A replication of Warming increases the risk of civil war in Africa, Burke et al. (2009)*

Joseph Shen Jonathan Fu Jesse Cazares-Cruz
Keynes Le Christopher Mahoney

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Member Name	Participation
Joseph Shen	20%
Jonathan Fu	20%
Jesse Cazares-Cruz	20%
Keynes Le	20%
Christopher Mahoney	20%

Abstract

This study replicates Burke et al.'s 2009 analysis linking rising temperatures to an increased risk of civil conflict incidence in sub-Saharan Africa. Using a panel dataset spanning 1981–2002, the original study used fixed-effects regression models to examine the historical relationship between annual temperature fluctuations and civil war incidence. The authors found that a 1°C increase in temperature led to a 4.5% increase in civil war in the same year (SE = 0.0218) and a 0.9% increase in the next year (SE = 0.0210). In this replication, we reproduce the authors' empirical strategy, data structure, and key models to evaluate the robustness and validity of their findings. Despite minor quantitative variations between our replication and the original paper, likely due to the nature of the original paper's bootstrapping methodology, we validate Burke et al.'s findings on the link between climate change and internal armed conflict as both quantitatively sound and a matter of grave consequence.

KEYWORDS: civil conflict, climate change, Africa, panel data, regression

*Authors: Joseph Shen: University of California, Berkeley. E-mail: jsheny@berkeley.edu, Jonathan Fu: University of California, Berkeley. E-mail: jonrfu@berkeley.edu, Jesse Cazares-Cruz: University of California, Berkeley. E-mail: cazarescruzjesse@berkeley.edu, Keynes Le: University of California, Berkeley. E-mail: $key_2 112@berkeley.edu$, Christopher Mahoney: University of California, Berkeley. E-mail: christophermahoney@berkeley.edu. We have no affiliation with the authors, we are not receiving financial support, and we have no conflicts of interest.

1 Introduction

The paper by Marshall Burkea, Edward Miguel, Shanker Satyanath, John A. Dykema, and David B. Lobell investigates the connection between rising temperatures and the incidence of civil conflict (here defined as any armed conflict which resulted in at least 1,000 battle-related deaths and where one party is the government of a state) in sub-Saharan Africa, using panel data from 1981-2002. The study, a response to the shocking prevalence of civil conflict in the region over this period, set out to understand the causes of the conflict, whether global climate change played a role, and analyze confounding structural and demographic factors. If climate were a significant cause of internal armed conflict, it would have a large impact over time as the temperatures in Africa, as well as the rest of the world, were projected to increase.

Conflict data were sourced from an armed conflict dataset by [4]Gleditsch et al. (2002), a battle death dataset by [3]Lacina and Gleditsch (2005), and a civil war incidence dataset by [2]Fearon and Laitin (2003). Historical climate data were sourced from [5] Mitchell and Jones (2005), and projections for future climate numbers were sourced from [1]Christensen et al. (2007).

The paper tested the effect of temperature on civil conflict incidence in African countries from 1981-2002, using panel fixed-effects regressions. The main results show that "temperature variables are strongly related to conflict incidence over our historical panel, with a 1 $^\circ$ C increase in temperature in our preferred specification leading to a 4.5% increase in civil war in the same year" with a standard error of 0.0218, and "a 0.9% increase in conflict incidence in the next year" with a standard error of 0.0210 (20670). Their findings were robust to the inclusion of precipitation, 1-year lagged impacts of climate, income, and political regime type (a measure of how democratic a nation's institutions are) in their regression analysis, as well as different model specifications and different data sets. This suggests that such a relationship between climate and civil war incidence cannot be singularly explained by political, structural, temporal, demographic, or economic factors. Furthermore, the paper extrapolated their results, combining them with climate model projections, to create predictive models of the incidence of climate-driven civil wars in the future and the potential danger of future exogenous climate-induced economic shocks. Sourced directly from the author's replication data, our own reproduction validates these findings entirely and their robustness to a variety of checks, all of which will be discussed further in the coming sections.

2 Reproducibility

This replication was carried out using Python. The original R code from the authors did not contain any coding errors and successfully reproduced Figures 1 and 2, as well as Table 2 from Burke et al. (2009). Table 1, however, was generated using the accompanying Stata code.

2.1 Challenges

2.1.1 Table 1: The numbers in our version of Table 1 differ slightly from those in the original report, likely due to differences in our bootstrapping method and the random variation characteristic of it. As mentioned earlier, we based our table on Stata code from the original study, which turned out to be challenging. Since our group had limited experience with Stata, we turned to ChatGPT for help translating the code into Python.

2.1.2 Figure 1: We were able to achieve similar results, but the visual presentation of our figures is different from the original. We were unable to align the map projections as precisely, so we opted to include only the box plots. That being said, our figure conveys the same implications as the one in the original.

