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Journal of
Peace Research

Journal of Peace Research
2015, Vol. 52(2) 158–170
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sagepub.co.uk/journalsPermissions.nav
DOI: 10.1177/0022343314557508
jpr.sagepub.com
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Weathering unrest: The ecology of urban social disturbances in Africa and Asia

Adam Yeeles

School of Economic, Political and Policy Sciences, University of Texas at Dallas

Abstract

Over the last several years research has examined anew the potential for climate change to induce political conflict and potentiate social unrest. Several explanations for the relationship between weather and social unrest have been proposed, including the idea that temperature, acting through a physiological response mechanism, gives rise to collective aggression. This proposition first appeared in the aftermath of the 1960s US riots, which occurred primarily in the heat of summer, and has re-emerged within the contemporary literature on conflict and climate, in addition to explanations rooted in political economic processes. Building on both bodies of work, this article utilizes a case-crossover time-series design to explore the relationship between meteorological factors derived from high resolution spatial data of temperature and precipitation and social disturbances occurring in 50 major cities in Africa and Asia between 1960 and 2006. Poisson regression and generalized additive modeling are utilized to model linear and non-linear effects, respectively. A significant, but qualified, association between heat and urban social disturbances is found. The general relationship is non-linear, with peak levels of unrest occurring in the upper 20s (°C). The relationship between temperature and social unrest within individual cities is linear. In addition, there are differential effects of heat on lethal versus non-lethal episodes of unrest. The non-linear response to temperature is much more pronounced among lethal events than it is among non-lethal episodes. The conclusion taken from this research is that heat is associated with urban social conflict, but generally does not trigger episodes and instead acts to supplement aggression while other factors govern the primary timing of social unrest.

Keywords

Africa, Asia, political ecology, temperature-aggression, urban social unrest

Introduction

Over the last decade the human consequences of climate change have received increasing attention in several disciplines. As it pertains to political unrest, the research has considered deviations from temperature and precipitation trends as causes of African civil wars (Burke et al., 2009; Hendrix & Salehyan, 2012; O'Loughlin et al., 2012). A few studies have examined long cycles of conflict and climate in Europe (Tol & Wagner, 2010) and China (Zhang et al., 2006). Short-term meteorological effects, including natural disasters (e.g. Nel & Righarts, 2008; Slettebak, 2012), have also been considered. An earlier corpus of work examines the relationship between heat and collective violence from a social psychological perspective – motivated by the tendency for violence to occur amid the long hot summer (Baron & Ransberger, 1978; Schwartz, 1968).[1] This work has focused on episodes of urban-based social unrest in the United States (e.g. Baron & Ransberger, 1978; Carlsmith & Anderson, 1979) and on cross-national variation in temperature and levels of political violence (e.g. Schwartz, 1968; Van de Vliert et al., 1999). The idea that climate warming, and by association heat and extreme weather, increases the risk of sociopolitical violence is now commonly used in

[1] The primary debate here is whether the relationship between heat and social unrest is linear (Carlsmith & Anderson, 1979) or curvilinear (Baron & Ransberger, 1978).

Corresponding author:
adam.yeeles@utdallas.edu

service of climate change politics. For this reason, it is paramount that we develop a better understanding of when and where weather has a positive effect on the frequency and intensity of social disturbances and work to further identify causal pathways.

Contemporary research on climate change and conflict is extensive and growing. Hsiang, Burke & Miguel (2013) recently conducted a meta-analysis of 60 studies analyzing 45 different datasets and concluded that human conflict is associated with temperature increases and extreme weather events. They are careful to note that the research is not conclusive on the causal mechanisms. Multiple pathways and complex feedback mechanisms are likely at work (Scheffran et al., 2012). Still, several competing explanations have been forwarded by scholars. The most likely causal paths are as follows. First, climate events impact economic productivity in the aggregate, and can have a direct effect on local economic conditions. As a consequence, a state's ability to maintain control declines. Second, climate change strains resources, leading to non-universal redistribution, inequalities, and ultimately grievances. Third, migration and urbanization generated by climate events lead to conflict over scarce resources. Fourth, climate events, especially warming, increase aggression and anger through a physiological mechanism, leading to unrest. This causal mechanism has its origins in criminology and psychology, where the relationship between temperature and violence has long been a topic of research (for an overview of this literature, see Anderson & Anderson, 1998). Whether and in what ways the temperature–aggression dynamic applies to collective social unrest remains a matter of debate.

This article examines the weather–unrest hypothesis, focusing on the contemporaneous relationship between temperature, precipitation, and social disturbances in African and Asian cities between 1960 and 2006. Monthly counts of social disturbances are modeled as a function of temperature and precipitation using a stratified case-crossover design. The results indicate that temperature has a significant effect on the rate of unrest in Asian and African cities. The effect is non-linear. The highest rates of unrest are experienced during months when the temperature is in the upper 20s (°C). This relationship holds for both lethal and non-lethal events. In sum, events occur at a higher rate during warmer months. This result is not robust to the inclusion of a control for event clustering, indicating that hot weather is associated with episodes of social unrest, but it does not act to intensify levels of violence or supersede other factors influencing the timing and intensity of unrest. Also, the within-city effect on violence is linear, rather than non-linear. A decomposition of this result also shows that the expected relationship only holds in a select few cases; however, a general positive association between heat and urban social disturbances obtains.

The climate for conflict

Interest in the relationship between the environment and political change is a perennial issue in the social sciences. For example, several works published in the early 20th century considered the effects of climate and climate change on the course of history (e.g. Huntington, 1913, 1917). The ideas were revisited mid-century. For instance, Wheeler (1943) used sunspots to calculate long and short phases of climatic conditions in relation to episodes of conflict, determining among other things when nations fail and when international wars occur. Few of Wheeler's specific hypotheses have been thoroughly tested, but they attest to the enduring interest in the effect of climate on social behavior. More recently, and for similar purpose, historic conflict data and climate reconstructions have been used to examine 1,000 years of conflict history in Europe (Tol & Wagner, 2010) and dynastic changes in China over the last millennium (Zhang et al., 2006). All of this research, which tends to focus on history's long cycles, is complemented by a growing corpus of work examining the relationship over shorter time periods and in more proximate spatial frames.

