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Lecture 17

The paper we discuss today is a very broad survey on climate and conflict written by some of the main researchers we've been studying in recent weeks.

Here is a similar recent example of characters coming together to solve common problems.

I will refer to the authors as HBM (Hsiang, Burke and Miguel) since we already used up "Hsiang et al." on the ENSO paper.

The nature of this paper is quite different from anything we have studied before because it is not a single piece of research on one dataset but, rather, a survey that ranges over a large quantity of research. In fact, the scale of this work is remarkable.

The next bunch of slides gives the main table (singular) of the paper.

Study	Sample period	Sample region	Time unit	Spatial unit	Independent variable	Dependent variable	Stat. test	Large effect	Reject β = 0	Reject β = 10%	Ref.
					Interpersonal conflict (15)						
Anderson *et al*. 2000*	1950–1997	USA	Annual	Country	Temp	Violent crime	Y	Y	Y	–	(*34*)
Auliciems *et al*. 1995†	1992	Australia	Week	Municipality	Temp	Domestic violence	Y	Y	Y	–	(*29*)
Blakeslee *et al*. 2013	1971–2000	India	Annual	Municipality	Rain	Violent and property crime	Y	Y	Y	–	(*42*)
Card *et al*. 2011†‡	1995–2006	USA	Day	Municipality	Temp	Domestic violence	Y	Y	Y	–	(*37*)
Cohn *et al*. 1997§	1987–1988	USA	Hours	Municipality	Temp	Violent crime	Y	Y	Y	–	(*30*)
Jacob *et al*. 2007†‖	1995–2001	USA	Week	Municipality	Temp	Violent and property crime	Y	Y	Y	–	(*35*)
Kenrick *et al*. 1986¶	1985	USA	Day	Site	Temp	Hostility	Y	Y	Y	–	(*27*)
Larrick *et al*. 2011†‡‖	1952–2009	USA	Day	Site	Temp	Violent retaliation	Y	Y	Y	–	(*36*)
Mares 2013	1990–2009	USA	Month	Municipality	Temp	Violent crime	Y	Y	Y	–	(*39*)
Miguel 2005†‡	1992–2002	Tanzania	Annual	Municipality	Rain	Murder	Y	Y	N	N	(*40*)

Study	Sample period	Sample region	Time unit	Spatial unit	Independent variable	Dependent variable	Stat. test	Large effect	Reject β = 0	Reject β = 10%	Ref.
Mehlum *et al*. 2006	1835–1861	Germany	Annual	Province	Rain	Violent and property crime	Y	Y	Y	–	(*43*)
Ranson 2012†‖	1960–2009	USA	Month	County	Temp	Personal violence	Y	Y	Y	–	(*38*)
Rotton *et al*. 2000§	1994–1995	USA	Hours	Municipality	Temp	Violent crime	Y	Y	Y	–	(*31*)
Sekhri *et al*. 2013†	2002–2007	India	Annual	Municipality	Rain	Murder and domestic violence	Y	Y	Y	–	(*41*)
Vrij *et al*. 1994¶	1993	Netherlands	Hours	Site	Temp	Police use of force	Y	Y	Y	–	(*28*)
<u>Intergroup conflict (30)</u>											
Almer *et al*. 2012	1985–2008	SSA	Annual	Country	Rain/temp	Civil conflict	Y	Y	N	N	(*65*)
Anderson *et al*. 2013	1100–1800	Europe	Decade	Municipality	Temp	Minority expulsion	Y	Y	Y	–	(*63*)
Bai *et al*. 2010	220–1839	China	Decade	Country	Rain	Transboundary	Y	Y	Y	–	(*50*)
Bergholt *et al*. 2012‡#	1980–2007	Global	Annual	Country	Flood/storm	Civil conflict	Y	N	N	Y	(*75*)
Bohlken *et al*. 2011‖#	1982–1995	India	Annual	Province	Rain	Intergroup	Y	Y	N	N	(*44*)
Buhaug	1979–	SSA	Annual	Country	Temp	Civil conflict	Y	N	N	N	(*22*)

