Is Temperature Exogenous?

Conflict Related Uncertainty in the Instrumental Climate Record in Sub-Saharan Africa

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ABSTRACT

Research into the effects of climate on political and economic outcomes assumes that short-term variation in weather is exogenous to the phenomena being studied. However, the instrumental record is derived from weather stations operated by national governments, whose political capacity and stability affect the quality and continuity of coverage. This paper shows that civil conflict risk in Sub-Saharan Africa (SSA) is negatively correlated with the number and density of weather stations contributing to a country's temperature record. This effect is both cross-sectional (i.e., countries with higher average conflict risk tend to have poorer coverage) and cross-temporal (i.e., the incidence of civil conflict leads to loss of weather stations). We then show that poor coverage induces a small downward bias in the widely used temperature estimates produced by the University of East Anglia's Climatic Research Unit (CRU) and greater variation in temperature estimates across observational data sets. Collectively, these results imply that estimates of the effect of temperature on conflict risk could understate the magnitude of the relationship. Re-estimating the relationship between temperature and civil conflict in SSA using four observational data sets shows that the largest effect obtains when using data from the Berkeley Earth surface temperature (BEST) project, which are shown to be less vulnerable to conflict-related station loss.

A growing body of research has examined the effect of climate variation on economic and political outcomes, including the incidence of violent conflict (for reviews, see, Carleton and Hsiang 2016; Hsiang, Burke, and Miguel 2013). In particular, a number of studies have found that high temperature anomalies are associated with an elevated risk of civil conflict, particularly in the developing world (Burke et al. 2009; O'Loughlin et al. 2012; O'Loughlin, Linke, and Witmer 2014; Bollfrass and Shaver 2015; Witmer et al. 2017). A central assumption underlying these studies is that the climate variables of interest—i.e., temperature, precipitation, drought—are exogenous to the outcome being explained. Indeed, weather shocks are increasingly used as instrumental variables in models of civil conflict and political instability because there is no plausible mechanism through which the weather is influenced by such events (see, e.g., Miguel, Satyanath, and Sergenti 2004; Dube and Vargas 2013; Ritter and Conrad 2016).

However, while actual temperature and precipitation are not affected by economic and political outcomes—at least in the short run—their measurement may be. The most extensive modern records are derived from readings taken at weather stations distributed unevenly around the globe, and the tasks of establishing, staffing, and maintaining these stations fall under the jurisdiction of national governments.[1] As a result, political conditions could influence the instrumental record in at least two ways. First, the ability to establish and maintain weather stations may be related to the state's governing and bureaucratic capacity, factors that have been shown to influence a variety of outcomes, including civil conflict and economic growth (Fearon and Laitin 2003; Besley and Persson 2010; Hendrix 2010). Second, violence and instability may lead to the destruction of facilities or divert government resources away from the collection of

[1] While ground stations remain the main source of these data, there are several data sets generated from satellite observations. However, these data series are relatively recent and generally reported at lower spatial resolution than those derived from ground stations. We return to this issue in the conclusion.

weather data, creating gaps in the record that are directly caused by the outcome of interest. For example, when the Central African Republic fell into civil war in December 2012, nine of the twelve weather stations in the Global Climate Observing System (GCOS) Surface Network (GSN) stopped reporting within months.[2] Reports from the country indicate that the stations were destroyed by fighting and the staff forced to flee (Yambele 2017).

Given the importance of research into climate impacts, we need to know whether and how the instrumental climate record might be influenced by political and economic outcomes of interest. This is particularly pressing given the fact that the number of weather stations has declined globally in recent decades, and this decline has been particularly pronounced in sub-Saharan Africa. Although estimates of local conditions do not require the presence of weather stations in the immediate vicinity, or even within the same country, fewer stations leads to greater reliance on interpolation and thus greater potential for bias or measurement error (Dell, Jones, and Olken 2014, 747–50). Previous work has shown that station loss has no appreciable impact on estimates of global average temperature (Lawrimore et al. 2011, 16–17), though there is concern that coverage gaps, particularly in the polar regions, have downwardly biased some estimates of recent warming (Cowtan and Way 2014; Karl et al. 2015). But there has been no examination of the causes of station loss or whether coverage gaps affect the high resolution climate data that are used in research on political and economic impacts.[3]

In this paper, we examine the effect of civil conflict risk on the instrumental temperature record in sub-Saharan Africa (SSA), the region that has been the subject of most of the scholarly

[2] Based on station performance data located at http://www1.ncdc.noaa.gov/pub/data/gcos/WW_REG1_POR_summary (accessed Sept. 28, 2017). This count in based on stations that were reporting regularly prior to Dec. 2012.

[3] Dell, Jones, and Olken (2012, appendix table 15) examine ground station coverage to determine whether it is driven by any of their variables of interest and find that it is not.

attention to this topic (Burke et al. 2009; Burke et al. 2010; Couttenier and Soubeyran 2014; O'Loughlin et al. 2012; O'Loughlin, Linke, and Witmer 2014; Miguel, Satyanath, and Sergenti 2004; Witmer et al. 2017). We establish four main results. First, civil conflict risk is negatively associated with the number and density of weather stations contributing to a country's temperature record. There is evidence of both a cross-sectional effect—i.e., countries with higher conflict risk tend to have poorer coverage—as well as a cross-temporal effect—i.e., the incidence of civil conflict leads to loss of weather stations. Second, the most severe coverage gaps are associated with a downward bias in estimated temperature anomalies in the widely used high resolution temperature series generated by the University of East Anglia's Climatic Research Unit (CRU), the data set used in many of the studies (5 of the 7) cited above. This cold bias is due to manner in which those data deal with areas of sparse coverage. Third, coverage gaps are also associated with greater measurement error in temperature estimates. Comparing four observational data sets, we show that variation in temperature estimates is greater in more sparsely covered areas. Collectively, these results imply that estimates of the effect of temperature on conflict risk could *understate* the magnitude of the relationship. The final result establishes the plausibility of this conjecture by re-estimating the relationship between temperature and civil conflict in SSA using the four observational data series. The largest effect obtains when using data from the Berkeley Earth surface temperature (BEST) project, which, by design, maximizes the use of existing station data and hence is less vulnerable to the problems identified here.