For example, Burke et al. (2009), in what has become the index case for the contemporary study of the climate–conflict nexus utilizing temperature data, provide evidence that annual incidences of civil wars in African countries increase during warmer years. The effect of temperature on agricultural and rural livelihoods is considered the driving force behind these empirical results. The wider body of research, however, has not reached consensus on the issue. Several alternative conclusions and criticisms have been forwarded. First, the relationship is not encompassing of all conflicts. Buhaug's (2010) re-analysis of the work of Burke et al. (2009) concludes that the relationship between climate variability and civil conflict is not robust to alternative definitions of conflict. Second, using the country as the unit of analysis can mask major variations in climatic conditions and conflict locations. Both variables are heterogeneous across space. O'Loughlin et al. (2012) utilize a database that contains individually georeferenced violent events occurring in East Africa and find that temperature anomaly indicators are statistically significant, but are not the primary drivers of conflict. Third, a majority of quantitative large-N studies focus on long-term trends or interannual variation in weather conditions (e.g. Klomp & Bulte, 2013). Annual aggregates are especially problematic because they are somewhat removed from the time scale at which action is expected to occur. Third, temperature and precipitation are not the only way climate change manifests and alternative measures imply different causal paths. For instance, Theisen, Gleditsch & Buhaug (2013) identify change in precipitation and temperature, natural disasters, and sea-level change as ways in which climate may affect conflict. There is also the case for studying agricultural performance and environmental degradation more specifically (Meierding, 2013).

Regarding precipitation-based studies of climate change and conflict, many studies imply a neo-Malthusian scarcity process. The fundamental claim is that climate change, most notably extreme weather and increased drought conditions, gives rise to resource pressures that lead to conflict. This idea is consistent with several generations of research conducted under the rubric of 'environmental security' (see Rønnfeldt, 1997, for an overview of the earlier generations of work). A recent review by Theisen, Gleditsch & Buhaug (2013) describes the evidence for and against the scarcity case. No consensus on the validity of this causal path and its empirical articulation appears near. For example, Fjelde & von Uexkull (2012) find that large negative deviations from rainfall shortages increase the risk of communal conflict. Similarly, Maystadt & Ecker (2014) find evidence that the likelihood of conflict in Somalia increases with drought intensity. Conversely, Hendrix & Salehyan (2012) find evidence that positive and negative rainfall deviations are associated with social conflict, but abundance, rather than scarcity, is associated with violent events.

The idea that temperature and conflict are linked by a human physiological mechanism has also been proposed. The research cited by Hsiang, Burke & Miguel (2013) on this topic has its origins in the *Report of the National Advisory Commission on Civil Disorders* (National Advisory Commission on Civil Disorders, 1968), which sought causes for the 1960s race riots in the United States. Notably, the 1967 Detroit riots occurred in the middle of a summer heat wave. This observation gave rise to what is referred to as the *long hot summer* hypothesis, describing the belief that warm temperatures breed irritability and anger, ultimately leading to outbursts of collective aggression. There are two issues at stake in this literature: (1) how to study the relationship between weather and violence, and (2) what is the functional form of the relationship.

Anderson & Anderson's (1998) review of the temperature–aggression paradox distinguishes between two types of studies: geographic region studies and time-period studies. Geographic region studies exploit differences in temperature between locations and time-period studies exploit temperature differences over time to study the relationship between temperature and violence. The two approaches are not mutually exclusive. For example, Schwartz's (1968) cross-national study of the temporal distribution of coups, assassinations, terrorism, guerilla warfare, and revolution shows that violent events are most common during periods of moderately warm weather within countries and that moderately warm countries experience more violence overall. Van de Vliert et al.'s (1999) more recent study in this tradition is part replication Schwartz (1968) and part cultural modification of the temperature–violence link. Most notably, the authors highlight an inflection point in the temperature–violence relationship at a mean daytime temperature of 24°C (76°F). Countries with average daytime temperatures above and below this inflection point experience less violence.

Other research examines the co-occurrence of weather and aggression over time within smaller geographies. For instance, Baron & Ransberger (1978) show that there is a curvilinear relationship between temperature and collective violence in the United States, with the number of events rising monotonically until the mid-80s Fahrenheit ($\sim$ 28°C), whereupon a decrease in the risk of collective violence occurs with further increases in temperature. The curvilinear relationship is also demonstrated by Schwartz (1968) and Van de Vliert et al. (1999). It exemplifies the negative escape model, espousing the idea that temperature can reach a point at which the need to escape the heat overcomes the aggressive drive (Anderson & DeNeve, 1992). However, the curvilinear relationship is not without criticism. For example, Carlsmith & Anderson's (1979) analysis of the relationship between ambient temperature and collective violence show a linear relationship. Importantly, their research design controls for seasonal changes in the propensity to engage in collective violence.

