. This suggests that exposure to one additional month at a temperature 1°C higher (1 additional "heating degree-month") reduces annual output by $\frac{2.65\%}{3} = 0.88\%$. This estimate, derived exclusively from macro-economic data, is very close to (albeit slightly smaller) than laboratory-based estimates for reductions in worker productivity (see Fig. 5B in [Hsiang, 2010]).

Initially ignoring the potential for high income individuals to adapt, we can use this study's pooled estimate that an average person will be exposed to an additional 8.69 heating degree-months above 27°C (see the bottom panel of Table 5.3). Thus, if no workers are able to adapt, then we estimate that an average worker's output will fall $0.88\% \times 8.69 = 7.65\%$ annually due only to reduced productivity (for scale, 7.65% of the global economy in 2009 is \$4.4 trillion; at 3-5% annual growth the corresponding value will be \$63-355 trillion in 2099). However, if we imagine that the third of workers with highest income can invest in adaptive measures (eg. air conditioning) then we should focus only on the impacts for medium and low income workers. The output of medium and low income workers is probably below that of high income workers in absolute value, but medium and low income populations are exposed to twice the heating degree days of high income workers. Low income workers are exposed to 10.76 heating degree-months above 27°C, suggesting that the average worker's output will decline $0.88\% \times 10.76 = 9.47\%$ due only to productivity impacts of high temperatures. Meanwhile medium income workers are exposed to 10.11 heating degree-months, suggesting their output would decline by almost as much: 8.9%.

These estimated impacts via worker productivity are large. Global economic losses for the same scenario estimated by damage functions in the DICE [Nordhaus, 2008] and PAGE [Stern, 2006] models suggested that global output would fall 1.14% and 0.67% respectively (recall Table 5.2). Even if the above estimates for productivity losses are too large by a factor of five, the damage functions currently used would still be dramatically underestimating the costs of warming by omitting impacts on worker productivity[12].

5.6 Discussion

We have combined six global and spatially explicit datasets[13] to describe the exposure of the global economy to future temperature changes if the spatial distribution of economic units remains relatively fixed[14]. Since it is difficult to know how the spatial distribution of economic activity will shift over the coming century, this description should be interpreted carefully. In our view, there is no credible way to characterize uncertainty in the spatial distribution of future economic activity, so we encourage moderate and level-handed skepticism of our findings. It is possible that over the next century economic growth in the tropics will be rapid as historically poor countries "catch up" by importing technologies, increasing public investments, progressing through demographic transitions and improving their governing institutions [Barro and Sala-i-Martin, 2003, Sachs, 2005, Acemoglu, 2008]. In this scenario, global economic exposure to climate change might be higher since more activity would be concentrated in the low and middle income regions where future heating degree months are greatest.

[12] In this simple example, we do not consider increases in worker productivity associated with rising temperatures for workers at initially cold temperatures [Wyon, 2001, Pilcher et al., 2002]. We avoid constructing this estimate because we know of no studies that have estimated the economic impact of workers warming from low temperatures. However, we do not think it would be nearly enough to offset the effects of warming from high temperatures for three reasons. (1) Cross-sectional analysis [Nordhaus, 2006b] and panel analysis [Dell et al., 2009a] fail to find that output per capita increases for warming from initially low temperatures. (2) The exposure to warming from initially low temperatures is small compared to the exposure to warming from initially high temperatures (recall Fig. 5.6) since most of the additional exposure to high temperatures is compensated for by reductions in exposure to optimal temperatures (20-25°C). (3) The technology needed to keep working environments warm (when climates are cold) is dramatically simpler and cheaper than the technology needed to keep working environments cool (when climates are hot). This technological asymmetry is a general result from the second law of thermodynamics and is unlikely to change with future innovations.

[13] We actually combine twenty five datasets if one counts all 20 GCMs as separate datasets.

[14] We defended this assumption in Section 5.2.

On the other hand, it is possible that gains in wealth may enable these populations to adapt to climate changes more effectively, thereby reducing the economic impact of their higher exposure. Alternatively, these economies might fail to converge to the output of high income regions, perhaps as a result of climate changes. This would probably keep the global distribution of economic activity closer to the one observed presently and described in this paper.

Climate induced migration is another mechanism through which the spatial distribution of the modern economy might adjust to future temperature changes. Given the wide range of temperatures in which current populations reside, it seems unreasonable to assume that entire societies will relocate sufficiently far that our estimates here be wildly erroneous. It seems more likely that marginal individuals will find it privately advantageous to migrate [Deschenes and Moretti, 2009,Feng et al., 2010], leading to small but limited displacements of economic activity. However, using the data we have collected we can conduct the simple thought-experiment of asking how much displacement would have to occur in order to maintain the current annual temperatures experienced by all economic units. This thought experiment represents an extreme assumption that is opposite to the "no migration" assumption maintained throughout this paper. Fig. 5.9 displays the distribution of distances that individuals would have to migrate in order to ensure that their annual mean temperature in 2080-2099 was equal to the temperature over 2011-2030 at their original location[15]. The distances migrated range from a few kilometers (for individuals living near mountains that they can ascend) to 2,000 km (1,240 mi) and the distance traveled by a randomly selected individual is approximately 470 km (290 mi). The cost of relocating all durable infrastructure (eg. cities) to support this kind of global movement would be fantastic, heuristically supporting the notion that climate-compensating migrations will likely only be undertaken by marginal populations

[15]This thought experiment constrains individuals to remain living on land and to settle in the location nearest to their original location that has a temperature equal or cooler than the temperature at their original location.

