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Temperature seasonality and violent conflict: The inconsistencies of a warming planet

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Abstract

Current climate change research suggests that certain seasonal weather patterns will be extended and others attenuated as global temperature increases. This is important because seasonal temperature change affects both the scarcity of resources during certain times of the year and the overall mobility of people living in countries that have seasonality. Consequently, these seasonal changes have implications for the onset of violent conflict, particularly as it relates to distinguishing when, where, and how it is most likely to occur. This article evaluates the relationship between monthly temperature changes, civil war onset, and various, less-organized conflict events, offering theoretical expectations for how seasonal changes and climate aberrations are related to an increased risk of violence. The results show that prolonged periods of stable, warm weather are consistently associated with an increased risk of civil war onset and non-state conflict. These findings are best explained through the strategic viability mechanism of temperature change, which allows actors to resolve their collective action problems that are often associated with poor weather conditions, while simultaneously increasing their strategic and behavioral incentives for engaging in violent conflict. Warm weather generates more resources for rebel looting and permits predictability for coordinating troop movements and strategy development. These findings are particularly salient in areas of the world affected by strong seasonality, where prolonged extensions of warm weather conditions would be regarded as both peculiar and attractive for participating in violent action. Although these findings are notable, even under the most extreme climate change scenarios, the substantive effects for these relationships are comparatively minor relative to other well-known intrastate conflict covariates.

Keywords

country-month, seasonality, strategic viability, temperature, unit of analysis, violent conflict

Introduction

Although the existence of climate change no longer seems subject to serious debate, the social consequences of this phenomenon are poorly understood and have been the focus of much discussion (*Economist*, 2011; Gleditsch, 2012). Most accept that the effects of climate change will usher in a new set of political and environmental challenges, and research suggests that these will place significant stress on vulnerable communities and developing nations (Mendelsohn, Dinar & Williams, 2006; Piguet, Pécoud & De Guchteneire, 2011). The prospect of a changing climate conjures a frightening future, which is serious enough for the Pentagon to include 'climate change' on its list of threats to US national security (Department of Defense, 2010). Yet, despite this inclusion, disagreements remain.

Wide variation in findings, dubious data quality, and inaccurate predictions are often on the short list of reasons to disregard any connection between climate change and national security. Correctly anticipating the social consequences of global warming is difficult, because it is unclear whether rising temperatures should systematically increase the risk of violent conflict throughout the world. And although new research shows that changes in temperature are connected to violence, there is no

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understanding as to which causal mechanisms are most important for explaining this relationship (Hsiang, Burke & Miguel, 2013).

I argue that this is due to an underappreciation of how seasonality contributes to actors' willingness to engage in violent conflict. Most studies of this relationship have relied on either a systemic research design that uses global temperature data in studying the international system as a single annually observed unit or country-year designs that use yearly mean temperature data, which necessarily mask seasonal variability.[1] In either case, these designs are problematic because they ignore the inherent temperature variability as seasons change, which discounts the influence these seasonal changes have for social stability in developing nations.[2]

Seasonality affects both the scarcity of resources during certain times of the year and the strategic conditions that make conflict likely to occur. I argue that the effects of seasonal temperature change are best channeled through a 'strategic viability mechanism' by which actors seeking to engage in conflict are more likely to do so during seasons that are most amenable to engage in conflict – namely during periods of warm, predictable weather. I contrast this argument with the more familiar 'eco-shock' contention, which claims that interyear deviations from longstanding climate trends increase the probability of violent conflict.

I evaluate the evidence for these different mechanisms using a country-month research design, which allows for the development of specific causal mechanisms tied to seasonal changes. Furthermore, because these changes may matter more in certain areas of the world than others, I offer theoretical expectations for the likelihood of these relationships based on a country's geographic climate classification. My findings only support the strategic viability mechanism, showing that conflict is more likely to occur during warmer months of the year. This finding is present in both the all-inclusive country samples, and perhaps more notably, in country samples that are affected by strong seasonality, that is, where countries have significant temperature changes from season to season.

Theoretical origins

Case studies provide some evidence that environmental scarcities are associated with an increased risk of violent conflict (Homer-Dixon, 1999). However, many empirical studies have found little support for substantiating this mechanism.[3] Subsequently, newer research has argued that climate variability is a more plausible pathway to conflict because of the social and economic disruptions resulting from the 'shock' in the predictability of climate patterns. Studies have found support for this causal pathway as it relates to changes in the annual variability of rainfall (Hendrix & Glaser, 2007; Hendrix & Salehyan, 2012; Fjelde & von Uexkull, 2012); however, studies of this variability as it relates to changes in temperature are largely unexplored.

Recent research on temperature and violent conflict

The difficulty in studying the effects of changes in temperature on the onset of violent conflict is that they are theorized to produce a host of different effects across the world through various mechanisms, which may or may not impact the risk of conflict.[4] Consequently, this relationship is subject to much dispute. Burke et al. (2009, 2010a,b) find evidence that conflict in Africa is associated with temperature increases, but do not investigate how conflict may relate to seasonal temperature variability. These findings are challenged by Sutton et al. (2010) and Buhaug (2010), who show that these results change depending on sample size, outlying observations, and a redefinition of the dependent variable, and by the inclusion of fixed effects covariates. Others have found an association between temperature changes and an increased risk of civil war via the El Niño/Southern Oscillation, which is responsible for the intermittent increases in global surface temperatures, showing that civil war onsets are more likely in warmer years than in colder years (Hsiang, Meng & Cane, 2011). Finally, even the most recent work on these relationships has produced results that vary widely (Bai & Kai-sing Kung, 2011; O'Loughlin et al., 2012; Theisen, Holtermann & Buhaug, 2011).

The majority of these studies test for this relationship primarily against data on civil conflict in Africa. Given that violent response to environmental changes is more plausible at less-organized levels of violence, it seems reasonable to test for this relationship as broadly as possible in order to paint the clearest picture (Raleigh & Kniveton, 2012). Furthermore, by allowing for broader testing at a finer degree of temporal disaggregation, one can also incorporate a consideration of other causal

[1] Corresponding country-year empirical tests of the theoretical arguments made in this article are included in the online appendix for comparison.

[2] O'Loughlin et al. (2012) and Theisen, Holtermann & Buhaug (2011) are notable exceptions.

[3] For a comprehensive review, see Theisen (2008).

[4] See IPCC (2007) for a discussion of these various changes.

mechanisms that furthers our understanding of the environmental conflict literature.

Seasonality & strategic viability

Existing research on climate change indicates that seasonal patterns will likely shift as global temperature increases, leading to milder winters, earlier springs, and extended summers (IPCC, 2007). These seasonal extensions not only have implications for climate adaption strategies, they also are influential for the onset of violent conflict. Generally, a prolonged summer climate should provide more opportunities for social organization and criminal activity because mobility is easier, resources more available, and targets more plentiful.[5] Interestingly, there is a small, but growing body of evidence to support the argument that seasonality affects the strategic interaction of conflict participants.