The broader point is that there are both geographic and temporal components underlying the relationship between weather and collective violence to be examined. For this reason, the remainder of this article approaches the idea that there are contemporaneous meteorological determinants of urban social disturbance by considering geography and time jointly. It uses monthly data covering more than 40 years and 50 cities in Asia and Africa. In short, these city-level panel data facilitate a discussion

Table I. Summary of weather and urban social disturbance data

	Mean	*Min*	*Max*
All events ($N = 3{,}288$)			
by cities	65.76	2	219
by years	69.96	22	106
Lethal events ($N = 1{,}346$)			
by cities	26.92	0	132
by years	28.64	8	48
Non-lethal events ($N = 1{,}942$)			
by cities	38.84	1	126
by years	41.32	12	69
Temperature (°C)			
full sample	21.62	–28.20	35.60
by cities	21.62	–1.04	29.14
by years	21.62	21.01	22.26
Precipitation (cm)			
full sample	10.63	0.00	240.10
by cities	10.63	1.10	33.25
by years	10.63	9.42	12.05

of the source (geographic or time-based) of the relationship between weather and collective aggression, and the nature (exacerbating or triggering) of the relationship between weather and collective aggression. Several questions are explored. Is there a contemporaneous relationship between temperature, precipitation, and episodes of urban social unrest? Is the effect driven by geographic or temporal variation in the data? Is heat correlated with lethal violence or social disturbances specifically? And finally, is the relationship between temperature and social unrest best described as linear or curvilinear?

Urban social disturbances in Asian and African cities (1960–2006)

In the following section, I present an analysis of the relationship between temperature, precipitation, and episodes of unrest in Asian and African cities. The data on urban unrest are taken from the 'Urban Social Disturbance in Africa and Asia' dataset (USDAA), collected by the Peace Research Institute Oslo (PRIO), which contains violent and nonviolent forms of contention occurring in 50 major cities in 49 countries in sub-Saharan Africa and Central and East Asia (Urdal & Hoelscher, 2012). The USDAA dataset includes 'urban social disturbances' occurring between 1960 and 2006. The events are recorded from Keesing's Record of World Events. All instances of politically motivated protests, demonstrations, riots, urban terror, and armed conflict are recorded in episode format. The utility of these data is demonstrated in Buhaug & Urdal (2013), in addition to Urdal & Hoelscher (2012). With respect to meteorological conditions, monthly temperature and precipitation means were extracted from the University of Delaware Air Temperature and Precipitation dataset (UDel_AirT_Precip, 2012) for the 50 cities. The dataset is a high resolution (0.5 degree latitude x 0.5 degree longitude) grid based on meteorological station data. The grid cell containing each city was extracted from the data for the years 1960 to 2006 on a monthly basis ($T = 564$). It should be noted that these are monthly means extrapolated from daily mean temperatures. Temperature maximums and even daily temperature and precipitation data would be optimal for the question at hand, but they are generally not available for a wide set of cities over long periods.

Table I summarizes the data. There are 3,288 events overall, 1,346 deadly events, and 1,924 non-lethal events. The number of events varies across years and cities. On average, there are 69.96 social disturbances per year and 65.76 per city. The mean number of lethal events per year is 28.64 and the mean number per city is 26.94. There are slightly more non-lethal events per city and per year, 38.84 and 41.32, respectively. The range of values between cities is also worth noting. Some cities experienced only two events (Ashgabat, Turkmenistan) over the 47-year period, while others had more than 200 (Tehran, Iran, 219 events). Both temperature and precipitation have a similarly wide range. The minimum temperature recorded in the dataset is –28.2°C for February 1977 in Ulan Bator and the maximum temperature is 35.6°C for New Delhi, India (June 1976) and also Niamey, Niger (June 2002). Zero precipitation was experienced for a total of 3,587 city-months. The maximum precipitation (240 cm) was experienced Mumbai, India (August 1961).

Some mention of how these data differ from existing research on climate and political conflict is in order. First, many of the studies looking at the relationship between temperature and conflict, especially those examining African conflict, utilize annual mean meteorological conditions (e.g. Buhaug, 2010; Burke et al., 2009). A similar trend can be seen among studies utilizing precipitation to study climate change effects. An annual measure of weather mostly captures small changes in climate over long periods. This is perhaps appropriate for studying climate change and political violence, but it precludes finding support for a more specific relationship between heat and collective unrest, as proposed by the temperature–aggression hypothesis. Second, both the unrest data and the weather data used here are specific to cities. This partially rectifies the geographic aggregation problem present in studies that utilize country-level observations. For example, several studies demonstrate a link between rainfall and social conflict in Africa, but they may in fact be misstating the relationship due to considerable variation in rainfall over a country's territory. The use of absolute monthly temperature, particularly in combination with urban unrest data, offers an opportunity to test the temperature–aggression hypothesis with the best data currently available for a large number of cases.

Statistical methods

I adopt a stratified case-control design to control for seasonality and long-term trends. In so doing, this research design captures contemporaneous weather effects, rather than slow moving increases in temperature and precipitation that one would need to identify the effects of climate change more broadly. A stratified case-control design matches case and control days in specific windows (strata). Here, the strata were defined by city-specific temperature terciles. Specifically, each year was broken into three equal parts corresponding to hot, moderate, and mild temperature months. Stratified case-control designs of this sort are understood as special case of time-series analysis in which strata enter the analysis as control variables (Basu, Dominici & Samet, 2005; Lu & Zeger, 2007; Navidi, 2008). This equivalency allows us to use generalized linear models and generalized additive modeling to describe the relationship, rather than utilize conditional or multinomial logistic regression as is the case with the standard case-crossover design. Leveraging this flexibility, I model the data in two different ways. A Poisson regression and generalized additive modeling (GAM) with a Poisson response were estimated. The stratified case-crossover design for measuring incident counts for a single city takes the following form:

$$Y_t \sim \text{Poisson}(\mu_t)$$

$$\log(\mu_t) = \alpha + [S(T_t) \text{ or } \beta T_t] + \lambda(P_t) + \eta\ \text{Strata}_t \quad (1)$$

where t is the month of the observation, Y_t is the observed monthly event counts of social unrest, α is the intercept, $S(T_t)$ is the cubic regression spline for Temperature in degrees Celsius and T_t is temperature in its raw form, P_t is the monthly mean precipitation, and Strata_t is a categorical variable consisting of city-year specific temperature terciles that create a general step function to control for seasonality and long-run trends in the data. The Poisson regression captures the relationship between weather and the frequency/intensity of collective unrest. The Poisson-GAM approach explores the possibility that unrest frequency and temperature form a non-linear relationship.

