Climate Shocks and Female Targeted Political Violence*

Siwan Anderson[†] Daniel Jaramillo Calderon[‡]

October 31, 2025

Abstract

This paper investigates whether climate shocks exacerbate gender-based violence perpetrated by armed political actors. To causally identify these effects, we leverage geo-referenced panel data across Africa. Our outcome of interest includes direct killings, abductions, torture, and sexual violence explicitly targeting women and girls. We find that extreme temperature shocks significantly increase the incidence of female-targeted civilian conflict. However, this effect is attenuated in areas where indicators of female empowerment are higher. These findings support the view that gender-based violence under climate stress is more pronounced in contexts where women are socially and economically marginalized, suggesting that social valuation of women plays a critical role in moderating climate-induced conflict dynamics.

*We are grateful to the Social Sciences and Humanities Research Council (SSHRC) and ReCIPE for funding. We thank Patrick Baylis for their valuable comments and suggestions. This paper has benefited from the comments of seminar participants at ReCIPE (Paris) and Monash University (Prato).

[†]Vancouver School of Economics and CEPR

[‡]Inter-American Development Bank

1 Introduction

Political violence against women is a global phenomenon whose incidence has risen over the past decades ((Kishi et al., 2019)). The causes of this increase remain underexplored, with descriptive and qualitative studies pointing to biased gender norms, gendered political competition, and generalized political violence as potential drivers (Anderson and Sviatschi, 2025). In this study, we focus on a factor that has been shown to influence overall conflict: climate change. Specifically, we examine whether fluctuations in climate conditions contribute to increased political violence against women.

Deviations in climate variables have been associated with a wide range of conflict outcomes, from individual-level violence and aggression to large-scale political instability and civil conflict (Hsiang et al., 2013; Burke et al., 2015, 2024). However, existing research on the relationship of climate change and violence against women has focused primarily on intimate partner violence (IPV), finding that adverse climate shocks, particularly elevated temperatures and droughts, are associated with increased domestic abuse.[1] In contrast, our focus is on political violence against women, which occurs outside the household. This form of violence takes multiple expressions and involves a wide range of perpetrators, both during armed conflict and in periods of relative peace (Kishi et al., 2019; Kishi, 2022). Reported incidents include sexual and non-sexual assaults, abductions, forced disappearances, mob attacks, suppression of women's participation in political processes, and punishments for perceived violations of gender norms, such as non-compliance with public veiling mandates or accusations of witchcraft. Perpetrators include organized armed groups –such as state security forces, rebel organizations, militias, gangs, and cartels– that pursue political objectives and employ violence as a strategic tool.

In this paper, we test whether climatic variation has a causal impact on political violence against women. Our identification strategy follows Burke et al. (2024), who use a two-way fixed effects model with location and time fixed effects to evaluate the impacts of climate change on conflict. This approach compares how a fixed population responds to periods with different climate conditions. Importantly, it requires a long panel, which allows us to detect unusual climate shocks and trace how violent outcomes respond. For this reason, we focus on Africa, where geo-coded data on political violence against women is available since 1997. The data is compiled by the Armed Conflict Location and Event Data Project (ACLED), which classifies an event as political violence against women (PVTW) if women and girls either constitute the majority of victims or are explicitly targeted. Using the geo-location of all such events, we construct a one-degree resolution raster covering the African continent and focus on two yearly outcomes: the probability of observing a PVTW incident and the probability that the incident resulted in at least one fatality.

We find evidence that excessively high temperatures significantly increase PVTW by armed political actors. We find that a one standard deviation increase in temperature increases the probability of observing a PVTW event by 0.4 percentage points (15% of the mean) and the deadly event by 0.2 percentage points (11% of the mean). These effects are present for both the contemporaneous and one-year lagged temperature shocks. We further confirm that the incremental effects of excessive temperatures on PVTW are found in grid-cells which house crops. Both of these findings echo core findings in the broader literature on climate-induced conflict (Burke et al., 2024). Related patterns also emerge in the literature focusing solely on IPV (Mannell et al., 2024; Zhu et al., 2023; Nguyen,

[1] For example, refer to: Epstein et al. (2020); Cooper et al. (2021); Dehingia et al. (2023); Cools et al. (2020); Diaz and Saldarriaga (2023); Munala et al. (2023); Zhu et al. (2023); Nguyen (2024); Mannell et al. (2024); Munala et al. (2023); Guimbeau et al. (2024); Mannell et al. (2025); Guo et al. (2025); Sanz-Barbero et al. (2018); Wang et al. (2024). In addition, related outcomes include dowry deaths (Sekhri and Storeygard, 2014), witch killings (Miguel, 2005), and increases in police calls (Auliciems and DiBartolo, 1995).

2024).

To explore how climate shocks exacerbate the victimization of women in the context of political violence, we examine whether women's relative status shapes these effects. Explanations in the broader climate–conflict literature typically emphasize how climate variability changes the incentives and behavior of perpetrators. For instance, through reductions in the opportunity cost of violence (Harari and La Ferrara, 2018), heightened competition for scarce resources (McGuirk and Nunn, 2025), logistical constraints on mobilization (Rogall, 2021), or psychological stress that increases aggression (Baylis, 2020). Our approach shifts the focus to the potential victims, asking whether women's relative social and economic status shapes the extent to which climate variability influence political violence against them.

Whether women's empowerment mitigates the adverse effects of climate change is conceptually ambiguous. On the one hand we could expect a backlash mechanism, whereby women who are perceived as relatively well-off or empowered become targets of violence by male perpetrators. In this view, increased visibility or autonomy of women may provoke a violent response aimed at reasserting male dominance. This aligns with findings in the broader literature linking climate shocks to heightened (actual or perceived) social and economic inequality, which can intensify social tensions and grievances (McGuirk and Nunn, 2025; Koren and Schon, 2023). The backlash mechanism is also consistent with the *instrumental* motive for intimate partner violence (IPV) within household bargaining models, where male partners use violence strategically to restore control and bargaining power in the face of women's growing autonomy.[2]

On the other hand, in areas where women are relatively more empowered, we may expect lower levels of political violence targeting them. In the IPV literature, this corresponds to the *expressive* motive for violence, in which perpetrators derive emotional or psychological gratification from the act itself. In such settings, greater female bargaining power can reduce IPV by enabling women to negotiate better outcomes or deter violence altogether.[3] In the context of political violence, however, bargaining dynamics may be less relevant. Instead, a reduction in violence against empowered women may reflect a deterrence or opportunity cost mechanism. Where women hold greater social, economic, or political status, targeting them may carry higher risks, such as public resistance, reputational damage, or the loss of valuable resources. In this sense, empowerment can act as a protective factor by raising the costs or lowering the perceived benefits of violent targeting by politically motivated actors.

To investigate these distinct channels, we incorporate into the empirical analysis two exogenous sources of variation in women's relative social status. First, following the approach of Alesina et al. (2013), we distinguish between grid cells where the main crops traditionally relied on female labour as opposed to male labour. This measure captures the traditional economic role of women within local production systems, an influence that has been shown to shape contemporary gender norms and labour division. Second, we draw on the work of Guarnieri and Tur-Prats (2023) to construct an ethnic-based gender inequality index using pre-modern ethnographic data. This index aggregates nine relevant ethnic traits to reflect traditional norms surrounding gender equality at the ethnic group level. By leveraging this variation, we examine whether long-standing cultural attitudes toward gender mediate the effects of climate shocks on political violence targeting women. Using both measures, we compare the impacts of

[2] See, for example, Alesina et al. (2021); Luke and Munshi (2011); Bulte and Lensink (2021); Erten and Keskin (2018); Erten and Keskin (2021); Bhalotra et al. (2021); Erten and Keskin (2024); Eswaran and Malhotra (2011); Bloch and Rao (2002); Haushofer et al. (2019); Adams et al. (2024); Bergvall (2024); among others.

[3] See, for example: Aizer (2010); Farmer and Tiefenthaler (1997); Tauchen et al. (1991); Anderson (2021); González and Rodríguez-Planas (2020); Roy et al. (2024); Hidrobo et al. (2016); Rodriguez (2022); among others.

climate variability on female-targeted conflict across grid cells characterized by high versus low female relative status, allowing us to test whether women's empowerment mitigates or exacerbates the risks of gender-targeted political violence under climate stress.

Our results indicate that the direct effect of high temperatures on PVTW is mitigated in areas where women hold greater economic or social status. That is, the interaction terms between our climate variable and the female empowerment measures have a negative sign. These findings run counter to a backlash hypothesis, which would predict increased violence against empowered women in times of stress. Instead, the evidence suggests that politically motivated actors are less inclined to target women in areas where they are relatively more empowered — either because such women are better protected by social structures or because the costs (economic, reputational, or resistance-based) of targeting them are higher.

Focusing specifically on the result which compares whether grid cells are primarily cultivated with female focused crops, the finding that the intensifying reactions to excessive temperatures are lower in these female oriented grid cells could also be consistent with an opportunity cost explanation on behalf of male perpetrators, while relatively speaking excessive temperatures on their own crops are exacerbating conflict violence against women.

To explore this channel more closely, we borrow from the careful work of Harari and La Ferrara (2018) who consider the relevance of the growing season, when crops are most sensitive to unfavorable conditions. To this end, we explore the impact of the Standardised Precipitation-Evapotranspiration Index (SPEI)[4] which takes into account both precipitation and potential evapotranspiration in determining drought, so that it captures the main impact of increased temperatures on water demand.

When we compare the impacts of SPEI during the growing season on female versus male crop-dominated cells, we can distinguish between two conceptual mechanisms driving PVTW. The first is the standard opportunity cost perspective, in which male perpetrators respond to changes in their own economic welfare. The second is the social conflict or backlash perspective, where male perpetrators react to changes in the economic welfare of female victims.

Under the opportunity cost motive, PVTW is less likely to occur under favorable agricultural conditions in areas dominated by male crops. In this view, when adverse climatic events reduce male economic productivity, the relative value of engaging in gender-based violence increases compared to participating in regular economic activities.[5] In contrast, the social conflict perspective suggests that female-targeted violence is more likely to occur under favorable agricultural conditions in areas dominated by female crops.

Our results do not support either of these predictions directly. Instead, we find that PVTW is lowest in grid cells where females are enjoying a relative economic advantage. This is consistent with the alternative type of opportunity cost explanation discussed above, in which male perpetrators are less likely to target women when those women serve as the primary economic providers (i.e., women are experiencing relative economic success). In such contexts, attacking women may entail higher economic

[4]The SPEI is a drought index constructed by Vicente-Serrano et al. (2010), which considers the joint effects of precipitation, potential evaporation, and temperature in estimating the amount of water that the soil is able to capture.

[5]This motivation is widely discussed in the climate–conflict literature (e.g., Hsiang et al. (2013), Harari and La Ferrara (2018), McGuirk and Burke (2020)). It is also consistent with behavioral theories, which suggest that economic stress from unpredictable weather can lead to irritability and aggression among male perpetrators (Baylis (2020), Baylis et al. (2018), Baysan et al. (2019), Burke et al. (2018), Blakeslee et al. (2021)). Such behavioral responses are often used to explain why extreme weather events correlate with increases in intimate partner violence (Nguyen (2024), Cools et al. (2020), Card and Dahl (2011), Auliciems and DiBartolo (1995)).

or social costs, reducing the likelihood of violence.

The results from the SPEI-based empirical specification are consistent with our overall findings: indicators of female empowerment appear to mitigate the climate-induced risks of political violence targeting women.

This aspect of our analysis aligns with a wider body of literature on climate-driven conflict that emphasizes the role of social and institutional factors in determining whether climate shocks escalate into violence (Burke et al., 2024). In particular, this literature highlights that conflict risk is lower when power asymmetries between groups are reduced—i.e., when parties have more equal bargaining power. An illustrative example comes from the work of McGuirk and Nunn (2025), who examine conflict between sedentary agriculturalists and transhumant pastoralists whose seasonal migrations—often triggered by drought—bring them into contested spaces. Their findings show that such climate-induced conflicts are less likely to erupt when the transhumant groups retain some degree of political representation or bargaining power, suggesting that empowerment and institutional inclusion can serve as conflict-mitigating forces.

In our context, a similar logic may apply: where women have greater social or economic status, they may be better protected—either through formal institutions or community norms—from becoming targets of politically motivated violence in the face of climate stress. Empowerment, in this sense, reduces not only individual vulnerability but also broader structural susceptibility to gender-targeted violence during periods of climatic disruption.

More broadly, our findings contribute to three strands of literature. First is the extensive literature establishing a causal link from climate variables to conflict incidence (as surveyed by Burke et al. (2015, 2024)). To this literature, we add to the analysis a novel outcome measure of female targeted violence by armed actors. In this sense, our work relates most directly to two conflict outcomes already studied: civilian targeted conflicts by armed actors and IPV targeting women.[6] To the literature on these two related outcomes, aside from also assessing the impact of climate change we further contribute to the discussion on mechanisms behind the results.