With respect to civil wars, warmer weather may increase their risk if it extends the time and environmental conditions in which armed conflict is strategically viable. Warmer temperatures in colder regions of the world grant governments and rebels an easier time transporting resources and troops in remote regions of countries that usually are inaccessible when conditions are harsh. Unseasonably warm winter weather has been cited as a reason for an increase the observed violence throughout Afghanistan because it affords the Taliban extended supply routes across the Afghanistan–Pakistan border and provides easier mobility throughout the Afghan countryside (King & Yaqubi, 2012; Partlow, 2011). Higher temperatures also increase the availability of resources by extending growing seasons and encouraging intensive agricultural practices.[6] These changes create opportunities for rebel looting in order to sustain their movements. Indeed, the Free Syrian Army has benefited substantially in the recent past in its fight against the Assad regime by a bountiful harvest of crops, due directly to an increase in unusual weather patterns (Chivers, 2012).

Seasonal temperature changes also influence the frequency of intercommunal and non-state conflict by altering adaptive agricultural strategies, exacerbating social cleavages between husbandry and farming communities in the developing world (Mortimore & Adams, 2001). Disagreements over access to seasonal grazing land and watering holes have been shown to impact farmer–herder conflict throughout the Sahel (Turner, 2004). Changes in foliage growth and an increased value of livestock, due to prolonged periods of drought, have also been tied to increased frequency of livestock raiding in the Karamoja Cluster (Meier, Bond & Bond, 2007).

Seasonality influences the frequency of other, less-organized forms of violence as well. Higher temperatures alter people's routine activity (Cohen & Felson, 1979), which encourages them to spend more time outdoors engaging in social interaction. This pattern was recently demonstrated in the summer of 2012 with higher temperatures cited as being responsible for bringing large numbers of protestors into the streets of Tel Aviv (AFP, 2012). Higher temperatures have also been shown to be associated an increase in the frequency of violent crime through increased social interaction and by triggering human aggression (Anderson, 1989; Mares, 2013).

Inclement seasonal weather, however, limits the opportunities for violent conflict. Lujala (2010) notes that monsoon seasons, which transform jungle paths and mountain roads into impassable terrain, are a limiting factor for the prolonging of insurgencies in Southeast Asia. Overcast skies and unfavorable visibility have been regarded by the Free Syrian Army as a major determinant in preventing Assad's air force from effectively bombing rebel positions in Northern Syria (NBC News, 2012). Even US news reports have noted that the extremely low winter temperatures of January 2012 were responsible for dispersing the large and notable 'Occupy' protests in Washington, DC (Samuels & Gowen, 2012).

Thus, if one accepts that climate change alters the length and timing of seasons from year to year, then actors looking to participate in violent conflict should be more likely to do so when seasonal conditions support their strategies – with the expectation being that this is more likely in months with higher temperatures. This logic motivates the following two hypotheses:

> *Hypothesis 1a:* The probability of civil war onset increases as monthly temperatures increase.
> *Hypothesis 1b:* The onset of non-state conflict, social protest, and other forms of spontaneous violence increases as monthly temperatures increase.

Because equatorial and polar climates have a higher degree of stationarity within their monthly temperatures, one must take into account general climate differences. Thus, in order to evaluate whether strategic viability of conflict is truly influenced by extended

[5] However, there may be some instances where this is not always the case, such as in extremely arid climates.

[6] Higher temperatures are shown to increase cropping intensity and suitability for double cropping in previous unsuitable areas (Zhang et al., 2013).

periods of favorable weather, then one would expect to observe this relationship more often in regions of the world that exhibit strong seasonality. This leads to two additional hypotheses:

Hypothesis 1c: The probability of civil war onset increases as monthly temperatures increase in countries with climates that have strong seasonality.
Hypothesis 1d: The onset of non-state conflict, social protest, and other forms of spontaneous violence increases as monthly temperatures increase in countries with climates that have strong seasonality.

Temperature shocks and equilibrium disruption

The second mechanism that may influence the onset of violent conflict is the 'temperature shock' (aka 'eco-shock'), which is essentially a substantial deviation from a climate pattern (for further discussion, see Hendrix & Salehyan, 2012). Research suggests that increasing global temperature will also bring increasing weather variability at an increasing rate (Steinbruner, Stern & Husbands, 2013). This increased variability can cause disruptions in economic and social systems if temperature shocks become the main determinant for altering access to basic necessities.

With regard to less-organized conflict, Raleigh & Kniveton (2012) contend that small-scale violence may be more likely a product of resource competition and individual frustration brought about by climate change. Starting a civil war requires individuals to overcome a variety of large-scale resource and collective action problems. If one assumes that temperature shocks lead to more abundant resources then this may be the outcome; however, if one assumes that temperature shocks create fewer resources, then it may be easier to 'beggar thy neighbor' than attempt to overthrow a government. As Fjelde & von Uexkull (2012: 446) note, 'violent appropriation of resources from other communities is also more feasible, in terms of organizational capacity and resources, than launching a rebellion against the state'. Alternatively, an individual may simply decide the lack of 'lootable' resources created by climate change leaves nothing worth fighting over (Witsenburg & Adano, 2009).

Doubtless, temperature shocks can have a dramatic influence on the scarcity of resources, yet there is little empirical evidence to suggest what type of temperature shock is most important. The theoretical expectations that come with considering the temperature shock mechanism as a determinant for violent conflict seem to lead to contradictory conclusions, because it is not obvious if positive deviations (i.e. high temperatures) and negative deviations (i.e. low temperatures) impact rebel groups and non-state actors differently. Studies suggest that colder than average years and warmer than average years are both tied to an increase in civil war onset (Zhang et al., 2007; Tol & Wagner, 2010; Hsiang, Meng & Cane, 2011),[7] while less-organized forms of violent conflict are more often associated with higher than average temperature changes (Hsiang, Burke & Miguel, 2013).

These ambiguities motivate a general set of hypotheses in order to establish whether there exists a statistical tendency in one deviational direction over another:

Hypothesis 2a: The probability of civil war onset increases as monthly temperatures deviate positively from their long-term monthly means.
Hypothesis 2b: The onset of non-state conflict, social protest, and other forms of spontaneous violence increases as monthly temperatures deviate positively from their long-term monthly means.
Hypothesis 2c: The probability of civil war onset increases as monthly temperatures deviate negatively from their long-term monthly means.
Hypothesis 2d: The onset of non-state conflict, social protest, and other forms of spontaneous violence increases as monthly temperatures deviate negatively from their long-term monthly means.