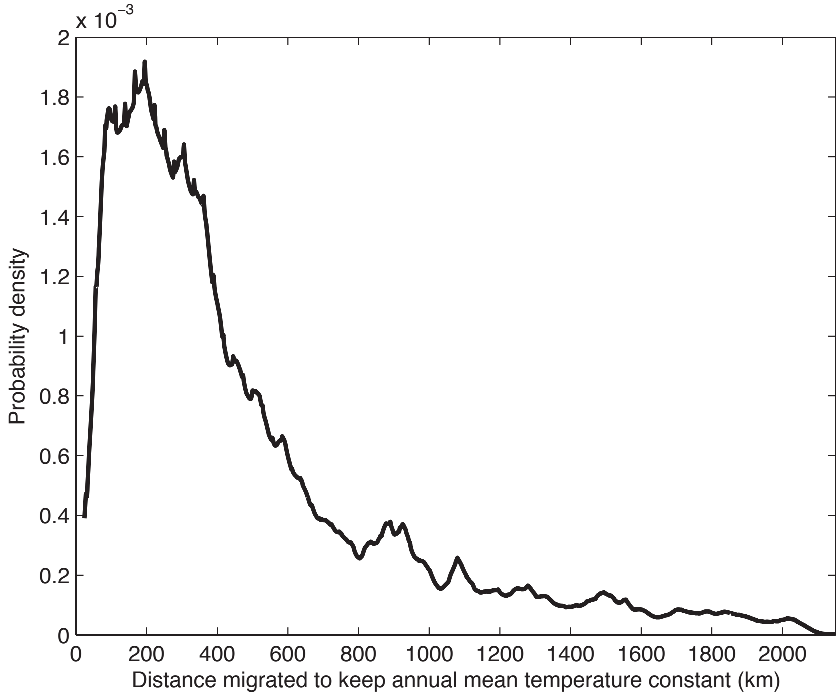


Figure 5.9: **Migration distances required to keep average temperatures constant.** For each individual, we compute the minimum distance they would need to migrate in order for their annual mean temperature to remain unchanged. The probability density function is the distribution of distances for a randomly selected individual.

It is certain that populations will adapt to future temperature changes, so one must be cautious when projecting global measures of exposure onto response functions estimated with time series or panel data (as we did in Section 5.5). However, it is generally not known how fast or effectively populations are able to adapt to environmental changes [Patt et al., 2010], a fact that underscores the importance of research efforts that focus on this problem [Graff Zivin and Neidell, 2010, Dell et al., 2009b, Hsiang and Narita, 2011, Meng et al., 2011]. Moreover, while adaptation is often assumed to minimize costs [Deschenes and Greenstone, 2007, Patt et al., 2010] some social responses to environmental changes, such as civil unrest [Burke et al., 2009, Hsiang et al., 2011], may exacerbate small environmental changes by introducing economic inefficiencies.

Finally, we reiterate that only the direct exposure of economic units to future temperature changes was analyzed here. There are many climatological variables other than temperature (eg. rainfall) that will exhibit shifting climatologies in the future. Furthermore, there may exist many indirect mechanisms (eg. ecosystem responses) through which temperature changes will themselves affect economic output for which direct exposure to temperature changes is an inappropriate measure. Nonetheless, our estimates for the direct exposure of the global economy to temperature changes are simple, general and robust; so we are hopeful that they will prove useful as a step towards simplifying what is otherwise an overwhelmingly complex and conceptually challenging problem of unprecedented global scale.

Appendix

5.A Supplementary Tables and Figures

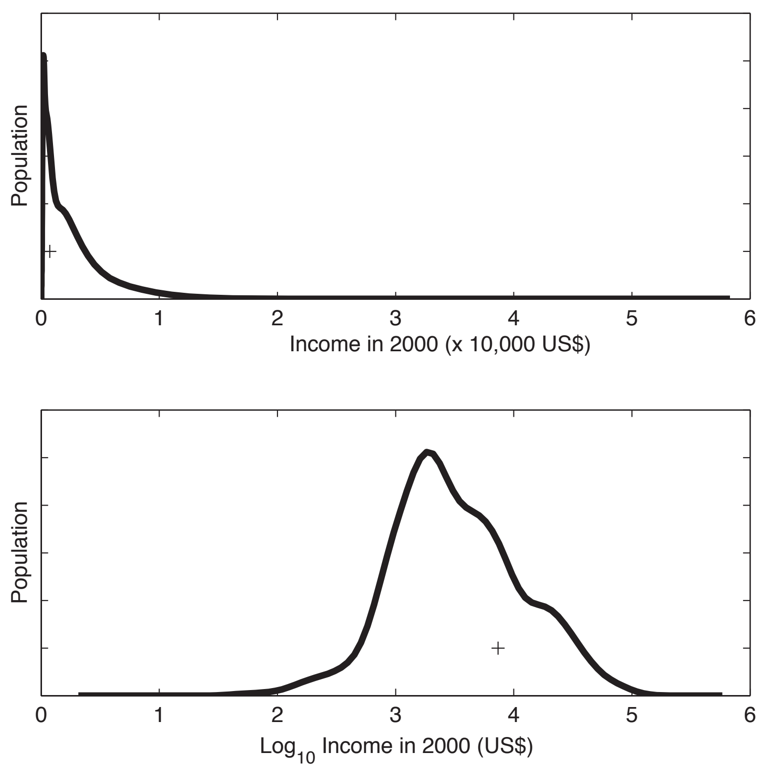


Figure 5.10: The global distribution of income in 2000 based on [Sala-i Martin, 2006] in linear units (top) and logarithmic units (bottom). Global mean income is showed with a '+'.

Chapter 6

Implications and future work

In general, these studies have shown that relatively broad social outcomes, such as national income or political stability, are sometimes strongly coupled to climatological variations. These results suggest that in modern development or climate policy, we must be wary not to underestimate the social impact of the climate. However, these results also show that we should not be fatalistic about social conditions that we attribute to the climate because many populations have successfully decoupled their lives from their climate, suggesting that the costs described in these studies are not unsurmountable. It seems that the first step towards managing these climate impacts is to acknowledge that they exist and identify where they persist. This has been the central contribution of this dissertation.

6.1 Climate policy

Ceteris paribus, all the chapters in this dissertations suggest that previous cost estimates for the social cost of future climate change are too low. This, in turn, implies that efficient greenhouse gas emissions will be lower than previous recommendations. Previous estimates for the cost of climate changes did not include the costs of thermal stress on workers, civil conflicts or lost income to tropical cyclones. These findings suggest that we should generally exhibit humility with respect to the completeness of our cost estimates. In his recent review of the subject, [Tol, 2009] stated:

> Research in this area has reached the point that we can now identify our areas of ignorance; I believe that there are no more unknown unknowns, or at least no sizeable ones. But my belief here may suffer from overconfidence. In a survey article I co-authored more than

> a decade ago on the social costs of climate change, we suggested that all aspects of the problem were roughly known, and that research would be complete within a few years. This view turned out to be so overoptimistic as to be entirely mistaken.