2.1.3 Table 2: Our replication of Table 2 yielded similar results to the original. As with Table 1, our results show slight numerical differences.

2.1.4 Figure 2:
We successfully reproduced the figure and obtained comparable results. While the formatting of our version is different, the underlying implications remain consistent.

3 Replication

Our replication is an example of computational reproducibility, as defined by the ability to duplicate the results of a prior study using the same data and procedures, but implemented in a different software environment. While the original analysis by Burke et al. (2009) was conducted in R, our goal was to test whether their main findings could be faithfully reproduced in Python without altering the model specifications, dataset, or analytic structure. To do this, we focused on accurately translating the author's R code to Python line by line using Python libraries such as Pandas, NumPy, and Statsmodels. The resulting estimates closely matched those in the original paper in both sign and magnitude, confirming that the findings are computationally reproducible across platforms and quantitatively sound.

3.0.1 Precipitation Checks
When adding precipitation (Table 1, Model 2), the temperature's effect remains significant and similar in magnitude ($\beta_2 = 0.043$, SE = 0.0217). Precipitation itself shows a negative association with conflict (β = -0.023, SE = 0.0519), though with higher standard error. This check was performed to account for potential confounding effects of rainfall patterns that might influence both temperature and conflict dynamics.

3.0.2 Socioeconomic Robustness Checks
Adding per capita income and political regime type (Table 1, Model 3) maintains temperature's effect ($\beta_3 = 0.0489$, SE = 0.0275). The political regime variable shows a small negative association (β = -0.0005, SE = 0.0058), while per capita income shows a negligible effect (β = -0.0, SE = 0.0). This check was conducted to ensure climate effects aren't simply proxying for economic or institutional factors.

3.0.3 Lagged Effect Checks Given the often delayed impact of temperature and climate on human agriculture, where for example, a dry season may only affect output many months later, we tested our models against lagged temperature and precipitation effects. We found that our model is robust to one year lagged temperature effects ($\beta_1 = 0.0447$, SE = 0.0218) and only shows a small, non-statistically significant effect on conflict ($\beta = 0.0087$, SE = 0.021) (Table 1, Model 1). This also holds true for lagged precipitation checks in Table 1, Model 2, which only slightly affect our temperature estimate ($\beta_2 = 0.043$, SE = 0.0217) and itself shows only a small, non-statistically significant effect on conflict ($\beta = 0.025$, SE = 0.0489).

3.1 Regression models

Table 1 shows the regression coefficients for three different models.
The first model can be represented as:

$$y_t = \beta_0 + \beta_1 \cdot \text{Temperature}_t + \beta_2 \cdot \text{Temperature}_{t-1}$$

where y_t represents the amount of conflict incidence in year t, β_0 is the constant term, and β_1, β_2 are the coefficients for current and lagged temperature, respectively. This is the specification referred to in the authors' claim:

> "A 1 °C increase in temperature in our preferred specification lead[s] to a 4.5% increase in civil war in the same year and a 0.9% increase in conflict incidence in the next year."

The second model adds precipitation controls and is written as:

$$y_t = \beta_0 + \beta_1 \cdot \text{Temperature}_t + \beta_2 \cdot \text{Temperature}_{t-1} + \beta_3 \cdot \text{Precipitation}_t + \beta_4 \cdot \text{Precipitation}_{t-1}$$

This model includes precipitation for both the current and previous years. It yields similar temperature coefficients, supporting the robustness of the original result against the inclusion of precipitation variables.

The third model adds more controls and is written as:

$$y_t = \beta_0 \cdot \beta_1 \cdot \text{Temp}_t + \beta_2 \cdot \text{Temp}_{t-1} + \beta_3 \cdot \text{Prec}_t + \beta_4 \cdot \text{Prec}_{t-1} + \beta_5 \cdot \text{Income}_{t-1} + \beta_6 \cdot \text{Regime}_{t-1}$$

Income represents the income per capita of the previous year, and regime represents the political regime type of the previous year measured from +10 (most democratic) to -10 (least democratic). Both are lagged in the study since institutional and economic effects are potentially endogenous to internal armed conflict and "using predetermined values reduces the most immediate endogeneity concerns" (20674). Once again, the model yields similar temperature coefficients, further proving the robustness of the authors' claims.