There is reason to believe that these deviations in temperature are more salient for some areas of the world over others. In countries located near the equator,[8] deviations from monthly temperatures are unlikely to affect the decisions of actors because temperatures are relatively stable from month to month. Ironically, to the extent there is any relationship, evidence suggests that deviations may actually inhibit the onset of conflict in these areas. *Intensely high* temperature shocks (> 38° Celsius) may literally reduce the physical ability of actors to participate in conflict. Indeed, the extreme heat of the Saharan desert in Northern Mali – heat so hot that it makes 'it difficult to draw breath' – has been cited as a contributing factor that prevents Malian government troops from sustaining combat operations for more than

[7] These studies do not consider modern societies, which is the focus of this article. Therefore, their implications for the present day are somewhat ambiguous.
[8] Iceland is the only polar country that meets these conditions. My theory is geared primarily toward equatorial countries.

six hours per day against Al-Qaeda in the Islamic Maghreb and the Movement for Unity and Jihad in West Africa insurgencies (*Economist*, 2012). This leads to two additional hypotheses:

Hypothesis 3a: The probability of civil war onset decreases as monthly temperatures deviate positively from their long-term monthly means in countries with climates that have weak seasonality.

Hypothesis 3b: The onset of non-state conflict, social protest, and other forms of spontaneous violence decreases as monthly temperatures deviate positively from their long-term monthly means in countries with climates that have weak seasonality.

Conversely, in climates where temperatures do exhibit significant fluctuations, deviations may be much more salient. An unseasonable frost or a blanketing heat wave may have adverse effects on both agricultural productivity and state infrastructure, which can increase human misery and inflame widespread grievances. Thus, in these types of climates and under certain conditions, the onset of low-scale conflict to full-out rebellion may be possible. These distinctions motivate a final set of hypotheses regarding temperature shocks:

Hypothesis 4a: The probability of civil war onset increases as monthly temperatures deviate positively from their long-term monthly means in countries with climates that have strong seasonality.

Hypothesis 4b: The onset of non-state conflict, social protest, and other forms of spontaneous violence increases as monthly temperatures deviate positively from their long-term monthly means in countries with climates that have strong seasonality.

Hypothesis 4c: The probability of civil war onset increases as monthly temperatures deviate negatively from their long-term monthly means in countries with climates that have strong seasonality.

Hypothesis 4d: The onset of non-state conflict, social protest, and other forms of spontaneous violence increases as monthly temperatures deviate negatively from their long-term monthly means in countries with climates that have strong seasonality.

Research design and data

Tests of temperature and intrastate conflict use a state-based measure from the Armed Conflict Database (ACD) (Gleditsch et al., 2002; Themnér & Wallensteen, 2013), which provides a binary variable indicating the monthly onset of an internal or internationalized intrastate conflict which results in 25 or more annual battle deaths. Because I am interested in the onset of civil war, I use the standard convention in the civil war literature of assigning a value of 1 to indicate when a new onset emerges, when a conflict re-emerges after two years of peace, or when a rebel party becomes a new combatant in an ongoing war to which it was not a party in the previous year. I also include separate models that estimate the effect of temperature change on high intensity civil war onset using the threshold of 1,000 or more battle deaths.

In order to address instances of less-organized conflict with the greatest degree of focus, I use non-state conflicts from the Uppsala Conflict Data Program's (UDCP) Non-State Conflict Dataset Version 2.4 (Sundberg, Eck & Kreutz, 2012). Non-state conflicts are defined as 'the use of armed force between two organized armed groups, neither of which is a government of a state, which results in at least 25 battle related deaths in a year' (Sundberg, Eck & Kreutz, 2012: 352–353). For analyzing more spontaneous forms of violent conflict, I use three regional databases. The first is the Social Conflict in Africa Database (SCAD), which 'provides information on protests, riots, and other social disturbances in Africa' (Salehyan & Hendrix, 2012: 1). From SCAD, I use the count of violent social protest events – specifically organized violent riots, spontaneous violent riots, progovernment violence, antigovernment violence, extragovernment violence, and intragovernment violence in a given month (see Salehyan et al., 2012). The second is the Integrated Conflict Early Warning System (ICEWS) Asia dataset, which collects data on a variety of political instability indicators including violent conflict events (see O'Brien, 2010). From ICEWS, I use the count of assaults, fights, and unconventional mass violence in a given month. The third is the Armed Conflict Events Location Database (ACLED), which 'collects data on disaggregated internal political conflict by date, location, and actor – with actors defined as governments, rebel groups, militaries, and organized political groups' (Raleigh et al., 2010: 651–654). The ACLED data are spatially aggregated to the country level, with two different dependent variables that address events related to civil war and those related to less-organized forms of violence: (1) 'rebel violence' is the count of rebel–government violent interactions in a given month; (2) 'civilian violence' is the count of riots, protests, and violence against civilians in a given month.

These regional datasets are preferable for this study because the negative effects of climate change are believed to be felt disproportionately in underdeveloped countries with agricultural-based economies (Mendelsohn, Dinar & Williams, 2006). Countries with these characteristics are located primarily within the African and Asian continents. Thus, if we are to expect the onset of violent conflict from changes in temperature, particularly at lower levels of organization, as eco-violence theory suggests (Homer-Dixon, 1999), it is reasonable to assume that these are the areas of the world where we should observe it.[9]

Unlike civil wars, non-state conflict, SCAD, ICEWS, and ACLED violent events are far more frequent and often correlated across time as one event makes another more likely to occur. This tendency makes it difficult to discern independence from one event to another for the purposes of coding unique and independent onsets. Therefore, the dependent variables for these models use ‘counts’.

Independent variables

Temperature data are from NOAA’s NCEP/NCAR Reanalysis Monthly Means Dataset 1948–2011 (in degrees Celsius) (Kalnay et al., 1996). These data provide surface or near surface air temperatures (.995 sigma level) with spatial coverage of a 2.5 $\times$ 2.5 degree longitude native resolution (144 $\times$ 72). These data are spatially aggregated into country-month units of analysis. ‘Temperature mean’ is measured as the monthly mean temperature for country *i* in month *t* in year *z*. The foundation for this temperature shock measure uses the monthly deviation from a country’s long-term monthly mean, indicated by $(X_{itz} - X_{it\text{-}bar})/\sigma_{it}$ where X_{itz} is the mean temperature of country *i* in month *t* in year *z* and $X_{it\text{-}bar}$ is the panel mean of country *i*’s long-term monthly (*t-bar*) mean temperature from the period 1948–2011, and σ_{it} is the standard deviation of that panel. This approach is akin to Hendrix & Salehyan’s (2012: 41) measure of rainfall deviation, where the authors argue that deviations from the panel mean are an optimal operationalization of the ‘eco-shock’ mechanism. A deviational measure like this is preferable to other measures of climate variability because its construction acknowledges that climate is different than weather, speaking to extended periods rather than changes from month to month. Moreover, this measure is standardized, allowing for meaningful comparisons of deviational differences between countries.