It seems unfortunate that he should once again be mistaken that there were not sizable and uncharacterized mechanisms. Perhaps, rather than ever assuming that all costs are known (recall Equation 1.1 and its discussion), we should simply recognize that costs will be systematically underestimated, accept that the remaining distribution of undiscovered costs is unknowable and design our policy-making institutions accordingly. Future work is required to examine how this can be done. Perhaps all we can do is to mimic civil engineers and include a "margin of safety" in the design of our policies. An alternative might be to employ a "precautionary principle" in decision-making, placing the legal onus of demonstrating costs are low (on those who benefit from altering the climate) rather than requiring a demonstration that costs are high (from those who prefer the status quo).

The fact that global "damage functions" are systematically too low suggests that a more transparent and less *ad-hoc* approach to their construction may have large benefits. Maybe the best we can do is to "make it easy" to identify our own errors by making tools to streamline the research process. In Chapter 5, I developed a single tool that may help to systematize the process, however a complete procedure remains undeveloped should be pursued in future work.

All chapters, but particularly Chapter 4, suggest that the vulnerability of populations can decline and that a simplistic view of climate changes with zero adaptation is inappropriate. However, these results suggest that the process through which this occurs may not be obvious and that generalizations, at this stage, are also inappropriate. From this work, we know the following facts about vulnerability reduction or adaptation: (1) vulnerability to some events can decline rapidly but may not decline for all sectors; (2) while declines in vulnerability may be *correlated* with higher income, it is not at all clear that the decline is *caused* by higher income; (3) our results are consistent with (but do not prove) a hypothesis that costs must be observable for them to be intentionally mitigated, suggesting that simply identifying costs may itself spur adaptation; and (4) there may exist forms of adaptation, for example predation or expropriation, that amplify the costs of climate changes rather than minimizing them as is often assumed. Collectively, these facts provide mixed support for the belief that future vulnerability reductions will limit the costs of climate change. Although, in net, they suggest that effective adaptation is possible but that its structure remains unknown. Further research into each of the above points is required to limit future social losses, however the second point deserves further discussion.

It is frequently suggested that money provides the strongest defense against climate change and that instead of focusing on mitigation, policy should instead focus on economic growth or monetary transfers to countries that are exposed to large changes. In Chapters 2, 3 and 4, we found that higher income countries exhibited lower vulnerability to climatological fluctuations, a fact that might support these policy proposals. However, as mentioned, it might not be the case that high income *per se* causes the bulk of reductions in vulnerability, as we found in Chapter 4. As discussed in Chapter 3, it might be the case that reductions in vulnerability cause incomes to rise, or that some other unobserved social or technological changes that are correlated with income cause vulnerability to fall. If the latter case is true, this is extremely important for the design of climate policy. If fungible income is itself not the key ingredient for reducing vulnerability, than transfers of income between countries or growth in income might have zero impact on global vulnerability.

For example, it could be the case that extensive road networks and high levels of market integration are the key traits of economies that are resilient to ENSO and do not lapse into civil conflicts with El Niño, perhaps because food shortages are less severe. Road networks and market integration are probably beneficial for economic growth, so we would observe that high income countries do not respond to El Niño with conflict (as we found). If this is the case, transfers of incomes or growth in incomes that do not translate into the development of road networks and improvements in market integration will not reduce a country's vulnerability to ENSO. Road networks and market integration are not goods that can be directly transferred from rich countries to poor countries; and there are many ways in which economic growth can be encouraged but that allow roads and market integration to stagnate. Thus, income transfers or growth policies are not themselves sufficient to guarantee that climate vulnerabilities decline.

Even if income is less relevant for climate vulnerability than its correlates, it may be the case that enough different growth policies will eventually reduce climate vulnerability by chance because we may eventually address the important source of climate resilience. However, without more research into the keys variables that are the proximate cause of climate resilience, such a policy seems both inefficient and risky. For example, if emissions reductions are weak explicitly because we are relying on transfers or growth to "save" future generations from otherwise heavy losses and, upon arriving in the year 2100, we discover that tacit social infrastructure is far more important for adaptation than tradable income, we will be in trouble.

For the above reasons, this dissertation provides strong support to the notion that rapid adaptation to climate can occur, but we do not yet know how such an objective should be efficiently pursued. Addressing this issue is central to future work because without such knowledge in hand, adaptation as an operational policy cannot be relied on as a substitute for mitigation policies.

6.2 Economic Development

Because low income countries are strongly affected by the climate phenomena explored in this dissertation, it also generates implications for development policy in the current (rather than future) world. In some cases, identifying causal pathways helps to identify informational or market failures that can be addressed directly, for example the benefits of temperature control systems in working environments could be publicized to firm owners. In other cases the mechanisms are less clear (eg. Chapter 3) and policy prescriptions may be somewhat weaker.

It may be that the largest contribution for some of these chapters, in terms of development policy, may be their techniques for measuring the economic losses to climate. Measurement is itself valuable because it is a requirement of efficient contracting and, in some of these cases, properly designed contracts may be all that are needed to help mitigate social losses. For example, the design of tropical cyclone index insurance could effectively manage the annual cyclone risk of $30-40 billion in losses, if a correct index can be specified. This and other applications are topics for future work.

In the study of economic development, there has been a perennial debate about the relative importance of culture, geography and institutions. This dissertation cannot settle this debate, however its results suggest two comments that may inform it.

First, the effect of climate is sizable. In Chapter 2 it was found that a one standard-deviation increase in September-October-November temperature altered average overall growth by approximately one percentage point, with the effect being as large as two percentage points in some industries. In Chapter 3 we found that a one standard-deviation increase in NINO3 increased the risk of civil conflict in the topics by approximately 23%. Finally, in Chapter 4 we found that a one standard-deviation in tropical cyclone wind exposure reduced total agricultural growth by approximately one percentage point, a loss that persists unmitigated for at least three years. It is not immediately clear if these climatological effects are "larger" or "smaller" than the effects of most cultural or institutional variables. But they are clearly not small in absolute terms, suggesting that environmental influences on development are not ignorable. Although, in the case of ENSO and conflict, we can say that climatological variables were at least as good, if not better, than any social or economic variables for explaining the timing of conflicts.