The second related literature is the extensive interdisciplinary work on women and conflict (Anderson and Sviatschi, 2025). One central focus of this research is on sexual violence in armed conflict and a recent empirical paper in the economics literature by Guarnieri and Tur-Prats (2023) who demonstrate how armed actors from ethnic groups with more gender unequal norms are significantly more likely to be perpetrators of sexual violence. Our analysis builds directly on this work and uncovers related mechanisms in the context of climate-induced stressors of conflict.

The third strand of related literature encompasses the growing body of interdisciplinary research on the intersection of gender and climate change (Pinho-Gomes and Woodward, 2024). One key focus is the heightened vulnerability of women to climate-related shocks, particularly in settings marked by pre-existing gender inequalities and social norms (Afridi et al., 2022; Eastin, 2018; Fruttero et al., 2023)). At the same time, this literature highlights the important role women can play in climate adaptation, as they often exhibit greater concern about environmental changes and are active agents in community responses (Bush and Clayton, 2023). Our findings contribute to both aspects of this discussion: on

[6]For the literature on the impact of climate shocks on the likelihood of civil conflict, refer to: Maystadt et al. (2014); Miguel et al. (2013); O'Loughlin et al. (2012); Burke et al. (2009); Mack et al. (2021)); Buhaug (2010),; Caruso et al. (2016); Dell et al. (2012); and Harari and La Ferrara (2018), among many others. For the literature on IPV refer to: Zhu et al. (2023); Nguyen (2023); Epstein et al. (2020); Munala et al. (2023); Diaz and Saldarriaga (2023); Cools et al. (2020); Cooper et al. (2021), among others.

the one hand, women face increased risks, including heightened exposure to gender-based violence in the context of climate stress; on the other hand, these adverse effects are significantly mitigated when women are empowered.

In what follows, we begin with a description of the data on political violence against women. Section 2 presents descriptive statistics about PVTW in Africa. Section 3 presents the baseline estimation results, examining the impact of climate variation on gender-targeted political violence. In Sections 4 and 5, we explore how these effects are moderated by measures of female empowerment. Section 6 concludes.

2 Political Violence Against Women

Our core outcome measure, Political Violence Targeting Women (PVTW), captures civilian targeting events in which women or girls are the targets of violence. The data are sourced from a curated database developed by the Armed Conflict Location and Event Data Project (ACLED), in collaboration with the Robert Strauss Center for International Security and Law at The University of Texas at Austin (Raleigh et al., 2023).[7]

ACLED classifies an event as PVTW when the victims are composed entirely of women or girls, when women or girls constitute the majority of victims, or when the primary target is identified as a woman or girl. It is important to note that ACLED distinguishes between female victims and female-targeted violence. Women and girls may still be victims in broader civilian targeting events without meeting the criteria for inclusion under PVTW. As such, PVTW should not be interpreted as a gender-disaggregated subset of all civilian targeting or political violence in the ACLED dataset, but rather as a distinct category focused specifically on gendered targeting.

The dataset focuses only on political or public forms of violence and excludes domestic, interpersonal, or IPV. Furthermore, only incidents involving physical violence, or attempted physical violence, are included. This encompasses sexual violence but excludes non-physical forms such as threats, intimidation, psychological abuse, or online harassment. Common actions entail: extrajudicial killings of detainees or prisoners of war; direct physical harm—including beating, shooting, torture, rape, and mutilation; abductions and forced disappearances through kidnappings; wartime sexual violence; mob attacks on civilian women and girls; suppression of women involved in political processes; and punishments for violating gender norms, such as not adhering to public veiling mandates, or accusations of witchcraft. These incidents are limited to cases where violence is directed at civilians and are not events that occur simultaneously with, or as part of, other types of political activity such as protests, riots, or demonstrations.[8]

The perpetrators of political violence events in the PVTW dataset include organized armed actors such as state forces and their affiliates, rebel groups, militias, external or private military entities (e.g., United Nations missions), and other political organizations engaged in contestation over political authority, such as control over territory, governance, or access to resources. All actors classified as perpetrators of political violence are organized, politically motivated, and use violence strategically to pursue political objectives. To be identified as an organized political actor, as opposed to a spontaneous

[7]See: https://acleddata.com/political-violence-targeting-women/#analysis

[8]Coverage within the dataset is limited to reported incidents. ACLED sources its data from a range of local, national, and international outlets, including media reports, vetted social media accounts, government and NGO publications, and information from partner organizations.

or riotous group, the organization must demonstrate cohesion, exist beyond a single event, and engage in activity connected to a broader political purpose.

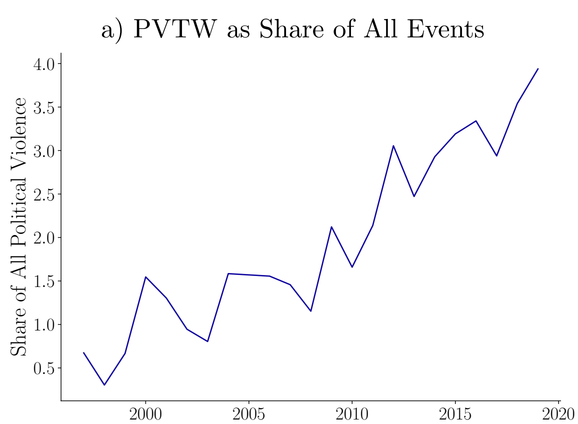
Importantly, in the PVTW dataset specifically, perpetrators are primarily male, and the recorded events include only those in which women or girls are the targets of political violence. Women are not recorded as perpetrators in this dataset.

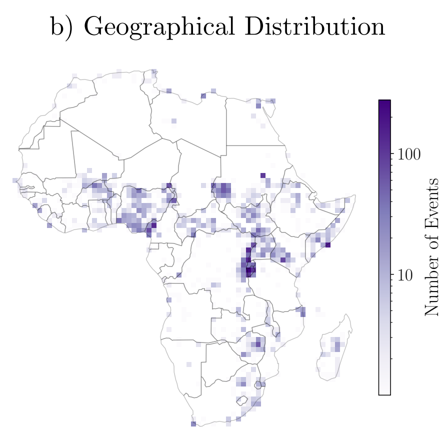
Over the past five years, state military forces in Cameroon, the Democratic Republic of the Congo, Mali, and Sudan have been among the most prominent perpetrators of PVTW incidents. National police forces in Nigeria, the Democratic Republic of the Congo, Morocco, South Africa, Zimbabwe, and Eswatini have also been implicated. In addition, communal militias in areas such as Darfur, Zamfara, and various regions of Nigeria have played a significant role. Militant groups — including the Islamic State's West Africa Province (ISWAP), Boko Haram, Ambazonian separatists, the Mayi Mayi militia, the Coalition of Patriots for Change (CPC), Fulani ethnic militias, the Allied Democratic Forces (ADF), and the Cooperative for the Development of Congo (CODECO) — have been responsible for widespread gender-based violence.

For our empirical analysis, we assemble a yearly panel of 1x1 degree cells (approximately 110Km at the equator) covering 48 African countries from 1997 until 2019, resulting in a total of 2,749 grid cells. While incidences of PVTW have been recorded across the African continent, certain countries have experienced disproportionately high numbers. The Central African Republic and Mali have each recorded close to 100 incidents, while Niger has experienced well over 100 across this time span. In Burkina Faso, the number approaches 200. Cameroon and Sudan have each recorded between 400 and 500 incidents, and the highest counts are observed in Nigeria and the Democratic Republic of the Congo, each with well over 700 documented events.

Panel (a) of Figure 1 plots the yearly evolution of the share of political violence events in which women were targeted. Since 2000, this share has increased from 1% to 7%, while fatalities in these events have risen nearly fourfold, outpacing the 46% increase observed in events not specifically targeting women. Panel (b) illustrates the geographic distribution of PVTW, showing the total number of incidents at the grid-cell level across the continent.

Figure 1: Political Violence Against Women, 1997 - 2019





Notes: Panel (a) shows the evolution of the yearly share of political violence events classified as political violence against women (PVTW). Panel (b) displays a heatmap of the total number of PVTW events across Africa at the grid cell level. The sample is restricted to events coded by ACLED with high spatial precision (levels 1 or 2). Dark solid lines represent national boundaries. Both panels cover the period 1997–2019. Source: ACLED (2025).

3 Empirical Analysis

Climate events can generate dynamic effects, particularly through economic hardship, where the consequences of a negative shock may persist or even intensify in subsequent years.[9] To test whether climate shocks affect PVTW, we estimate a distributed lag panel regression that includes both contemporaneous and lagged climate shocks:

$$Conflict_{ict} = \sum_{j=0}^{1} \beta_j Climate_{i,t-j} + \alpha_i + \phi_t + \theta_c t + \mu_{ict}, \tag{1}$$

where, $Conflict_{ict}$ measures the probability that an event occurs in cell i, belonging to country c, in year t. We consider two outcomes: (i) whether any PVTW event occurred in a cell–year, and (ii) whether any deadly PVTW event occurred. The explanatory variables are included in the vector $Climate_{i,t-j}$, which capture contemporaneous and lagged climate conditions. Following Harari and La Ferrara (2018), we standardize the climate variables relative to the long-term (1979–2019) mean and variance of each cell and we use reanalysis data as the source for all climate measures, which mitigates potential bias from the under representation of weather stations in conflict-prone areas. Further details on data sources and construction are provided in Appendix A. Table A1 in the appendix presents the summary statistics for the PVTW and climate variables used in the analysis. To provide context on the source of spatial variation, Figure B1 maps the share of observations in which residualized temperature, after removing grid and year fixed effects, exceeds one standard deviation, identifying areas that experience temperature shocks more frequently.

Our baseline specification includes grid-cell fixed effects (α_i) and year fixed effects (ϕ_t). In some specifications, we also allow for country-specific linear time trends ($\theta_c t$). We discuss alternative lagged specifications in Section 3.1.1. Standard errors (μ_{ict}) are corrected for spatial and temporal autocorrelation following Hsiang (2010), we allow spatial correlation of up to 300 Km and temporal correlation up to two years. Appendix B8 considers alternative inference methods by clustering at the country level. The parameters of interest are the coefficients β_j, where each β_j captures the effect of a climate fluctuation in period $t-j$ on conflict in year t. The overall effect of climate is given by the linear combination of its contemporaneous and lagged coefficients. By including both grid and time fixed effects, the analysis accounts for the non-random exposure of regions to climate shocks and allows a causal interpretation of β_j (Burke et al., 2024).

Just to benchmark our findings to the previous literature, we also estimate an alternative specification (commonly used) in which we exclude grid-cell fixed effects and instead include a vector of grid-cell-level control variables, denoted by X_i, which have been shown to determine conflict outcomes. These controls include: population density, an indicator of whether the grid was split by a national border, log distance to the closest river, log elevation, share of land covered by water, an indicator for whether the grid cell is crossed by a primary road, terrain ruggedness, and an indicator for the presence of a discriminated ethnic group.[10]

As alternative outcomes, ACLED also provide the total number of PVTW events, the total number of deadly PVTW events, and the total number of PVTW-related deaths. We do not report results for these additional outcomes, as they closely mirror our core findings. In particular, the effects of climate

[9] See, for example, Harari and La Ferrara (2018), Burke et al. (2015), and Burke et al. (2024).

[10] Refer to, for example, Moscona et al. (2020) and Michalopoulos and Papaioannou (2016). Section A in the appendix provides further details on these control variables.

variation on the total number of PVTW events resemble those for the binary indicator of any event, while the effects on the total number of deadly events and PVTW-related deaths align with those for the occurrence of any deadly PVTW event.

3.1 Estimation Results

This section reports the estimation results on the impact of climate deviations on the incidence of PVTW, using two outcome measures: (i) an indicator for whether any PVTW event occurred in a given cell–year, and (ii) an indicator for whether any deadly PVTW event occurred in a given cell–year.

Table 1 presents estimates of Equation 1, where the explanatory variables are standardized deviations in temperature relative to the long-term mean. Columns (1) to (4) report results on the probability of observing any PVTW event, while columns (5) to (8) focus on the probability of observing a PVTW event with at least one fatality. Column (1) presents the raw correlation, and subsequent columns progressively add controls and fixed effects. The specification with grid and year fixed effects (columns (3) and (7)) aligns with the benchmark model of Miguel et al. (2004) and Burke et al. (2024), while the inclusion of country-specific linear trends (columns (4) and (8)) follows the approach of Harari and La Ferrara (2018).[11]

Table 1 shows that temperature shocks increase the likelihood of PVTW. A one-standard deviation increase in contemporaneous temperature raises the probability of observing a PVTW event by 0.35 percentage points (15% of the mean) and the one of a deadly PVTW event by 0.25 percentage points (22% of the mean). These effects are statistically significant not only for contemporaneous temperature but also for its first lag. Combining the contemporaneous and lagged effects, a one-standard deviation increase in temperature increases the probability of any PVTW event by 0.82 percentage points (35% of the mean) and the probability of a deadly PVTW event by 0.46 percentage points (40% of the mean).