Because of the inconsistency in existing studies of whether high or low temperature shocks are more likely associated with conflict in periods that are unseasonably warm or unseasonably cold, I divide this variable into ‘positive deviation’ and ‘negative deviation’ measures according to Fjelde & von Uexkull’s (2012) coding method. ‘Positive deviation’ is measured as the absolute value for all observations with positive deviations, with all negative values set to zero; and ‘negative deviation’ is measured as the absolute value for all observations with negative deviations, with all positive values set to zero (see Fljede & von Uexkull, 2012: 449). Because it may be possible that risk of conflict declines at the most extreme values of temperature shocks (e.g. reducing incentives to fight because it is too warm or too cold), I also include squared transformations of these measures to account for this possibility.

Control variables and estimators

The start dates of civil wars and non-state conflicts are not known with precision in Uppsala datasets, and because the focus of this analysis seeks to explain the importance of seasonality and temperature, I include a binary variable indicating the first month of the year in these models to address the uncertainty of Uppsala’s coding method.[10] Because temperature changes often bring about changes in precipitation patterns, I also include controls for monthly levels of precipitation and precipitation deviations[11] using monthly precipitation data (mm/month) from the Global Precipitation Climatology Project Version 2.2. These data have a spatial coverage of 2.5 $\times$ 2.5 degrees with a longitude resolution (144 $\times$ 72) from 1979–2011 (Adler et al., 2003). I also control for El Niňo/Southern Oscillation (ENSO) years, which have been demonstrated to be associated with an increased risk of civil war (Hsiang, Meng & Cane, 2011). I include a binary variable indicating years influenced by the ESNO in accordance with the Center for Ocean-Atmospheric Prediction Studies ENSO Index (2012).

In order to accurately evaluate the differences in climate resulting from changes in geography for Hypotheses 1c, 1d, 3a, 3b, and 4a–4d, I parse the data according to the Koppen-Geiger Climate Classification Index (Kottek et al., 2006), which maps the global climate according vegetation, precipitation, and temperature. These data have a 0.5 $\times$ 0.5 spatial coverage and are aggregated into six different country-level climate variables (‘equatorial’,

[9] An attractive alternative is the UCDP-GED dataset (Sundberg & Melander, 2013), which also covers sub-Saharan Africa.

[10] Uppsala uses 1 January as its default date when the month is unknown.

[11] These measures are akin to the construction of my independent variables.

Table I. Strong seasonal countries

Afghanistan *Ω*	India ø	Pakistan *Ω*
Albania	Iran	Paraguay
Algeria *ΩΔ*	Iraq	Poland
Angola *ΩΔ*	Ireland	Portugal
Argentina	Israel	Qatar
Armenia	Italy	Romania
Australia ø	Japan ø	Russia ø
Austria	Jordan	Saudi Arabia
Azerbaijan	Kazakhstan	Senegal *ΩΔ*
Belarus	Kuwait	Slovakia
Belgium	Kyrgyzstan	Slovenia
Bhutan ø	Latvia	Somalia *ΩΔ*
Bosnia & Herzegovina *Ω*	Lebanon *Ω*	South Africa *ΩΔ*
Botswana *ΩΔ*	Lesotho *ΩΔ*	South Korea ø
Bulgaria	Libya *ΩΔ*	Spain
Burkina Faso *ΩΔ*	Lithuania	Sudan *ΩΔ*
Canada	Luxembourg	Swaziland *ΩΔ*
Chad *ΩΔ*	Macedonia *Ω*	Sweden
Chile	Malawi *ΩΔ*	Switzerland
China ø	Mali *ΩΔ*	Syria
Croatia *Ω*	Mauritania *ΩΔ*	Tajikistan
Cyprus	Mexico	Tunisia *ΩΔ*
Czech Republic	Moldova	Turkey
Denmark	Mongolia ø	Turkmenistan
Djibouti *Ω*	Montenegro	UAE
Egypt *ΩΔ*	Morocco *ΩΔ*	Ukraine
Eritrea *ΩΔ*	Myanmar *Ω*ø	United Kingdom
Estonia	Namibia *ΩΔ*	United States
Ethiopia *ΩΔ*	Nepal *Ω*ø	Uruguay
Finland	Netherlands	Uzbekistan
France	New Zealand ø	Yemen
Georgia	Niger *ΩΔ*	Yugoslavia
Germany	North Korea ø	Zambia *ΩΔ*
Greece	Norway	Zimbabwe *ΩΔ*
Hungary	Oman	

104 countries total; *Δ* denotes SCAD countries; *Ω* denotes ACLED countries; ø denotes ICWES countries.

'arid', 'temperate', 'snow', 'polar', and 'mixed') based on the percentage of pixels that fall into a given climate type. I define a country to have one of these six climate types if it contains > 50% (or < 50% in the case of 'mixed') in a given classification. Given the varying climate values of the Koppen-Gieger index, I define strong seasonality to include climates denoted 'temperate', 'snow', 'arid', and 'mixed' due to their large fluctuation in temperatures throughout the year, while countries having weak seasonality are denoted as 'equatorial' and 'polar' because their temperatures are comparatively constant. Countries denoted as having strong vs. weak seasonality are displayed in Tables I and II.

I also include a number of common controls identified in the intrastate conflict literature. First is regime type, taken from the Polity IV dataset and covering the period 1946–2011 (Marshall & Jaggers, 2010). Findings show that democratic institutions mitigate the effects of political disagreements and make violent conflict less likely to occur (Hegre & Sambanis, 2006). I use Vreeland's (2008) recommendation of deconstructing the Polity IV index into its component parts, when estimating the impact of regime type on civil war onset. The resulting measure of regime type is 'xpolity', which ranges from values of 1 to 14, with 14 being most democratic.

Larger, poorer countries are more likely to experience violent conflict (Hegre & Sambanis, 2006). Hence, I control for 'population' size and 'GDP per capita' using data from Gleditsch's (2002) Version 5.0 Expanded GDP Data, supplemented with data from the Penn World Tables 7.0 (Heston, Summers & Aten, 2011) and the World Bank (2012) to extend the time series through 2010. These measures are also logged to reduce skewness because some countries are much wealthier and larger than other countries. In order to address issues of simultaneity, 'xpolity', 'GDP per capita', and 'population' are lagged by one year. Finally, I control for temporal dependence using Carter & Signorino's (2010) recommendation of a cubic polynomial approximation of time.