Even though a case-crossover design resolves most issues of seasonality, time series of events still demonstrate strong autoregressive properties. The primary reason is that social unrest tends to occur in waves. For the event count time series of this type, Brandt et al. (2000) have recommended the use of a Poisson exponentially weighted moving average (PEWMA). The reason is that traditional time-series models, including Gaussian ARIMA models, are inappropriate for strictly positive event counts and the use of lagged-dependent event counts in Poisson or negative binomial regression implies period over period growth. This modeling strategy does not have the same immediate flexibility as the stratified case-crossover design, which is commonly employed in environmental epidemiology. To deal with temporal correlation in excess of that managed by the case-crossover design, I include a lagged binary variable that describes whether an event has occurred in the previous month. This effectively captures the tendency for episodes of unrest to occur in waves. The use of this variable is not a general recommendation for event time series. There are several arguments against using a lagged indicator which are well documented and debated in the social science methods literature. Two issues are at stake. First, the lagged indicator tends to reduce the magnitude and significance of other explanatory variables (Achen, 2000). Second, and more specific to this analysis, if heat waves and protest waves were to coincide, observing them would be made more difficult by the inclusion of a lagged indicator. In other words, the lagged indicator is an especially stringent test of the temperature–unrest hypothesis and implies a separable exacerbation effect. For these reasons, I present models with and without the lagged indicator.

Results

Table II describes the result of the Poisson regression models. Each of the regression models includes 50 cities over 564 months. Model 1 pools the cities. The model includes temperature, precipitation, and city-specific strata variables. The effect of temperature on the rate of unrest is positive, while the effect of precipitation is negative. Both variables are statistically significant.[2] For

[2] Model 1 was subject to sensitivity analysis (leaving one city out at a time). Of the 50 regressions estimated, temperature is significant at the 0.05 level 39 times and precipitation is significant 46 times. These results suggest two things. First, the effects are heterogeneous between cities, and second, the results are attributable to a between-city effect.

Table II. Poisson regression estimates for monthly urban social disturbances

	All events			
	(1)	*(2)*	*(3)*	*(4)*
Temperature	0.006*	0.004	0.010*	0.006
	(0.002)	(0.002)	(0.005)	(0.005)
Precipitation	–0.003**	–0.003**	–0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Lag indicator		1.654**		1.220**
		(0.037)		(0.039)
City fixed effects?	No	No	Yes	Yes

Poisson regression coefficients reported; standard errors in parentheses; $^{\dagger}p < 0.10$; $^{*}p < 0.05$; $^{**}p < 0.01$ (two-tailed).

a one-degree change in temperature, the incidence rate ratio (IRR) is 1.006. The effect is small, illustrating a less than 1% increase in the number of events for a single degree change. However, because there are large intercity differences in mean monthly temperature, the coefficient describes a reasonable association between heat and occurrences of urban unrest. This effect is demonstrated even more clearly by the graphical results of the nonlinear modeling presented in subsequent sections. Model 2 includes temperature, precipitation, city-specific strata, and a variable indicating whether social disturbances occurred in the preceding month. Precipitation is again negative and statistically significant. However, the inclusion of the lagged variable reduces the size of the temperature coefficient. It is also no longer statistically significant. However, it is positively signed, further confirming the general association between temperature and rate of unrest. As expected, the lagged indicator is large and statistically significant. The incident rate for a month experiencing at least one event in the previous month is roughly 5.23 times that of one without a preceding event. This result is a clear indication that events tend to cluster in time, irrespective of ecological conditions.

Models 3 and 4 report the estimates of the effects of temperature and precipitation on the number of urban social disturbances with city fixed effects included. These models specifically test whether temporal variation in weather is associated with the temporal variation in unrest. Models 1 and 2 included city-specific strata as controls. The inclusion of fixed effects in Models 3 and 4 accounts for any additional between-city heterogeneity. Thus, they constitute a strict test of the relationship between heat and unrest in the temporal domain. Precipitation is still negative, but no longer statistically significant. This indicates that the effect of precipitation on urban social disturbance is primarily a between-city effect (i.e. a geographic effect). In reporting their results, Hendrix & Salehyan (2012) were circumspect about the effects of precipitation on conflict outside of Africa. While this is not a definitive answer to the question they set forth, it does indicate that more research needs to be done on the topic, especially given that the majority of the contemporary research on the climate change–conflict nexus focuses on Africa. In other words, more needs to be done to separate the geographic basis of the relationship from the temporal basis of the relationship. In Model 3, temperature is positive and statistically significant.[3] A one-degree change in temperature corresponds to an incidence rate ratio of 1.01. The temperature ranges within each city are much smaller than the combined sample. Thus, the effect is clearly small. Also, the temperature variable becomes insignificant with the inclusion of the lagged variable (Model 4). The interpretation of the lagged variable is the same as in Model 2. Experiencing unrest in a previous month increases the rate of unrest in the subsequent month several times over.

Table III splits the sample into lethal and non-lethal events. Poisson regression models with identical explanatory variables and control variables to those reported in Models 1 through 4 were run on the split sample. Model 5 includes all of the same variables as Model 1. Temperature is again statistically significant at conventional levels. The incidence rate ratio is 1.014. The increased rate of unrest from a one-degree change in temperature is again small, but notably larger than for all types of events combined. Precipitation is negative and statistically significant, indicating that high levels of precipitation depress the occurrence of urban-based violent conflict. Model 6 includes the lagged indicator for unrest in the preceding month. The coefficients for temperature and precipitation are slightly smaller, but remain statistically significant. The incidence rate ratio for a one-degree change in temperature is 1.012 and for a one-centimeter change in precipitation is 0.997. Precipitation is no longer statistically significant with the inclusion of city fixed effects (Model 7). Temperature, however, remains statistically significant, and has an incidence rate ratio of 1.016. This result indicates that warmer months are more prone to deadly social

[3] A sensitivity analysis was also conducted on Model 3. Of the 50 regressions (leaving one city out at a time), temperature was significant at the 0.05 level or better in 44 of the cases.