To put these estimates in context, it is useful to compare them with findings from the broader climate–conflict literature. Burke et al. (2024) provide a meta-analysis of over 40 studies examining the effect of temperature on civil conflict, reporting a median effect as share of the mean of 2.3%. However, the estimated effects vary widely, with the 95th percentile of the distribution reaching roughly 47%. While these studies do not directly address political violence against women, the magnitude of the coefficients we find for PVTW falls near the upper end of the distribution, suggesting that women-targeted political violence may be particularly sensitive to extreme heat.

Table 1 further distinguishes between cells with and without agricultural production. The literature emphasizes agricultural income as a key mechanism linking climate fluctuations to conflict. In areas with agricultural activity, high temperatures can directly reduce crop yields, potentially lowering rural incomes and increasing competition over resources. By contrast, in areas without agriculture, such as deserts or major water bodies, exposure to agricultural shocks is minimal, and any relationship between temperature and violence is more likely to operate through alternative channels, such as psychological stress. Separating the analysis along this dimension therefore helps clarify whether the temperature–violence link is mediated by dependence on agricultural livelihoods or reflects more general effects of heat.

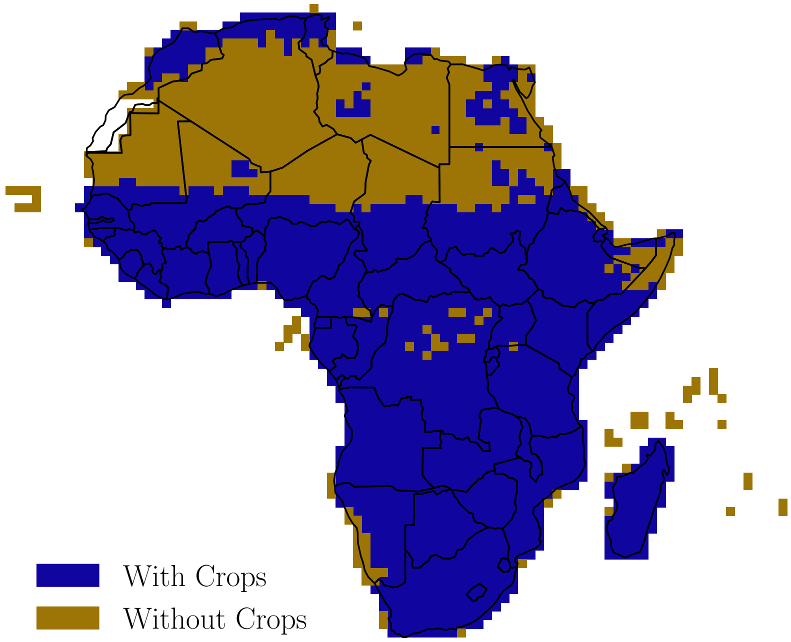
[11] See Burke et al. (2024) for a survey of related methods.

Table 1: Temperature and Political Violence Against Women

	Event Indicator				Deadly Event Indicator			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Full Sample								
Temperature	0.041***	0.041***	0.015**	0.016**	0.024***	0.024***	0.011**	0.011**
	(0.008)	(0.008)	(0.007)	(0.008)	(0.005)	(0.005)	(0.005)	(0.005)
L1.Temperature	0.038***	0.039***	0.020***	0.019***	0.020***	0.020***	0.009**	0.009*
	(0.008)	(0.007)	(0.007)	(0.007)	(0.005)	(0.005)	(0.005)	(0.005)
Mean Dep. Var.	0.024	0.024	0.024	0.024	0.012	0.012	0.012	0.012
Observations	60,236	60,236	60,236	60,236	60,236	60,236	60,236	60,236
Panel B: Cells With Crops								
Temperature	0.038***	0.040***	0.005	0.004	0.023***	0.024***	0.006	0.006
	(0.009)	(0.009)	(0.008)	(0.009)	(0.006)	(0.006)	(0.006)	(0.006)
L1.Temperature	0.038***	0.040***	0.016**	0.014*	0.019***	0.020***	0.005	0.005
	(0.008)	(0.008)	(0.008)	(0.008)	(0.005)	(0.005)	(0.005)	(0.006)
Mean Dep. Var.	0.033	0.033	0.033	0.033	0.016	0.016	0.016	0.016
Observations	41,536	41,536	41,536	41,536	41,536	41,536	41,536	41,536
Panel C: Cells Without Crops								
Temperature	0.012	0.012	0.008	0.010	0.003	0.003	0.001	0.002
	(0.008)	(0.008)	(0.008)	(0.009)	(0.004)	(0.004)	(0.004)	(0.004)
L1.Temperature	0.009	0.008	0.003	0.004	0.006	0.006	0.004	0.005
	(0.007)	(0.007)	(0.007)	(0.007)	(0.004)	(0.004)	(0.004)	(0.004)
Mean Dep. Var.	0.003	0.003	0.003	0.003	0.001	0.001	0.001	0.001
Observations	18,700	18,700	18,700	18,700	18,700	18,700	18,700	18,700
Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Grid FEs	No	No	Yes	No	No	No	Yes	No
Year FEs	No	No	Yes	Yes	No	No	Yes	Yes
Country-time trend	No	No	No	Yes	No	No	No	Yes

Notes: The table reports estimates from regressions of temperature on two measures of political violence against women: (i) an indicator for the occurrence of any PVTW event, and (ii) an indicator for the occurrence of a deadly PVTW event (at least one fatality). The unit of observation is a cell–year and the time frame is between 1997 and 2019. Panel (a) shows the estimates for all the cells covering Africa. Panel (b) restricts the estimation sample to those areas that have at least one crop. Panel (c) uses as sample the grid cells with no harvested crops. Standard errors corrected for spatial and temporal autocorrelation following Hsiang (2010) in parentheses. Significance levels: $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$.

Figure 2: Crop Information by Grid Cell

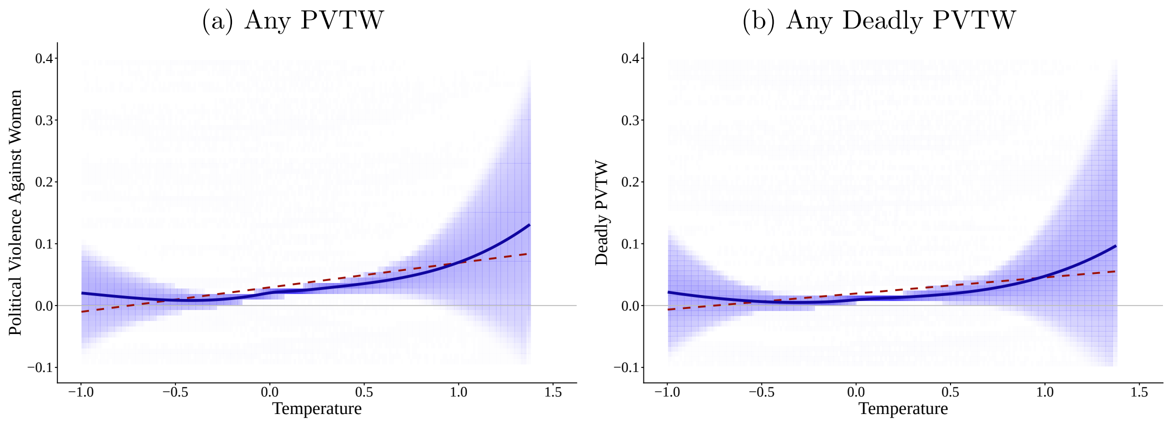


Notes: The figure shows 1 × 1 degree cells, color-coded according to the availability of crop data. We classify a cell as "without crops" if the harvested area of all the crops reported in Monfreda et al. (2008) that intersects with the cell is equal to zero.

To this end, we use crop information from Monfreda et al. (2008), who created a dataset reporting the harvested area of 175 crops circa 2000 on a $5' \times 5'$ ($\sim$ 10 km × 10 km) latitude–longitude grid covering the entire world. We classify a grid cell in our sample as having crops if it intersects with the harvested area of any of the 175 crops. Figure 2 plots the geographical distribution of the cells based on this classification. Areas without crops typically correspond to deserts (e.g., the Sahara Desert) and large bodies of water (e.g., Lake Victoria).

Panels (b) and (c) of Table 1 show that the increase in PVTW associated with high temperatures originates from cells with at least one harvested crop. On average, a one standard deviation increase in lagged temperature raises the probability of a PVTW event by 0.36 percentage points (approximately 11% of the mean) in cells with crops. The coefficients for deadly PVTW are not statistically significant, nor are the effects of temperature on conflict in cells without harvested crops. Although the coefficients for cells without crops are statistically zero, we cannot fully rule out the possibility that mechanisms such as psychological stress or migration play a role. These cells are relatively few, tend to have lower baseline conflict levels, and are concentrated over dessert areas, which reduces the statistical power to detect significant effects.

Figure 3: Effect of Temperature on PVTW



Notes: The figure presents non-parametric local linear regressions of residualized measures of political violence against women (PVTW) on residualized temperature, after removing grid and year fixed effects. Panel (a) reports results for the probability of observing any PVTW event in a given cell–year, while Panel (b) focuses on the probability that a PVTW event resulted in at least one fatality. The red dashed line shows the linear OLS fit, and the solid line shows the median bootstrapped curve. The plots use a watercolor visualization to indicate variability in the data as introduced in Hsiang et al. (2013).

In an alternative specification, we tested for potential nonlinearities by including higher-order polynomial terms (see Table B3 in Appendix B). We did not find consistent or statistically significant effects for these additional terms. Figure 3 further examines this by plotting non-parametric local linear regressions of residualized measures of PVTW on residualized temperature, after removing cell and year fixed effects. The figure indicates that the relationship between temperature and PVTW is approximately linear and increasing, with little evidence that the results are driven by extreme values of temperature. Overall, we find no evidence of strong nonlinearities in the effect of climate deviations on political violence targeting women.

3.1.1 Robustness Checks

The results reported in Table 1 reflect our baseline specification. To check for robustness of our findings, we consider alternative empirical specifications as well as climate variables.

In Tables B4 and B5 in the Appendix B.2 we report the findings from our baseline specification, for two other alternative climate variables most commonly used in the literature: precipitation and a drought index, the Standardised Precipitation-Evapotranspiration Index (SPEI).[12] We see that unlike, for temperature, we do not tend to observe direct consistent significant effects from these two alternative measures.

Also in the Appendix B.2, we report instead the no-lag specification for all three climate measures. First on their own (Table B6), and then all together (Table B7). We see that the consistent findings are again found only for climate measured by deviations in temperature.

In our main specification, we define climate change as yearly deviations from the long term mean (over the period 1979-2019). We alternatively considered computing these deviations relative to the historical long-term mean, so for a given year t, we compute the deviations relative to period 1979 to $t-1$. The estimated results from this specification are not reported here but are very similar to those of the baseline specification as presented in Table 1.

[12] The SPEI is a drought index constructed by Vicente-Serrano et al. (2010), which considers the joint effects of precipitation, potential evaporation, and temperature in estimating the amount of water that the soil is able to capture.

Though not reported here, we also considered computing our climate change measures on a monthly basis instead. Our general results found for the yearly variation generally corroborate with this case too. One difference is that the contemporaneous effects of climate deviations seem more salient when we diminish the time frame to month. At times, the monthly specification can be more sensitive to the inclusion of controls and fixed effects. In these alternative specifications, significance is harder to detect as the monthly incidence of female targeted conflict is much lower than the yearly.

Finally, the main results are robust to alternative inference methods that adjust for spatial dependence differently. Table B8 reports the estimates obtained when clustering standard errors at the country level instead of using Conley corrections. The statistical significance of the coefficients remains unchanged under this specification.

4 Female Empowerment

To investigate how climate shocks affect the victimization of women in political violence, we examine whether women's relative status moderates these effects. As discussed in the introduction, higher levels of female empowerment may influence the relationship between climate variability and political violence in two opposing ways. On the one hand, empowerment may amplify the effects of climate through a backlash mechanism, whereby empowered women are targeted as a reaction to perceived challenges to male dominance. On the other hand, empowerment may attenuate these effects through bargaining mechanisms, as empowered women have greater agency to protect themselves in the face of violence.

To analyze these channels, we incorporate two exogenous sources of variation in women's relative social status into the analysis. First, following Alesina et al. (2013), we distinguish between grid cells where traditional agricultural practices primarily relied on female rather than male labour, capturing gender roles in agricultural production. Second, we draw on Guarnieri and Tur-Prats (2023), who construct an ethnic-based gender inequality index derived from pre-modern ethnographic data, to capture historical differences in women's social and political status.