1. The Effect of Conflict on Coverage

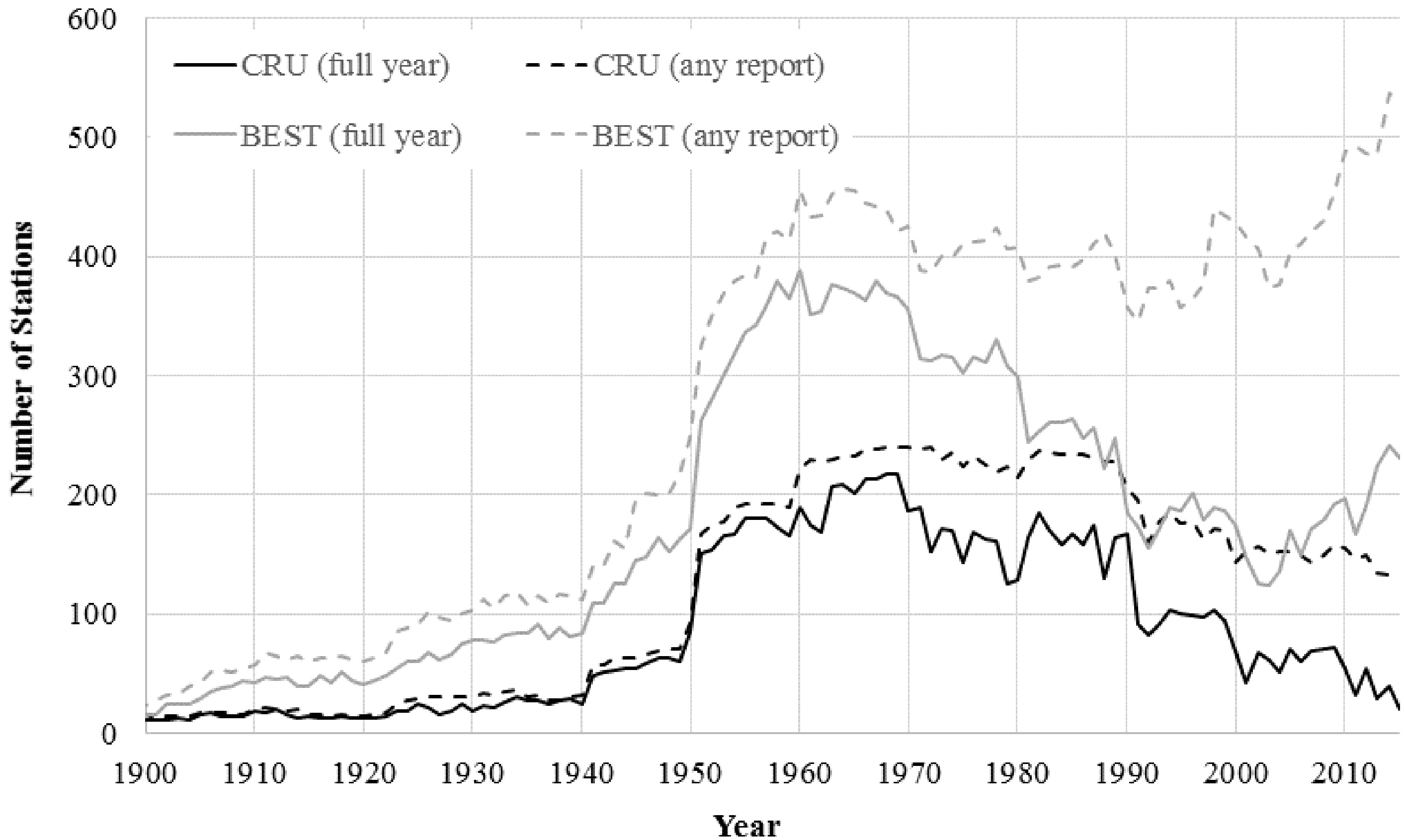
Patterns of Weather Station Coverage

Figure 1 shows the number of stations per year in SSA in the period 1900-2015. Station data are derived from two sources: the CRU high resolution times-series data (Harris et al. 2014) and the BEST monthly gridded data (Rohde et al. 2013).[4] We focus on these two data sets because of their widespread use in the literature on climate impacts and because both projects make the underlying station data easily available. There is significant overlap between the two sources, but they have different standards for station inclusion. The CRU data are most restrictive because they require a station to have sufficient coverage in the 1961-90 period to establish the local climatology. The BEST data include the CRU stations but also draw on additional sources and make use of techniques that allow for the inclusion of stations with relatively short reporting periods. For each source, two series are drawn: solid lines represent the number of stations that reported a valid temperature in all 12 months of the year, and dashed lines count the number of stations that reported at least one monthly temperature in that year. Both series tell a similar story. Weather station coverage in SSA grew sharply in the decade after World War II, reaching its maximum during the 1960s, when most countries in this region became independent states. From that point on, there is a decline in the number of stations, particularly those that report for the full year. The decline is less pronounced in the BEST data, which experience a recovery in numbers in the last decade, though much of that growth is due to a single country, South Africa.

This pattern broadly mirrors global trends, though SSA has experienced both the poorest coverage and the deepest losses (United Nations Economic Commission for Africa 2011). Some of the decline is due to artifacts of the data collection process. The pronounced drop after 1990 has been attributed to a change in the reporting criterion used by Global Historical Climatology

[4] The CRU data are version 3.24.01, which covers 1901-2015. The BEST data are continually updated; the data were accessed May 4, 2017.

Figure 1. Weather Stations in Sub-Saharan Africa, 1900-2015

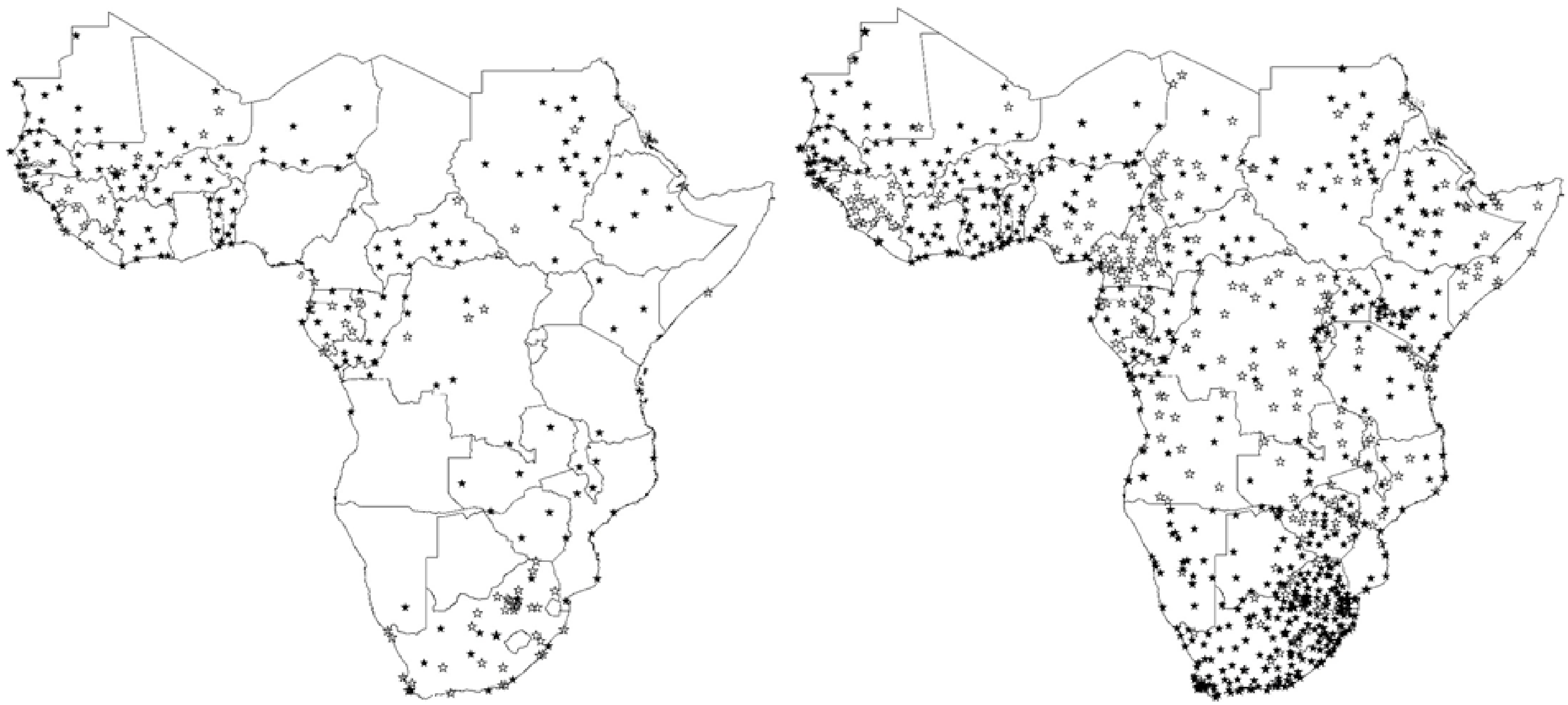


Network (GHCN), which forms the backbone of most data sets, and to the collapse of the Soviet Union, which supported weather data collection in several regions (Rohde et al. 2013, 7–8; Dell, Jones, and Olken 2014, 747–48). Concerted efforts to retrospectively fill in historical data, combined with the fact that many stations do not report in real time, can inflate past observations relative to current ones. Moreover, the CRU requirement that stations report consistently in the 1961-90 baseline period means that newly established stations cannot be added to that data set. That said, the pattern also reflects actual station loss as well as declining performance, evident in the growing gap between the number of stations that report at least one monthly average and those that report the full year. This gap suggests that many stations that physically exist either fail to record a temperature in some months or record a temperature that is discarded due to quality concerns.[5]

Crucially, the decline in weather stations in SSA is not uniform, as some areas have been more affected than others. Figure 2 depicts the location of all weather stations reporting temperature in the CRU (panel a) and BEST (panel b) data post-World War II. Those indicated with a solid star reported for at least one month in the period 2010-15, while hollow stars identify stations that did not report in those years. The map shows significant regional disparity in both existing and defunct stations. Coverage was historically densest in French West Africa and in South Africa, although both regions have seen significant declines as well. Coverage is sparser in central Africa, particularly the zone running from Angola northeast through the Congo to Somalia and north to Chad. Notably, some countries lack a single station in the CRU data, including Nigeria, Uganda, and Botswana. The additional coverage available in the BEST data is also striking, though they exhibit similar regional variation in station density.

[5] Both CRU and BEST apply a variety of quality control criteria to screen out temperature reports that are highly anomalous relative to past readings and/or readings in nearby stations.

Figure 2. Location of Active and Defunct Weather Stations



(a) (b)

Note: The figures shows the location of weather stations that contributed to CRU (panel a) and BEST (panel b) high resolution times series temperature data in the period 1946-2015. Solid stars indicate stations that reported at least once in the period 2010-15.