4 Conclusion

Our replication of Burke et al. confirms the core result of the study: rising temperatures significantly increased the risk of civil war in sub-Saharan Africa from the period of 1981-2002. We were able to closely analyze the empirical design and gain a better understanding of the paper's broader implications by reproducing results using separate code and workflows. We transformed the original R and Stata techniques into Python and re-coded the simulation-based forecasting and regression models. This underlined the importance of reproducibility and transparency in empirical economics while deepening our understanding of panel data analysis and fixed-effects modeling. One significant finding was how the projected conflict risk is influenced by decisions on data aggregation, lag structure, and model assumptions. Technical implementation choices can influence the dependability of findings even when general trends are constant, as we showed in our mention of the bootstrapping process and its, albeit quite minor, effect on our quantitative findings. We see opportunities to expand this research by including data after 2002 to test whether the relationship between climate change and conflict has evolved over time and across different regions. Future research could also look at how climate stress leads to conflict by examining mechanisms such as institutional quality or agricultural productivity. Additionally, reproducing this across other continents would be fascinating, as there is so much variation in climates, staple crops, government institutions, and other variables. For example, it would be interesting to see if such a strong correlation holds in areas with more drought-resistant plants (such as in the deserts of South America or the Arabian Desert), generally stronger democratic institutions (perhaps in G10 countries), or richer citizens (such as in OECD countries). While internal armed conflict is a very shocking and important measure, it may also be worth adjusting the threshold (from at least 1000 battle deaths) or including other forms of violence and violent crimes, especially when looking at countries which may have a higher capacity to quickly end civil conflicts before they become large enough to cause such widespread damage. Further geographic variation would also strengthen the main thrust of Burke et al.'s paper, as there may be other confounding variables left unaccounted for with an analysis limited only to sub-Saharan Africa. Overall, this replication project not only validated the key findings of a significant paper but also provided us with hands-on experience in meticulous coding, documentation, and critical evaluation.

References

[1] Jens Christensen, Bruce Hewitson, and Aristita Busuioc. Regional climate projections. in climate change 2007: the physical science basis. contribution of working group 1 to the fourth assessment report of the intergovernmental panel on climate change. university press, cambridge. *IPCC 2007*, 01 2007.

[2] David D. Laitin James D. Fearon. Ethnicity, insurgency, and civil war. *American Political Science Review*, 97(1):75–90, 2003.

[3] Bethany Lacina and Nils Petter Gleditsch. Monitoring trends in global combat: A new dataset of battle deaths. *European Journal of Population / Revue européenne de Démographie*, 21(2):145–166, 2005.

[4] Mikael Eriksson Margareta Sollenberg NNils Petter Gleditsch, Peter Wallensteen and Håvard Strand. Armed conflict 1946-2001: A new dataset. *Journal of Peace Research*, 39(5):615–637, 2002.

[5] Philip D. Jones Timothy D. Mitchell. An improved method of constructing a database of monthly climate observations and associated high-resolution grids. *International Journal OF Climatology*, 25:693–712, 2005.