All estimations are conducted in STATA 10. Substantive effects of all the results are generated using the CLARIFY software (King, Tomz & Wittenburg, 2000; Tomz, Wittenberg & King, 2003). Models testing the onset of civil war use logistic regression, which include robust standard errors clustered on country. Models testing the onset of non-state conflict use negative binomial regression due to the overdispersion in the dependent variable, and also include robust standard errors clustered on country. One issue when using these data (i.e. 'state-based' and 'non-state' conflicts) is that there are many cases in which a country never experiences the onset of these conflicts. Hendrix & Salehyan (2012: 42) note that the use of fixed effects estimators is 'inappropriate in situations where there is no variation in the dependent variable because fixed effects are perfectly collinear with the dependent variable'. I avoid this practice for models using 'state-based' and 'non-state' conflict dependent variables.[12] Estimations of social

[12] I include these tests in the online appendix. However, one should regard these tests with caution. Given the bluntness that is often imposed by fixed effects in models with sparse DVs – my tests incur over 60% on average observation loss – many of the coefficients for the variables of interest tend to lose their statistical significance.

Table II. Weak seasonal countries

Bahamas	Gabon ΩΔ	Nigeria ΩΔ
Bangladesh ø	Gambia Ω Δ	Panama
Belize	Ghana ΩΔ	Papua New Guinea ø
Benin ΩΔ	Guatemala	Peru
Brazil	Guinea ΩΔ	Philippines ø
Brunei	Guinea-Bissau Ω Δ	Rwanda ΩΔ
Burundi ΩΔ	Guyana	Sierra Leone ΩΔ
Cambodia Ωø	Haiti Ω	Solomon Islands ø
Cameroon ΩΔ	Honduras	South Sudan Ω
Central African Republic ΩΔ	Iceland	Sri Lanka ø
Colombia	Indonesia ø	St Vincent and the Grenadines
Comoros ø	Ivory Coast ΩΔ	Suriname
Congo ΩΔ	Jamaica	Tanzania ΩΔ
Costa Rica	Kenya ΩΔ	Thailand ø
Cuba	Kiribati	Togo ΩΔ
Dominican Republic	Laos Ωø	Uganda ΩΔ
DRC ΩΔ	Liberia ΩΔ	Vanuatu
East Timor	Madagascar Ω øΔ	Venezuela
Ecuador	Malaysia ø	Vietnam ø
El Salvador	Mauritius øΔ	
Equatorial Guinea Ω	Mozambique ΩΔ	
Fiji ø	Nicaragua	

63 countries total; Δ denotes SCAD countries; Ω denotes ACLED countries; ø denotes ICWES countries.

protest and other spontaneous events of violent conflict from SCAD, ICWES, and ACLED use negative binomial regression with robust standard errors clustered on country in addition to separate models that use conditional fixed effects. Because these latter models are estimated twice, I regard the findings from these models as supportive of my hypotheses only in circumstances where statistical significance is attained under both their pooled and fixed effect specifications.

Results

The results reveal some interesting patterns and are displayed in Tables III, IV, and V, where Table III displays the results from an all-inclusive country sample, Table IV displays the results from a strong-seasonality country sample, and Table V displays the results from a weak-seasonality country sample. With regard to Hypotheses 1a and 1b, Table III shows that increases in mean temperatures are associated with a positive increase in the probability of low and high intensity civil wars, and non-state conflict onsets in the global sample.

In an effort to establish substantive context to these results, I simulate two different global temperature scenarios based on conclusions of the IPCC's Fifth Assessment Report (IPCC, 2014). Specifically, I use the Representative Concentration Pathways 4.5 (RPC 4.5) and the RPC 8.5 projections as 'stand-ins' for moderate ($\sim$ 2 degrees Celsius) and extreme ($\sim$ 4.5 degrees Celsius) warming scenarios stemming from the radiative forcing of the continuing emission of greenhouse gases throughout the remainder of this century (see van Vuuren et al., 2011 for further discussion).

A simulated 2°C increase from mean monthly temperatures raises the risk of low intensity civil war onset by 4.55%, high intensity civil war onset by 8.42%, and the expected count of non-state conflict events by 11.65%. Correspondingly, an increase of 4.5°C is associated with an increase of 10.25% in the probability of low intensity civil war onset, an increase of 19.41% in the probability of high intensity civil war onset, and an increase of 25.39% in the expected count of non-state conflict events.

The results are less stable, and occasionally in the opposite direction of the hypothetical expectations, when examining models using regional datasets because they show that 2°C and 4.5°C increases in monthly temperature are associated with notable decreases in the expected count of ACLED civilian violent events (6.98% and 15.50%, respectively). Interestingly, an increase in mean precipitation levels is also statistically significant for high intensity civil war onset (state-based) and non-state conflict events, but in the opposite direction than changes in mean temperature. A one standard