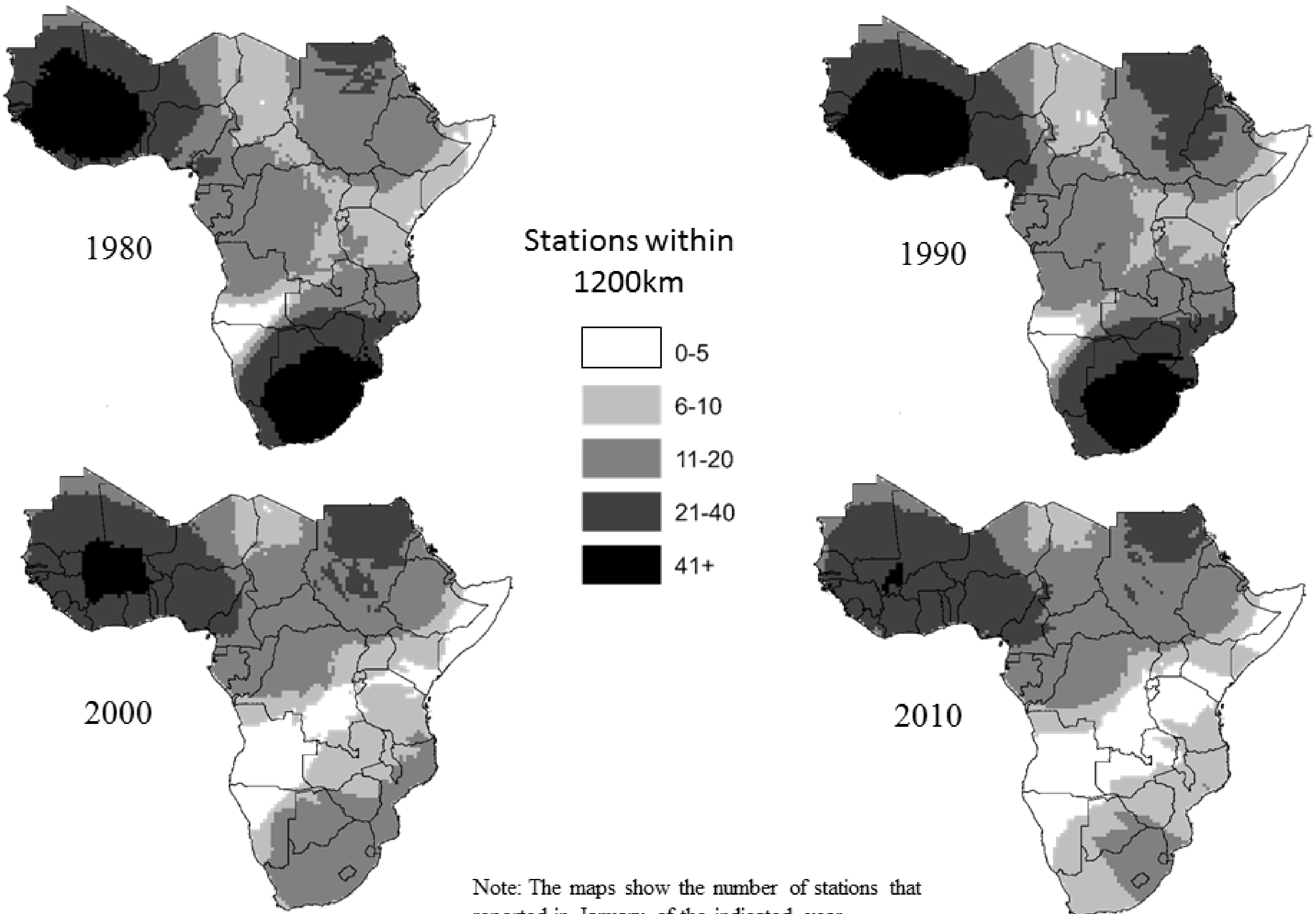
A country does not need to have a weather station within its borders for researchers to estimate its temperature, as monthly temperature anomalies are significantly correlated at distances of 1200km or more (New, Hulme, and Jones 2000). Figure 3 shows, for each 0.5° grid cell, the number of CRU stations within 1200km of the cell's centroid that reported temperature in January of the years 1980, 1990, 2000, and 2010. Since 1990, areas of sparse coverage opened up from the Horn of Africa to the southwestern coast. Notably, most of the affected countries—Angola, Rwanda, Burundi, Somalia, Uganda, Ethiopia, and the Democratic Republic of the Congo—experienced civil conflict in at least half of years since 1990.

Conflict risk and country coverage

To what extent might variation in station coverage be explained by the underlying risk or actual incidence of civil conflict? Following convention, we define civil conflict as organized political violence between the government and one or more rebel groups that claims at least 25 battle-related deaths in a year. The data for identifying such conflicts comes from the Uppsala Conflict Data Program (UCPD) Armed Conflict Database, version 4-2016 (Gleditsch et al. 2002; Melander, Pettersson, and Themnér 2016). Figure 4 presents evidence of a cross-sectional association between conflict risk and weather station coverage based on two kinds of indicators. First, two "in-country" indicators count the number of weather stations located within the country in a given year, per 100,000 sq. km of country area. Second, two distance-based indicators indicate the average number of stations that are within 1200km of each grid cell in the country, based on the grid cell resolution of the respective data sets.[6] For each indicator, the figure plots each country's average level of coverage against the proportion of years that the

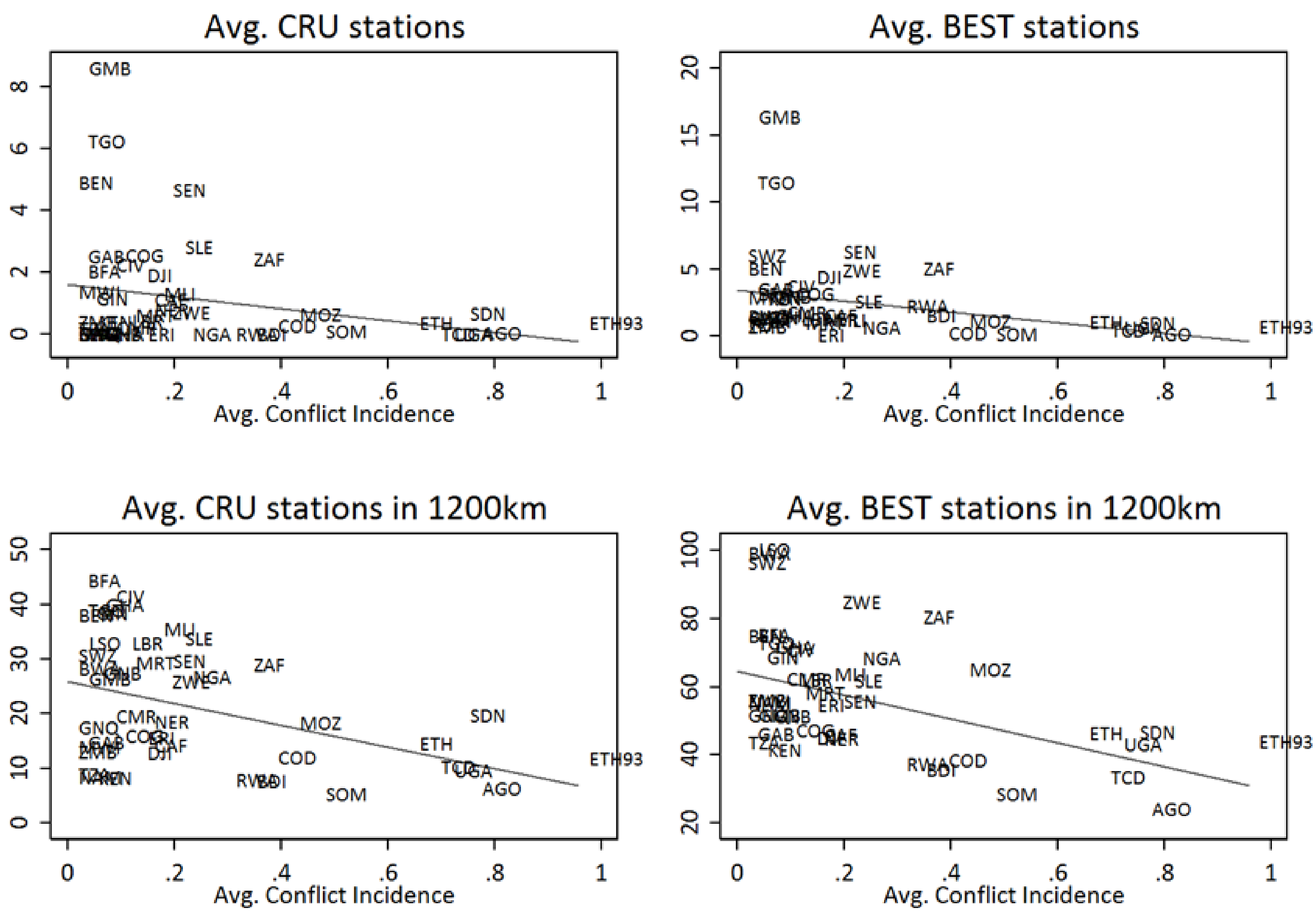
[6] The CRU data use 0.5° grid cells, while the BEST data use 1° cells. Yearly counts are weighted by the proportion of months in the year that the station made valid report.

Figure 3. The Evolution of Coverage in the CRU Data



Note: The maps show the number of stations that reported in January of the indicated year.

Figure 4. Average Coverage and Civil Conflict Risk, 1946-2015



Note: The figures shows the cross-sectional relationship between each coverage measure and the proportion of years that a country experienced civil conflict as an independent state in the period 1946-2015. Station counts in the top row are per 100,000 sq. km. of country area.

country experienced a civil conflict as an independent state in the period 1946-2015.[7] In each case, the relationship is negative.

Two broad mechanisms could contribute to this negative correlation. First, there could be country-level factors—such as poverty, poor state capacity, inhospitable terrain, or low bureaucratic quality—that both make a state vulnerable to conflict and compromise its ability to establish and maintain stations. Second, conflict itself could cause station loss or performance problems either due to direct damage caused by violence or the diversion of government resources away from station staffing and maintenance.[8] Since some station reports are physically collected by international scholars, both of these factors could also create variation in data accessibility, a phenomenon that Hendrix (2017) has documented in a related context.

Before turning to an exploration of these possibilities, it is important to note some complications with time series analysis of the coverage data. First, the majority of stations in these data sets do not report temperatures in real (or near real) time. Reports are collected retroactively, often with some delay. For example, many stations are updated via the World Weather Records (WWR), a compilation that is published once a decade. A station that disappears sometime in a given decade might appear to be lost from the beginning of the decade. Second, there have been continual efforts to add stations to the existing data sets, which means

[7] Whereas weather station and temperature data exist for all countries and years regardless of when they became independent, civil conflict data pertain to independent states. Thus, the sample for these tests is constructed from country-years in the period 1946-2015 during which a country was independent. Since the independence of South Sudan occurred close to the end of the data series (2011), it is not included in these tests, and Sudan is only included prior to 2011. Ethiopia is treated as a different state before and after the secession of Eritrea in 1993, and is indicated in the figures by the label "ETH93." Namibian stations are not included in South Africa's in-country coverage measures prior to the former's independence in 1990.