Table III. Poisson regression estimates for monthly urban social disturbances

	Lethal				*Non-lethal*			
	(5)	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*	*(11)*	*(12)*
Temperature	0.014**	0.012**	0.016*	0.012	0.001	0.000	0.007	0.004
	(0.004)	(0.003)	(0.008)	(0.008)	(0.003)	(0.003)	(0.006)	(0.006)
Precipitation	–0.004*	–0.003†	0.002	0.002	–0.003	–0.002	–0.002	–0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Lag indicator		1.814**		1.149**		1.648**		1.186**
		(0.066)		(0.070)		(0.053)		(0.055)
City fixed effects?	No	No	Yes	Yes	No	No	Yes	Yes

Poisson regression coefficients reported; standard errors in parentheses; $^{\dagger}p < 0.10$; $^{*}p < 0.05$; $^{**}p < 0.01$ (two-tailed).

disturbances. However, as we see from Model 8, this result is not robust to the inclusion of a lagged indicator to control for event clustering. Deadly events do not occur at a significantly greater rate in response to either temperature or precipitation when the tendency for events to cluster in time is taken into account. This is a particularly stringent test of the temperature–violence hypothesis given that episodes of social unrest are sporadic and control cases are already implemented in the model. If temperature were to be significant in Model 8, we would have strong case that heat intensifies and exacerbates social unrest. Instead, we have the result from Model 7 indicating only that violent unrest occurs in the warmest months of the year. Finally, the rate of deadly violence is more than three times greater if an event occurred in the previous month than if it did not.

Models 9 through 12 report the results of identical models with non-lethal events as the response variable. Neither temperature nor precipitation is statistically significant in any of the models. With respect to temperature effects, this result indicates that social disturbances generally are not ecologically determined, but collective aggression tends to have deadly consequences during the warmest months of the year. The results are consistent across pooled and fixed effect specifications, suggesting that the differential impact of temperature on lethal and non-lethal social disturbances is consistent across both geographic and time domains.

We now turn to general additive modeling to test whether there are non-linear effects of temperature on the frequency of urban social disturbances. Table IV shows the statistical results for this analysis. Each model includes temperature fitted with a cubic regression spline. Precipitation and strata are included as control variables. A lagged indicator and city fixed effects (operationalized with city-specific dummy variables) are included in select models. The Poisson-GAMs mirror the models shown in Tables II and III. The values reported in Table IV are interpreted as follows. The effective degree of freedom (EDF) describes the number of knots and the shape of the line that minimizes deviance with penalization for over-fitting. The Chi-square statistic and associated p-value are used to test whether the curved line is significantly different from a straight line. The analysis is useful in determining whether a non-linear fit is better than a linear fit, but not whether the variable is statistically significant in the linear case. Thus, we also need to consider the results from the preceding tables when interpreting the GAM results.

From Table IV, we see that the curvilinear relationship follows a specific pattern. Temperature is definitively non-linear in the pooled regressions, irrespective of the inclusion of a lagged indicator. For the entire sample and for lethal events, the best fitting line for temperature is one with approximately eight degrees of freedom. For non-lethal events, a line with four or five degrees of freedom best describes the relationship between temperature and the rate of social disturbances. The inclusion of city fixed effects changes this result. The best fitting line for temperature is essentially a straight line (EDF $\approx$ 1.008), for all specifications. In light of the results from the Poisson regressions, we can conclude that the general associative effect between temperature and urban social disturbance is a non-linear effect. However, there is no curvilinear response within cities over time and the linear effect is limited to lethal events. Temperature is therefore not a causal factor, but can be interpreted as a supplementary factor with measurable effects on the propensity towards violence.

Table IV. Poisson-GAM estimates for monthly urban social disturbances

			Significance of smoothed term		
Model	*Lag*	*F.E.*	*EDF*	*Chi-square*	*p-value*
All events					
(1)	No	No	7.593	62.570	0.000
(2)	Yes	No	7.400	37.245	0.000
(3)	No	Yes	1.009	4.618	0.033
(4)	Yes	Yes	1.010	1.570	0.214
Lethal					
(5)	No	No	7.670	46.360	0.000
(6)	Yes	No	7.651	37.420	0.000
(7)	No	Yes	1.008	4.249	0.040
(8)	Yes	Yes	1.008	2.440	0.120
Non-lethal					
(9)	No	No	4.684	25.750	0.000
(10)	Yes	No	4.129	15.420	0.009
(11)	No	Yes	1.008	1.497	0.224
(12)	Yes	Yes	1.005	0.491	0.487

The Chi-square test and *p*-values test for equality to zero of the smoothed terms. The *p*-values are approximated and do not reflect uncertainty in the smoothing parameters. See Wood (2013) for details.

The predicted responses for the six pooled models are plotted in Figure 1.[4] They are interpreted as follows. Temperature points with incidence rate ratios (relative risk) above 1 demonstrate a positive relationship between temperature (x-axis) and the rate of unrest (y-axis). An incidence rate ratio below 1 represents a negative relationship and an incidence rate ratio of 1 indicates no relationship. From Figure 1(Model 1), showing the predictions for GAM-Model 1, we see that months with mean temperature below 0°C are negatively correlated with the rate of unrest. The relationship is marginally positive between 0°C and 21°C. From 21°C to 35°C, we observe the relationship as described in Schwartz (1968) and Van de Vliert et al. (1999). The relationship is protective until 24°C, at which point a monotonic increase occurs, peaking at 28°C and declining thereafter. Figure 1(Model 2), showing predictions for GAM-Model 2 (w/lagged indicator), closely resembles Figure 1(a). The substantive interpretation is the same.