5 Figures

5.1 Figure 1

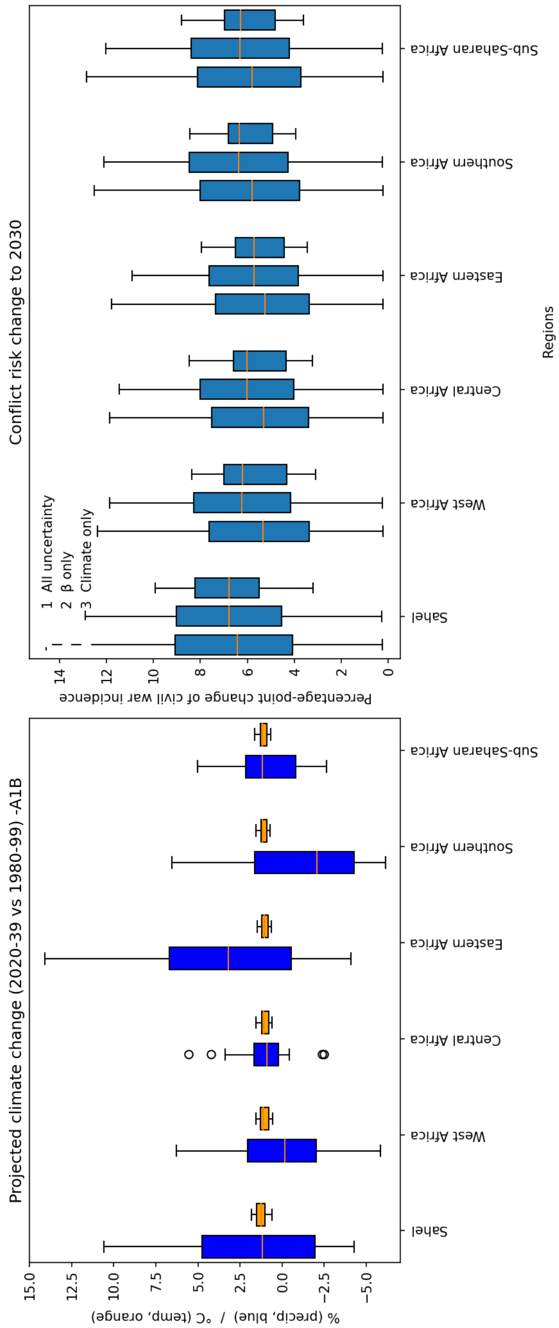

Figure 1: Projected Changes in Climate and Conflict to 2030

5.2 Figure 2

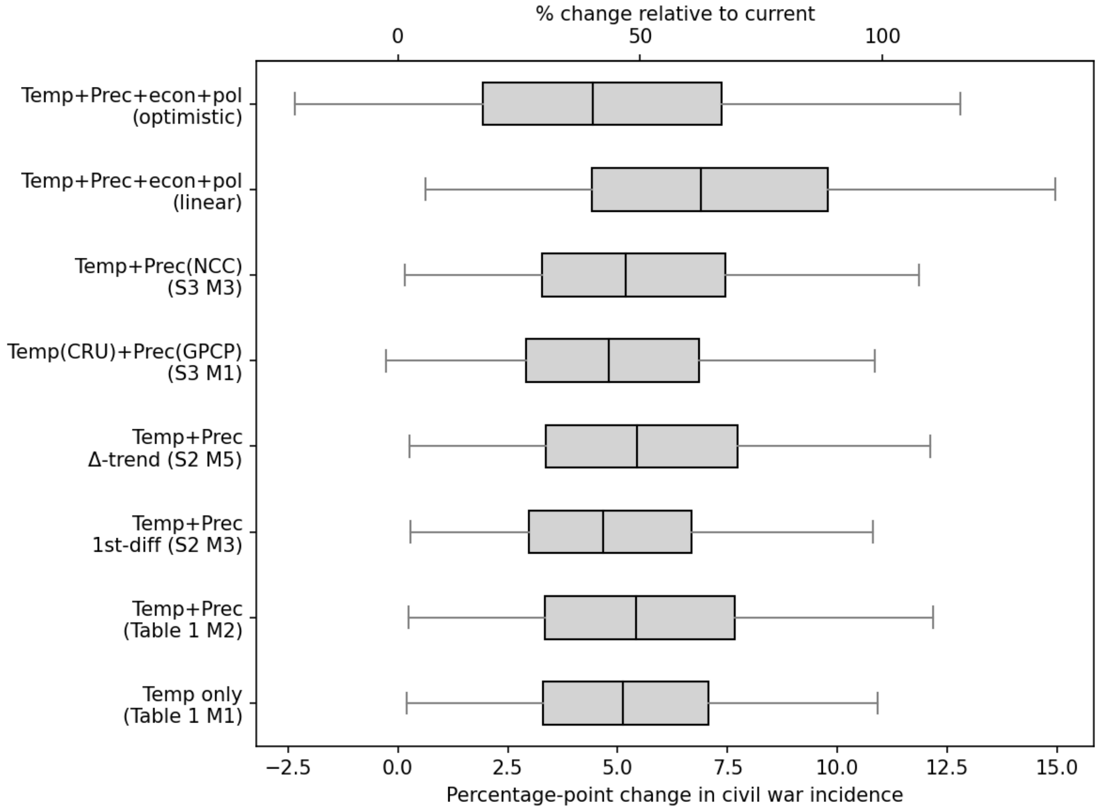

Figure 2: Projected Percent Changes in the Incidence of Civil War

6 Tables

Table 1: Regression coefficients on climate variables, with civil war as a dependent variable

Variable	**Model 1**		**Model 2**		**Model 3**	
	coefficient	SE	coefficient	SE	coefficient	SE
Temperature	0.0447	(0.0218)	0.043	(0.0217)	0.0489	(0.0275)
Temperature lagged 1 year	0.0087	(0.021)	0.0132	(0.0233)	0.0206	(0.0299)
Precipitation			-0.023	(0.0519)	0.0165	(0.085)
Precipitation lagged 1 year			0.025	(0.0489)	0.0278	(0.0813)
Per capita income lagged 1 year					-0.0	(0.0)
Political regime type lagged 1 year					-0.0005	(0.0058)
Constant	-1.1099	(0.7692)	-1.1771	(0.7722)	-1.5215	(1.1449)
Observations	889		889		815	
R^2	0.657		0.657		0.389	
RMSE	0.193		0.193		0.241	

Table 2: Projected changes in African civil war incidence to 2030, by emissions scenario

	Median % change	**% increase in civil war relative to baseline**	**5th–95th percentile observations of projected % increase**	**% obs<0**
A1B				
Model 1	5.6501	51.2543	7.1231-116.1667	2.7000
Model 2	6.1162	55.4824	2.6466 -130.2190	4.4667
A2				
Model 1	4.9645	45.0353	6.2488-98.9702	2.7000
Model 2	5.4498	49.4375	-10.4028-117.4294	8.0600
B1				
Model 1	4.5827	41.5715	5.7482-96.5693	2.7000
Model 2	4.9159	44.5947	-0.2584-110.9175	5.0833