[8] It is also possible that factors associated with conflict risk influenced a country's initial endowment of weather stations from the colonial era. Indeed, there is a negative correlation between country coverage in 1955—a year that preceded independence for all but three countries in SSA—and post-independence conflict incidence. This correlation is largely driven by lower coverage in states with large area, mountainous terrain, and French colonial administration.

that station counts often increase retroactively from one data release to the next. This suggests that, at any given time, the existing station count may not reflect all of the data that could exist. Third, to be included in the CRU data, a station had to report consistently through the period 1961-90. This criterion means that any instability-related station loss during this period extends both forward and backward in time: short-lived stations that appeared and died during the baseline period never appear in the data set; stations that functioned in the pre-independence period but died shortly afterwards are retroactively deleted; and new stations that emerge later cannot be added due to the lack of historical data. There would also be survivorship bias if stations that managed to persist through those decades are, for whatever reason, relatively robust. In principle, the BEST station data do not face this latter problem, but to the extent that the project draws on CRU and other sources with similar criteria, it is no wholly immune. Thus, the correlations reported here have to be interpreted as such, not as causal effects, and temporal dynamics are not well modeled.

With those caveats in mind, Table 1 presents the coefficients from bivariate regressions of each of the four country-year coverage measures on each of a number of indicators of conflict incidence and state capacity. Three measures of civil conflict are included: a contemporaneous indicator for whether the country experienced a civil conflict in a given year; a cross-sectional measure of the number of years in the period 1961-90 the country experienced civil conflict, to account for the effect of instability in the baseline period; [9] and an indicator for whether any country within 1200km was experiencing a civil conflict in that year, which captures both regional instability as well as coverage effects of weather stations in neighboring states. The

[9] Some countries experienced civil conflict on their territory prior to becoming independent (e.g., Eritrea). These conflicts are captured in the UCDP data, which codes the location of separatist conflict. These cases are included in the count of 1961-90 conflicts. For the neighborhood measure, neighbors were included if any part was located within 1200km of the country's centroid.

table also explores correlations with several different characteristics that are related to state capacity (Hendrix 2010):

- Economic development: Real GDP per capita (logged) and the rate of infant mortality per 1000 live births.[10]
- Extractive capacity: A measure of total government revenue as a percentage of GDP.[11]
- Governance: Indicators of government effectiveness, regulatory quality, and the rule of law developed by the World Bank's World Governance Indicators (WGI) project (Kraay, Kaufmann, and Mastruzzi 2010).[12]
- Country features: Indicators for population density, mean elevation, and area (logged)

To aid in comparison of coefficients, all independent variables were standardized.[13] The final column in the table shows the correlation between each independent variable and the incidence of conflict in the country.

Several patterns stand out. First, there is strong negative correlation between all three indicators of conflict—contemporaneous, historical, and regional—and all coverage indicators. The correlations with the WGI measures are all in the expected (positive) direction, and several are statistically significant. There is also a pronounced relationship between mountainous terrain (proxied by mean elevation) and poorer coverage. Associations with other indicators, including economic development and extractive capacity, are inconsistently and/or unexpectedly signed. Further analysis comparing between and within estimates of the same relationships suggests that

[10] Both of these indicators are from the World Bank's World Development Indicators.
[11] From the International Centre for Tax and Development's Government Revenue Dataset, June 2016 release (Prichard, Cobham, and Goodhall 2014)
[12] These data are only available for 1996-2015.
[13] Standard errors were clustered by country.

Table 1. Correlations between Coverage, Conflict, and State Capacity

	CRU Stations	CRU in 1200km	BEST Stations	BEST in 1200km	Civil Conflict
Civil Conflict	-0.29**	-2.97***	-0.62***	-5.81***	
	(0.13)	(1.00)	(0.21)	(1.34)	
Conflict in 1961-90	-0.44**	-3.52**	-0.71**	-4.04	0.18***
	(0.20)	(1.33)	(0.34)	(2.78)	(0.03)
Conflict w/in 1200km	-0.31**	-3.47***	-0.58**	-5.94***	0.05**
	(0.13)	(1.02)	(0.25)	(1.48)	(0.02)
GDP per capita	-0.10	-3.07**	0.43	2.07	-0.02
	(0.16)	(1.27)	(0.32)	(3.38)	(0.02)
Infant mortality	0.19	5.42***	-0.43*	0.47	0.00
	(0.16)	(1.05)	(0.25)	(2.52)	(0.03)
Revenue/GDP	-0.09	-0.27	0.31	7.87**	-0.09***
	(0.17)	(1.26)	(0.35)	(3.89)	(0.03)
Gov. effectiveness	0.22	0.90	0.80**	12.51***	-0.13***
	(0.19)	(1.16)	(0.34)	(3.02)	(0.03)
Regulatory quality	0.33*	1.39	0.94***	9.72**	-0.12***
	(0.18)	(1.07)	(0.30)	(3.96)	(0.04)
Rule of law	0.38	1.10	0.94***	11.66***	-0.14***
	(0.24)	(1.15)	(0.34)	(3.47)	(0.03)
Population density	-0.02	-2.95***	0.54	-2.85	0.03
	(0.23)	(0.93)	(0.44)	(1.75)	(0.02)
Mean Elevation	-0.83***	-5.06**	-0.94*	0.10	0.06
	(0.29)	(2.33)	(0.49)	(3.94)	(0.04)
Area (logged)	-0.60	-2.29	-1.54**	-3.48	0.10***
	(0.40)	(1.57)	(0.65)	(3.07)	(0.03)

Note: This table reports coefficients from bivariate regressions of each independent variable on the coverage and conflict indictors. All independent variables were standardized. Standard errors corrected for clustering by country. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

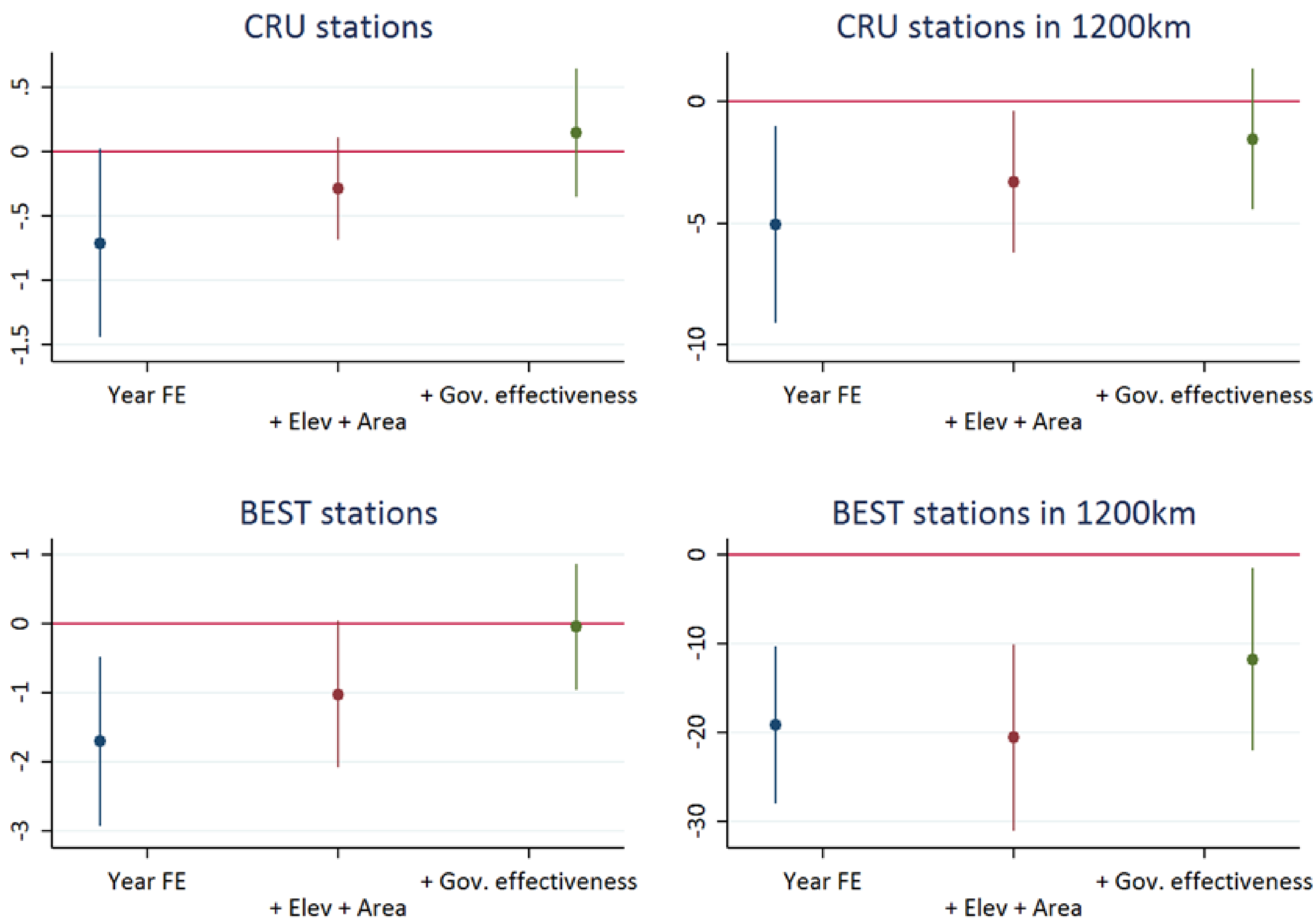
the correlations in Table 1 are mostly accounted for by the cross-sectional (between) variation. This is not surprising given that most of these factors are constant or slowly changing; weaker cross-temporal effects may also reflect the concerns expressed earlier about the nature of the coverage data (a point to which we will return in the next section).

Figure 5 reports the results of select multivariate regressions. For each coverage indicator, the figure shows the estimated effect of civil conflict in three specifications: (1) the conflict indicator and year fixed effects, (2) when controls for mean elevation and area are added, and (3) when the government effectiveness indicator is included as well.[14] As the figure makes clear, much of the effect of civil conflict on the in-country station counts (CRU Stations and BEST Stations) can be explained by the elevation and area controls. Including the index of government effectiveness reduces the estimated effect of conflict even further. Using the CRU distance-based measure, the correlation between conflict and coverage washes away once government effectiveness is introduced alongside controls for elevation and area; using the BEST distance-based measure, conflict is negatively associated with coverage in all specifications, but the effect is reduced somewhat when government effectiveness is taken into account.