To formally test whether women's relative economic and social status moderates the effects of climate on PVTW, we introduce heterogeneous effects to Equation 1. Specifically, we estimate the following specification:

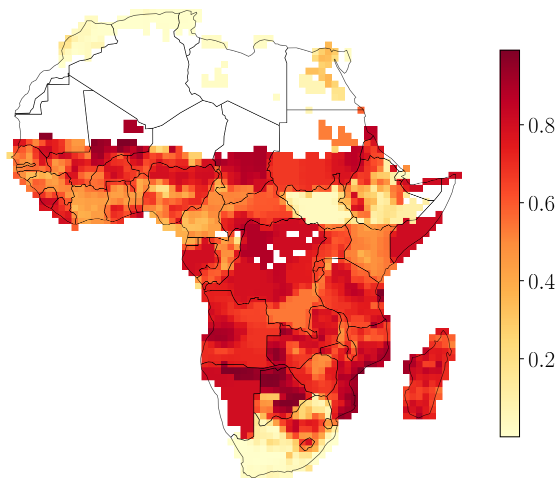
$$Conflict_{ict} = Female_i + \sum_{j=0}^{1} \beta_{1j} Climate_{i,t-j} + \sum_{j=0}^{1} \beta_{2j} Climate_{i,t-j} * Female_i + \alpha_i + \phi_t + \theta_c t + \mu_{ict}, \quad (2)$$

where $Female_i$ represents women's empowerment at the grid-cell level. We measure women's empowerment by using three alternative variables. The first two capture women's relative economic status in the agricultural sector: (i) the share of harvested area devoted to *female positive* crops, and (ii) an indicator equal to one if the major crop (by harvested area) in grid cell i is *female positive*. Following Alesina et al. (2013), we define a crop as *female positive* if its traditional cultivation did not require the use of the plough. The classification of crops by plough dependence follows Pryor (1985), who document traditional agricultural practices in pre-mechanized systems, and data on harvested area by crop are drawn from Monfreda et al. (2008).

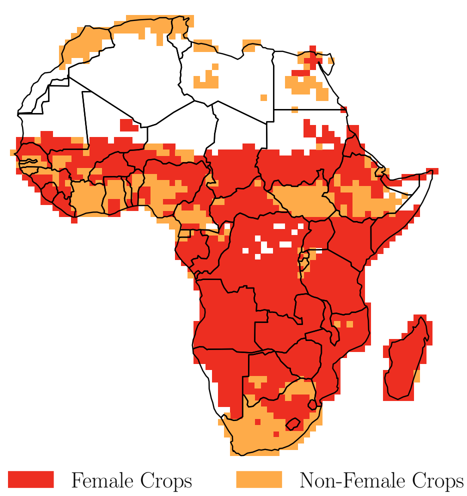
The third measure is the inverse of the Male Dominance Index (MDI) developed by Guarnieri and Tur-Prats (2023). This index is based on ten ethnographic traits from Murdock (1967)'s Ethnographic

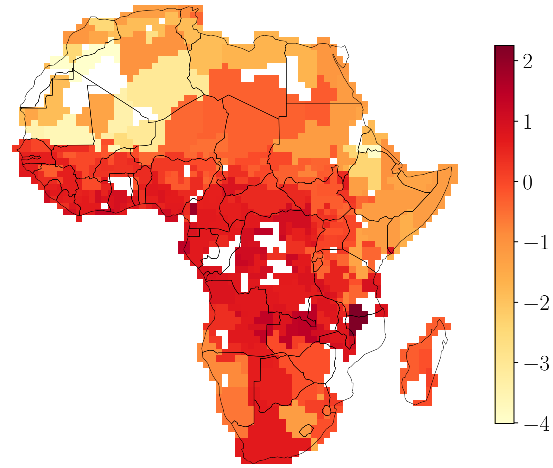
Atlas that capture anthropological dimensions of gender (in)equality. Traits such as matrilineality, bride price, polygyny, dependence on gathering, fishing, shifting cultivation, and non-herding animal husbandry are associated with more gender-equal practices, whereas nuclear families, pastoralism, and plough use are linked to male-dominated systems. Using principal component analysis, Guarnieri and Tur-Prats (2023) combine these traits into an ethnic-level MDI and validate it as a strong predictor of contemporary gender norms. We translate this index to the grid level by computing the weighted average of each ethnic group's index based on the share of its homeland area overlapping with each grid cell. Figure 4 depicts the geographical variation of these three measures, where darker colors means a higher level of women's empowerment.

Figure 4: Female Empowerment Indicators



(a) Share of Female Crops





(b) Major Crop Female

(c) Inverse of Male Development Index (MDI)

Notes: Each map displays an indicator of female empowerment at the one-degree cell level. Panel (a) shows the share of land used to harvest non-plough crops (female-positive). Panel (b) shows the geographic distribution of grid cells by whether the major crop, by harvested area, requires a plough or not. The classification of female-positive (non-plough) crops follows Alesina et al. (2013), and crop data are from Monfreda et al. (2008). Panel (c) presents the inverse of the Male Development Index for each grid cell, calculated following Guarnieri and Tur-Prats (2023). Across all panels, darker colors indicate higher levels of female empowerment. White cells represent missing data, primarily corresponding to areas with no crops.

In this specification, our focus is on the coefficients β_{2j}. Since all three indicators are increasing in women's empowerment, these coefficients capture how the effect of climate on PVTW differs between cells with higher levels of female empowerment and those with lower levels of gender equality. A positive coefficient would provide evidence consistent with the backlash hypothesis, in which greater empowerment amplifies the effect of climate shocks on political violence against women. Conversely, a negative coefficient would support the view that female empowerment mitigates the impact of climate variation. Table 2 presents these estimates.

Table 2: Temperature, Female Empowerment, and PVTW

	Event Indicator				Deadly Event Indicator			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Share of Female Crops by Grid								
Temperature	0.098***	0.105***	0.047**	0.050**	0.058***	0.062***	0.025**	0.028**
	(0.024)	(0.024)	(0.019)	(0.021)	(0.015)	(0.015)	(0.012)	(0.013)
L1.Temperature	0.109***	0.116***	0.069***	0.072***	0.059***	0.062***	0.033***	0.036***
	(0.024)	(0.025)	(0.020)	(0.021)	(0.014)	(0.015)	(0.012)	(0.013)
Share Female Crops × Temperature	-0.090***	-0.096***	-0.061**	-0.066**	-0.052***	-0.056***	-0.026*	-0.030*
	(0.033)	(0.033)	(0.026)	(0.028)	(0.020)	(0.020)	(0.016)	(0.017)
Share Female Crops × L1.Temperature	-0.107***	-0.114***	-0.078***	-0.086***	-0.061***	-0.064***	-0.040**	-0.046***
	(0.034)	(0.034)	(0.026)	(0.029)	(0.019)	(0.020)	(0.016)	(0.017)
Mean Dep. Var.	0.033	0.033	0.033	0.033	0.016	0.016	0.016	0.016
Observations	41,536	41,536	41,536	41,536	41,536	41,536	41,536	41,536
Panel B: Major Crop in Grid								
Temperature	0.091***	0.096***	0.040**	0.046***	0.055***	0.057***	0.024**	0.029**
	(0.020)	(0.020)	(0.016)	(0.017)	(0.014)	(0.014)	(0.011)	(0.012)
L1.Temperature	0.074***	0.079***	0.036**	0.039**	0.041***	0.043***	0.017	0.020
	(0.020)	(0.020)	(0.015)	(0.016)	(0.016)	(0.016)	(0.013)	(0.013)
Major Crop Female=1 × Temperature	-0.063***	-0.066***	-0.041***	-0.048***	-0.038***	-0.039***	-0.020*	-0.026**
	(0.019)	(0.019)	(0.015)	(0.016)	(0.013)	(0.013)	(0.011)	(0.011)
Major Crop Female=1 × L1.Temperature	-0.043**	-0.046**	-0.023	-0.029*	-0.026*	-0.028*	-0.013	-0.018
	(0.020)	(0.019)	(0.015)	(0.016)	(0.015)	(0.015)	(0.012)	(0.013)
Mean Dep. Var.	0.033	0.033	0.033	0.033	0.016	0.016	0.016	0.016
Observations	41,536	41,536	41,536	41,536	41,536	41,536	41,536	41,536
Panel C: Female Positive Norms								
Temperature	0.048***	0.050***	0.010	0.009	0.030***	0.031***	0.010	0.010
	(0.010)	(0.010)	(0.009)	(0.010)	(0.007)	(0.007)	(0.007)	(0.007)
L1.Temperature	0.048***	0.050***	0.022***	0.020**	0.026***	0.027***	0.010*	0.010
	(0.009)	(0.009)	(0.008)	(0.009)	(0.006)	(0.006)	(0.006)	(0.006)
Inv. MDI × Temperature	-0.017**	-0.017**	-0.008	-0.009	-0.015***	-0.015***	-0.009**	-0.009**
	(0.007)	(0.007)	(0.005)	(0.006)	(0.005)	(0.005)	(0.004)	(0.004)
Inv. MDI × L1.Temperature	-0.017**	-0.016**	-0.010*	-0.009	-0.012**	-0.012**	-0.008*	-0.008*
	(0.007)	(0.007)	(0.006)	(0.006)	(0.005)	(0.005)	(0.004)	(0.005)
Mean Dep. Var.	0.035	0.035	0.035	0.035	0.017	0.017	0.017	0.017
Observations	37,378	37,378	37,378	37,378	37,378	37,378	37,378	37,378
Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Grid FEs	No	No	Yes	No	No	No	Yes	No
Year FEs	No	No	Yes	Yes	No	No	Yes	Yes
Country-time trend	No	No	No	Yes	No	No	No	Yes

Notes: The table reports the heterogeneous effects of temperature on political violence against women across alternative measures of female empowerment. Panel A compares grid cells according to the share of female crops, defined as the fraction of total harvested area devoted to crops primarily cultivated without the use of ploughs. Panel B contrasts cells where the major crop (by harvested area) traditionally does not require plough use. Panel C employs the inverse of the Male Development Index (MDI) as the heterogeneity variable, with higher values indicating greater female relative empowerment. The unit of observation is a cell–year and the time frame is between 1997 and 2019. Standard errors corrected for spatial and temporal autocorrelation following Hsiang (2010) in parentheses. Significance levels: $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$.

Table 2 shows that as women's participation in agricultural production and gender equality increase, the adverse impact of higher temperatures on political violence against women weakens. For instance, holding temperature constant, a ten percentage point rise in the share of female-positive crops is associated with a 0.61 percentage point reduction in the marginal effect of temperature on political violence against women. Likewise, in regions where the main crop is female-positive, the marginal effect of temperature on PVTW is approximately four percentage points lower than in areas dominated by male-associated crops. A similar pattern emerges when considering gender norms. Regions characterized by more egalitarian gender norms (captured by higher values of the inverse MDI) exhibit a weaker link between temperature and political violence. A one standard deviation increase in the inverse MDI reduces the marginal effect of temperature on conflict by 0.9 percentage points.

In contrast, in areas where women's historical participation in agriculture is minimal (meaning that no crop is female-positive or the dominant crop is not typically cultivated by women) or where gender norms are highly biased toward men (i.e., the inverse of the MDI equals zero), temperature increases are associated with higher rates of PVTW, including lethal events.

The results so far indicate that women's empowerment (both economic and social) plays a role in mitigating the adverse effects of temperature on political violence against women. To better understand the underlying mechanisms, we further examine whether specific cultural dimensions historically associated with gender relations contribute to this moderating effect.

The MDI of Guarnieri and Tur-Prats (2023) identifies ten ethnic traits linked to anthropological notions of gender (in)equality. These include traditional cultivation practices and the use of the plough (factors already captured in our economic measures of women's relative status) as well as broader cultural practices such as matrilineality, bride price, polygyny, and pastoralism.

We estimate Equation 2 for alternative specifications in which $Female_i$ corresponds to each of these four cultural traits. The results, presented in Table 3 indicate that two traits: pastoralism and matrilineality, are particularly salient. In societies that were historically matrilineal or non-pastoral, the increase in PVTW associated with excessively high temperatures is significantly attenuated. A large body of research documents the persistent positive impacts of matrilineality on women's welfare and empowerment (Anderson, 2025). By contrast, pastoralism has been consistently linked to more restrictive gender norms, limiting women's mobility and autonomy (Becker, 2024). It is noteworthy that these two traits —representing opposite poles of historical gender hierarchies— emerge as the key dimensions explaining the extent to which female empowerment mitigates the climate–violence relationship. Table B9 in the Appendix further shows that the remaining cultural traits, bride price and polygyny, do not exhibit significant mitigating effects.[13]

Overall, these results indicate that the rise in political violence against women associated with higher temperatures, documented in Section 3, is attenuated in grid cells with greater female empowerment. Across all specifications, the coefficient on the interaction between temperature and empowerment is negative, suggesting that women's economic and social agency mitigates the adverse effects of climate stress on gendered political violence. This pattern is consistent across both economic participation measures (the share of crops cultivated by women and whether the major crop relies on female labour), the social indicator reflecting more egalitarian gender norms (the inverse MDI), and, particularly, in historical matrilineal and non-pastoral societies.