Table III. Country-month global sample results

Country-month, global	*1 State-based 1979–2010*	*2 State-based 1000+ 1979–2010*	*3 Non-state 1989 –2010*	*4 SCAD 1990–2010*	*5 SCAD 1990–2010*	*6 ICEWS 2000–09*	*7 ICEWS 2000–09*	*8 ACLED 1997–2010*	*9 ACLED 1997–2010*	*10 ACLED 1997–2010*	*11 ACLED 1997–2010*
DV Lag			0.006	0.109**	0.060**	0.035**	0.011**	0.109**	0.022**	0.102**	0.013**
			0.409	0.031	0.013	0.003	0.000	0.017	0.000	0.013	0.000
Temperature mean	0.021*	0.039**	0.044**	−0.006	0.014†	−0.002	0.012**	−0.027†	−0.001	−0.039**	−0.015**
	0.009	0.013	0.015	0.009	0.007	0.006	0.002	0.015	0.005	0.014	0.004
Positive temperature deviation	0.050	−0.402	0.202	0.210†	0.118	0.057	0.071	−0.075	0.063	0.114	0.092
	0.336	0.465	0.271	0.112	0.112	0.145	0.068	0.131	0.097	0.139	0.072
Positive temperature deviation^2	−0.111	0.090	−0.030	−0.077†	−0.047	−0.016	−0.034	0.042	−0.012	0.006	−0.017
	0.172	0.225	0.118	0.044	0.047	0.061	0.030	0.050	0.039	0.062	0.029
Negative temperature deviation	0.250	0.074	0.199	0.074	−0.004	0.100	0.121	−0.779	−0.040	0.277	0.308*
	0.222	0.234	0.485	0.178	0.182	0.137	0.113	0.592	0.178	0.291	0.134
Negative temperature deviation^2	0.005	0.112†	−0.160	−0.090	−0.045	−0.060	−0.071	0.634	0.004	−0.066	−0.204*
	0.088	0.066	0.261	0.099	0.106	0.064	0.066	0.488	0.103	0.199	0.080
Precipitation mean	−0.047	−0.111**	−0.068*	−0.006	−0.023*	0.002	−0.007	−0.009	−0.035**	−0.000	−0.007
	0.029	0.036	0.029	0.012	0.011	0.013	0.005	0.017	0.008	0.015	0.006
Positive precipitation deviation	−0.364†	0.289	−0.131	0.099	0.144	0.186	−0.004	−0.104	0.039	−0.070	−0.023
	0.207	0.283	0.262	0.102	0.098	0.119	0.069	0.144	0.084	0.103	0.065
Positive precipitation deviation^2	0.116†	−0.049	0.079	−0.009	−0.026	−0.067†	0.005	0.042	−0.016	0.016	−0.001
	0.067	0.105	0.092	0.038	0.035	0.039	0.029	0.040	0.029	0.029	0.023
Negative precipitation deviation	−0.016	0.751	−0.043	0.211	0.223†	0.071	−0.060	−0.032	−0.092	−0.106	−0.096
	0.382	0.531	0.338	0.139	0.132	0.141	0.075	0.233	0.117	0.133	0.089
Negative precipitation deviation^2	−0.052	−0.450	0.032	−0.088	−0.096	0.046	0.087*	0.021	−0.006	0.038	0.038
	0.261	0.327	0.191	0.082	0.071	0.068	0.036	0.129	0.065	0.082	0.049
Xpolity (lag)	−0.021	−0.054*	−0.042†	0.023*	0.020*	0.021	−0.039**	−0.026	−0.018**	−0.009	−0.013*
	0.015	0.026	0.024	0.011	0.008	0.022	0.008	0.018	0.006	0.015	0.005
GDP per capita (log, lag)	−0.216**	−0.051	−0.368**	0.022	−0.049	−0.091†	0.168**	−0.154†	0.052†	−0.031	0.024
	0.068	0.115	0.072	0.046	0.043	0.050	0.021	0.079	0.030	0.061	0.021
Population (log, lag)	0.270**	0.306**	0.281**	0.349**	0.189*	0.071†	0.169**	0.107*	0.096**	0.218**	0.101**
	0.047	0.061	0.031	0.047	0.082	0.039	0.020	0.047	0.011	0.036	0.009
El Niño	−0.044	−0.245	0.148	0.080	0.102†	−0.059	0.043	−0.117	0.067	−0.039	−0.013
	0.156	0.262	0.223	0.053	0.054	0.053	0.032	0.099	0.051	0.069	0.038
January	1.295**	1.701**	0.145								
	0.276	0.349	0.216								
Constant	−5.228**	−7.122**	−3.727**	−3.945**	−1.283	1.462†	−2.448**	1.345	−1.677**	−0.496	−1.034**
	0.743	1.074	1.028	0.722	0.973	0.766	0.301	0.916	0.311	0.769	0.237
Observations	53,484	53,484	40,256	10,071	10,071	3,885	3,885	8,241	8,086	8,241	8,086
Fixed effects?	N/A	N/A	N/A	N	Y	N	Y	N	Y	N	Y

Each value is followed by its standard error listed below; significance †$p < .10$, *$p < .05$, **$p < .001$; time controls omitted.

Table IV. Country-month strong seasonality results

Country-month, strong seasonality	*1 State-based 1979–2010*	*2 State-based 1000+ 1979–2010*	*3 Non-state 1989 –2010*	*4 SCAD 1990–2010*	*5 SCAD 1990–2010*	*6 ICEWS 2000–09*	*7 ICEWS 2000–09*	*8 ACLED 1997–2010*	*9 ACLED 1997–2010*	*10 ACLED 1997–2010*	*11 ACLED 1997–2010*
DV Lag			−0.54	0.115**	0.078*	0.030**	0.008**	0.101**	0.021**	0.095**	0.012*
			0.632	0.034	0.036	0.005	0.000	0.020	0.000	0.015	0.000
Temperature mean	0.026*	0.040**	0.035*	−0.013†	−0.002	−0.002	0.011**	−0.018	0.007	−0.031*	−0.013*
	0.012	0.015	0.016	0.008	0.010	0.005	0.002	0.014	0.006	0.014	0.004
Positive temperature deviation	0.261	−0.216	0.624†	0.405*	0.358*	−0.066	−0.084	0.019	0.126	0.032	0.116
	0.368	0.518	0.365	0.168	0.143	0.184	0.094	0.202	0.149	0.169	0.108
Positive temperature deviation^2	−0.175	−0.048	−0.264†	−0.152†	−0.140*	0.0216	0.031	0.084	−0.022	0.055	−0.015
	0.173	0.221	0.14	0.079	0.070	0.086	0.041	0.119	0.063	0.071	0.046
Negative temperature deviation	0.495	0.163	0.685	0.104	0.072	0.237†	0.086	−0.390	0.268	0.437	0.423**
	0.430	0.508	0.832	0.182	0.198	0.130	0.133	0.552	0.214	0.307	0.155
Negative temperature deviation^2	−0.134	0.079	−0.431	−0.121	−0.105	−0.087	−0.052	0.464	−0.116	−0.115	−0.248**
	0.250	0.253	0.468	0.097	0.105	0.061	0.071	0.438	0.119	0.231	0.089
Precipitation mean	−0.047	−0.130	−0.123†	0.001	−0.026	−0.016*	−0.015†	−0.035	−0.058**	0.007	−0.025*
	0.060	0.082	0.068	0.021	0.017	0.007	0.008	0.024	0.014	0.027	0.010
Positive precipitation deviation	−0.317	0.488	0.234	0.189	0.238†	0.067	−0.037	0.286	0.139	0.123	0.038
	0.221	0.386	0.474	0.120	0.124	0.166	0.102	0.198	0.123	0.133	0.089
Positive precipitation deviation^2	0.118	−0.115	−0.010	−0.043	−0.061	−0.032	0.006	−0.041	−0.048	−0.040	−0.014
	0.077	0.155	0.192	0.039	0.041	0.063	0.046	0.061	0.043	0.045	0.031
Negative precipitation deviation	0.346	0.914	0.020	0.254	0.279	−0.175	−0.070	0.577†	−0.065	0.203	0.015
	0.506	0.695	0.379	0.213	0.205	0.131	0.096	0.299	0.181	0.169	0.146
Negative precipitation deviation^2	−0.464	−0.52	0.030	−0.073	−0.096	0.159**	0.092*	−0.295	0.030	−0.143	−0.042
	0.411	0.487	0.170	0.127	0.121	0.060	0.043	0.209	0.112	0.121	0.096
Xpolity (lag)	−0.033	−0.083*	−0.056	0.023†	0.005	−0.013	−0.048**	−0.042	−0.048**	−0.009	0.001
	0.021	0.039	0.038	0.012	0.014	0.035	0.013	0.031	0.010	0.024	0.008
GDP per capita (log, lag)	−0.232*	−0.013	−0.414**	0.062	0.066	−0.059	0.239**	−0.109	0.056	0.042	0.030
	0.094	0.170	0.124	0.051	0.054	0.042	0.029	0.110	0.042	0.087	0.027
Population (log, lag)	0.317**	0.332**	0.295**	0.307**	0.149	0.184*	0.203**	0.124†	0.096**	0.214**	0.111*
	0.061	0.089	0.042	0.057	0.669	0.078	0.035	0.068	0.016	0.044	0.012
El Niño	−0.007	0.004	0.349	0.116†	0.150*	−0.016	0.055	−0.159	0.035	−0.030	−0.040
	0.199	0.323	0.227	0.066	0.067	0.045	0.044	0.161	0.074	0.078	0.051
January	1.581**	1.854**	−0.471								
	0.339	0.46	0.568								
Constant	−5.754**	−7.753**	−3.465*	−3.831**	−0.313**	0.451	−3.150**	0.363	−1.917**	−1.291	−1.401
	0.922	1.594	1.561	0.676	0.078	0.943	0.478	1.102	0.434	0.929	0.306
Observations	32,964	32,964	25,462	5,330	5,330	1,740	1,740	4,551	4,396	4,551	4,396
Fixed effects?	N/A	N/A	N/A	N	Y	N	Y	N	Y	N	Y