All of this suggests that the cross-sectional correlation between coverage and conflict risk is due in part to sparse station density in relatively large countries with mountainous terrain, both factors that are thought to increase civil conflict risk at the country level due to the difficulties that long distances and challenging terrain pose to government security forces (Fearon and Laitin 2003). Variation in government effectiveness also contributes to the correlation, as ineffective

[14] To ensure comparability, all regressions were run on the sample for which the government effectiveness indicator was available.

Figure 5. The Effect of Conflict on Coverage with Select Controls



Note: The figures shows the estimated effect of civil conflict on each coverage indicator in three specification: with year fixed effects only, with mean elevation and area controls along with year fixed effects, and with the WGI government effectiveness indicator added to the others. The bars show 95 percent confidence intervals.

governments are unable to both monitor the weather and keep domestic peace.

Conflict and station loss

For reasons discussed earlier, the coverage data are not ideal for understanding cross-temporal dynamics and thus do not speak to the direct role of conflict, if any, on station loss over time. To examine this, we turn to station performance data collected by the GCOS. These data report, for each station in the network, the number of hourly observations reported by that station in each month and whether the station reported a monthly summary using CLIMAT, an electronic reporting system. Although some records go back to 1948, there is a very significant missingness from 1961-72, including some years in that period with no reports from any station. Thus, a station enters the sample the first time it makes a report after December 1972 or when the country in which it is located became independent, whichever is later.

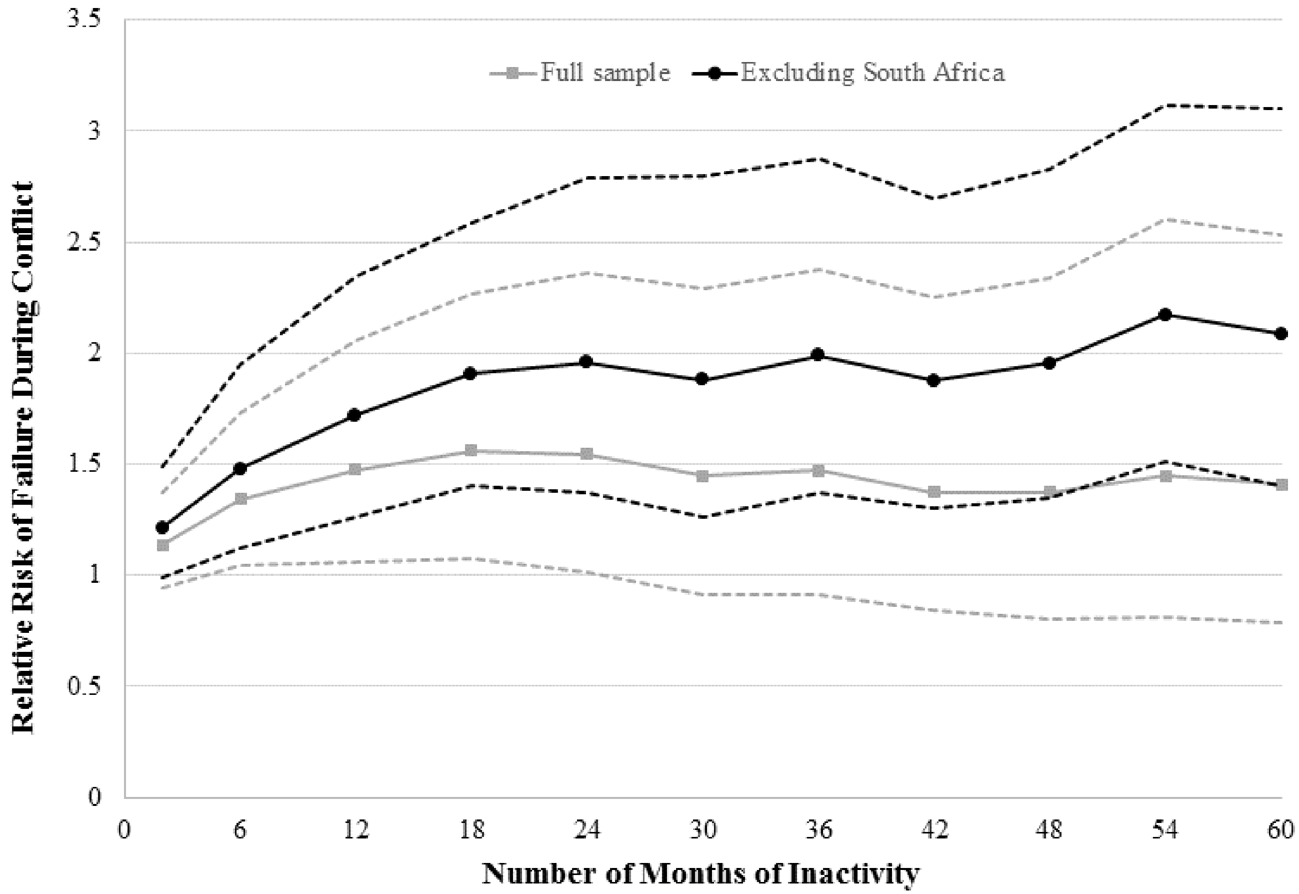
The data are organized into spells of activity, allowing us to estimate the effect of civil conflict on the probability that such a spell will end. Specifically, we code each station as giving a sign of life in any month in which it made at least one hourly report or produced a CLIMAT summary. Since many stations have intermittent, short-term gaps in reporting, a station is coded as "dead" if it goes for some minimum number of months without any sign of life, where the minimum threshold is varied. A spell of activity is then defined as a period of consecutive months in which the station did not experience a reporting gap long enough to be considered dead. If a station comes back to life after being dead for the minimum period, a new spell of activity begins.

Inspection of the data revealed that South Africa accounts for 320 of the 1199 stations in the data set, or 27 percent; by comparison, the next most common country, the DRC, has only

62, or 5.2 percent. Given that South Africa is also the most developed country in SSA, we might worry that this over-representation will skew the results. And, indeed, South Africa appears to be an outlier in that it experienced the most pronounced station loss in the 2000s, even though its civil conflicts took place in the 1970s and 80s. As a result, we present results both including and omitting South Africa from the sample.

Figure 6 shows the estimated effect of a civil conflict on the likelihood that a station will die, varying the minimum number of months of inactivity that are required to consider a station dead. The predictions are based on estimates from a logit model applied to the sample of station-months during which a station was alive, with the dependent variable equal to zero during active months and one in a month in which the station dies. The independent variables are an indicator for whether there was a new or ongoing civil conflict in the state during the month, a measure of how long the current spell of activity has been going on (introduced as a cubic polynomial), and country and year fixed effects. Because of the latter, the predictions are expressed as the relative risk that a spell of activity will end in a month with conflict compared to one without. Estimates for the sample with and without South Africa are shown, as are 95 percent confidence intervals. The estimates show that conflict increases the risk that a station will die, particularly when death is defined by periods of inactivity six months or longer. The magnitude and significance of the effect is sensitive to whether or not South African stations are included in the sample. When they are, conflict is predicted to increase the risk of failure by about 50 percent, but the effect is significant only when the minimum period activity needed to consider a station dead ranges from 6 month to 2 years. When South Africa is removed from the sample, conflict is estimated to double the risk of failure in any given month, and this estimate is significant at every death criterion considered, except for the shortest (2 months).

Figure 6. The Relative Risk of Station Loss Due to Civil Conflict



Note: This figures shows the relative risk that a station will fail during a month with civil conflict, relative to a month without conflict, varying the number of months of inactivity needed to consider a station as having failed. Dashed lines show 95 percent confidence intervals.

While the effects expressed in terms of relative risk are large, the underlying failure probabilities in any given month are quite small. In the full sample, a death that lasts at least 24 months happens in about 0.4 percent of months. Longer outages are even less common. Even so, 60 percent of stations in the sample experienced at least one failure of at least 2 years, and 45 percent experienced a failure of at least five years. In the sample without South Africa, even though conflict occurred in 18 percent of active station-months, months with conflict account for 32 percent of deaths lasting at least five years.

2. The Effects of Coverage Gaps on Temperature Estimates

We have seen evidence, then, of a negative correlation between weather station coverage and the risk civil conflict. This correlation appears to be driven both by cross-sectional factors, such as terrain and government effectiveness, as well as by a direct effect of conflict on the likelihood that an existing station will go dark. To understand the implications of this pattern for studies of the climate-conflict link, it is important to consider the effects that variation in coverage have on observational temperature data. There are two potential concerns: bias and measurement error. Bias would arise if poorly covered areas report systematically higher or lower temperatures than areas that have higher station network density. Measurement error arises if there is greater uncertainty around the temperature estimates as fewer stations contribute observations.

