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A Bayesian framework for studying climate anomalies and social conflicts

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Abstract

Climate change stands to have a profound impact on human society, and on political and other conflicts in particular. However, the existing literature on understanding the relation between climate change and societal conflicts has often been criticized for using data that suffer from sampling and other biases, often resulting from being too narrowly focused on a small region of space or a small set of events. These studies have likewise been critiqued for not using suitable statistical tools that (*i*) address spatio-temporal dependencies, (*ii*) obtain probabilistic uncertainty quantification, and (*iii*) lead to consistent statistical inferences. In this article, we propose a Bayesian framework to address these challenges. We find that there is a strong and substantial association between temperature anomalies on aggregated material conflicts and verbal conflicts globally. Going deeper, we also find significant evidence to suggest that positive temperature anomalies are associated with social conflict primarily through government-civilian and government-rebel material conflicts, as in civilian protests, rebel attacks against government resources, or acts of state repression. We find that majority of the conflicts associated with climate anomalies are triggered by rebel actors, and others react to such acts of conflict. Our results exhibit considerably nuanced relationships between temperature deviations and social conflicts that have not been noticed in previous studies. Methodologically, the proposed Bayesian framework can help social scientists explore similar domains involving large-scale spatial and temporal dependencies. Our code and a synthetic dataset has been made publicly available.

KEYWORDS

Bayesian model, global trade, social conflict, temperature anomalies

1 | INTRODUCTION

Climate change is now widely acknowledged as a global threat to contemporary human society (Pinkse & Kolk, 2009), and to social conflict in particular (Froese & Schilling, 2019).[1] At the international level, such concerns began to crystallize with the adoption of the Kyoto Protocol in the United Nations Framework Convention on Climate Change in 1997 (Böhringer, 2003; Freedman & Jaggi, 2005) and have accelerated since that point in time. International cooperation on climate change mitigation efforts have accordingly become predicated upon the notion that harmful social and economic activities in one region can spill-over into other regions through greenhouse gas emissions, global warming, and the impacts of extreme climate events (Esty, 2008). Through these pathways and others, climate change is accordingly seen as an increasing threat to natural resource availability in areas such as arable land and water security. Abnormal increases in temperatures in some regions of the world are likewise associated with serious population health issues with adverse implications for human productivity (Linnenluecke & Griffiths, 2010). By and large, the current and future impacts of climate change in each of these areas can be viewed as arising due to extreme environmental conditions (Coumou & Rahmstorf, 2012), with serious implications for social displacement and conflict (Froese & Schilling, 2019; Scheffran, 2020; Taylor, 2014).

How can data science inform our understandings of these posited relationships between climate change and social conflict? Extant research offers preliminary insights to this question, thanks in large part to social scientists' increasing focus on quantifying the relationship(s) between environmental anomalies and various forms of societal conflict. While not all studies in this area have identified robust effects (see, e.g., Buhaug, 2010; BÃühmelt et al., 2014), a number of prominent analyses have indeed established linkages between social conflict and climate anomalies. For example, Hsiang et al. (2013) find that climate anomalies such as rainfall and temperature deviations are systematically related to increases in social and political conflict such that a one standard deviation increase in temperature or rainfall from median values is associated with a 14% increase in incidences of social conflict. Similarly, Bollfrass and Shaver (2015) and Landis (2014) each found that increases in temperatures beyond normal levels are associated with significant escalations in the incidence of social conflicts.

These findings notwithstanding, many past studies of climate variability and societal conflicts have failed to fully account for the interdependencies that commonly underpin these respective processes. Climate change and social conflict each have spatial and temporal dependencies at the regional as well as global levels. To this end, the impacts of climate change often are regional in scale, ensuring that multiple neighboring countries face similar impacts. Likewise, conflict frequently spills-over from one location to another (Metternich et al., 2017). As such, considering the spatial and temporal dependencies of climate change and conflict is essential for any quantitative analysis of these variables. As we argue below, failures to account for these complex dependencies at the modeling stage has impeded comprehensive understandings of the relationship between climate anomalies and social conflicts. A second strong criticism of parts of the existing literature on climate change and conflicts is that the presence of sampling bias, in particular, the fact that the data is analyzed in small samples from regions with high levels of conflict and without accounting for spatio-temporal dependencies, have lead to distorted findings and some unscientific stigmatization (Adams et al., 2018). A third criticism that we may add is the lack of proper uncertainty quantification and inference associated with some of these studies.