Second, the fact that a single doctoral dissertation can uncover three large impacts of climate on development suggests that the problem is under-studied. There are a large number of studies finding large correlations between economic performance and institutional or cultural variables, however there are very few that carefully examine the influence of environmental or geographic variables. Perhaps one reason environmental variables are infrequently studied may be the difficulty that social scientists have had measuring them. In each chapter of this dissertation, new techniques for measuring environmental variables was developed at high cost to the researcher[s]; however, in each case, large economic impacts were detected. If the difficulty of these studies explains why there are so few of them, and the small number of studies explains why environmental variables are considered less important than institutional or cultural variables, then the relative dominance of cultural and institutional explanations for economic underperformance might simply be an epistemological artifact.

Another classical challenge in development economics is to explain cross-country differences in performance. Yet, it is unclear if any results in this dissertation should contribute to that discussion. In each chapter, the relationships that were identified always compared a country to itself in different states of its environment. While the internal validity of this approach is strong, its external validity is less obvious. Countries differ in many important and unobservable ways, so relationships that hold within two countries may not hold between them. Based on these results, one could hypothesize that the environmental mechanisms identified also explain cross-country patterns; however these results alone are insufficient to prove such a claim.

Finally, it is worth noting the above discussion regarding vulnerability and adaptation to climate does not only apply to the future. Many resources are currently dedicated to understanding and improving adaptive capacity for future climate changes, however this dissertation suggests that many low income populations *currently* suffer large losses that are attributable to climatological variations. Therefore, when future work elucidates why some populations are less vulnerable to climatological variations, those results should be immediately applied in current development policies.

Bibliography

[Acemoglu, 2008] Acemoglu, D. (2008). *Introduction to Modern Economic Growth.* Princeton University Press.

[Acemoglu et al., 2002] Acemoglu, D., Johnson, S., and Robinson, J. A. (2002). Reversal of fortune: Geography and institutions in the making of the modern world income distribution. *The Quarterly Journal of Economics*, 117(4):1231–1294.

[Albouy et al., 2010] Albouy, D., Graf, W., Kellogg, R., and Wolff, H. (2010). Aversion to extreme temperatures, climate change and quality of life. *Working paper.*

[Anderson et al., 2000] Anderson, C. A., Anderson, K. B., Dorr, N., DeNeve, K. M., and Flanagan, M. (2000). Temperature and aggression. *Advances in Experimental Social Psychology*, 32:63–133.

[Angrist and Pischke, 2008] Angrist, J. D. and Pischke, J.-S. (2008). *Mostly Harmless Econometrics: An Empiricist's Companion.* Princeton University Press.

[Arellano, 1987] Arellano, M. (1987). Computing robust standard errors for within-groups estimators. *Oxford Bulletin of Economics and Statistics*, 49(4):431–434.

[Arrow et al., 2004] Arrow, K., Dasgupta, P., Goulder, L., Daily, G., Ehrlich, P., Heal, G., Levin, S., Maler, K.-G., Schneider, S., Starrett, D., and Walker, B. (2004). Are we consuming too much? *The Journal of Economic Perspectives*, 18:147–172.

[Auffhammer et al., 2010] Auffhammer, M., Hsiang, S., Schlenker, W., and Sobel, A. (2010). Global climate models: a user guide for economists. *Working paper.*

[Auffhammer et al., 2006] Auffhammer, M., Ramanathan, V., and Vincent, J. R. (2006). Integrated model shows that atmospheric brown clouds and greenhouse gases have reduced rice harvests in India. *Proceedings of the National Academy of Sciences*, 103:19668–19672.

[Bank and the United Nations, 2010] Bank, W. and the United Nations (2010). *Natural Hazards, UnNatural Disasters.* The World Bank.

[Barro and Sala-i-Martin, 2003] Barro, R. J. and Sala-i-Martin, X. (2003). *Economic Growth, 2nd edition.* The MIT Press.

[Barron et al., 2004] Barron, P., Kaiser, K., and Pradhan, M. (2004). Local conflict in Indonesia: Measuring incidence and identifying. World bank WP no. 3384, World Bank.

[Bertrand et al., 2004] Bertrand, M., Duflo, E., and Mullainathan, S. (2004). How much should we trust differences-in-differences estimates? *The Quarterly Journal of Economics*, 119(1):249–275.

[Bister and Emanuel, 1998] Bister, J. C. and Emanuel, K. A. (1998). Dissipative heating and hurricane intensity. *Met. and Atm. Phys.*, 65:233–240.

[Blattman and Miguel, 2010] Blattman, C. and Miguel, E. (2010). Civil war. *Journal of Economic Literature*, 48:3–57.

[Bruckner, 2010] Bruckner, M. (2010). Population size and civil conflict risk: is there a causal link? *The Economic Journal*, 120:535–550.

[Brunner, 2002] Brunner, A. D. (2002). El nino and world primary commodity prices: Warm water or hot air? *Review of Economics and Statistics*, 84(1):176–183.

[Buhaug, 2010] Buhaug, H. (2010). Climate not to blame for African civil wars. *PNAS*, Early Edition: Sep. 7.

[Burke et al., 2010] Burke, M., Dykema, J., Lobell, D., Miguel, E., and Satyanath, S. (2010). Climate and civil war: is the relationship robust? *NBER working paper 16440*.

[Burke et al., 2009] Burke, M., Miguel, E., Satyanath, S., Dykema, J., and Lobell, D. (2009). Warming increases risk of civil war in Africa. *PNAS*, 106:20670–20674.

[Camargo et al., 2007] Camargo, Suzana, J., Sobel, A. H., Barnston, A. G., and Emanuel, K. A. (2007). Tropical cyclone genesis potential index in climate models. *Tellus*, 59A:428–443.

[Cane et al., 1994] Cane, M. A., Eshel, G., and Buckland, R. W. (1994). Forcasting Zimbabwean maize yeild using eastern equatorial pacific sea surface temperature. *Nature*, 370:204–205.

[Carmargo and Sobel, 2005] Carmargo, S. J. and Sobel, A. H. (2005). Western north pacific tropical cyclone intensity and ENSO. *J. Climate*.

[Cavallo and Noy, 2009] Cavallo, E. and Noy, I. (2009). The economics of natural disasters: A survey. RES Working Papers 4649, Inter-American Development Bank, Research Department.