[13]Some of these societal traits have been demonstrated to also have direct impacts on social conflict incidence. The literature has focused on polygyny (e.g. Koos and Neupert-Wentz (2020); Gleditsch et al. (2011); Rexer (2022)), pastoralism (e.g. Ntumva (2022); McGuirk and Nunn (2024)), and brideprice (e.g. Rexer (2022)).

Table 3: Components of MDI and PVTW

	Event Indicator				Deadly Event Indicator			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Pastoralism								
Temperature	0.033***	0.036***	0.003	0.001	0.014**	0.015**	0.001	-0.001
	(0.010)	(0.010)	(0.009)	(0.010)	(0.007)	(0.006)	(0.007)	(0.007)
L1.Temperature	0.023**	0.025**	0.006	0.004	0.007	0.007	-0.003	-0.004
	(0.010)	(0.010)	(0.010)	(0.010)	(0.006)	(0.006)	(0.006)	(0.007)
Pastoralism × Temperature	0.056*	0.054*	0.026	0.033	0.060***	0.059***	0.035*	0.042**
	(0.031)	(0.030)	(0.025)	(0.026)	(0.021)	(0.021)	(0.018)	(0.019)
Pastoralism × L1.Temperature	0.097***	0.097***	0.061**	0.064**	0.075***	0.076***	0.051***	0.056**
	(0.031)	(0.031)	(0.025)	(0.028)	(0.023)	(0.023)	(0.020)	(0.022)
Mean Dep. Var.	0.035	0.035	0.035	0.035	0.017	0.017	0.017	0.017
Observations	37,378	37,378	37,378	37,378	37,378	37,378	37,378	37,378
Panel B: Matriliniality								
Temperature	0.053***	0.055***	0.015	0.017	0.031***	0.032***	0.011	0.012
	(0.012)	(0.011)	(0.009)	(0.011)	(0.008)	(0.008)	(0.007)	(0.008)
L1.Temperature	0.051***	0.053***	0.026***	0.026**	0.026***	0.027***	0.011	0.011
	(0.011)	(0.011)	(0.009)	(0.010)	(0.007)	(0.007)	(0.007)	(0.007)
Matrilineal=1 × Temperature	-0.051***	-0.051***	-0.039***	-0.049***	-0.028***	-0.029***	-0.021***	-0.026***
	(0.014)	(0.013)	(0.010)	(0.012)	(0.009)	(0.008)	(0.007)	(0.008)
Matrilineal=1 × L1.Temperature	-0.038**	-0.039***	-0.033***	-0.038***	-0.017*	-0.017*	-0.013*	-0.016**
	(0.015)	(0.015)	(0.012)	(0.013)	(0.009)	(0.009)	(0.007)	(0.008)
Mean Dep. Var.	0.035	0.035	0.035	-0.000	0.017	0.017	0.017	0.000
Observations	37,378	37,378	37,378	37,378	37,378	37,378	37,378	37,378
Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Grid FEs	No	No	Yes	No	No	No	Yes	No
Year FEs	No	No	Yes	Yes	No	No	Yes	Yes
Country-time trend	No	No	No	Yes	No	No	No	Yes

Notes: The table reports the heterogeneous effects of temperature on political violence against women across two dimensions of the Male Development Index (MDI): Pastoralism (Panel A) and Matrilineality (Panel B). Each interaction variable is derived from the Ethnographic Atlas and aggregated to the grid level using area-weighted averages. The unit of observation is a cell–year, covering the period 1997–2019. Standard errors, shown in parentheses, are corrected for spatial and temporal autocorrelation following Hsiang (2010). Significance levels: $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$.

5 Perpetrators' Motives

The broader literature examining the relationship between climate change and conflict emphasizes economic incentives as a central mechanism driving perpetrators' behaviour. This perspective builds on the concept of opportunity costs: when climatic shocks diminish agricultural or economic productivity, the relative value of engaging in violent activities rises compared to lawful economic pursuits. To capture this mechanism empirically, studies have focused on crop's growing season, when crops are most vulnerable to adverse weather conditions, to isolate the effects of climate shocks on conflict outcomes based on economic incentives.[14]

Our female empowerment results (Table 2, Panels A and B) indicate that the effect of extreme temperatures on political violence against women is less pronounced in cells where female crops predominate. This pattern may also be consistent with an opportunity cost explanation from the perspective of male perpetrators. When high temperatures disproportionately harm male-dominated crops, the resulting economic disruption may reduce men's productive opportunities, thereby increasing the relative incentive, or lowering the opportunity cost, of engaging in violence against women.

To examine this mechanism, we follow the empirical strategy of Harari and La Ferrara (2018), who analyze the effects of climatic shocks on conflict using deviations in the Standardized Precipitation-Evapotranspiration Index (SPEI). The SPEI measures the balance between precipitation and potential evapotranspiration, and when combined with information on crop growing seasons, it captures short-term fluctuations in water availability during periods that directly affect agricultural productivity (Vicente-Serrano et al., 2010). Moreover, integrating this measure with our classification of female and non-female crops allows us to test the opportunity-cost mechanism from the perspective of men: if favorable SPEI conditions (i.e., the absence of drought) improve the productivity of male-dominated crops, the resulting economic stability raises men's opportunity costs of engaging in violence, thereby reducing political violence against women.

Complementary to the opportunity-cost mechanism, a second channel is the social conflict or backlash mechanism. According to this perspective, male perpetrators may react negatively to improvements in women's relative economic position or social visibility. Under this mechanism, favorable growing conditions that enhance the productivity of female-dominated crops could unintentionally increase PVTW, as men perceive these gains as a challenge to their relative economic or social status.

To test these hypotheses, we estimate the following regression model:

$$\begin{aligned} Conflict_{ict} = \sum_{k=0}^{1} \beta_{1k} SPEI\ GS_{i,t-k} + \sum_{k=0}^{1} \beta_{2k} SPEI\ GS_{i,t-k} * FemaleCrop_i \\ + \sum_{k=0}^{1} \beta_{3k} SPEI_{i,t-k} + \sum_{k=0}^{1} \beta_{4k} SPEI_{i,t-k} * FemaleCrop_i + \\ FemaleCrop_i + \alpha_i + \phi_t + \theta_c t + \mu_{ict} \end{aligned} \tag{3}$$

In this specification, $SPEI\ GS_{i,t}$ denotes the average value of the SPEI within year t, calculated only for the months corresponding to the growing season of the major crop in grid cell i. The variable $SPEI_{i,t}$ represents the yearly average of SPEI across all months in year t. $FemaleCrop_i$ is a binary indicator equal to one if the major crop in the grid cell traditionally relies on female labour (i.e., if its

[14] See, for example: Von Uexkull et al. (2016), Harari and La Ferrara (2018), Linke and Ruether (2021), O'loughlin et al. (2012), among others.

cultivation does not require the use of a plough). As in the previous specifications, we include grid-cell fixed effects (α_i), year fixed effects (ϕ_t), and country-by-year fixed effects ($\theta_c t$).

We construct these variables by combining climatic and agricultural data. We identify, for each grid cell, the largest crop by harvested area and compute the annual average SPEI considering only the months corresponding to that crop's growing season. Information on growing seasons is obtained from the MIRCA2000 dataset, which provides global monthly data on irrigated and rainfed crop areas around the year 2000 at a spatial resolution of five arc-minutes (approximately 9.2 km at the equator), covering all major food crops as well as cotton (Portmann et al., 2010). For crops not included in MIRCA2000, we supplement this information with country and crop specific growing seasons from the FAO Crop Calendar.

In this setting, the opportunity cost channel would predict β_{1k} $(k = 0, 1)$ to be negative. This would indicate that higher agricultural returns accruing to men (such as those generated by favorable SPEI, lower drought intensity, conditions for male-associated crops), reduce the incentives for engaging in violence. The social conflict or backlash mechanism predicts β_{2k} $(k = 0, 1)$ to be positive, implying that relative economic gains accruing to women (reflected in favorable SPEI conditions for female-associated crops) may increase social tensions or conflict. Alternatively, from a female-empowerment perspective, one might instead expect β_{2k} to be negative, suggesting that improvements in women's relative economic standing mitigate the likelihood of political violence against them.

Table 4 presents the results from estimating Equation 3. The estimates show that in cells where the main crop is not female-positive, increases in SPEI during the growing season are associated with higher levels of political violence against women. In particular, a one–standard deviation increase in growing-season SPEI raises the probability of observing a PVTW event by approximately one percentage point. In contrast, in areas where production is oriented toward female-associated crops, this adverse effect of higher SPEI during the growing season is completely offset.

Overall, the results provide little support for either the opportunity cost mechanism on male attackers or the social-conflict (backlash) hypothesis. Contrary to the opportunity cost prediction, political violence against women tends to rise when climatic conditions are favorable for male-associated production, suggesting that improved male economic conditions do not reduce violent behavior. At the same time, the interaction terms with female-associated crops indicate the opposite of what the backlash hypothesis would predict: when women experience relatively better economic conditions (captured by higher SPEI values during the growing season for female-dominated crops) the effect of climatic variation on PVTW diminishes.

This pattern points to an alternative form of the opportunity cost mechanism: male attackers may be less inclined to target women when women are the primary economic providers, that is, when they experience relative economic success. More broadly, these results align with the earlier findings in Section 4, which showed that a relative economic advantage for women can help mitigate gender-based attacks.

Table 4: Perpetrators' Motives - PVTW and SPEI

	Event Indicator				Deadly Event Indicator			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SPEI GS	0.024*	0.028**	0.013	0.014	0.010	0.012	0.002	0.002
	(0.013)	(0.013)	(0.011)	(0.011)	(0.008)	(0.008)	(0.007)	(0.007)
L1.SPEI GS	0.044***	0.047***	0.025***	0.025**	0.022***	0.023***	0.009	0.009
	(0.013)	(0.013)	(0.009)	(0.010)	(0.008)	(0.008)	(0.006)	(0.007)
Major Crop Female=1 × SPEI GS	-0.043***	-0.049***	-0.024*	-0.025*	-0.018*	-0.020*	-0.005	-0.004
	(0.016)	(0.016)	(0.013)	(0.013)	(0.010)	(0.010)	(0.009)	(0.009)
Major Crop Female=1 × L1.SPEI GS	-0.056***	-0.060***	-0.034***	-0.036***	-0.026***	-0.028***	-0.013*	-0.013
	(0.016)	(0.016)	(0.012)	(0.012)	(0.010)	(0.010)	(0.008)	(0.008)
SPEI	-0.028**	-0.032***	-0.011	-0.011	-0.013*	-0.014*	-0.001	-0.001
	(0.012)	(0.012)	(0.009)	(0.009)	(0.007)	(0.007)	(0.006)	(0.006)
L1.SPEI	-0.044***	-0.047***	-0.017**	-0.017**	-0.021***	-0.023***	-0.005	-0.005
	(0.011)	(0.012)	(0.008)	(0.009)	(0.007)	(0.007)	(0.006)	(0.006)
Major Crop Female=1 × SPEI	0.034***	0.038***	0.021**	0.023**	0.012	0.013*	0.003	0.004
	(0.013)	(0.013)	(0.010)	(0.010)	(0.008)	(0.008)	(0.007)	(0.007)
Major Crop Female=1 × L1.SPEI	0.037***	0.040***	0.020**	0.022**	0.018**	0.019**	0.008	0.009
	(0.013)	(0.013)	(0.009)	(0.010)	(0.008)	(0.008)	(0.006)	(0.006)
Mean Dep. Var.	0.033	0.033	0.033	0.033	0.016	0.016	0.016	0.016
Observations	41,338	41,338	41,338	41,338	41,338	41,338	41,338	41,338
Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Grid FEs	No	No	Yes	No	No	No	Yes	No
Year FEs	No	No	Yes	Yes	No	No	Yes	Yes
Country-time trend	No	No	No	Yes	No	No	No	Yes
Mean Dep. Var.	0.0334	0.0334	0.0334	0.0334	0.0164	0.0164	0.0164	0.0164
Observations	41,338	41,338	41,338	41,338	41,338	41,338	41,338	41,338

Notes: The table reports the heterogeneous effects of SPEI on political violence against women. The table considers two heterogeneity dimensions both based on the largest crop in a cell by harvested area: 1) the crop's growing season and 2) whether its cultivation does not require the use of a plough (i.e., female-positive crops). The unit of observation is a cell–year, covering the period 1997–2019. Standard errors, shown in parentheses, are corrected for spatial and temporal autocorrelation following Hsiang (2010). Significance levels: $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$.

6 Conclusions

This paper endeavors to test for whether climate change shocks threaten to intensify gender based violence by armed male political actors. We find evidence that excessive temperatures exacerbate female targeted civilian conflict which encompass direct killings, forced kidnappings, torture, sexual violence and more.