Bias

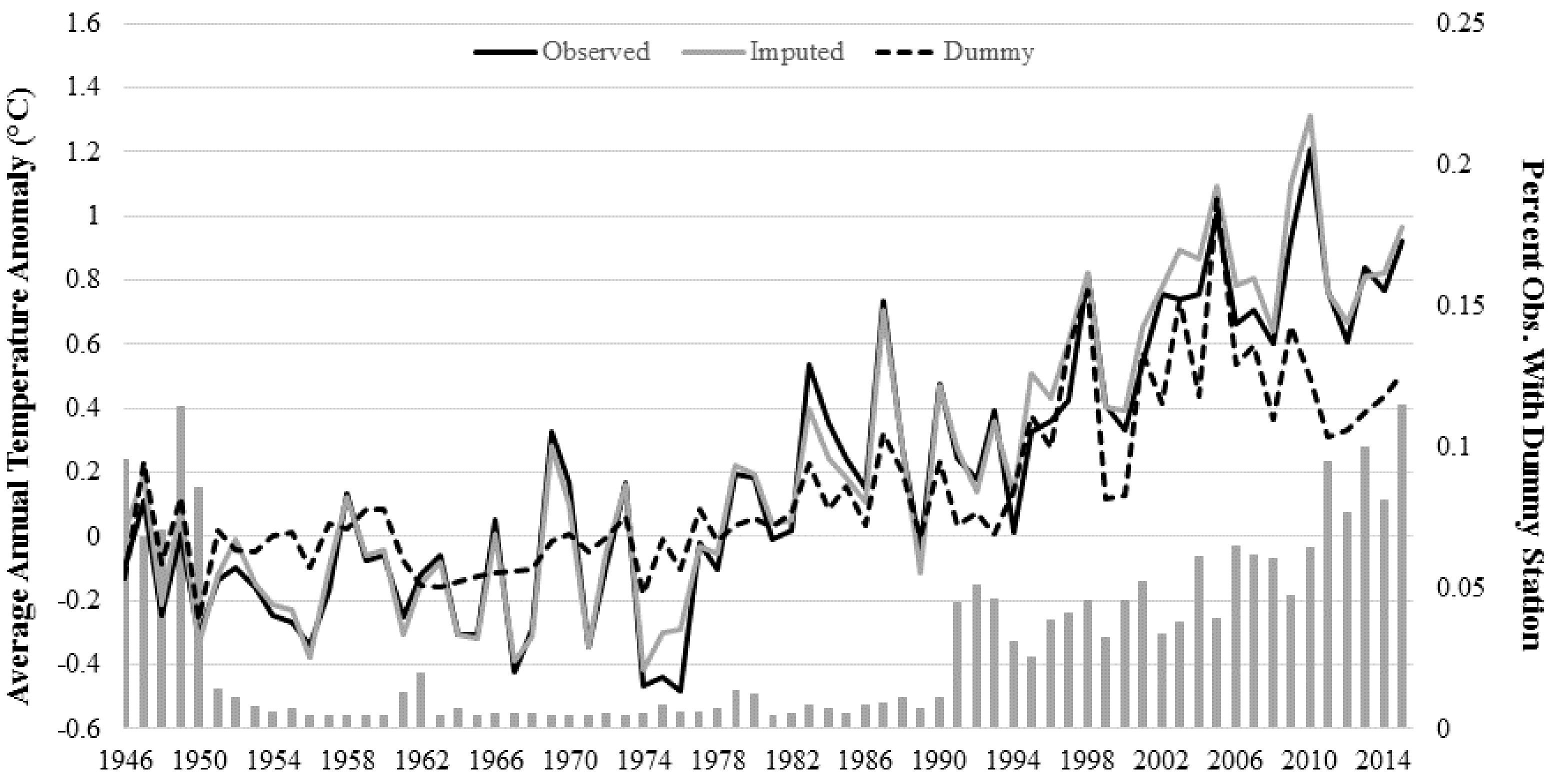
In general, interpolation should not induce predictably signed biases. The main concern would be if station loss occurs in regions that are systematically warmer or cooler than those in which stations remain. There is no reason to believe that this is the case. The CRU data, however, rely on one practice that could induce a predictable bias. As noted earlier, CRU produces high resolution time series data for each 0.5° cell (Harris et al. 2014). For each cell that does not have a weather station located within it, the temperature is interpolated from the three closest stations within 1200km.[15] In the event that there are fewer than three stations within that range, one or more "dummy" stations were created with a temperature anomaly (relative to 1961-90 baseline) of zero. In the context of a warming climate, this raises the danger that cells influenced by these dummy stations will receive artificially low temperatures.

Figure 7 presents preliminary evidence for this concern. For each year, the figure plots the average temperature anomaly reported by CRU across three kinds of grid cells: those in which the temperature was observed by a station in that cell, those in which the temperature was imputed from a full set of three neighboring stations, and those in which the temperature was influenced by at least one dummy station. While the observed and imputed temperature anomalies track one another very closely (correlation of 0.98), the temperature anomalies influenced by dummy stations do not track the observed series as closely (correlation=0.86) and are systematically lower starting in the early 1990s, when temperatures started to climb significantly higher than the baseline climatology. The figure also shows the percentage of cell-month observations that required at least one dummy station. Over the last two decades, coverage gaps have grown alongside rising temperatures.

Figure 8 presents two different estimates of the effect of these coverage gaps on interpolated temperatures: one using cell-month observations, the second using country-year

[15] More precisely, stations are connected using Dalaunay triangles, and the temperature in grid cells without a station are interpolated from the three stations at the vertices of the triangle in which the cell's centroid falls (Harris et al. 2014).

Figure 7. The Effect and Frequency of Dummy Stations in the CRU Data



Note: This figure shows the average CRU temperature anomaly in each year for three kinds of grid cells: those that were directly observed by a station in the cell, those that were imputed from three nearby stations, and those whose imputation was influenced by at least one dummy station.

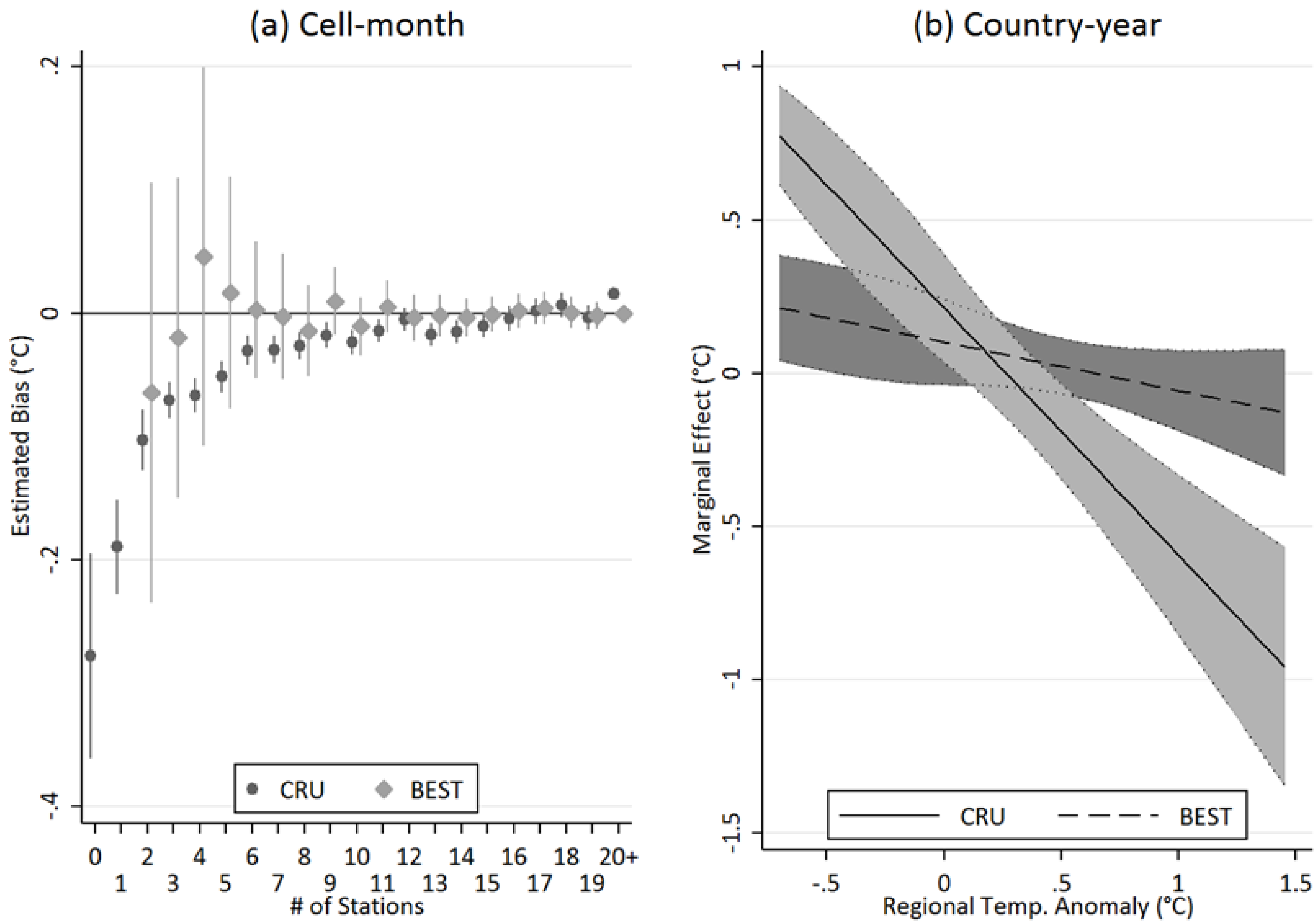
observations. Panel (a) reports the estimated bias in the CRU and BEST temperature anomalies as function of the number of reporting weather stations in the respective data set that was located within 1200km of the cell. The estimates were obtained non-parametrically, by regressing the temperature anomaly on a series of dummy variables for each of the indicated station counts. The baseline case consists of cells that contained a weather station in the given month and therefore had their temperatures observed directly.[16] The regression includes controls for the average temperature anomaly in all cells within 1200km, thereby capturing regional conditions, as well as the cell's mean elevation and its latitude (linear and squared).[17] Standard errors are corrected for cross-sectional spatial dependence within 1200km and panel-specific serial correlation over 12 months using the method proposed by Conley (2008) and implemented by Hsiang (2010). As the figure shows, there is a pronounced negative bias in the CRU estimates for cells with sparse coverage, particularly those that had fewer than three stations within range and therefore were influenced by one or more dummy stations. By comparison, the BEST data set has no cells with fewer than two weather stations within 1200km, and there is no systematic effect of station density on temperature estimates.