Study	Sample period	Sample region	Time unit	Spatial unit	Independent variable	Dependent variable	Stat. test	Large effect	Reject β = 0	Reject β = 10%	Ref.
2010#	2002										
Burke 2012‡‖#	1963–2001	Global	Annual	Country	Rain/temp	Political instability	Y	Y	N**	N	(*71*)
Burke *et al*. 2009‡‖#††	1981–2002	SSA	Annual	Country	Temp	Civil conflict	Y	Y	Y	–	(*64*)
Cervellati *et al*. 2011	1960–2005	Global	Annual	Country	Drought	Civil conflict	Y	Y	Y	–	(*54*)
Chaney 2011	641–1438	Egypt	Annual	Country	Nile floods	Political Instability	Y	Y	Y	–	(*70*)
Couttenier *et al*. 2011#	1957–2005	SSA	Annual	Country	PDSI	Civil conflict	Y	Y	Y	–	(*53*)
Dell *et al*. 2012#	1950–2003	Global	Annual	Country	Temp	Political instability and civil conflict	Y	Y	Y	–	(*21*)
Fjelde *et al*. 2012‡#	1990–2008	SSA	Annual	Province	Rain	Intergroup	Y	Y	N**	N	(*55*)
Harari *et al*. 2013#	1960–2010	SSA	Annual	Pixel (1°)	Drought	Civil conflict	Y	Y	Y	–	(*52*)
Hendrix *et al*. 2012‡‖#	1991–2007	SSA	Annual	Country	Rain	Intergroup	Y	Y	Y	–	(*46*)
Hidalgo *et al*. 2010‡‖#	1988–2004	Brazil	Annual	Municipality	Rain	Intergroup	Y	Y	Y	–	(*25*)

Study	Sample period	Sample region	Time unit	Spatial unit	Independent variable	Dependent variable	Stat. test	Large effect	Reject β = 0	Reject β = 10%	Ref.
Hsiang *et al*. 2011‖#	1950–2004	Global	Annual	World	ENSO	Civil conflict	Y	Y	Y	–	(*51*)
Jia 2012	1470–1900	China	Annual	Province	Drought/flood	Peasant rebellion	Y	Y	Y	–	(*56*)
Kung *et al*. 2012	1651–1910	China	Annual	County	Rain	Peasant rebellion	Y	Y	Y	–	(*47*)
Lee *et al*. 2013	1400–1999	Europe	Decade	Region	NAO	Violent conflict	Y	Y	Y	–	(*57*)
Levy *et al*. 2005‡‖#	1975–2002	Global	Annual	Pixel (2.5°)	Rain	Civil conflict	Y	Y	N**	N	(*49*)
Maystadt *et al*. 2013#	1997–2009	Somalia	Month	Province	Temp	Civil conflict	Y	Y	Y	–	(*66*)
Miguel *et al*. 2004#‡‡	1979–1999	SSA	Annual	Country	Rain	Civil war	Y	Y	Y	–	(*48*)
O'Laughlin *et al*. 2012‡‖#	1990–2009	E. Africa	Month	Pixel (1°)	Rain/temp	Civil/intergroup	Y	Y	Y	–	(*23*)
Salehyan *et al*. 2012	1979–2006	Global	Annual	Country	PDSI	Civil/intergroup	Y	Y	Y	–	(*76*)
Sarsons 2011	1970–1995	India	Annual	Municipality	Rain	Intergroup	Y	Y	Y	–	(*45*)
Theisen *et al*. 2011‡#	1960–2004	Africa	Annual	Pixel (0.5°)	Rain	Civil conflict	Y	N	N	N	(*24*)
Theisen	1989–	Kenya	Annual	Pixel	Rain/temp	Civil/intergroup	Y	Y	N**	N	(*14*)

Study	Sample period	Sample region	Time unit	Spatial unit	Independent variable	Dependent variable	Stat. test	Large effect	Reject β = 0	Reject β = 10%	Ref.
2012‡ǁ#	2004			(0.25°)							
Tol *et al*. 2009	1500–1900	Europe	Decade	Region	Rain/temp	Transboundary	Y	Y	Y	–	(*60*)
Zhang *et al*. 2007§§	1400–1900	N. Hem.	Century	Region	Temp	Instability	Y	Y	Y	–	(*59*)
Institutional breakdown and population collapse (15)											
Brückner *et al*. 2011#	1980–2004	SSA	Annual	Country	Rain	Inst. change	Y	Y	Y	–	(*78*)
Buckley *et al*. 2010ǁǁ	1030–2008	Cambodia	Decade	Country	Drought	Collapse	N	–	–	–	(*85*)
Büntgen *et al*. 2011ǁǁ	400 BCE–2000	Europe	Decade	Region	Rain/temp	Instability	N	–	–	–	(*62*)
Burke *et al*. 2010‡#	1963–2007	Global	Annual	Country	Rain/temp	Inst. change	Y	Y	Y	–	(*77*)
Cullen *et al*. 2000ǁǁ	4000 BCE–0	Syria	Century	Country	Drought	Collapse	N	–	–	–	(*83*)
D'Anjou *et al*2012	550 BCE–1950	Norway	Century	Municipality	Temp	Collapse	Y	Y	Y	–	(*89*)
Ortloff *et al.*1993ǁǁ	500–2000	Peru	Century	Country	Drought	Collapse	N	–	–	–	(*80*)
Haug *et al*.	0–1900	Mexico	Century	Country	Drought	Collapse	N	–	–	–	(*84*)