Each value is followed by its standard error listed below; significance $^{\dagger}p < .10$, $^{*}p < .05$, $^{**}p < .001$; time controls omitted.

Table V. Country-month weak seasonality results

Country-month, weak seasonality	1 State-based 1979–2010	2 State-based 1000+ 1979–2010	3 Non-state 1989–2010	4 SCAD 1990–2010	5 SCAD 1990–2010	6 ICEWS 2000–2009	7 ICEWS 2000–2009	8 ACLED 1997–2010	9 ACLED 1997–2010	10 ACLED 1997–2010	11 ACLED 1997–2010
DV Lag			0.226	0.079†	0.038*	0.036**	0.016**	0.116**	0.030**	0.091**	0.014**
			0.350	0.043	0.017	0.005	0.000	0.024	0.001	0.018	0.000
Temperature mean	−0.052	−0.051	−0.002	0.025	0.077**	0.043	0.017	−0.055	−0.079**	−0.062	−0.011
	0.035	0.037	0.066	0.028	0.022	0.043	0.017	0.042	0.017	0.038	0.013
Positive temperature deviation	0.009	−0.326	0.099	0.027	−0.161	0.021	0.160	−0.377†	−0.078	0.066	0.048
	0.654	0.722	0.352	0.176	0.147	0.210	0.099	0.206	0.132	0.197	0.105
Positive temperature deviation^2	−0.093	0.131	0.047	−0.017	0.041	−0.006	−0.067	0.097	0.037	−0.018	−0.012
	0.337	0.317	0.136	0.063	0.058	0.082	0.043	0.060	0.050	0.061	0.038
Negative temperature deviation	0.180	0.017	−0.122	−0.027	−0.424	−0.063	−0.048	−0.864	−0.454	−0.335	0.106
	0.362	0.406	0.441	0.494	0.324	0.181	0.257	0.738	0.478	0.467	0.341
Negative temperature deviation^2	0.033	0.121	0.006	0.088	0.352†	0.040	−0.041	0.312	0.095	0.148	−0.210
	0.086	0.081	0.194	0.296	0.212	0.131	0.192	0.462	0.378	0.281	0.270
Precipitation mean	−0.023	−0.147**	−0.079*	−0.019	−0.006	−0.005	−0.003	−0.006	−0.040**	−0.023	−0.002
	0.041	0.052	0.038	0.014	0.014	0.015	0.006	0.015	0.011	0.020	0.008
Positive precipitation deviation	−0.352	0.010	−0.432	0.017	0.055	0.310†	−0.035	−0.384*	−0.048	−0.255†	−0.037
	0.441	0.482	0.341	0.126	0.13	0.166	0.092	0.182	0.114	0.138	0.096
Positive precipitation deviation^2	0.081	0.053	0.155	0.021	0.002	−0.092†	0.026	0.092†	0.021	0.072*	−0.000
	0.135	0.132	0.11	0.047	0.045	0.047	0.033	0.053	0.038	0.036	0.034
Negative precipitation deviation	−0.003	0.438	−0.168	0.121	0.093	0.400*	0.021	−0.372	−0.106	−0.287	−0.156
	0.547	0.871	0.515	0.199	0.176	0.170	0.132	0.315	0.159	0.182	0.122
Negative precipitation deviation^2	0.097	−0.337	0.066	−0.070	−0.047	−0.150†	0.0341	0.143	−0.023	0.100	0.073
	0.291	0.465	0.313	0.114	0.088	0.083	0.077	0.162	0.082	0.101	0.061
Xpolity (lag)	−0.007	−0.006	−0.033†	0.020	0.036**	0.047†	−0.031**	0.001	0.024*	−0.011	−0.024**
	0.022	0.026	0.019	0.023	0.01	0.026	0.011	0.019	0.009	0.019	0.008
GDP per capita (log, lag)	−0.072	0.120	−0.220*	−0.026	−0.047	−0.045	0.089**	−0.088	0.239**	−0.114	0.030
	0.107	0.179	0.096	0.084	0.069	0.112	0.031	0.090	0.048	0.086	0.039
Population (log, lag)	0.160*	0.299**	0.281**	0.366**	0.274*	0.023	0.190**	0.083	0.101**	0.198**	0.087**
	0.070	0.093	0.036	0.055	0.111	0.059	0.031	0.057	0.015	0.051	0.013
El Niño	−0.090	−0.730*	0.035	0.054	0.066	−0.067	0.054	−0.039	0.149*	−0.066	0.059
	0.257	0.330	0.322	0.066	0.076	0.093	0.048	0.101	0.069	0.087	0.056
January	0.898†	1.391*	0.393								
	0.536	0.600	0.357								
Constant	−3.703*	−5.955**	−3.402*	−3.831**	−4.278**	−3.642*	0.181	−2.331**	2.086	−1.166*	1.273
	1.532	1.661	1.672	0.676	1.303	1.450	1.657	0.620	1.540	0.570	1.222
Observations	19,212	19,212	13,910	4,741	4,741	1,990	1,990	3,690	3,690	3,690	3,690
Fixed effects?	N/A	N/A	N/A	N	Y	N	Y	N	Y	N	Y

Each value is followed by its standard error listed below; significance †$p < .10$, *$p < .05$, **$p < .001$; time controls omitted.

deviation increase in rainfall is associated with a 28.28% reduction in the probability of high intensity civil war onset, while a two standard deviation increase reduces it by 47.39%; a one standard deviation increase in rainfall reduces the expected count of non-state conflicts by 18.01% , while a two standard deviation increase reduces it by 31.53%.