[Chen et al., 2004] Chen, D., Cane, M., Kaplan, A., Zebiak, S., and Huang, D. (2004). Predictability of El Niño over the past 148 years. *Nature*, 428(6984):733–736.

[Chiang and Sobel, 2002] Chiang, J. C. H. and Sobel, A. H. (2002). Tropical tropospheric temperature variations caused by ENSO and their influence on the remote tropical climate. *J. of Climate*, 15:2616–2631.

[CIESIN, 2009] CIESIN (2009). Gridded Population of the World Version 3.

[Collier and Hoeffler, 2004] Collier, P. and Hoeffler, A. (2004). Greed and grievance in civil war. *Oxford Economic Papers*, 4(56).

[Conley, 1999] Conley, T. (1999). GMM estimation with cross sectional dependence. *Journal of Econometrics*, 92(1):1–45.

[Conley, 2008] Conley, T. (2008). Spatial econometrics. In Durlauf, S. N. and Blume, L. E., editors, *New Palgrave Dictionary of Economics*. Elsevier, 2nd edition.

[Daly, 1996] Daly, H. E. (1996). *Beyond growth: the economics of sustainable development*. Beacon Press.

[Dasgupta, 2008] Dasgupta, P. (2008). Nature in economics. *Environment and Resource Economics*, 39:1–7.

[Davis, 2002] Davis, M. (2002). *Late Victorian Holocausts: El Niño Famines and the Making of the Third World*. Verso.

[Dell et al., 2009a] Dell, M., Jones, B. F., and Olken, B. A. (2009a). Climate change and economic growth: Evidence from the last half century. NBER Working Papers 14132, National Bureau of Economic Research, Inc.

[Dell et al., 2009b] Dell, M., Jones, B. F., and Olken, B. A. (2009b). Temperature and income: Reconciling new cross-sectional and panel estimates. *American Economic Review: Papers and Proceedings*, 99(2):198–204.

[Deschenes et al., 2011] Deschenes, O., Burgess, R., Donaldson, D., and Greenstone, M. (2011). Climate change and mortality in India. *Mimeo*.

[Deschenes and Greenstone, 2007] Deschenes, O. and Greenstone, M. (2007). The economic impacts of climate change: Evidence from agricultural output and random fluctuations in weather. *American Economic Review*, 97:354–385.

[Deschenes et al., 2009] Deschenes, O., Greenstone, M., and Guryan, J. (2009). Climate change and birth weight. *American Economic Review: Papers and Proceedings*, 99:211–217.

[Deschenes and Moretti, 2009] Deschenes, O. and Moretti, E. (2009). Extreme weather events, mortality and migration. *The Review of Economics and Statistics*, 91:659–681.

[Diamond, 1997] Diamond, J. (1997). *Guns, Germs and Steel: the Fates of Human Societies*. W. W. Norton and Co.

[Diamond, 2005] Diamond, J. (2005). *Collapse: How Societies Choose to Fail or Succeed*. Viking.

[Easterly and Levine, 2003] Easterly, W. and Levine, R. (2003). Tropics, germs and crops: how endowments influence economic development. *J. of Monetary Econ.*, 50:3–39.

[Elsner et al., 2008] Elsner, J. B., Kossin, J. P., and Jagger, T. H. (2008). The incresing intensity of the strongest tropical cyclones. *Nature*, 455:92–95.

[Emanuel, 1991] Emanuel, K. A. (1991). The theory of hurricanes. *Annual Reviews of Fluid Mechanics*, 23:179–196.

[Emanuel, 1999] Emanuel, K. A. (1999). Thermodynamic control of hurricane intensity. *Nature*, 41.

[Fagan, 2009] Fagan, B. (2009). *Floods, Famines and Emperors: El Niño and the Fate of Civilizations*. Basic Books.

[Fankhauser, 1995] Fankhauser, S. (1995). *Valuing Climate Change: the Economics of the Greenhouse*. Earthscan Publications Limited.

[Fearon and Laitin, 2003] Fearon, J. D. and Laitin, D. D. (2003). Ethnicity, insurgency and civil war. *American Political Science Review*, 97:75–90.

[Feng et al., 2010] Feng, S., Krueger, A. B., and Oppenheimer, M. (2010). Linkages among climate change, crop yields and mexico-us cross-border migration. *Proceedings of the National Academy of Sciences*, 107(32):14257–14262.

[Food and Agriculture Organization, 2009] Food and Agriculture Organization (2009). FAOStat database. `http://faostat.fao.org`.

[Frisch and Waugh, 1933] Frisch, R. and Waugh, F. V. (1933). Partial time regressions as compared with individual trends. *Econometrica*, 1(4):387–401.

[Gallup et al., 1999] Gallup, J. L., Sachs, J. D., and Mellinger, A. D. (1999). Geography and economic development. *Consulting Assistance on Economic Reform II, Discussion Papers*, (39).

[Giannini et al., 2003] Giannini, A., Saravanan, R., and Chang, P. (2003). Oceanic forcing of Sahel rainfall on interannual to interdecadal time scales. *Science*, 302(5647):1027–1030.

[Gleditsch et al., 2002] Gleditsch, N. P., Wallensteen, P., Eriksson, M., Sollenberg, M., and Strand, H. (2002). Armed conflict 1946-2001: a new dataset. *J. Peace Research*, 39:615–637.

[Graff Zivin and Neidell, 2010] Graff Zivin, J. and Neidell, M. J. (2010). Termperature and the allocation of time: Implications for climate change. *NBER Working paper.*

[Greene, 2003] Greene, W. H. (2003). *Econometric Analysis, Fifth Edition.* Prentice Hall.

[Grove, 2007] Grove, R. H. (2007). The great El Niño of 1789-93 and its global consequences: Reconstructing an extreme climate event in world environmental history. *The Medieval History Journal*, 10(1&2).

[Hancock et al., 2007] Hancock, P. A., Ross, J. M., and Szalma, J. L. (2007). A meta-analysis of performance response under thermal stressors. *Human Factors*, 49(5).

[Hancock and Vasmatzidis, 2003] Hancock, P. A. and Vasmatzidis, I. (2003). Effects of heat stress on cognitive performance: the current state of knowledge. *International Journal of Hyperthermia*, 19:355–372.