In general our findings do not support an opportunity cost explanation for the increased violence on behalf of male perpetrators. Neither do we uncover support for the social conflict view or backlash repercussions for female targeted political violence. Instead, when women gain an economic or social advantage, the violence by armed male perpetrators falls rather than increases their efforts to regain control or re-appropriate perceived or actual resource losses.

These findings underscore the critical role women can play in climate adaptation—not only because of their often greater concern for environmental change, but also due to their increased capacity to withstand climate-induced gender-based political violence when they are socially and economically empowered. Conversely, the results suggest that in contexts characterized by entrenched gender biases and discriminatory norms, heightened climate stress and vulnerability may intensify the violent targeting of women by armed male actors.

References

ACLED (2025): "Armed Conflict Location & Event Data (ACLED)," https://acleddata.com/, accessed: 2023-01-16.

Adams, A., K. Huttunen, E. Nix, and N. Zhang (2024): "The dynamics of abusive relationships," *The Quarterly Journal of Economics*, 139, 2135–2180.

Afridi, F., K. Mahajan, and N. Sangwan (2022): "The Gendered Effects of Droughts: Production Shocks and Labor Response in Agriculture," *Labour Economics*, 78, 102227.

Aizer, A. (2010): "The gender wage gap and domestic violence," *American Economic Review*, 100, 1847–59.

Alesina, A., B. Brioschi, and E. La Ferrara (2021): "Violence against women: a cross-cultural analysis for Africa," *Economica*, 88, 70–104.

Alesina, A., P. Giuliano, and N. Nunn (2013): "On the Origins of Gender Roles: Women and the Plough," *The Quarterly Journal of Economics*, 128, 469–530.

Anderson, S. (2021): "Intimate Partner Violence and Female Property Rights," *Nature Human Behaviour*, 5, 1021–1026.

——— (2025): "Gender Biased Norms," *CEPR Working Paper*.

Anderson, S. and M. Sviatschi (2025): "Gender and Armed Conflict," *Working Paper*.

Auliciems, A. and L. DiBartolo (1995): "Domestic Violence in a subtropical environment: Police calls and weather in Brisbane," *International Journal of Biometerology*, 39, 34–39.

Baylis, P. (2020): "Temperature and temperament: Evidence from Twitter," *Journal of Public Economics*, 184.

Baylis, P., N. Obradovich, Y. Kryvasheyeu, H. Chen, L. Coviello, E. Moro, M. Cebrian, and J. H. Fowler (2018): "Weather impacts expressed sentinent," *PLOS ONE*, 13, e0195750.

Baysan, C., M. Burke, F. González, S. Hsiang, and E. Miguel (2019): "Non-economic factors in violence: Evidence from organized crime, suicides and climate in Mexico," *Journal of Economic Behavior & Organization*, 168, 434–452.

Becker, A. (2024): "On the Economic Origins of Concerns Over Women's Chastity," *Review of Economic Studies*.

Bergvall, S. (2024): "Women's economic empowerment and intimate partner violence," *Journal of Public Economics*, 239, 105211.

Bhalotra, S., U. Kambhampati, S. Rawlings, and Z. Siddique (2021): "Intimate partner violence: The influence of job opportunities for men and women," *The World Bank Economic Review*, 35, 461–479.

Blakeslee, D., R. Chaurey, R. Fishman, D. Malghan, and S. Malik (2021): "In the heat of the moment: Economic and non-economic drivers of the weather-crime relationship," *Journal of Economic Behavior & Organization*, 192, 832–856.

Bloch, F. and V. Rao (2002): "Terror as a bargaining instrument: A case study of dowry violence in rural India," *American Economic Review*, 92, 1029–1043.

Buhaug, H. (2010): "Climate not to blame for African civil wars," *Proceedings of the National Academy of Sciences*, 107, 16477–16482.

Bulte, E. and R. Lensink (2021): "Empowerment and intimate partner violence: Domestic abuse when household income is uncertain," *Review of Development Economics*, 25, 148–162.

Burke, M., J. Ferguson, S. Hsiang, and E. Miguel (2024): "New evidence on the economics of climate and conflict," in *Handbook of the Economics of Conflict*, ed. by O. Dube, M. Morelli, and D. Ray, North-Holland, vol. 1, 249–305.

Burke, M., F. González, P. Baylis, S. Heft-Neal, C. Baysan, S. Basu, and S. Hsiang (2018): "Higher temperatures increase suicide rates in the United States and Mexico," *Nature climate change*, 8, 723–729.

Burke, M., S. Hsiang, and E. Miguel (2015): "Climate and Conflict," *Annual Review of Economics*, 7, 577–617.

Burke, M. B., E. Miguel, S. Satyanath, J. A. Dykema, and D. B. Lobell (2009): "Warming increases the risk of civil war in Africa," *Proceedings of the National Academy of Sciences*, 106, 20670–20674.

Bush, S. S. and A. Clayton (2023): "Facing change: Gender and climate change attitudes worldwide," *American Political Science Review*, 117, 591–608.

Card, D. and G. B. Dahl (2011): "Family violence and football: The effect of unexpected emotional cues on violent behavior," *The quarterly journal of economics*, 126, 103–143.

Caruso, R., I. Petrarca, and R. Ricciuti (2016): "Climate change, rice crops, and violence: Evidence from Indonesia," *Journal of Peace Research*, 53, 66–83.

Cools, S., M. Flatø, and A. Kotsadam (2020): "Rainfall shocks and intimate partner violence in sub-Saharan Africa," *Journal of Peace Research*, 57, doi.org/10.1177/0022343319880252.

Cooper, M., A. Sandler, S. Vitellozzi, Y. Lee, G. Seymour, B. Haile, and C. Azzari (2021): "Re-examining the effects of drought on intimate-partner violence," *PLOS One*, doi.org/10.1371/journal.pone.0254346.

Dehingia, N., L. McDougal, J. Silverman, E. Reed, L. Urada, J. McAuley, A. Singh, and A. Raj (2023): "Climate and gender: association between droughts and intimate partner violence in India," *American Journal of Epidemiology*, doi.org/10.1093/aje/kwad222.

Dell, M., B. F. Jones, and B. A. Olken (2012): "Temperature Shocks and Economic Growth: Evidence from the Last Half Century," *American Economic Journal: Macroeconomics*, 4, 66–95.

Diaz, J. and V. Saldarriaga (2023): "A drop of love? Rainfall shocks and spousal abuse: Evidence from rural Peru," *Journal of Health Economics*, 89.

Eastin, J. (2018): "Climate change and gender equality in developing states," *World Development*, 107, 289–305.

Epstein, A., E. Bendavid, D. Nash, E. Charlebois, and S. Weiser (2020): "Drought and intimate partner violence towards women in 19 countries in sub-Saharan Africa during 2011-2018: A population-based study," *PLOS Medicine*, doi.org/10.1371/journal.pmed.1003064.

Erten, B. and P. Keskin (2018): "For better or for worse?: Education and the prevalence of domestic violence in turkey," *American Economic Journal: Applied Economics*, 10, 64–105.

——— (2021): "Female employment and intimate partner violence: evidence from Syrian refugee inflows to Turkey," *Journal of Development Economics*, 150, 102607.

——— (2024): "Trade-offs? The impact of WTO accession on intimate partner violence in Cambodia," *Review of Economics and Statistics*, 106, 322–333.

Eswaran, M. and N. Malhotra (2011): "Domestic violence and women's autonomy in developing countries: theory and evidence," *Canadian Journal of Economics/Revue canadienne d'économique*, 44, 1222–1263.

Farmer, A. and J. Tiefenthaler (1997): "An economic analysis of domestic violence," *Review of Social Economy*, 55, 337–358.

Fruttero, A., D. Halim, C. Broccolini, B. Coelho, H. Gninafon, and N. Muller (2023): "Gendered impacts of climate change," .

Gleditsch, K., J. Wucherpfennig, S. Hug, and K. Reigstad (2011): "Polygyny or Misogyny? Reexamining the First Law of Intergroup Conflict," *Journal of Politics*, 73, 265–270.

González, L. and N. Rodríguez-Planas (2020): "Gender norms and intimate partner violence," *Journal of Economic Behavior & Organization*, 178, 223–248.

Guarnieri, E. and A. Tur-Prats (2023): "Cultural Distance and Conflict-Related Sexual Violence," *Quarterly Journal of Economics*, 138, 1817–1861.

Guimbeau, A., X. Ji, and N. Menon (2024): "Climate Shocks, Intimate Partner Violence, and the Protective Role of Climate-Resilience Projects," *Working Paper*.

Guo, Y., Y. Zhu, Z. Fatmi, L. Zhou, C. He, J. Bachwenkizi, H. Kan, and R. Chen (2025): "Flood exposure and intimate partner violence in low-and middle-income countries," *Nature Water*, 3, 296–306.

Harari, M. and E. La Ferrara (2018): "Conflict, climate, and cells: a disaggregated analysis," *Review of Economics and Statistics*, 100, 594–608.

Haushofer, J., C. Ringdal, J. P. Shapiro, and X. Y. Wang (2019): "Income changes and intimate partner violence: Evidence from unconditional cash transfers in Kenya," Tech. rep., National Bureau of Economic Research.

Hidrobo, M., A. Peterman, and L. Heise (2016): "The effect of cash, vouchers, and food transfers on intimate partner violence: evidence from a randomized experiment in Northern Ecuador," *American Economic Journal: Applied Economics*, 8, 284–303.

Hsiang, S., M. Burke, and E. Miguel (2013): "Quantifying the Influence of Climate on Human Conflict," *Science*, 341, DOI: 10.1126.

Hsiang, S. M. (2010): "Temperatures and cyclones strongly associated with economic production in the Caribbean and Central America," *Proceedings of the National Academy of Sciences*, 107, 15367–15372.

Kishi, R. (2022): "Political violence targeting women in West Africa," *OECD West African Papers*, 34.

Kishi, R., M. Pavlik, and H. Matfess (2019): "'Terribly and terrifyingly normal' Political violence targeting women," *ACLED Report*.

Koos, C. and C. Neupert-Wentz (2020): "Polygynous neighbors, excess men, and intergroup conflict in rural Africa," *Journal of Conflict Resolution*, 64, 402–431.

Koren, O. and J. Schon (2023): "Climate change, cash crops, and violence against civilians in the Sahel," *Regional Environmental Change*, 23, 112.

Linke, A. M. and B. Ruether (2021): "Weather, wheat, and war: Security implications of climate variability for conflict in Syria," *Journal of Peace Research*, 58, 114–131.

Luke, N. and K. Munshi (2011): "Women as agents of change: Female income and mobility in India," *Journal of development economics*, 94, 1–17.

Mack, E., E. Bunting, J. Herndon, R. Marcantonio, A. Ross, and A. Zimmer (2021): "Conflict and its relationship to climate variability in Sub-Saharan Africa," *Science of The Total Environment*, 775, 145646.

Mannell, J., L. J. Brown, E. Jordaan, A. Hatcher, and A. Gibbs (2024): "The impact of environmental shocks due to climate change on intimate partner violence: A structural equation model of data from 156 countries," *Plos Climate*, 3, e0000478.

Mannell, J., P. Tevaga, P. E. Isaako, F. Alisi-Fesili, L. Apelu, K. Moananu, T. Faumuina, L. Sinclair, H. Tanielu, H. Lowe, et al. (2025): "Is exposure to a climate-related disaster associated with recent experiences of intimate partner violence among women? A post hoc analysis of survey data from rural Samoa," *BMJ Public Health*, 3.

Maystadt, J.-F., M. Calderone, and L. You (2014): "Local warming and violent conflict in North and South Sudan," *Journal of Economic Geography*, 15, 649–671.

McGuirk, E. and M. Burke (2020): "The economic origins of conflict in Africa," *Journal of Political Economy*, 128, 3940–3997.

McGuirk, E. and N. Nunn (2024): "Transhumant Pastoralism, Climate Change, and Conflict in Africa," *Review of Economic Studies*, forthcoming.

McGuirk, E. F. and N. Nunn (2025): "Transhumant pastoralism, climate change, and conflict in Africa," *Review of Economic Studies*, 92, 404–441.

Michalopoulos, S. and E. Papaioannou (2016): "The Long-Run Effects of the Scramble for Africa," *American Economic Review*, 106, 1802–1848.

Miguel, E. (2005): "Poverty and witch killing," *Review of Economic Studies*, 72, 1153–1172.

Miguel, E., S. Satyanath, and E. Sergenti (2004): "Economic Shocks and Civil Conflict: An Instrumental Variables Approach," *Journal of Political Economy*, 112, 725–753.

Miguel, E., H. Solomon, and M. Burke (2013): "Reconciling Temperature-conflict Results in Kenya," *UC Berkeley: Center for Effective Global Action.*

Monfreda, C., N. Ramankutty, and J. A. Foley (2008): "Farming the planet: 2. Geographic distribution of crop areas, yields, physiological types, and net primary production in the year 2000," *Global Biogeochemical Cycles*, 22.

Moscona, J., N. Nunn, and J. Robinson (2020): "Segmentary Lineage Organization and Conflict in Sub-Saharan Africa," *Econometrica*, 88, 1999–2036.