Figures 1(Model 5) and 1(Model 6) show the predicted responses of temperature on lethal events. The relationship between temperature and unrest is negative through 0°C, non-distinct between 0°C and 20°C, and curvilinear between 20°C and 35°C. The peak number of events occurs when monthly mean temperatures is 28°C. The shape of the response in this temperature range is the same as the response for the full sample, indicating that the response is driven primarily by the effects of temperature on lethal events. The incidence rate ratio declines in both directions at similar rates from this peak. Figures 1(Model 9) and 1(Model 10) show a different response pattern. Again, the primary area of interest is between 20°C and 35°C. When a lagged indicator is not included in the generalized regression, the non-lethal response is similar to that of lethal events. The relationship is negative or non-distinct through the mid-20s, becomes clearly negative until 28°C, then becomes positive and inversely U-shaped, ultimately declining towards higher temperatures. The same response is not seen when a lag indicator is included. Again, this suggests temperature does not have a strong intensifying effect.

Finally, the analysis is conducted using urban social disturbance counts for each city individually. This portion of the analysis opens up the results reported in Poisson Models 3, 7, and 11. For each city, a Poisson regression was estimated with temperature, precipitation, and strata included as variables. To reiterate, the linear specification is utilized because the relationship is essentially linear within cities (see Table IV for the fixed effect models using the data in panel form). The sample was once again split between lethal and non-lethal events. Thus, an identical case-crossover design to the fixed effects specification used in earlier panel regressions is shown.[5] Given the stringency of the test when a lagged indicator is included in the analysis, it was not included in the individual city models. Thus, the analysis tests for a general association between temperature and episodes of unrest, not exacerbation in a strict sense. The results for three models are shown graphically in Figure 2. The Poisson regression temperature coefficients are plotted as incidence rate ratios with 95% confidence intervals. The empty circles are coefficients with *p*-values greater than 0.05 and the solid squares indicate coefficients that are statistically significant at the 0.05 level or better. Significance is also indicated by the confidence intervals for the incidence rate ratios. Where the confidence intervals do not overlap with the vertical line plotted at 1, the variable is statistically significant.

[4] The fractional degrees of freedom were rounded to the nearest integer to make the plots smoother and therefore easier to interpret visually. This change has no effect on the substantive interpretation of the results.

[5] Due to low event counts in some cities, individual models cannot be estimated in a comparable manner. Thus, cities with fewer than six monthly events (< 0.01 rate of occurrence) are not modeled individually.