Study	Sample period	Sample region	Time unit	Spatial unit	Independent variable	Dependent variable	Stat. test	Large effect	Reject β = 0	Reject β = 10%	Ref.
2003‖‖											
Kelly *et al*. 2013	10050 BCE–1950	USA	Century	State	Temp/rain	Collapse	Y	Y	Y	–	(*88*)
Kennett *et al*. 2012	40 BCE–2006	Belize	Decade	Country	Rain	Collapse	N	–	–	–	(*87*)
Kuper *et al*. 2006	8000–2000 BCE	N. Africa	Millennia	Region	Rain	Collapse	N	–	–	–	(*81*)
Patterson *et al*. 2010	200 BCE–1700	Iceland	Decade	Country	Temp	Collapse	N	–	–	–	(*86*)
Stahle *et al*. 1998	1200–2000	USA	Multiyear	Municipality	PDSI	Collapse	N	–	–	–	(*82*)
Yancheva *et al*. 2007‖‖	2100 BCE–1700	China	Century	Country	Rain/temp	Collapse	N	–	–	–	(*79*)
Zhang *et al*. 2006	1000–1911	China	Decade	Country	Temp	Civil conflict and collapse	Y	Y	Y	–	(*58*)
			Number of studies (60 total):			**50**	**47**	**37**	**1**		
				Fraction of those using statistical tests:			**100%**	**94%**	**74%**	**2%**	

Table 1 Primary quantitative studies testing for a relationship between climate and conflict, violence, or political instability.

“Stat. test” is Y if the analysis uses formal statistical methods to quantify the influence of climate variables and uses hypothesis testing procedures (Y, yes; N, no). “Large effect” is Y if the point estimate for the effect size is considered substantial by the authors or is greater in magnitude than 10% of the mean risk level for a 1σ change in climate variables. “Reject β = 0” is Y if the study rejects an effect size of zero at the 95% confidence level. “Reject β = 10%” is Y if the study is able to reject the hypothesis that the effect size is larger than 10% of the mean risk level for a 1σ change in climate variables. –, not applicable. SSA, sub-Saharan Africa; PDSI; Palmer Drought Severity Index; ENSO, El Niño–Southern Oscillation; NAO, North Atlantic Oscillation; N. Hem., Northern Hemisphere.

The above text helps to decode the table.

When there is as much work as this to be surveyed there will also, inevitably, be issues of which studies to include and which to exclude.

HBM apply a methodological screen before they admit a study into the above table. (There are some exceptions for studies of collapses of whole civilisations but we will not cover those in this lecture anyway.)

Each study must estimate an equation of the form:

$$conflict\_variable_{it} = \beta \times \ climate\_variable_{it} + \mu_i + \theta_t + \epsilon_{it}$$

The many conflict variables are listed as the dependent variables in the above table.

Many are things like civil conflict or civil war - very much the kinds of things we discuss in this course.

But it also ranges all the way to interpersonal conflict, covering things like murders, assaults and rapes.

The climate variables are listed as the independent variables in the table.

They all have something to do with temperature or rain.

We will focus mostly on temperature in this lecture.

The μ_i dummy variables are for all the geographical locations covered in each study.

Recall from lecture 16 that having a dummy variable for each location is just one technique to account for geographical variation but for present purposes it will be fine to think of the dummy variables technique as the one used throughout the lecture. Note, however, that you will sometimes encounter the “fixed effects” terminology which means that variables are measured as deviations from their averages, a method that largely does the same work as having geographical dummies.

These locations can be various things depending on the particular study – countries, counties, municipalties, etc., and are indexed by the letter “i”.

The θ_t variables are time dummies indexed by the letter “t”.

Why have the locational and time dummies?

Locational dummies (fixed effects) –

Some locations can have higher inherent tendencies toward conflict than other locations do.

These inherent tendencies may have little or nothing to do with climate but might still, nevertheless, be correlated with climate.

For example, Norway is cold and has little tendency toward conflict. Nigeria, on the other hand, is hot and has a definite tendency toward conflict.

It is possible that temperatures have something to do with these differing tendencies toward conflict but it is farfetched that temperature fully explains them or even that temperature is one of the main reasons for the differences.