Munala, L., E. Allen, A. Frederick, and A. Ngunjiri (2023): "Climate Change, Extreme Weather, and Intimate Partner Violence in East African Agrarian-Based Economies," *International Journal of Environmental Research and Public Health*, 20, 7124.

Murdock, G. P. (1967): "Ethnographic Atlas," .

Nguyen, M. (2023): "Temperature and intimate partner violence," *Scottish Journal of Political Economy*, doi.org/10.1111/sjpe.12365.

——— (2024): "Temperature and intimate partner violence," *Scottish Journal of Political Economy*, 71, 197–218.

Ntumva, M. (2022): "Land conflict dynamics in Africa: A critical review on farmer-pastoralist conflict perspectives," *Journal of Peace and Development Studies*, 13, 17–28.

Nunn, N. and L. Wantchekon (2011): "The Slave Trade and the Origins of Mistrust in Africa," *American Economic Review*, 101, 3221–52.

O'loughlin, J., F. D. Witmer, A. M. Linke, A. Laing, A. Gettelman, and J. Dudhia (2012): "Climate variability and conflict risk in East Africa, 1990–2009," *Proceedings of the National Academy of Sciences*, 109, 18344–18349.

O'Loughlin, J., F. D. W. Witmer, A. M. Linke, A. Laing, A. Gettelman, and J. Dudhia (2012): "Climate variability and conflict risk in East Africa, 1990–2009," *Proceedings of the National Academy of Sciences*, 109, 18344–18349.

Pinho-Gomes, A.-C. and M. Woodward (2024): "The association between gender equality and climate adaptation across the globe," *BMC Public Health*, 24, 1394.

Portmann, F. T., S. Siebert, and P. Döll (2010): "MIRCA2000—Global monthly irrigated and rainfed crop areas around the year 2000: A new high-resolution data set for agricultural and hydrological modeling," *Global Biogeochemical Cycles*, 24.

Pryor, F. (1985): "The invention of the plow," *Comparative Studies in Society and History*, 27, 727–743.

Raleigh, C., R. Kishi, and A. Linke (2023): "Political instability patterns are obscured by conflict dataset scope conditions, sources, and coding choices," *Humanities and Social Sciences Communications*, 10, 1–17.

Rexer, J. M. (2022): "The brides of Boko Haram: Economic shocks, marriage practices, and insurgency in Nigeria," *The Economic Journal*, 132, 1927–1977.

Riley, S. J., S. D. DeGloria, and R. Elliot (1999): "A Terrain ruggedness index that quantifies topographic heterogeneity," *Intermountain Journal of Sciences*, 5, 23–27.

Rodriguez, Z. (2022): "The power of employment: Effects of India's employment guarantee on women empowerment," *World development*, 152, 105803.

Rogall, T. (2021): "Mobilizing the Masses for Genocide," *American Economic Review*, 111, 41–72.

Roy, S., M. Hidrobo, J. Hoddinott, B. Kolt, and A. Ahmed (2024): "Can Transfers and Complementary Nutrition Programming Reduce Intimate Partner Violence Four Years Post-Program?: Experimental Evidence from Bangladesh," *Journal of Human Resources*, 59, 1714–1740.

Sanz-Barbero, B., C. Linares, C. Vives-Cases, J. L. González, J. J. López-Ossorio, and J. Díaz (2018): "Heat wave and the risk of intimate partner violence," *Science of the total environment*, 644, 413–419.

Sekhri, S. and A. Storeygard (2014): "Dowry deaths: Response to weather variability in India," *Journal of Development Economics*, 111, 212–223, special Issue: Imbalances in Economic Development.

Tauchen, H., A. Witte, and S. Long (1991): "Domestic violence: A nonrandom affair," *International Economic Review*, 32, 491–511.

Vicente-Serrano, S. M., [1997, S. Beguería, and J. I. López-Moreno (2010): "A Multiscalar Drought Index Sensitive to Global Warming: The Standardized Precipitation Evapotranspiration Index," *Journal of Climate*, 23, 1696 – 1718.

Vogt, M., N.-C. Bormann, S. Rüegger, L.-E. Cederman, P. Hunziker, and L. Girardin (2015): "Integrating data on ethnicity, geography, and conflict: The ethnic power relations data set family," *Journal of Conflict Resolution*, 59, 1327–1342.

Von Uexkull, N., M. Croicu, H. Fjelde, and H. Buhaug (2016): "Civil conflict sensitivity to growing-season drought," *Proceedings of the National Academy of Sciences*, 113, 12391–12396.

Wang, P., L. Chu, J. Ban, E. Asare, M. Sivakami, A. R. Henao, L. Chimoyi, T. Sullivan, and K. Chen (2024): "The nexus of drought, extreme heat, and intimate partner violence in low-and middle-income countries," *Extreme Heat, and Intimate Partner Violence in Low-and Middle-Income Countries.*

Zhu, Y., C. He, M. Bell, Y. Zhang, Z. Fatmi, Y. Zhang, M. Zaid, J. Bachwenkizi, L. Liu, C. Zhou, R. Chen, and H. Kan (2023): "Association of Ambient Temperature With the Prevalence of Intimate Partner Violence Among Partnered Women in Low- and Middle-Income South Asian Countries," *JAMA Psychiatry*, 80, 952–961.

Appendix
For Online Publication

A Data Description

A.1 Climate Variables

The primary source for climate variables is the Copernicus Climate Change Service (C3S). We downloaded the *ERA5 monthly averages on single levels from 1940 to present* on October 4, 2022. The specific variables that we use in the paper are:

- **Temperature:** We use "2 metre temperature", which measures the temperature of air at 2 meters above the surface of land, sea or inland waters. It has a resolution of 0.1x0.1 degrees.
- **Precipitation:** We use "Total precipitation", which measures the accumulated liquid and frozen water, comprising rain and snow, that falls to the Earth's surface. It is the sum of large-scale precipitation and convective precipitation. It has a resolution of 0.1x0.1 degrees.
- **SPEI:** The Standardized Precipitation-Evapotranspiration Index was developed by Vicente-Serrano et al. (2010) as a climate drought index. In calculating it, we follow Harari and La Ferrara (2018) in using reanalysis data instead of projected climate information. The input rasters (potential evapotranspiration, precipitation, and temperature) come from from ERA5, at a resolution of 0.1x0.1 degrees.

For the main analysis, we standardize each climate variable relative to its long-term average. Since each variable is originally recorded at a monthly frequency, we first standardize it at the monthly level, as shown in Equation 4.

$$Std\ Climate_{imt} = \frac{Raw\ Climate_{imt} - \overline{Raw\ Climate_i}}{SD(Raw\ Climate)_i} \tag{4}$$

where, m denotes a month in year t and i represents a cell. $\overline{Raw\ Climate_i}$ and $SD(Climate)_i$ represent the mean and standard deviation of $Raw\ Climate_{imt}$ in grid i over all months, such as

$$\overline{Raw\ Climate_i} = \frac{1}{N} \sum_{t\in[1979,2019];m\in[1,12]} Raw\ Climate_{imt}$$
$$SD(Climate)_i = \frac{1}{N-1} \sum_{t\in[1979,2019];m\in[1,12]} (Raw\ Climate_{imt} - \overline{Raw\ Climate_i})^2$$

where, $N = 492$ is the total number of months in the sample.

Finally, since our main specification is at the yearly level, we compute the annual average of $Std\ Climate_{imt}$ by taking its mean over all months within a year, as shown in equation 5,

$$Climate_{it} = \frac{1}{12} \sum_{m=1}^{12} Std\ Climate_{imt}, \tag{5}$$

obtaining a grid-by-year measure of temperature, precipitation, and SPEI.

A.2 Female Empowerment Variables

- **Male Dominance Index**: We employ the index developed by Guarnieri and Tur-Prats (2023), which captures the first principal component of historical ethnic traits: matrilineality, polygyny, plough use, nuclear family, bride price and the reliance of societies on agriculture, husbandry, gathering, fishing, and pastoralism. All such variables come from the Ethnographic Atlas, compiled by Murdock (1967) and updated by Nunn and Wantchekon (2011). To compute the weights of the index we only used the ethnic groups located in Africa.

- **Female Crops**: The data on crops harvested come from Monfreda et al. (2008). They present data on the amount of land cultivated for over 150 crops. We classified crops as female positive if the plough is not required for cultivation of the crop. The list of plough positive crops comes from Pryor (1985) and Alesina et al. (2013). We create two variables with this data: (i) the share of area within a grid cell that is used for female crops, and (ii) an indicator of whether the major crop (by area harvested) in a grid cell does not require plough.

- **Crops' Growing Season**: To compute the growing season of each crop we used the information on MIRCA2000 from (Portmann et al., 2010). They report geographic data on the planting, growing, and harvesting season of all major food crops and cotton in each month of the year. For the crops not covered in the MIRCA dataset, we used the FAO crop Calendar which points to the growing season at the country-crop level.

A.3 Regression Control Variables

- **National Border Dummy**: Indicator if the grid cell is crossed by a national border.

- **Distance to water**: We compute the distance from the centroid of the grid cell to the closest available source of drinkable water (rivers or lakes). The data on the location of rivers and lakes comes from the FAO map catalog, and the relevant download is RWDB2 Rivers and Surface Water Body.

- **Share of area not covered by water**: This variable also uses the data from the FAO Map Catalog on surface water. It measures the share of land not covered by water.

- **Elevation**: This variable is calculated as the average elevation of the grid cell. The data come from USGS, specifically the ASTER Global Digital Elevation Model. It measures the elevation in a raster of 1 arc second across the world.

- **Ruggedness**: The topographic ruggedness index (TRI) was developed by Riley et al. (1999) to measure the amount of elevation difference between adjacent cells. We computed this variable using as an input the elevation data just described.

- **Primary Road**: Indicator variable of whether a major road or railroad intersects a grid cell. The data on roads come from the US National Geospatial Intelligence Agency, in the infrastructure section of the African Marine Atlas.

- **Mines**: Indicator variable for the presence of a mineral mine within a grid cell. The data on mines' location come from the USGS, specifically the Mineral Resources Data System (MRDS)

- **Discriminated ethnicity**: Indicator variable for the presence of a discriminated ethnicity within a grid cell. The data come from the Ethnic Power Relations database (Vogt et al., 2015).

A.4 Summary Statistics

Table A1: Summary Statistics - PVTW and Climate Variables

	Mean	SD	N
Political Violence Towards Women = 1	0.02	0.15	63,227
Deadly Political Violence Towards Women = 1	0.01	0.11	63,227
Temperature	0.11	0.23	63,227
Precipitation	-0.03	0.22	63,227
SPEI	-0.28	0.59	61,962

Notes: The table reports summary statistics for the main variables used in the analysis. The unit of observation is a cell–year, and the sample covers the period 1997–2019. Climate variables are expressed as standardized deviations from their long-term mean (1979–2019).

Table A2: Summary Statistics - Female Empowerment and Control Variables

	N	Mean	SD
Panel A: Female Empowerment			
Major Female Crop	43,424	0.743	0.437
Share Female Crops	43,424	0.585	0.268
Inverse MDI	39,077	-0.095	1.059
Pastoralism	39,077	0.272	0.224
Polygyny	39,077	0.940	0.238
Bride Price	39,077	0.906	0.291
Matrilineal	39,077	0.159	0.366
Panel B: Other Controls			
Crossed by National Border	43,424	0.301	0.459
Distance to Water (ln+1)	43,424	2.978	1.224
Elevation (ln+1)	43,424	6.154	1.008
Share of Area not Water	43,424	0.918	0.223
Primary Road Indicator	43,424	0.439	0.496
Ruggedness	43,424	2.822	4.024
Discriminated Ethnicity Indicator	43,424	0.308	0.462
Mines Indicator	43,424	0.280	0.449

Notes: The table reports the summary statistics for the female empowerment variables (Panel a) and the geographical controls (Panel b) used across the estimations in the paper. The unit of observation is a cell–year and the time frame is between 1997 and 2019. The sample includes cells in areas that have at least one crop.

B Additional Results

B.1 Non Linearities

Table B3: Temperature and PVTW, higher order polynomials

	Event Indicator				Deadly Event Indicator			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Temperature	0.050***	0.052***	0.012	0.004	0.026***	0.027***	0.005	0.001
	(0.009)	(0.009)	(0.007)	(0.008)	(0.006)	(0.006)	(0.006)	(0.006)
Temperature Squared	0.016	0.019	0.001	0.014	0.013	0.014	0.007	0.014
	(0.019)	(0.019)	(0.013)	(0.017)	(0.013)	(0.013)	(0.010)	(0.012)
Mean Dep. Var.	0.032	0.032	0.032	0.032	0.016	0.016	0.016	0.032
Observations	43,424	43,424	43,424	43,424	43,424	43,424	43,424	43,424
Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Grid FEs	No	No	Yes	No	No	No	Yes	No
Year FEs	No	No	Yes	Yes	No	No	Yes	Yes
Country-time trend	No	No	No	Yes	No	No	No	Yes

Notes: The table reports estimates from regressions of temperature and temperature squared on two measures of political violence against women: (i) an indicator for the occurrence of any PVTW event, and (ii) an indicator for the occurrence of a deadly PVTW event (at least one fatality). The unit of observation is a cell–year and the time frame is between 1997 and 2019. The sample includes cells in areas that have at least one crop. Standard errors corrected for spatial and temporal autocorrelation following Hsiang (2010) in parentheses. Significance levels: $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$.