The results are supportive of argument that in countries with climates that have strong seasonality violent conflict is more likely to occur when warm weather is prolonged. Seasonal extensions of warm weather increase the probability of low intensity (4.66% for a 2°C increase; 12.10% for a 4.5°C increase) and high intensity civil war onset (7.22% for a 2°C increase; 19.04% for 4.5°C increase), which supports Hypothesis 1c. The results are mixed, however, when considering less-organized forms of violent conflict. The expected count of non-state conflicts increases by 7.82% for a 2°C increase from mean monthly temperature and 18.64% for a 4.5°C increase. Differently, the results indicate a decrease in the expected count for ACLED violent events by 0.80% and 12.45%, for these corresponding temperature increases. Finally, changes in mean precipitation are largely insignificant for these models. In summary, the results support Hypotheses 1a and 1c, and show limited support for Hypotheses 1b and 1d.

Hypotheses 2a–2d consider contradictory arguments based on inconsistencies in existing research regarding temperature shocks. The results show little support for the argument that temperature shocks increase the probability of violent conflict, regardless of their direction. The lack of evidence leads me to reject the general arguments presented by Hypotheses 2a–2d. Moreover, at least in terms of the global sample, which does not consider variation in climate type, these results are also not supportive of the argument that precipitation shocks increase the risk of violent conflict.

For temperature shocks, these findings change only somewhat when one considers the differences in climate type. As indicated in Table V, positive temperature deviations are not consistently associated with a decrease in the probability of violent conflict in countries with weak seasonality, regardless of the dependent variable that is tested. Therefore, I reject Hypotheses 3a and 3b.

With regard to countries that have strong seasonality, Table IV shows that deviations in temperature, whether they are positive or negative, also show no statistical association with the onset of civil war. This trend also rejects Hypotheses 4a and 4b. Finally, the results in Table IV show little support for Hypotheses 4c and 4d. Positive deviations in temperature are only associated with a non-linear change in the probability of violent social protest in Africa. These results however, are not stable across changes in measurement or alternative regional datasets. Therefore, I also reject these hypotheses given these inconsistencies.

The standard panel of control variables in this study shows that 'xpolity', 'population', and 'GDP per capita' all tend to be statistically significant and supportive of existing arguments in the civil war literature. The results for 'xpolity' and 'GDP per capita' change, however, when considering less-organized forms of violent conflict. In terms of substantive significance, it is usually the case that the magnitudes of these control variables, when statistically significant, outweigh those of the independent variables of interest – this finding indicates the environmental measures are ultimately limited in their influence for explaining the onset of violent conflict. 'January' is statistically significant and positive, indicating the monthly, temporal bias in Uppsala's coding methods. I find no evidence suggesting that 'El Niño' is responsible for an increase in the risk of violent conflict (Hsiang, Meng & Cane, 2011), but rather a decrease in the probability of high intensity civil war in samples of countries that have weak seasonality.[13]

Discussion

The results of this study show some curious patterns with respect to changes in unit of analysis, sample size, and dependent variable. Broadly speaking, when considering units of analysis, there seems to be little information lost when a more disaggregated unit of analysis is used. Temporal disaggregation opens the door for a wider consideration of the causal mechanisms that tie changes in environmental indicators to the onset of conflict. Given the threat of ecological fallacy that emerges when aggregating meteorological measures to a yearly unit (or the system level), it seems reasonable to prefer 'months' for the sake of theory building.

With respect to theory, it appears that the 'strategic viability mechanism' is strongly related to highly organized forms of violent conflict and this suggests that seasonal extensions are more closely tied to the strategies of organized warring parties, which is echoed in anecdotal accounts of insurgent–government interactions. This

[13] I include in the online appendix an analysis that uses the same time period for the various dependent variables. The results are attenuated and less stable under these substantial domain restrictions. I suspect that these changes are due in large part to the significant loss of observations that results from limiting the all samples to 2000–09.

finding is particularly the case in countries that have strong seasonal trends throughout the year. This seems reasonable give that extensions in seasons make more strategic sense with respect to coordinating organized attacks given the reliability needed for developing logistics related to troop deployments and resource coordination.

Alternatively, there seems little to no relationship between temperature shocks and the onset of violent conflict, regardless of the dependent variable used. This is somewhat surprising considering that existing research suggests that these shocks should be channeled through agricultural production to influence the scarcity of resources, which one would assume would affect the frequency of social protests and other forms of violent crime more often in developing countries. These non-findings change little even when considering differences in climate types. Ironically, these findings may actually be explained by existing research from the field of political ecology. When considering the regional datasets used in this study, the majority of countries are located primarily in Africa and Southeast Asia. Given their degree of climate variability and the changing economic and political conditions these areas of the world regularly experience, it may be that their climatic disequilibrium motivates a variety of adaptive risk management strategies for mitigating the effects of climate change when these shocks occur, such as livestock diversification, seasonal migration, and resource pooling (see Mortimore & Adams, 2001). Therefore, what one may regard as a rational response for engaging in conflict may actually be an irrational response for societies that are efficient risk managers (Turner, 2004). A further explanation for the 'non-findings' of this article may be found in the literature on opportunistic raiding, where the lack of available resources produced by these temperature shocks leaves nothing worth fighting over (see Witsenburg & Adano, 2009; Adano et al., 2012).

Conclusion

Given the enormity and complexity of climate change, it should not come as a surprise that the findings tying changes in temperature to various forms of violent conflict may differ. I evaluated two different mechanisms relating temperature change to several types of violent conflict. Because changes in temperature may matter more in certain areas of the world than in others, I offered theoretical expectations for the strength of these causal mechanisms based on a country's geographic climate classification.

The findings show that strategic viability is a more important determinant for explaining the onset of highly organized intrastate violence, such as civil wars and non-state conflicts – particularly so in countries characterized as having strong seasonality. Temperature shocks show little association with any form of violent conflict, which is most notably absent at the lowest levels of organization. Because many of the dependent variables considered here cluster in space, the analysis of the causal mechanisms would have benefited even more from a more geographically disaggregated unit of analysis; however, given my focus on temporal restrictions tied to explaining seasonality, addressing this concern was simply beyond the scope of this article

If one accepts that the length of seasons will increase as the planet warms, then there are significant foreign policy implications with regard to counterinsurgency strategy. One might conclude that conflict will become more persistent throughout the year, placing a greater burden on government resources and increasing the need for more frequent troop rotations into and out of conflict zones with active (or latent) insurgencies. Warm weather and melting snows may 'put into play' geographic areas that have traditionally been regarded as strategically irrelevant, such as mountainous terrain and flood plains, changing battle zones and war-affected areas. Overall, the social effects of climate change represent a growing national security concern, which requires further testing in order to explain their risks in a changing world.

Replication data

All replication files for the empirical analysis in this article, as well as the online appendix, can be found at http://www.prio.org/jpr/datasets.

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