[Hegre and Sambanis, 2006] Hegre, H. and Sambanis, N. (2006). Sensitivity analysis of empirical results on civil war onset. *J. Conflict Resolution*, 50(4):508–535.

[Heming and Goerss, 2010] Heming, J. and Goerss, J. (2010). Track and structure forecasts of tropical cyclones. In Chan, J. C. L. and Kepert, J. D., editors, *Global Perspectives on Tropical Cyclones: From Science to Mitigation*, pages 287–323. World Scientific.

[Hendrix and Glaser, 2007] Hendrix, C. S. and Glaser, S. M. (2007). Trends and triggers: Climate, climate change and civil conflict in Sub-Saharan Africa. *Political Geography*, 26:695–715.

[Homer-Dixon, 1991] Homer-Dixon, T. F. (1991). On the threshold: Environmental changes as causes of acute conflict. *International Security*, 16:76–116.

[Hsiang, 2010] Hsiang, S. M. (2010). Temperatures and cyclones strongly associated with economic production in the Caribbean and Central America. *Proceedings of the National Academy of Sciences*, 107(35):15367–15372.

[Hsiang et al., 2011] Hsiang, S. M., Meng, K. C., and Cane, M. A. (2011). Global climate influences civil conflicts: Evidence from el niño. *Working paper.*

[Hsiang and Narita, 2011] Hsiang, S. M. and Narita, D. (2011). Global losses and declining vulnerability to tropical cyclones. *Working paper.*

[IPCC, 2007] IPCC (2007). *Climate Change 2007 - Impacts, Adaptation and Vulnerability.* Cambridge University Press.

[IPCC, 2007] IPCC (2007). *Climate Change 2007 - The Physical Science Basis.* Cambridge University Press.

[ISDR, 2009] ISDR (2009). *Global Assessment Report on Disaster Risk Reduction.* United Nations.

[Jensen and Gleditsch, 2009] Jensen, P. S. and Gleditsch, K. S. (2009). Rain, growth, and civil war: The importance of location. *Defense and Peace Economics*, 20(5):359–372.

[Jones and Olken, 2010] Jones, B. and Olken, B. (2010). Climate shocks and exports. *American Economic Review: Papers and Proceedings*, 100:454–459.

[Kahn, 2005] Kahn, M. E. (2005). The death toll from natural disasters: the role of income, geography, and institutions. *The Review of Economics and Statistics*, 87:271–284.

[Kalnay et al., 1996] Kalnay, E., Kanamitsu, M., Kistler, R., Collins, W., Deaven, D., Gandin, L., Iredell, M., Saha, S., White, G., Woollen, J., Zhu, Y., Leetmaa, A., Reynolds, B., Chelliah, M., Ebisuzaki, W., Higgins, W., Janowiak, J., Mo, K. C., Ropelewski, C., Wang, J., Jenne, R., , and Joseph, D. (1996). The NCEP/NCAR 40-year reanalysis project. *Bulletin of the American Meterological Society*, 77:437–471.

[Kaplan et al., 1998] Kaplan, A., Cane, M., Kushnir, Y., Clement, A., Blumenthal, M., and Rajagopalan, B. (1998). Analyses of global sea surface temperature 1856-1991. *Journal of Geophysical Research*, 103:18,567–18,589.

[Kellenberg and Mobarak, 2008] Kellenberg, D. K. and Mobarak, A. M. (2008). Does rising income increase or decrease damage risk from natural disasters? *Journal of Urban Economics*, 63:788–802.

[Klein et al., 1999] Klein, S. A., Soden, B. J., and Lau, N.-C. (1999). Remote sea surface temperature variations during ENSO: Evidence for a tropical atmospheric bridge. *Journal of Climate*.

[Knapp, 2009] Knapp, K. R. (2009). Archive compiles new resource for global tropical cyclone research. *Eos*, 90:46–47.

[Knutson et al., 2010a] Knutson, T., Landsea, C., and Emanuel, K. (2010a). Tropical cyclones and climate change: A review. In Chan, J. C. L. and Kepert, J. D., editors, *Global Perspectives on Tropical Cyclones: From Science to Mitigation*, pages 243–284. World Scientific.

[Knutson et al., 2010b] Knutson, T. R., l. Mcbride, J., Chan, J., Emanuel, K., Holland, G., Landsea, C., Held, I., Kossin, J. P., Srivastava, A. K., and Sugi, M. (2010b). Tropical cyclones and climate change. *Nature Geoscience*, 3:157–163.

[Kossin et al., 2007] Kossin, J., Knaff, J., Berger, H., Herndon, D., Cram, T., Velden, C., Murnane, R., and Hawkins, J. (2007). Estimating hurricane wind structure in the absence of aircraft reconnaissance. *Weather Forecasting*, 22:89–101.

[Kovats et al., 2003] Kovats, R. S., Bouma, M. J., Hajat, S., Worrall, E., and Haines, A. (2003). El Niño and health. *The Lancet*, 12:917–932.

[Kunreuther et al., 2009] Kunreuther, H. C., Michel-Kerjan, E. O., Doherty, N. A., Grace, M. F., Clein, R. W., and Pauly, M. V. (2009). *At War With the Weather*. MIT Press.

[Levy et al., 2005] Levy, M. A., Thorkelson, C., Vorosmarty, C., Douglas, E., and Humphreys, M. (2005). Freshwater availability anomalies and outbreak of internal war: Results from a global spatial time series analysis. *International Workshop for Human Security and Climate Change*.

[Liang and Zeger, 1986] Liang, K.-Y. and Zeger, S. L. (1986). Longitudinal data analysis using generalized linear models. *Biometrika*, 73(1):13–22.

[Loayza et al., 2009] Loayza, N., Olaberria, E., Rigolini, J., and Christiaensen, L. (2009). Natural disasters and growth: Going beyond the averages. Policy Research Working Paper 4980, The World Bank.

[Mallen et al., 2005] Mallen, K. J., Montgomoery, M. T., and Wang, B. (2005). Reexamining the near-core radial structure of the tropical cyclone primary circulation: Implications for vortex resiliency. *Journal of the Atmospheric Sciences*, 62:408–425.