B.2 Alternative Specifications

Table B4: PVTW and Precipitation

	Event Indicator				Deadly Event Indicator			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Precipitation	-0.011	-0.015**	0.003	0.007	-0.011**	-0.013***	-0.002	-0.001
	(0.008)	(0.007)	(0.006)	(0.006)	(0.005)	(0.005)	(0.004)	(0.004)
L1.Precipitation	-0.030***	-0.034***	-0.006	-0.004	-0.014***	-0.015***	0.001	0.002
	(0.007)	(0.007)	(0.005)	(0.006)	(0.004)	(0.004)	(0.004)	(0.004)
Mean Dep. Var.	0.033	0.033	0.033	0.033	0.016	0.016	0.016	0.016
Observations	41,536	41,536	41,536	41,536	41,536	41,536	41,536	41,536
Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Grid FEs	No	No	Yes	No	No	No	Yes	No
Year FEs	No	No	Yes	Yes	No	No	Yes	Yes
Country-time trend	No	No	No	Yes	No	No	No	Yes

Notes: The table reports estimates from regressions of precipitation on two measures of political violence against women: (i) an indicator for the occurrence of any PVTW event, and (ii) an indicator for the occurrence of a deadly PVTW event (at least one fatality). The unit of observation is a cell–year and the time frame is between 1997 and 2019. The sample includes cells in areas that have at least one crop. Standard errors corrected for spatial and temporal autocorrelation following Hsiang (2010) in parentheses. Significance levels: $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$.

Table B5: PVTW and SPEI

	Event Indicator				Deadly Event Indicator			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SPEI	-0.007**	-0.008***	0.003	0.004*	-0.005***	-0.006***	0.000	0.001
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)
L1.SPEI	-0.014***	-0.015***	-0.002	-0.001	-0.006***	-0.006***	0.001	0.002
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)
Mean Dep. Var.	0.033	0.033	0.033	0.033	0.016	0.016	0.016	0.016
Observations	41,338	41,338	41,338	41,338	41,338	41,338	41,338	41,338
Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Grid FEs	No	No	Yes	No	No	No	Yes	No
Year FEs	No	No	Yes	Yes	No	No	Yes	Yes
Country-time trend	No	No	No	Yes	No	No	No	Yes

Notes: The table reports estimates from regressions of SPEI on two measures of political violence against women: (i) an indicator for the occurrence of any PVTW event, and (ii) an indicator for the occurrence of a deadly PVTW event (at least one fatality). The unit of observation is a cell–year and the time frame is between 1997 and 2019. The sample includes cells in areas that have at least one crop. Standard errors corrected for spatial and temporal autocorrelation following Hsiang (2010) in parentheses. Significance levels: $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$.

Table B6: PVTW and Climate Variables, No-lagged

	Event Indicator				Deadly Event Indicator			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Temperature	0.059***	0.062***	0.012	0.012	0.033***	0.035***	0.009*	0.009
	(0.010)	(0.009)	(0.008)	(0.009)	(0.006)	(0.006)	(0.005)	(0.006)
Mean Dep. Var.	0.032	0.032	0.032	0.032	0.016	0.016	0.016	0.016
Observations	43,424	43,424	43,424	43,424	43,424	43,424	43,424	43,424
Precipitation	-0.021***	-0.025***	0.000	0.003	-0.015***	-0.017***	-0.004	-0.003
	(0.007)	(0.007)	(0.006)	(0.006)	(0.004)	(0.004)	(0.004)	(0.004)
Mean Dep. Var.	0.032	0.032	0.032	0.032	0.016	0.016	0.016	0.016
Observations	43,424	43,424	43,424	43,424	43,424	43,424	43,424	43,424
SPEI	-0.012***	-0.013***	0.002	0.003	-0.008***	-0.008***	-0.000	0.001
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)
Mean Dep. Var.	0.032	0.032	0.032	0.032	0.016	0.016	0.016	0.016
Observations	43,217	43,217	43,217	43,217	43,217	43,217	43,217	43,217
Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Grid FEs	No	No	Yes	No	No	No	Yes	No
Year FEs	No	No	Yes	Yes	No	No	Yes	Yes
Country-time trend	No	No	No	Yes	No	No	No	Yes

Notes: The table reports estimates from regressions of climate variables (temperature, precipitation, and SPEI) estimated on separate regressions on two measures of political violence against women: (i) an indicator for the occurrence of any PVTW event, and (ii) an indicator for the occurrence of a deadly PVTW event (at least one fatality). The unit of observation is a cell–year and the time frame is between 1997 and 2019. The sample includes cells in areas that have at least one crop. Standard errors corrected for spatial and temporal autocorrelation following Hsiang (2010) in parentheses. Significance levels: $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$.

Table B7: Climate Fluctuations on PVTW

	Event Indicator				Deadly Event Indicator			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Temperature	0.061***	0.063***	0.017*	0.019	0.033***	0.034***	0.010	0.012
	(0.012)	(0.012)	(0.009)	(0.011)	(0.008)	(0.008)	(0.007)	(0.008)
Precipitation	0.007	0.003	-0.004	-0.003	-0.001	-0.002	-0.006	-0.006
	(0.008)	(0.008)	(0.006)	(0.007)	(0.005)	(0.005)	(0.004)	(0.004)
SPEI	-0.000	-0.000	0.005*	0.007**	-0.000	0.000	0.003	0.004*
	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
Mean Dep. Var.	0.032	0.032	0.032	0.032	0.016	0.016	0.016	0.016
Observations	43,217	43,217	43,217	43,217	43,217	43,217	43,217	43,217
Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Grid FEs	No	No	Yes	No	No	No	Yes	No
Year FEs	No	No	Yes	Yes	No	No	Yes	Yes
Country-time trend	No	No	No	Yes	No	No	No	Yes

Notes: The table reports estimates from regressions of climate variables (temperature, precipitation, and SPEI) on two measures of political violence against women: (i) an indicator for the occurrence of any PVTW event, and (ii) an indicator for the occurrence of a deadly PVTW event (at least one fatality). The unit of observation is a cell–year and the time frame is between 1997 and 2019. The sample includes cells in areas that have at least one crop. Standard errors corrected for spatial and temporal autocorrelation following Hsiang (2010) in parentheses. Significance levels: $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$.

Table B8: PVTW and Temperature, Cluster SE

	Event Indicator				Deadly Event Indicator			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Temperature	0.038***	0.040***	0.005	0.004	0.023***	0.024***	0.006	0.006
	(0.011)	(0.010)	(0.009)	(0.007)	(0.007)	(0.007)	(0.006)	(0.005)
L1.Temperature	0.038***	0.040***	0.016**	0.014**	0.019***	0.020***	0.005	0.005
	(0.009)	(0.008)	(0.007)	(0.006)	(0.005)	(0.005)	(0.004)	(0.004)
Mean Dep. Var.	0.033	0.033	0.033	0.033	0.016	0.016	0.016	0.016
Observations	41,536	41,536	41,536	41,536	41,536	41,536	41,536	41,536
Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Grid FEs	No	No	Yes	No	No	No	Yes	No
Year FEs	No	No	Yes	Yes	No	No	Yes	Yes
Country-time trend	No	No	No	Yes	No	No	No	Yes

Notes: The table reports estimates from regressions of temperature on two measures of political violence against women: (i) an indicator for the occurrence of any PVTW event, and (ii) an indicator for the occurrence of a deadly PVTW event (at least one fatality). The unit of observation is a cell–year and the time frame is between 1997 and 2019. The sample includes cells in areas that have at least one crop. Clustered standard errors at the country level in parentheses. Significance levels: $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$.

B.3 Decomposing MDI

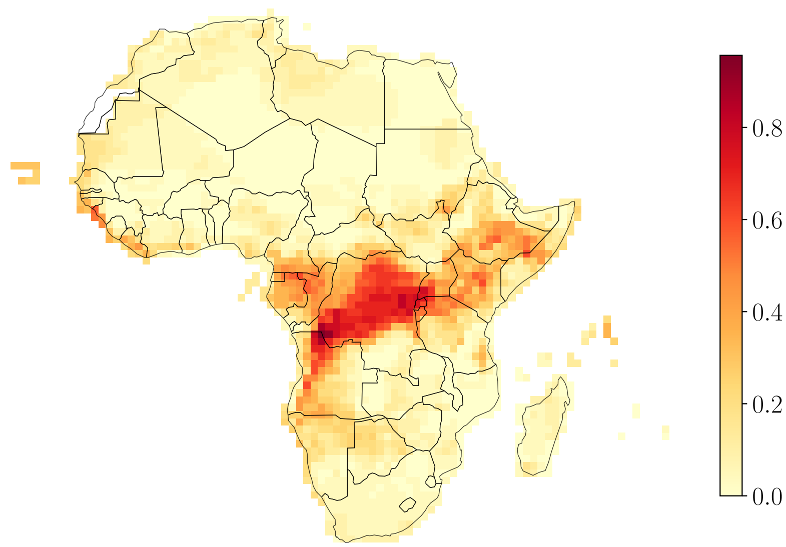
Table B9: Other Components of MDI

	Event Indicator				Deadly Event Indicator			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Bride Price								
Temperature	0.076***	0.079***	0.022	0.021	0.038***	0.040***	0.011	0.011
	(0.019)	(0.019)	(0.018)	(0.021)	(0.014)	(0.014)	(0.012)	(0.015)
L1.Temperature	0.041*	0.043**	0.006	0.006	0.034*	0.034*	0.014	0.014
	(0.021)	(0.022)	(0.019)	(0.022)	(0.018)	(0.018)	(0.016)	(0.019)
Bride Price × Temperature	-0.036*	-0.037*	-0.017	-0.016	-0.015	-0.015	-0.006	-0.004
	(0.020)	(0.020)	(0.017)	(0.021)	(0.014)	(0.014)	(0.011)	(0.014)
Bride Price × L1.Temperature	0.003	0.003	0.013	0.011	-0.013	-0.012	-0.007	-0.007
	(0.023)	(0.023)	(0.018)	(0.022)	(0.019)	(0.019)	(0.016)	(0.018)
Mean Dep. Var.	0.035	0.035	0.035	0.035	0.017	0.017	0.017	0.017
Observations	37,378	37,378	37,378	37,378	37,378	37,378	37,378	37,378
Panel B: Polygyny								
Temperature	0.074**	0.073**	0.027	0.024	0.037	0.036	0.010	0.009
	(0.037)	(0.037)	(0.028)	(0.030)	(0.031)	(0.031)	(0.021)	(0.025)
L1.Temperature	0.033	0.033	0.014	0.004	0.034	0.033	0.027	0.018
	(0.035)	(0.035)	(0.029)	(0.031)	(0.032)	(0.032)	(0.026)	(0.029)
Polygyny × Temperature	-0.033	-0.029	-0.022	-0.019	-0.013	-0.010	-0.003	-0.003
	(0.038)	(0.037)	(0.028)	(0.030)	(0.031)	(0.032)	(0.020)	(0.025)
Polygyny × L1.Temperature	0.010	0.012	0.005	0.013	-0.013	-0.011	-0.020	-0.012
	(0.035)	(0.036)	(0.029)	(0.031)	(0.033)	(0.033)	(0.026)	(0.029)
Mean Dep. Var.	0.035	0.035	0.035	0.035	0.017	0.017	0.017	0.017
Observations	37,378	37,378	37,378	37,378	37,378	37,378	37,378	37,378
Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Grid FEs	No	No	Yes	No	No	No	Yes	No
Year FEs	No	No	Yes	Yes	No	No	Yes	Yes
Country-time trend	No	No	No	Yes	No	No	No	Yes

Notes: The table reports estimates from regressions of temperature interacted with bride price or polygyny on two measures of political violence against women: (i) an indicator for the occurrence of any PVTW event, and (ii) an indicator for the occurrence of a deadly PVTW event (at least one fatality). The unit of observation is a cell–year and the time frame is between 1997 and 2019. The sample includes cells in areas that have at least one crop. Standard errors corrected for spatial and temporal autocorrelation following Hsiang (2010) in parentheses. Significance levels: $***p < 0.01$, $**p < 0.05$, and $*p < 0.1$.

B.4 Additional Figures

Figure B1: Spatial Distribution of Residualized Temperature



Notes: The figure shows the share of observations in which the residualized temperature, after removing grid and year fixed effects, exceeds one standard deviation. The time frame is between 1997 and 2019.