Rather, it is likely that much of the differing tendency toward violence, Norway versus Nigeria, comes from things like culture, economic conditions, history, etc..

Having the locational dummies in our regression builds in flexibility to allow for different countries to differ on their tendencies toward conflict for reasons unrelated to the relationship between temperature and conflict.

The key point is that if you omit the locational dummies then you distort the relationship between temperature and conflict.

In particular, if the Norway-Nigeria example is typical then you would tend to exaggerate the impact of warm weather on conflict because you would be attributing all differences in conflict risks between these types of countries to temperature.

In reality, only some or maybe none of the differences are really due to temperature differences.

The time dummies -

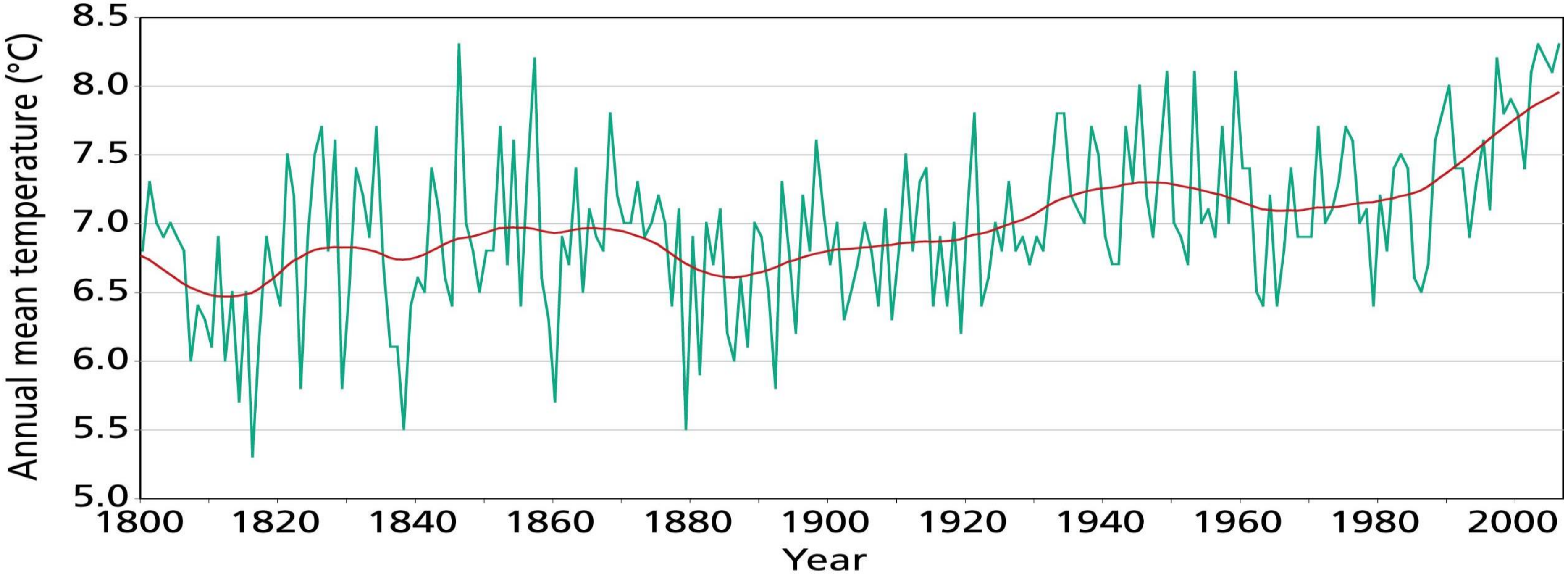
Suppose the tendency toward conflict varies systematically over time in a way that is correlated with temperature even though temperature changes are not causing these changes over time.

Then a regression that omits time dummies will tend to spuriously associate the changes in temperature with changes in conflict tendencies.

We will focus on figure 2 in HBM which is shown on slide 21.

But before reaching this slide there are a few things that require a bit more explanation which I give on the next two slides (slides 19 and 20).

First, both the conflict and climate variables are “detrended”. You can do this by plotting the variable over time, fitting a curve to it and then subtracting off the fitted curve from the original data. You are left with just deviations from the trend. The picture below gives raw temperature data for Scotland with a fitted curve (which is a 10-year moving average). Subtract off that curve (or a different one based on a different fitting method) and you have detrended data.



Second, for each location you average the detrended data over time and subtract off these averages from all the observations for that location. You get something like the picture below – no trend over time with all the observations measured as deviations from 0.