[Mann and Emanuel, 2006] Mann, M. E. and Emanuel, K. A. (2006). Atlantic hurricane trends linked to climate change. *Eos*, 87(24).

[Marshall et al., 2009] Marshall, M. G., Gurr, T. R., and Jaggers, K. (2009). Polity iv project. Technical report, Center for Systemic Peace.

[McNeil, 2000] McNeil, R. J. (2000). *Something New Under the Sun: an Environmental History of the 20th-Century World*. W. W. Norton and Co.

[Meehl et al., 2007] Meehl, G. A., Covey, C., Delworth, T., Latif, M., McAvaney, B., B., J. F., Mitchell, Stouffer, R. J., and Taylor, K. E. (2007). The WCRP CMIP3 Multimodel Dataset: A new era in climate change research. *Bulletin of the American Meterological Society*, 88:1383–1394.

[Meier et al., 2007] Meier, P., Bond, D., and Bond, J. (2007). Environmental influences on pastoral conflict in the Horn of Africa. *Political Geography*, 26:716–735.

[Mendelsohn et al., 2006] Mendelsohn, R., Dinar, A., and Williams, L. (2006). The distributional impact of climate change on rich and poor countries. *Environment and Development Economics*, 11:159–178.

[Mendelsohn et al., 2010] Mendelsohn, R., Emanuel, K., and Chonobayashi, S. (2010). The impact of climate change on global tropical storm damages. Technical report, The World Bank.

[Meng et al., 2011] Meng, K., Schlenker, W., and You, L. (2011). Responding to predictive weather: Evidence from Chinese farmers and the east asian summer monsoon. *Working paper*.

[Miguel et al., 2004] Miguel, E., Satyanath, S., and Sergenti, E. (2004). Economic shocks and civil conflict: An instrumental variables approach. *J. Political Economy*, 112(4):725–753.

[Millner et al., 2010] Millner, A., Dietz, S., and Heal, G. (2010). Ambiguity and climate policy. Working Paper 16050, National Bureau of Economic Research.

[Mutter, 2005] Mutter, J. C. (2005). The earth sciences, human well-being, and the reduction of global poverty. *Eos*, 86(16).

[Nadaraya, 1964] Nadaraya, E. A. (1964). On estimating regression. *Theory of Probability and Its Applications*, 9:141–142.

[Narita et al., 2009] Narita, D., Tol, R. S. J., and Anthoff, D. (2009). Damage costs of climate change through intensification of tropical cyclone activities: an application of fund. *Climate Research*, 39:87–97.

[Neumann et al., 1999] Neumann, C. J., Jarvinen, B. R., McAdie, C. J., and Hammer, G. R. (1999). *Tropical Cyclones of the North Atlantic Ocean, 18711998*. National Oceanic and Atmospheric Administration.

[Newey and West, 1987] Newey, W. K. and West, K. D. (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica*, 55(3):703–708.

[Nicholls, 1989] Nicholls, N. (1989). Sea surface temperatures and australian winter rainfall. *Journal of Climate*, 2:965–973.

[Nicholson and Kim, 1997] Nicholson, S. E. and Kim, J. (1997). The relationship of the El Niño-Southern Oscillation to African rainfall. *International Journal of Climatology*, 17:117–135.

[NIOSH, 1986] NIOSH (1986). *Criteria for a Recommended Standard: Occupational Exposure to Hot Environments (Revised Criteria 1986)*. Number 86-113. National Institute for Occupational Safety and Health.

[Nordhaus, 2008] Nordhaus, W. (2008). *A Question of Balance: Weighing the Options on Global Warming Policies*. Yale University Press.

[Nordhaus and Boyer, 2000] Nordhaus, W. and Boyer, J. (2000). *Warming the World: Economic Models of Global Warming*. The MIT Press.

[Nordhaus, 2006a] Nordhaus, W. D. (2006a). The economics of hurricanes in the United States. *Annual Meetings of the American Economic Association*.

[Nordhaus, 2006b] Nordhaus, W. D. (2006b). Geography and macroeconomics: New data and new findings. *PNAS*, 103(10).

[Noy, 2009] Noy, I. (2009). The macroeconomic consequences of disasters. *Journal of Development Economics*, 88:221–231.

[OFDA/CRED, 2009] OFDA/CRED (2009). The International Disaster Database.

[Parry et al., 2007] Parry, M., Canziani, O., Palutikof, J., van der Linden, P., and (eds.), C. H. (2007). *Climate Change 2007: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press.

[Patt et al., 2010] Patt, A. G., van Vuuren, D. P., Berkhout, F., Aaheim, A., Hof, A. F., Isaac, M., and Mechler, R. (2010). Adaptation in integrated assessment modeling: where do we stand? *Climatic Change*, 99:383–402.

[Pielke Jr. et al., 2008] Pielke Jr., R. A., Gratz, J., Landsea, C. W., Collins, D., Saunders, M. A., and Musulin, R. (2008). Normalized hurricane damage in the united states: 1900–2005. *Natural Hazards Review*, 9(1):29–42.

[Pielke Jr. and Sr., 1997] Pielke Jr., R. A. and Sr., R. A. P. (1997). *Hurricanes: Their Nature and Impacts on Society*. John Wiley and Sons.

[Pilcher et al., 2002] Pilcher, J. J., Nadler, E., and Busch, C. (2002). Effect of hot and cold temperature exposure on performace: a meta-analytic review. *Ergonomics*, 45:682–698.

[Ramankutty et al., 2008] Ramankutty, N., Evan, A. T., Monfreda, C., and Foley, J. A. (2008). Farming the planet: 1. geographic distribution of global agricultural lands in the year 2000. *Global Biogeochemical Cycles*, 22.

[Ramsey, 1928] Ramsey, F. P. (1928). A mathematical theory of saving. *Economic Journal*, 38:543–559.

[Ramsey and Morrissey, 1978] Ramsey, J. D. and Morrissey, S. J. (1978). Isodecrement curves for task performance in hot environments. *Applied Ergonomics*, 9(2).

[Reichler and Kim, 2008] Reichler, T. and Kim, J. (2008). How well do coupled models simulate todays climate? *Bulletin of the American Meteorological Society*, 89:303–311.

[Richards, 2005] Richards, J. F. (2005). *The Unending Frontier: an environmental history of the early modern world*. University of California Press.