Panel (b) reports the effect of station coverage gaps on a country's annual temperature anomaly as a function of the average regional temperature. The coverage gap indicator measures the (area-weighted) proportion of cell-month observations within each country that were influenced by at least one dummy station in a given year. Although only CRU uses dummy stations to fill in areas of poor coverage, we present the effect of CRU coverage gaps on both the CRU and BEST temperature anomalies for purposes of comparison. The regional average is

[16] It should be noted that the BEST kriging algorithm imputes all temperatures, even when there is a weather station within the cell. We treat such cells as the baseline case to ensure comparability with the CRU results.

[17] When calculating the average CRU temperature anomaly within 1200km, cells whose temperature was influenced bv at least one dummy station were dropped.

Figure 8. Estimated Effect of Coverage on Interpolated Temperatures



Note: Panel (a) shows the estimated effect on the monthly temperature reported by CRU and BEST as function of the number of weather stations in each respective data set within 1200km of the cell. The baseline case is a cell that contains a weather station. Panel (b) shows the marginal effect of CRU coverage gaps on the annual temperature for a country reported by CRU and BEST as a function of the regional temperature anomaly in that year.

based on the temperature anomaly in all countries within 1200km of the country's centroid; as before, the regression also controls for the country's mean elevation and latitude and uses the Conley (2008) correction for standard errors. In the CRU data (solid line), coverage gaps are associated with higher temperature estimates when the regional temperature anomaly is zero or lower; however, once the regional temperature anomaly is above 0.4°C, coverage gaps induce a statistically significant downward bias on the country's estimated temperature anomaly. By contrast, the BEST temperature anomalies are not influenced by this measure, as the effect of a coverage gap is small and/or indistinguishable from zero under all conditions (dashed line).

The predicted bias in the observed CRU data is relatively small but growing due to increasing temperatures and growing coverage gaps. Overall, at the country-year level, the proportion of cell-months affected by a dummy station ranges 0 to 0.91, but the mean is only 0.023. A shift from no gap to one standard deviation above the mean (0.098) is associated with a small upward bias of 0.0043°C at the average regional temperature anomaly of 0.21°C. However, from 2010-2015, the mean coverage gap was 0.070, and the average regional temperature anomaly had grown to 0.77°C. Under these conditions, moving from no gap to one standard deviation above the mean (0.21) is associated with a cold bias of -0.085°C, or just over 10 percent of the average temperature anomaly in this period. Thus, the bias caused by CRU's use of dummy stations is getting worse with time.

Measurement Error

The final possibility to consider is that station coverage influences measurement error in temperature estimates. Greater reliance on interpolation means that temperature estimates are more dependent on the interpolation methods and assumptions. Moreover, estimates from areas that are densely covered by weather stations are less sensitive to differences in station inclusion criteria. To assess this possibility, we collect data from two additional temperature data sets based on the instrumental record: National Climatic Data Center's GHCN-CAMS surface air temperature data (Fan and van den Dool 2008) and the Terrestrial Air Temperature Gridded Monthly Time Series by Willmott and Matsuura (2015). These data, like those from CRU, are reported at the 0.5° grid cell resolution. To make them compatible, the BEST data were downscaled to that resolution via bilinear interpolation. Due to limits on temporal coverage, the combined data set covers 1948-2014.

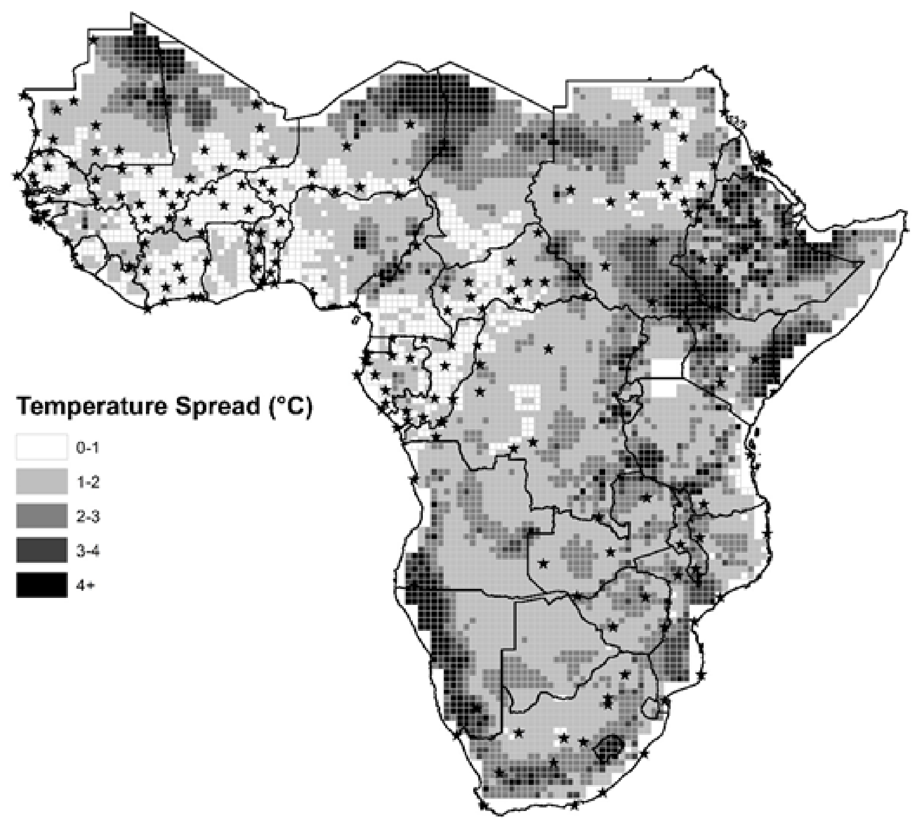
The four temperature series rely on overlapping, though not identical, station data and use different interpolation methods. As a result, they are highly correlated, though not perfectly so. Pairwise correlations in the temperature anomalies range from 0.68-0.81 in the grid cell-month data and 0.75-0.87 when the data are aggregated to country years. For each observation, the spread in temperature estimates can be measured using the difference between the highest and lowest anomaly reported across the four data sets. The average spread is 0.84°C.[18]

Figure 9 maps the average spread in each grid cell for all months 2000-14, along with the locations of CRU weather stations that were active for at least one month in this period. It is clear that more densely covered areas tend to have lower disagreement across the data sets, while the largest discrepancies occur in areas that are poorly covered.

Table 2 reports estimates from linear regressions of the temperature ranges on CRU and BEST coverage indicators using the grid cell-month (columns 1 and 2) and country-year (columns 3 and 4) as observations. The coverage indicators are the (logged) count the number of reporting stations within 1200km of each grid cell in each month; the country-year data set uses

[18] The data include a small number of outliers due to poor station data in the Willmott and Matsuura estimates for parts of Niger and Chad in some years. All of the results are unchanged if these observations are dropped.

Figure 9. Average Temperature Spread, 2000-2014



Note: The map shows the temperature spread across the four observational temperature series, average across all months 2000-14. Stars indicate the locations of CRU weather stations that gave at least one report in that period. Ungridded areas (around the edges and Lake Victoria) are not covered by the data.

Table 2. Estimated Effect of Coverage on Temperature Spread, 1948-2014

	(1)	(2)	(3)	(4)	(5)
	Cell-month observations		Country-year observations		
	CRU	BEST	CRU	BEST	Conflict
Coverage	-0.275***	-0.261***	-0.186***	-0.155***	
	(0.006)	(0.008)	(0.016)	(0.026)	
Avg. conflict incidence					0.206***
					(0.027)
Avg. regional conflict					0.264***
					(0.048)
Mean Temp. Anomaly	0.050***	0.070***	0.111***	0.168***	0.180***
	(0.006)	(0.006)	(0.023)	(0.023)	(0.022)
Mean Elevation	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Area (logged)			-0.037***	-0.029***	-0.039***
			(0.004)	(0.004)	(0.005)
Latitude	0.007***	0.004***	0.003***	0.001	0.000
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Latitude^2	0.000***	0.000***	0.000**	-0.000*	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	1.369***	1.636***	1.282***	1.229***	0.504***
	(0.017)	(0.032)	(0.087)	(0.129)	(0.065)
Observations	5,837,400	5,853,120	2,769	2,769	2,769
R^2	0.11	0.063	0.30	0.22	0.22

Note: The table shows the estimated effect of the CRU and BEST coverage indicators on the spread of temperature estimates at the cell-month and country-year levels of observation. Coverage indicator are the logged count of stations within 1200km of each cell, averaged across cells and months for the country-year data. Standard errors are corrected for cross-sectional spatial dependence within 1200km and panel-specific serial correlation over a year. *** p<0.01, ** p<0.05, * p<0.1

area- and time-weighted averages. All models include a control for the average temperature across the four data sets as well measures of the unit's mean elevation, latitude (linear and squatted), and, in the case of the country-level data, area (logged). As before, standard errors are corrected for cross-sectional spatial dependence within 1200km and panel-specific serial correlation over a year using the method proposed by Conley (2008) and implemented by (Hsiang 2010). As the table shows, the spread in temperature estimates is robustly decreasing in the density of weather station coverage. A change in the number of CRU stations within range of a grid cell from one standard deviation below the mean (6.3) to one standard deviation above (32.8) decreases the expected spread in temperatures by 0.39°C. In the country-year data, a similar change from 8.8 to 36.1 CRU stations is associated with a 0.24°C decrease in spread.[19]

Finally, there is direct evidence that civil conflict risk is associated with greater measurement error in the temperature series. Column (5) of Table 3 reports the estimated effect on the temperature spread of the proportion of years a country experienced civil conflict and the proportion of years that a state within 1200km experienced civil conflict. Estimated coefficients on both terms are positive, confirming that measurement error is systematically higher in states that experienced frequent conflict and/or were located in violent neighborhoods. On average, a country like Sudan that experienced civil conflict in three-quarters of its post-independence years and had a conflict its neighborhood in 92 percent of years would have an expected temperature spread 0.19°C greater than a country like Guinea that experienced civil conflict in only 2 years and had conflict in its neighborhood in 60 percent of years.