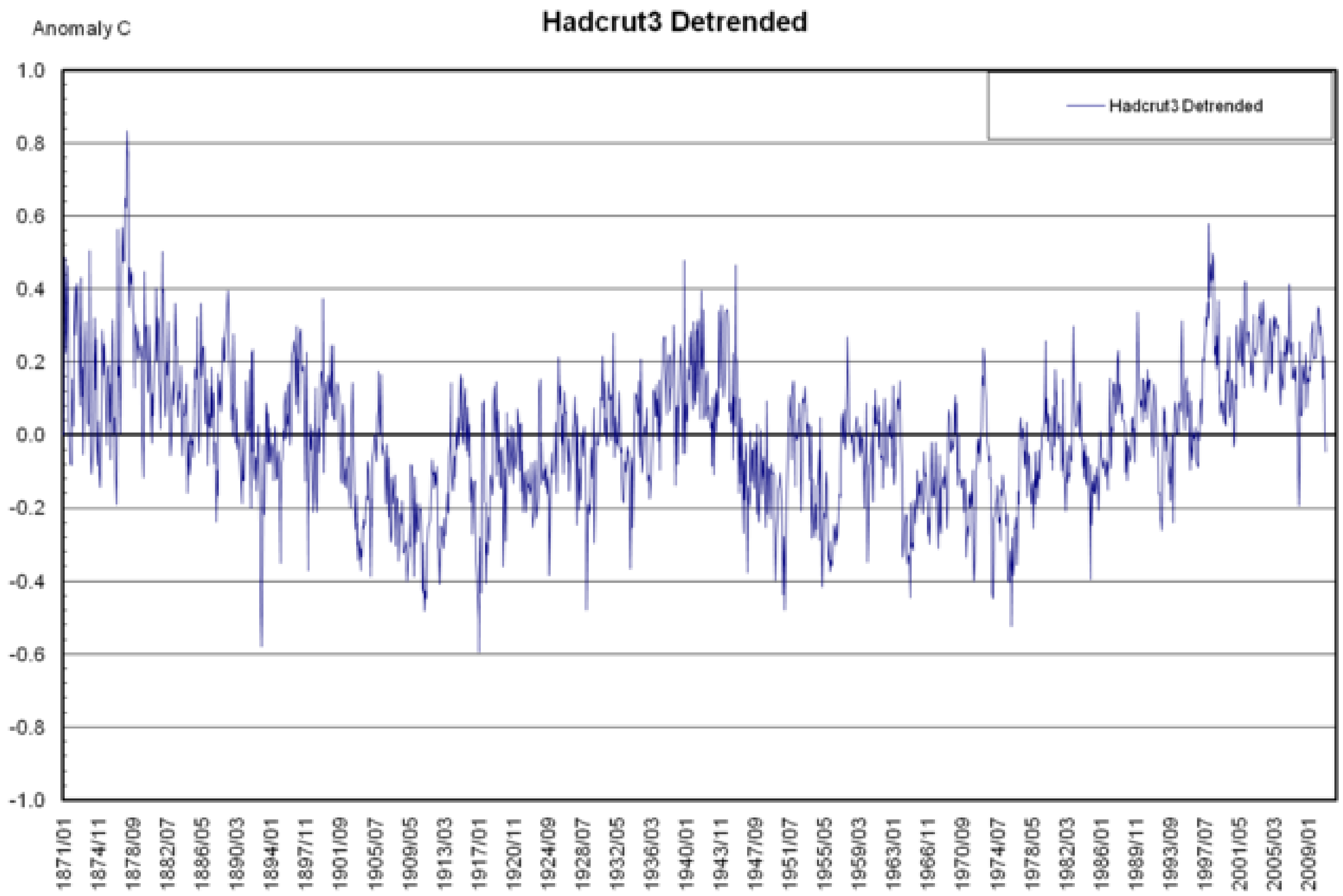
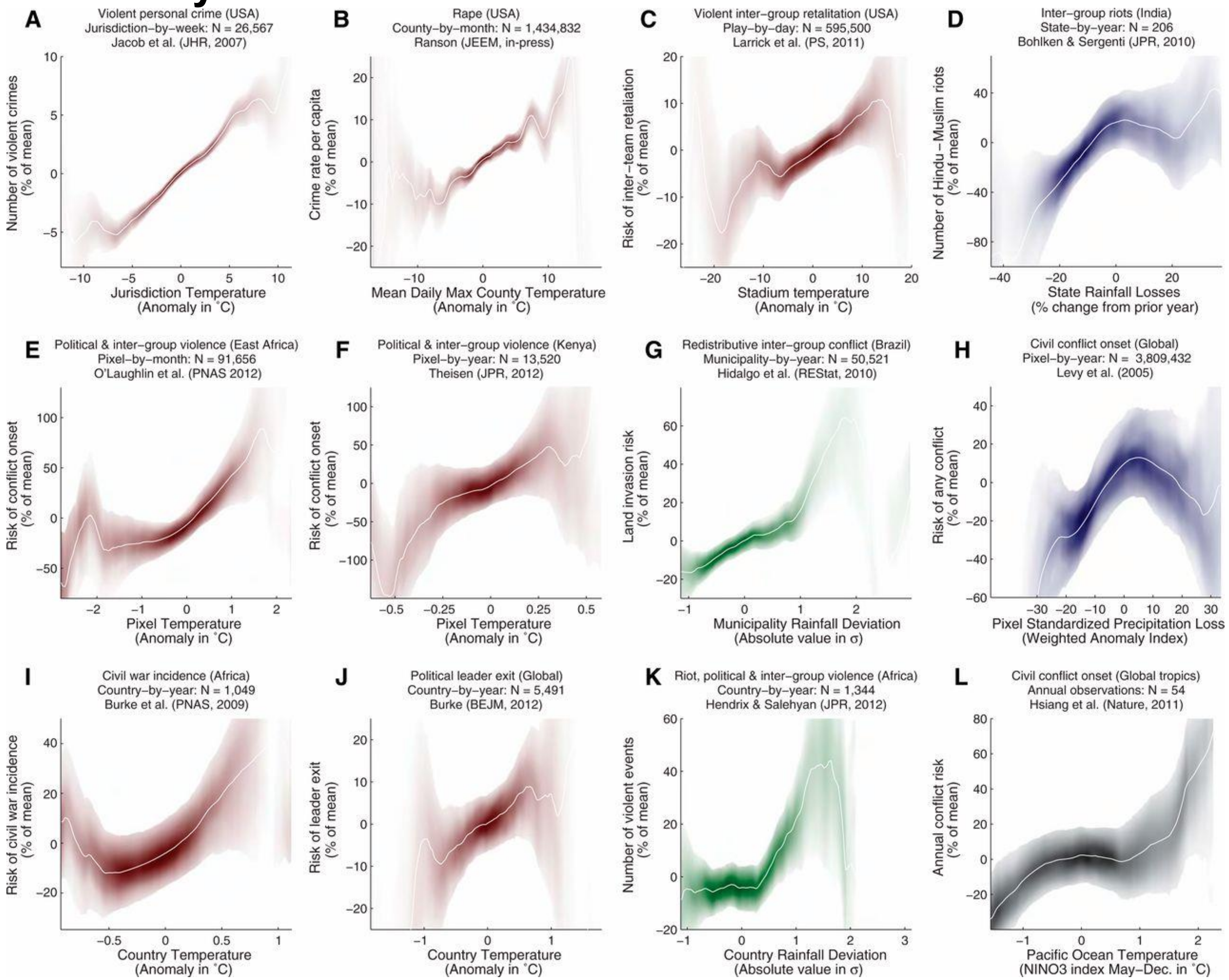