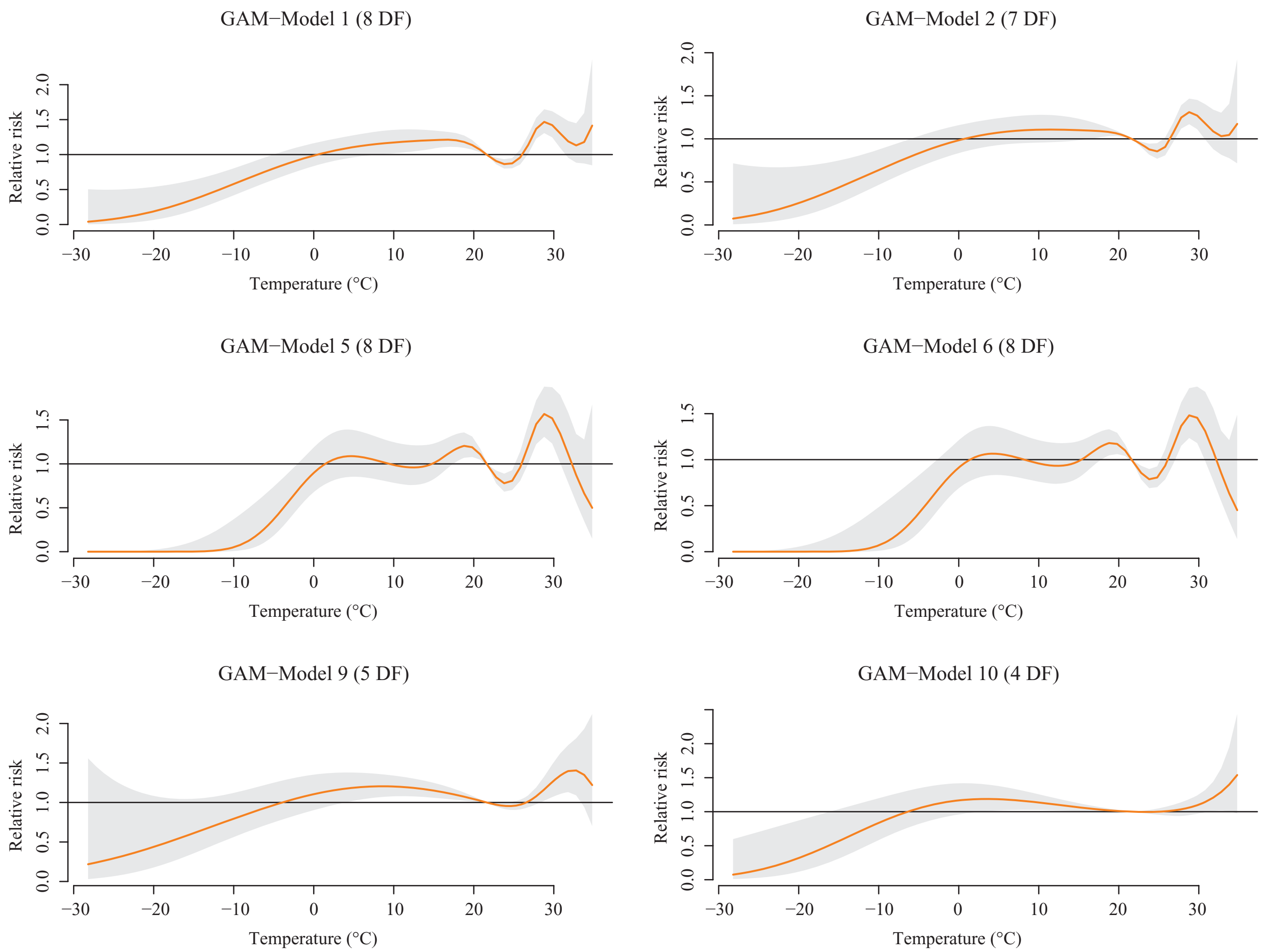

Figure 1. Predicted response for significant Poisson-GAMs

It is clear from these visualizations that there is a general trend in which warmer temperatures are correlated with urban social disturbances – the incidence rate ratios are generally above 1 – but few individual cities are statistically significant. Column 1 in Figure 2 shows the results of the Poisson regression for both lethal and non-lethal events ($N_{(cities)} = 49$). There are four cities in which heat and social unrest are statistically significant. They are not all signed positively. They are as follows (IRR in parentheses): Tehran, Iran (1.051); Manila, Philippines (0.67); Kampala, Uganda (3.12); and Kabul, Afghanistan (1.05). The size of the effects for individual cities varies. The average incidence rate ratio is 1.017, closely mirroring the results shown in Table III. The IRR range is from 0.362 to 3.117. Thus, for a one-degree change in temperature, the rate of unrest may decrease by 63% or increase by 211%. Overall, the results suggest a general, positive association between hotter temperatures and the rate of urban social disturbances, but a definitive temporal relationship between temperature and urban social disturbances is not strongly indicated by this analysis.

Interestingly, there is little overlap in the countries that are statistically significant for all events and for lethal and non-lethal events separately. Column 2 reports the results for only lethal events ($N = 42$). Only New Delhi (1.16) is statistically significant. For a one-degree change in temperature, we would expect a 16% increase in the number of deadly events. However, the mean IRR is 1.19, indicating that low event count cities had a suppressive effect on the temperature coefficient reported earlier in Model 7. The IRR ranges from 0.22 to 5.26, highlighting the varied and potentially large, but uncommon, effect of temperature on the rate of unrest. Column 3 shows the results from the analysis of non-lethal events ($N = 46$). Mumbai (1.61), Maputo (.39), Kampala (8.01), and Lusaka (.57) are statistically significant. Again, the effects range in size. For Kampala, a one-

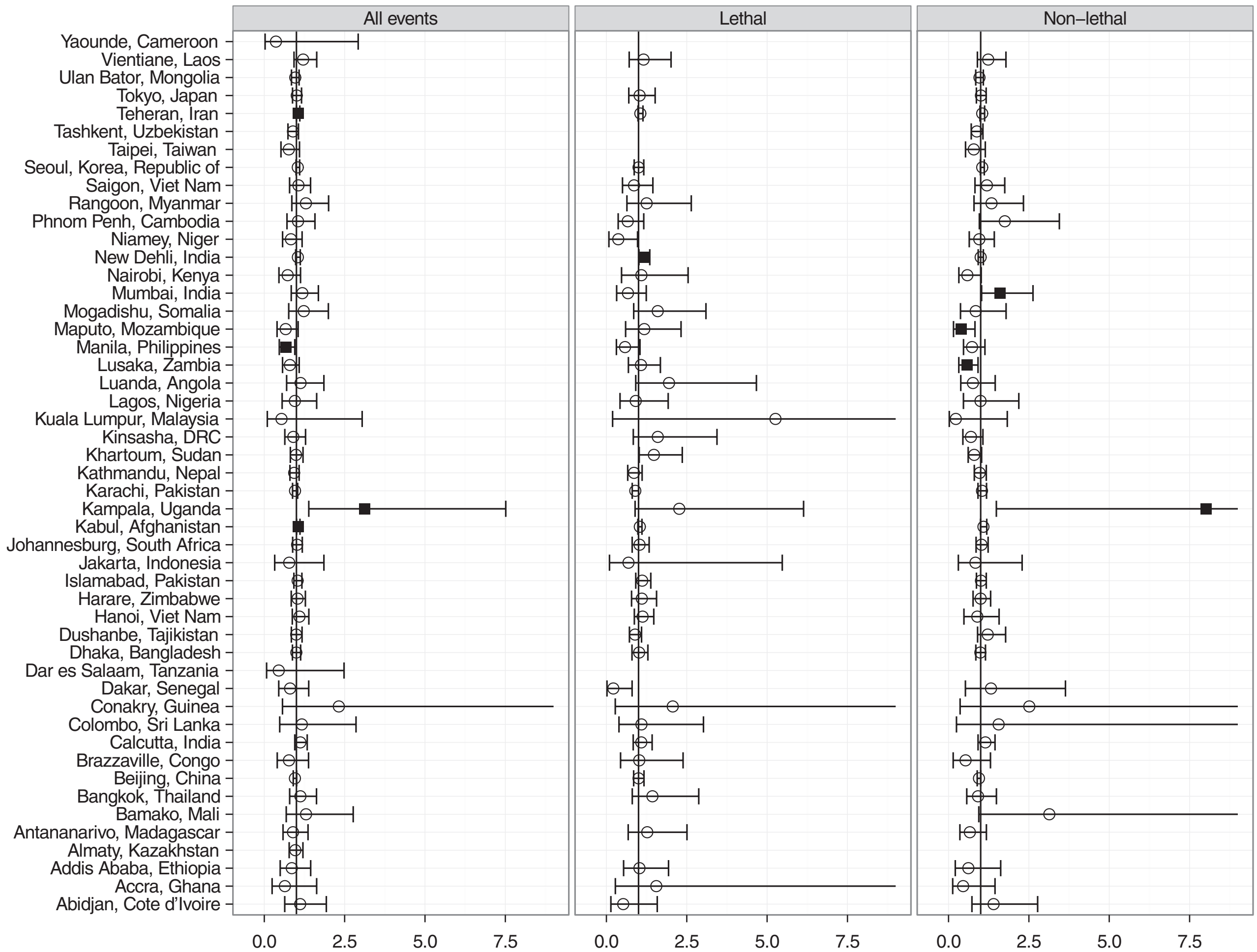

Figure 2. Incidence rate ratio (temperature) for individual city Poisson regressions