[Ropelewski et al., 1985] Ropelewski, C., Janowiak, J., and Halpert, M. (1985). The analysis and display of real time surface climate data. *The Monthly Weather Review*, 113:1101–1106.

[Ropelewski and Halpert, 1987] Ropelewski, C. F. and Halpert, M. S. (1987). Global and regional precipitation patterns associated with the El Niño/Southern Oscillation. *Monthly Weather Review*, 115:1606–1626.

[Ropelewski and Halpert, 1989] Ropelewski, C. F. and Halpert, M. S. (1989). Precipitation patterns associated with the high index phase of the Southern Oscillation. *Journal of Climate*, 2:268–284.

[Rosenzweig and Hillel, 2008] Rosenzweig, C. and Hillel, D. (2008). *Climate Variability and the Global Harvest: Impacts of El Niño and Other Oscillations on Agro-Ecosystems*. Oxford University Press.

[Sachs, 2005] Sachs, J. D. (2005). *The End of Poverty: Economic Possibilities for Our Time*. The Penguin Press.

[Sala-i Martin, 2006] Sala-i Martin, X. (2006). The world distribution of income: Falling poverty and...convergence, period. *The Quarterly Journal of Economics*, 71:351–397.

[Salehyan, 2008] Salehyan, I. (2008). From climate change to conflict? No consensus yet. *Journal of Peace Research*, 45(3):315–326.

[Sarachik and Cane, 2010] Sarachik, E. S. and Cane, M. A. (2010). *The El Niño-Southern Oscillation Phenomenon*. Cambridge University Press.

[Schlenker et al., 2005] Schlenker, W., Hanemann, W. M., and Fisher, A. C. (2005). Will U.S. agriculture really benefit from global warming? Accounting for irrigation in the hedonic approach. *American Economic Review: Papers and Proceedings*, 95(1):395–406.

[Schlenker and Lobell, 2010] Schlenker, W. and Lobell, D. (2010). Robust negative impacts of climate change on African agriculture. *Environmental Research Letters*.

[Schlenker and Roberts, 2009] Schlenker, W. and Roberts, M. (2009). Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change. *Proceedings of the National Academy of Sciences*, 106(37):15594–15598.

[Seppänen et al., 2003] Seppänen, O., Fisk, W. J., and Faulkner, D. (2003). Cost benefit analysis of the night-time ventilative cooling in office building. Technical Report LBNL-53191, Lawrence Berkeley National Laboratory.

[Smil, 2008] Smil, V. (2008). *Global Catastrophes and Trends*. The MIT Press.

[Smith, 1776] Smith, A. (1776). *An Inquiry into the Nature and Causes of the Wealth of Nations*. W. Strahan and T. Cadell.

[Smith et al., 2006] Smith, V. K., Carbon, J. C., Pope, J. C., Hallstrom, D. G., and Darden, M. E. (2006). Adjusting to natural disasters. *Journal of Risk and Uncertainty*, 33:37–54.

[Solow, 1956] Solow, R. (1956). A contribution to the theory of economic growth. *Quarterly Journal of Economics*, 70:65–94.

[Stern, 2006] Stern, N. (2006). *Stern Review: The Economics of Climate Change*. Cambridge University Press.

[Strand, 2006] Strand, H. (2006). Onset of armed conflict: A new list for the period 1946-2004, with applications. Technical report, Center for the Study of Civil War.

[Swanson, 2008] Swanson, K. L. (2008). Nonlocality of Atlantic tropical cyclone intensities. *Geochmistry Geophysics Geosystems*, 9(4).

[Taleb, 2007] Taleb, N. N. (2007). *The Black Swan: The Impact of the Highly Improbable*. Random House.

[Tol, 2002] Tol, R. S. J. (2002). Estimates of the damage costs of climate change. *Environmental and Resource Economics*, 21:47–73.

[Tol, 2009] Tol, R. S. J. (2009). The economic effects of climate change. *Journal of Economic Perspectives*, 23(2):29–51.

[Tol and Wagner, 2009] Tol, R. S. J. and Wagner, S. (2009). Climate change and violent conflict in europe over the last millennium. *Climatic Change*, 99:65–79.

[Toya and Skidmore, 2007] Toya, H. and Skidmore, M. (2007). Economic development and the impacts of natural disasters. *Economics Letters*, 94(1):20–25.

[UN, 2007] UN (2007). *National Accounts Statistics: Main Aggregates and Detailed Tables, 2007*. United Nations.

[UN, 2008] UN (2008). *International Recommendations for Tourism Statistics*. United Nations World Tourism Organization.

[UN, 2009] UN (2009). *National Accounts Statistics: Main Aggregates and Detailed Tables, 2009*. United Nations.

[Urdal, 2008] Urdal, H. (2008). Population, resources and violent conflict: A sub-national study of India 1956-2002. *Journal of Conflict Resolution*, 52(4):590–617.

[Watson, 1964] Watson, G. S. (1964). Smooth regression analysis. *Sankhya*, 26:359–372.

[Weitzman, 2009] Weitzman, M. L. (2009). On modeling and interpreting the economics of catastrophic climate change. *The Review of Economics and Statistics*, 91:1–19.

[Welch et al., 2010] Welch, J. R., Vincent, J. R., Auffhammer, M., Moya, P. F., Dobermann, A., and Dawe, D. (2010). Rice yields in tropical/subtropical asia exhibit large but opposing sensitivities to minimum and maximum temperatures. *Proceedings of the National Academy of Sciences*.

[White, 1980] White, H. (1980). A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica*, 48:817–838.

[World Bank, 2008] World Bank (2008). *World Development Indicators 2008*. World Bank.

[Wyon, 2001] Wyon, D. P. (2001). *Indoor Air Quality Handbook*, chapter Thermal Effects on Performance. McGraw-Hill.

[Xie and Arkin, 1996] Xie, P. and Arkin, P. A. (1996). Analyses of global monthly precipitation using gauge observations, satellite estimates, and numerical model predictions. *Journal of Climate*, 9:840–858.

[Zhang et al., 2007] Zhang, D. D., Brecke, P., Lee, H. F., He, Y.-Q., , and Zhang, J. (2007). Global climate change, war and population decline in recent human history. *PNAS*, 104(49):19214–19219.