Fig. 2 Empirical studies indicate that climatological variables have a large effect on the risk of violence or instability in the modern world.(A to L) Examples from studies of modern data that identify the causal effect of climate variables on human conflict.



S M Hsiang et al. Science 2013;341:1235367

Here are their explanatory notes for the slide:

> "Empirical studies indicate that climatological variables have a large effect on the risk of violence or instability in the modern world.(**A** to **L**) Examples from studies of modern data that identify the causal effect of climate variables on human conflict. Both dependent and independent variables have had location effects and trends removed, so all samples have a mean of zero. Relationships between climate and conflict outcomes are shown with nonparametric watercolor regressions, where the color intensity of 95% CIs depicts the likelihood that the true regression line passes through a given value (darker is more likely) (*128*). The white line in each panel denotes the conditional mean (*129*, *130*). Climate variables are indicated by color: red, temperature; green, rainfall deviations from normal; blue, precipitation loss; black, ENSO. Panel titles describe the outcome variable, location, unit of analysis, sample size, and study. Because the samples examined in each study differ, the units and scales change across each panel (see Figs. 4 and 5 for standardized effect sizes). "Rainfall deviation" represents the absolute value of location-specific rainfall anomalies, with both abnormally high and abnormally low rainfall events described as having a large rainfall deviation. "Precipitation loss" is an index describing how much lower precipitation is relative to the prior year's amount or the long-term mean." (HBM, page 4)

Let’s interpret panel A, using what we learned on slides 19 and 20. The Y axis is violent crimes measured as percent deviations from means in the detrended data.