degree increase in temperature indicates a 700% increase in the number of episodes. For Lusaka and Maputo, the relationship is negative, with expected rate changes of –43% and –61%, respectively. The overall takeaway is that there is a general association in which temperature leads to higher rates of social disturbances, but for the majority of individual cities higher temperatures generally do not determine the rate of social unrest in the statistical sense. This is true for all urban social disturbances, deadly events, and non-lethal events.

Conclusion

Recent studies have been unable to reach consensus as to whether climate change is positively or negatively associated with increased levels of conflict or the manner in which conflict and weather are linked. One concern is around the direct effects of climate warming. Several possible explanations for why a warmer climate may lead to increased political violence have been forwarded, including the idea that temperature produces physiological discomfort that ultimately manifests in collective aggression. Both observational and experimental research demonstrates a relationship between weather and individual behavior, including crime (both violent and nonviolent), vehicle horn honking, and fights between sporting participants. Much less is known about collective social responses to meteorological conditions. Even so, it has been widely believed since the mid-1960s that urban social disturbances are at a minimum exacerbated by warm temperatures. This article has found modest evidence that meteorological factors have an effect on the frequency of unrest in Asian and African cities. A comparative analysis covering 50 cities shows that this is a non-linear association. The highest rates of unrest occur near 28°C. However, the mean within-city relationship between temperature and social disturbances is linear. For a one-degree change in temperature, a small increase in the rate of social disturbances is observed. This result, however, is not robust to the inclusion of stringent controls for event clustering, suggesting that other social dynamics play an important role in shaping the periodicity of unrest, and temperature does not have a definitive exacerbating effect on the propensity of episodes of unrest to result in deadly violence. Moreover, few individual cities demonstrate through statistical significance the hypothesized link between weather factors and unrest. However, the size of the effect is potentially large for some cities. The general takeaway is that there is a small but positive relationship between temperature and the occurrence of urban social disturbances and this effect is not one of direct causation.

These findings both corroborate and extend the earlier work on temperature and collective aggression. First, until the recent surge of quantitative papers on climate change and conflict, a significant portion of the existing literature on temperature and collective aggression was geographic in nature. In other words, studies of between-location differences in the frequency of unrest. An answer to why there are major differences in political behavior across climate zones remains somewhat elusive. Explanations implying environmental determinism have generally been discredited (see Judkins, Smith & Keys, 2008, for a history of these arguments). At the same time empirical regularities between climate and all manner of personal and social traits continue to present a puzzle to researchers (see Pennebaker, Rime & Blankenship, 1996; Allik & McCrae, 2004; Fincher et al., 2008; Thornhill, Fincher & Aran, 2009, for examples of this research). Second, the climate change–conflict literature that has made use of temperature and precipitation variables has most often concerned itself with deviations from long-term trends or climate variability, rather than contemporaneous responses to meteorological conditions. This research cannot speak directly to the possibility of a physiological mechanism (i.e. physical discomfort leads to aggression). Testing hypotheses of this nature requires monthly or better yet daily or hourly data on weather and social unrest. This article makes some headway on this issue, but further work is warranted. Additionally, existing research on temperature and unrest within urban space is often limited to the United States and primarily associated with mid-20th-century race riots. The findings presented here are based on a much wider set of cities located in a different part of the world, use monthly data, and implement a stratified case-crossover design, following work in environmental epidemiology that tests the relationship between meteorological conditions and acute health problems. It is shown that weather, and specifically temperature, has a modest influence on episodes of unrest occurring in Asian and African cities.

What does this mean for the literature supporting the idea of a positive relationship between climate change and conflict? There are several issues that are in need of further examination. First, there are aspects of climate change that need to be considered more carefully and distinguished from contemporaneous weather effects. One the one hand, there is climate warming. On the other hand, weather volatility, increased prevalence of natural disasters, and sea level increases potentially matter as well. We might also ask whether the conflict response to climate change varies across urban and rural space. The analysis presented here indicates that meteorological conditions are correlated with social unrest in cities, but the effects of transitions between climate phases, extreme weather variations, and climate-induced land transformations may be limited to rural areas. Each potential empirical relationship carries with it implications for causal processes. It may be inferred that the relationship demonstrated here is an example of a physiological response mechanism (i.e. the long hot summer in comparative perspective) or it may be that agricultural and human migratory responses to temperature and precipitation spill over into cities. In sum, the evidence points towards a need for more refined analysis of the ecological dimensions of urban social unrest.

Replication data

The dataset and replication files for the empirical analysis in this article can be found at http://www.prio.no/jpr/datasets. The analysis was conducted in R 3.1.0.

Acknowledgements

The author would like to thank Jennifer Holmes, Clint Peinhardt, and Patrick Brandt for their support during the early stages of this research. I am also thankful for the anonymous reviewers at *JPR* who provided invaluable comments on earlier drafts that greatly influenced the content and approach taken in this article.

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ADAM YEELES, b. 1980, PhD in Political Science (The University of Texas at Dallas, 2014); Lecturer, School of Economic, Political and Policy Sciences, The University of Texas at Dallas (2014–); research interests in international development, geopolitics, and human-environmental systems.