[19] Re-doing the analysis dropping each temperature series on at a time showed that the results are generally stable. Dropping the GHCN-CAMS series decreases the magnitude of the effect, particularly when using the BEST coverage measure.

3. Re-estimating the Effect of Temperature on Civil Conflict

All of the foregoing suggests that conflict risk increases noise in temperature estimates and, the case of the CRU data, induces a downward bias during periods of warming. To see how these problems can affect estimates of the relationship between temperature shocks and conflict, consider the following standard empirical model:

$$Conflict_{it}^{*} = \beta Temp_{it}^{*} + \gamma X_{it} + \upsilon_i + \eta_t + \varepsilon_{it} \ , \tag{1}$$

where $Conflict_{it}^{*}$ denotes the (latent) risk of civil conflict in country *i* and year *t*, $Temp_{it}^{*}$ is the true temperature anomaly in that country-year, X_{it} captures other political and economic conditions that might influence civil war risk, υ_i and η_t are country and year fixed effects, respectively, and ε_{it} is the error term. The essential problem is that we observe not the true temperature anomaly, $Temp_{it}^{*}$, but rather an estimate, $Temp_{it}$, that is measured with error. Let

$$Temp_{it} = Temp_{it}^{*} + \mu_{it} \ , \tag{2}$$

where μ_{it} is the measurement error. Plugging (2) into (1) yields

$$Conflict_{it}^{*} = \beta Temp_{it} + \gamma X_{it} + \upsilon_i + \eta_t + e_{it} \, . \tag{3}$$

where $e_{it} = \varepsilon_{it} - \beta\mu_{it}$.

The foregoing analysis suggests that estimating β based on model (3) faces at three sources of bias. First, even if the measurement error were uncorrelated with the temperature anomaly and the conflict risk, its presence would attenuate the estimate of β due to the correlation between $Temp_{it}$ and e_{it}. Standard results show that the attenuation increases with the variance of the noise, $V(u_{it})$. Second, the implication of Table 2, column (5), is that the magnitude of the measurement error, $V(u_{it})$, is positively correlated with the mean conflict risk in country, or υ_i. This creates cross-sectional heteroscedasticity in the disturbance terms, e_{it}. While it is standard practice to calculate Huber-White robust standard errors with clustering on the country, heteroscedasticity can lead to inconsistent estimates in models with a dichotomous dependent variable. Simulations applying a linear probability model to equations (1) and (3) suggest that this effect further attenuates the estimate of β. Finally, the bias identified in the CRU data implies that $E(\mu_{it})$ is a function of both the conflict risk and the true temperature anomaly. In particular, the cold bias is larger the more conflict-prone the country is and the hotter the true temperature. This effect should induce a negative bias on the estimate of β. Collectively, then, our findings suggest that conflict-related gaps in weather station coverage tend to understate any positive association between temperature shocks and conflict.[20]

There is also reason to believe, however, that these problems are least acute in the case of the BEST data, due its reliance on a much larger set of underlying station data. To test this conjecture, we estimate the relationship between civil conflict and temperature using the four observational data sets employed above. The data are organized into country-year observations and the dependent variable records whether the country experienced a civil conflict that led to at least 25 battle deaths in that year. Following standard practice, the estimates come from a linear probability model with country and year fixed effects (Burke et al. 2009; Hsiang, Burke, and Miguel 2013). Prior work, however, has generally neglected to take into account the very pronounced first-order autocorrelation in the dependent variable, reflecting a strong tendency for conflicts, once started, to continue. There is good reason to think that the onset of a new conflict

[20] Measurement error in temperature can also produce unpredictable biases in the γ parameters on other covariates. Hsiang, Burke, and Miguel (2013) argue against the inclusion of other covariates out of concern for the "bad controls" problem that arises if climate variation affects or operates through those variables. The bias due to measurement error reinforces this argument.

Table 3. Estimated Effect of Temperature on Civil Conflict Incidence, 1948-2014

	(1) CRU	(2) Willmott & Matsurra	(3) GHCN-CAMS	(4) BEST	(5) Average
Temperature Anomaly	0.025 (0.026)	0.024* (0.014)	0.022 (0.016)	0.046*** (0.016)	0.041** (0.018)
Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	1,607	1,607	1,607	1,607	1,607
R-squared	0.092	0.092	0.092	0.093	0.093

Note: This table reports the estimates of linear regressions of civil conflict on temperature anomaly measured five different ways. The sample conditions on the absence of conflict in the previous year. Standard errors are clustered by country. *** p<0.01, ** p<0.05, * p<0.1

episode (or the re-ignition of a conflict after some spell of peace) is driven by different factors than the continuation of a conflict that has already begun. One solution to this problem is to condition the sample on observations in which there was no conflict in the previous year.

Table 3 summarizes the results of this exercise, showing the estimated effects of temperature anomaly on the likelihood of a civil conflict using the four different temperature data sets employed here, as well as a measure created by averaging across all four. Although all estimates are positive, the one obtained using the BEST data is the largest in magnitude and the only one that is statistically significant at the 5 percent level. Inspection of the data shows that BEST temperature anomalies exhibit smaller variation than do the other series. This observation is consistent with the idea that greater noise in the other series is attenuating the estimated effect of temperature on civil conflict. The estimate obtained using the average measure is similar in magnitude to that obtained using BEST, suggesting that averaging across the data sets also helps reduce the noise. Notice also that, despite the bias identified in the CRU data, the estimates obtained with those data are not appreciably different from the others (with the exception of BEST). This is consistent with the observation that the bias is still relatively small at the country-year level.

4. Conclusions

Several conclusions flow from this study. First, researchers interested in the link between climate and political, economic, or social outcomes such as civil conflict need to think about the processes that generate the climate data and choose sources that are robust to variation in the outcomes being explored. While the weather station data used by the BEST project are influenced with by civil conflict and its risk factors, the network is sufficiently dense that it is reasonably robust to station loss, and there are few effective gaps. Moreover, there is no evidence that variation in station coverage biases BEST temperature estimates in any way. For these reasons, researchers interested in estimating the effect of temperature on conflict should consider using this source.[21]

Second, if recent trends of station loss continue, the problem identified here is only going to get worse. The ideal solution, of course, would be to reverse the trend, which would require investment in new stations, maintenance of existing ones, and harvesting of existing data from stations not currently in the system (United Nations Economic Commission for Africa 2011). Unfortunately, the requirement by CRU that stations have a record of coverage in the 1961-90 period makes meaningful addition of new stations problematic. Moreover, the practice of filling

[21] We note that, while this paper has focused on temperature, there has also been interest in the effect of precipitation and drought on conflict risk (Miguel, Satyanath, and Sergenti 2004; Couttenier and Soubeyran 2014). Both of these variables could suffer from similar issues, an exploration that we leave to future work.

in coverage gaps with zero anomaly dummy readings may make sense as a conservative way to avoid overstating recent global warming; however, from the perspective of the research at grid cell or country-level spatial scale, this practice introduces a downward bias on temperature estimates. To the extent that coverage gaps are related to the outcome being studied, this bias can obscure the true relationship.

Going forward, the solution to this problem may be to rely on temperature estimates from a source that is not influenced by political and economic conditions in the places that are the object of study. Two main avenues suggest themselves. First, satellite-based measurements are a natural alternative, since they are not affected by conditions on the ground in the countries being observed. Existing satellite-based data, however, have limitations for the applications such as those considered here. The longest running satellite based temperature dataset, produced by the University of Alabama in Huntsville, goes back to Dec. 1978 and is only available at a 2.5° resolution, which is crude for country-level analysis. Higher resolution observations are available from the Moderate Resolution Imaging Spectroradiometer (MODIS), but data acquisition did not begin until 2000. There are also challenges in deriving surface air temperature estimates from satellites, due to the effects of soil moisture, solar radiation, and cloud cover (Vancutsem et al. 2010). Nevertheless, in a recent paper, Heft-Neal, Lobell, and Burke (2017) show that MODIS observations improve as a proxy for surface air temperature at higher levels of temporal aggregation, suggesting that these data may be useful for estimating climate response functions at the monthly, seasonal, or annual levels.

Second, researchers may be able to take advantage of the fact that sea surface temperatures (SST) are observed through a variety of mechanisms that are not directly affected by conditions in the countries of observation, such as shipboard measurements, floats, and satellites. Researchers can then take advantage of links between terrestrial air temperatures and climate patterns in the surrounding oceans or other large-scale variation in ocean temperatures, such the El Niño-South Oscillation (ENSO). For example, Hsiang, Meng, and Cane (2011) avoid terrestrial temperature observation altogether by showing an increase in civil war risk during El Niño years in countries whose climates are strongly affected by the ENSO cycle. In a recent paper, Witmer et al. (2017) simulate the historical temperature in SSA by using the Community Earth Systems Model (CESM) constrained by observations of the monthly SST. The simulations track the CRU temperature estimates reasonably well and generates similar result in their model of political violence.

Future advancement on these fronts would be helpful in insulating the measurement of temperature from the political, economic, and social conditions that we are trying to understand.

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