For simplicity let’s assume that there is no trend in violent crime so a value of, say, 5 in a particular location means that violent crime is 5% above its mean value for that location.

We can see that when temperature in a particular location is around 5 degrees centigrade above its average level in that location then violent crime is around 2% above its mean level for that location on average.

When temperature is around 10 degrees above its average level then violent crime is about 5% above average.

The other temperature panels are interpreted similarly and all are drawn in red.

The interpretation of rainfall pictures is more complicated and we will leave these aside.

Conclusion –

HBM seem to present a pretty impressive accumulation of evidence associating higher temperatures with more conflict where conflict is measured in a variety of different ways.

The authors admit that there is not a lot of research spelling out plausible mechanisms that might explain why higher temperatures are associated with more violence. More of this would help and, in fact, some good work on these mechanisms is vital if this work is to be ultimately convincing.

The Critique

Along come Buhaug et al. with a list of co-authors the size of a football team.

Buhaug et al. make three main points.

1. Although the list of studies considered by HBM looks very long, many of them are quite similar to one other.

For example, quite a few of them contain African countries and a number of them contain only African countries.

So the convergence of an apparently large number of studies on similar conclusions is less impressive than it appears to be at first glance.

2. There is a lot of variation in what is modelled and how it is modelled as you range across the studies.

The conflict variable can be non-violent land grabs, urban riots, civil war etc..

Climate events can be heat waves, ENSO cycles, heavy rainfall etc..

Geographic units range from very small ones to very big ones.

Models vary a lot across papers – stories about the impact of climate also vary a lot.

The point here is that the many studies do not really tell one coherent story…..however, one could argue that this is a strength of the HBM analysis…widely varying approaches lead to similar, if not identical, conclusions.

3. HBM omit other studies that reach other conclusions.

A variant of this critique is that HBM sometimes include studies that reach mixed conclusions but omit the parts of these papers that go against the conclusion that warming causes conflict. An example of this is the Couttenier and Soubeyran paper covered last week.

This point is much more powerful than the other two points in my opinion.

Buhaug et al. offer their own meta analysis which I copy onto slide 29

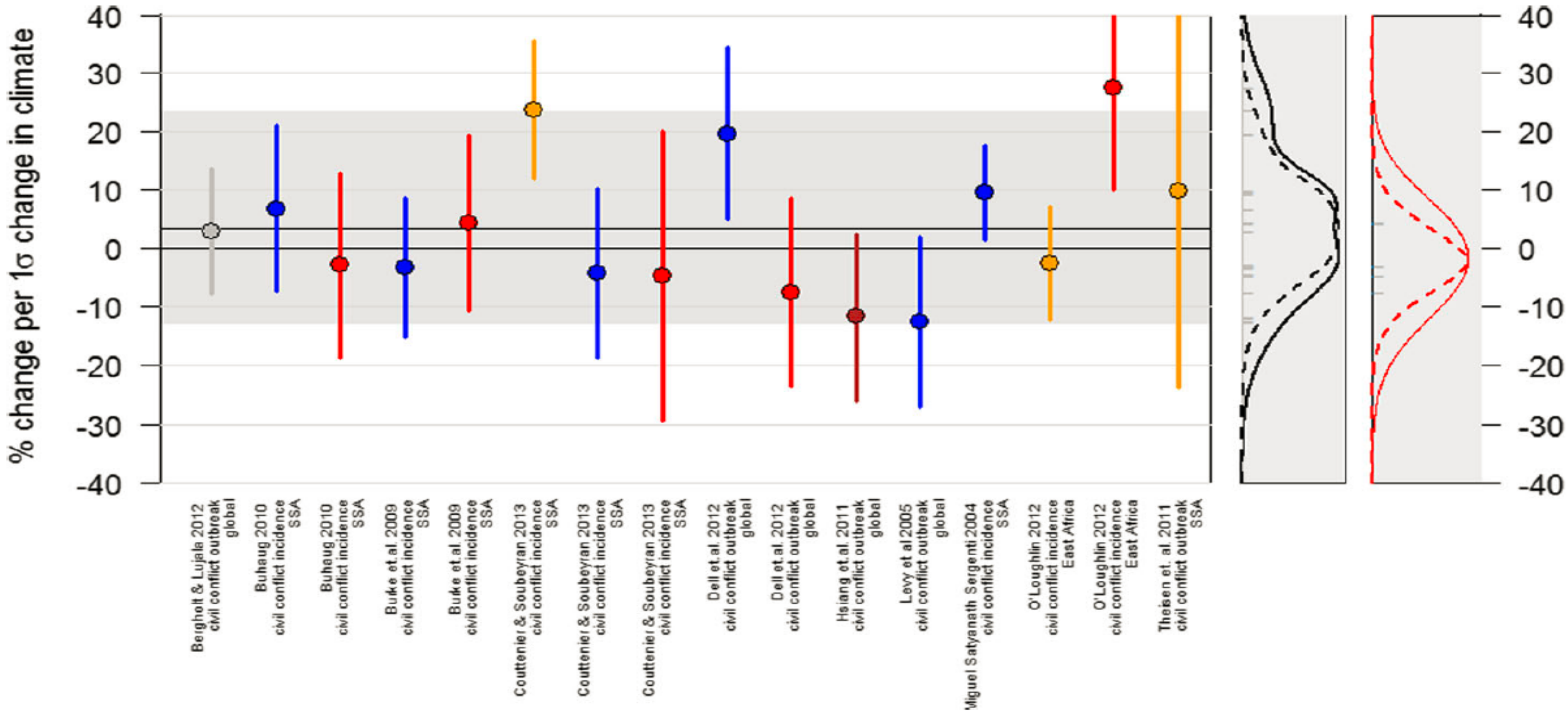


Fig. 1 Modern empirical estimates for the effect of climate variability on civil conflict. The markers illustrate the estimated percentage change in conflict with a 1σ increase in temperature (*red*), loss of rainfall (*blue*), increase in drought (*orange*), El Niño-like conditions (*brown*) or increase in severity of climatic natural disasters (*gray*). Whiskers denote the 95 % confidence interval. The solid horizontal line indicates the median climate effect with the 95 % highest density interval in grey, based on a Bayesian hierarchical model. The panels at the right show the distribution of results from all candidate studies (*black*) or those focusing squarely on temperature effects (*red*); solid lines represent the variance-weighted distribution while dashed lines depict the Bayesian hierarchical distribution. Studies listed alphabetically

This is a much more mixed picture than the one that HBM put forward.

Buhaug et al. do not argue that climate has no effect on conflict but, rather, that the effects of climate on conflict are less clear than claimed by HBM and that more research is needed to pin down what the real effects are.

We not completely shift gears to have a look at the war in Syria.

The war in Syria is probably the most important war in the world right now but it is hard for researchers to work on this war because it is very difficult to collect decent data in Syria.

Guha-Sapir et al. are able to produce some interesting and useful work using data collected by the Violations Documentation Center in Syria (VDC).

The VDC collects data using a methodology that is similar to that of the Iraq Body Count database (lecture 1).

In fact, the VDC data makes it possible to build a table for the Syrian conflict that are very much like an IBC-based table for the Iraq conflict that you already saw.

The next two slides provide two such tables that I produced for this blog post using the IBC data (slide 33) and VDC data given in the Guha Sapir et al. paper (slide 34).

Table 1. Percent women and children among Iraqi civilians killed by weapon type

Weapon	Percent women out of all civilians with known gender/age status	Percent children out of all civilians with known age status	Percent men out of all civilians with known gender/age status	Total
Air Attack	27	39	34	100
Mortar	24	44	32	100
Overall average	9	9	82	100
Small Arms Gunfire	8	5	87	100

Data: Iraq Body Count

We have seen these data before on slide 13 of lecture 1 although that table was organized a little differently than the above table is. (It is worth your while to go back and figure out why this table is consistent with the earlier table.)

Table 2. Percent women and children among Syrian civilians killed by weapon type

Weapon	Percent women out of all civilians with known gender/age status	Percent children out of all civilians with known age status	Percent men out of all civilians with known gender/age status	Total
Air Bombardments	14	27	59	100
Shells	14	21	65	100
Overall average	10	16	74	100
Shooting	7	9	84	100

Data: Center for the Documentation of Violations in Syria

Above are the same type of data as the Iraq data from slide 33 but now the data are for Syria.

The numbers are certainly not identical across the two tables. For example, women are only 14% of the recorded civilian victims of air strikes in Syria while they are 27% of the victims in Iraq.

Still, some qualitative patterns are consistent across the two conflicts – Air attacks and mortars (called “shells” in the Syrian data) claim higher percentages of women and children than do gun attacks for both Iraq and Syria.

This consistency across two conflicts suggests that these weapons are probably relatively indiscriminate in general, not just within the specific context of the Iraq conflict.

More case studies for specific conflicts would certainly be useful but there does seem to be a generalizable pattern.