In this article, we address these shortcomings by proposing a Bayesian model that (*i*) accounts for the spatial and temporal dependencies of climate anomalies and conflict events, (*ii*) considers data from all over the planet simultaneously, thus not suffering from sampling bias issues, (*iii*) obtains full posterior distributions of the quantities of interest, thus addressing uncertainty quantification and inferential aspects. Notice that by explicitly modeling spatio-temporal dependencies we address the issue of spill-over of conflicts. The issue of sampling bias is more complex, as there are many possible sources of such bias. However, the main point of (Adams et al., 2018) was that bias is created because researchers often report studies based on data from isolated pockets of the world collected during or near the times of conflicts in those places. In this article, we address these main issues by considering data from all over the world, during times of peace as well as conflict. While considering a near planet-wide dataset in times of violence as well as non-violence does not eliminate every bias, it goes a long way in addressing the major data-related shortcoming in several related publications.

We first obtain temperature anomalies or residuals from the observed temperature data by estimating and eliminating seasonality and long-term trends for each location. It can be reasonably argued that such temperature anomalies are more

[1]We define social conflict as any domestic (intrastate) conflict that rises above the purely interpersonal level. This includes conflict between two or more non-state groups, conflict between the government and non-state groups, conflict between an individual and non-state or state-based groups, or society-wide conflicts.

interesting and important explanatory variables to consider in the study of societal conflicts rather than raw temperature measurements, since such anomalies reflect deviations from the normal or baseline, and can potentially be triggers for food, water and energy security issues, which in turn can lead to conflicts. We then propose an intricate model for studying the count of conflict events as an over-dispersed discrete random variable, whose mean process is a latent random field with spatio-temporal dependencies that is potentially influenced by temperature anomalies as well as several social, economic and political factors. We control for such factors using measures for ethnic, religious, and linguistic fractionalizations, the human development index (HDI), and trade variables reflected in commodity, agriculture, and manufactured products exports.

Using the above modeling framework, we evaluate the relationship between temperature anomalies and different types of social conflicts, including "material conflicts" involving physical confrontations such as protests or roadside bombings, and "verbal conflicts" involving threats, ultimatums, or similar forms of non-physical confrontation. Diving deeper into material conflicts, we then disaggregate the data into the type of actors involved in the conflicts. These may be representatives of the nation-state or the government (sometimes termed "government" or "gov" below), armed non-government individuals or groups (sometimes termed "rebels" or "reb" below), and individuals or entities who are neither government representatives nor armed rebels and form the citizenry of a country (sometimes termed "civilians" or "civ" below). Further, we then study the matter of whether the effects of temperature on conflict differ across conflicts initiated by government agents, civilians, or armed non-state actors.

Our study makes several contributions. We address the major methodological challenges that have beset many of the previous studies concerning the role of climate anomalies on social and political conflicts. In particular, we propose a framework for big data with spatio-temporal dependencies, that can be used for statistical inference and probabilistic uncertainty quantifications. This addresses the past issues of focusing too narrowly on a small region of space, on using data that suffer from sampling and other biases, on restricting attention to only certain kinds of conflicts or actors in the conflicts, and of using statistical techniques that are not designed for dependent data with sampling biases.

We add to the literature on climate change and conflict by identifying and quantifying the relationships between temperature anomalies and conflict with unique attention to (i) spatial and temporal interdependencies and (ii) disaggregation with respect to societal actors and conflict types. These findings help to clarify past discrepancies and debates regarding the global association between temperatures and social conflicts. In doing so, our analysis speaks to the increasing scholarly emphasis on the identification of contingent and complex causal pathways linking climate change to social conflict (von Uexkull & Buhaug, 2021), wherein particular attention is given to understanding of how such pathways operate over space, time, actor, and conflict-type.

The remainder of the article is organized as follows. In Section 2, we briefly review the literature related to studies on the impact of climate change on social conflicts. In Section 3, we describe the proposed Bayesian model. In Section 4, we provide a detailed description of the data and the variables we create and study. In Section 5, we report our findings on the relationship between temperature deviations and different kinds of conflicts, controlling for several socio-political and economic variables. Our concluding remarks are collected in Section 6.

2 | LITERATURE REVIEW ON CLIMATE CHANGE AND CONFLICTS

The literature on the use of statistical and data science methodologies for modeling the physical processes of climate and climate change is vast, and we do not review it in full here. A recent review of data science techniques related to climate model evaluation may be found in Gong and Chatterjee (2020), and the references therein contain some details about the different manners in which statistical techniques have been brought into climate sciences. Bayesian techniques for understanding the effect of climate change and climate extremes on societal conflicts are present, to some extent, in Buhaug et al. (2014); Burke et al. (2015); Evans (2019); Gangopadhyay and Nilakantan (2018); Python et al. (2019); Sommer et al. (2018); van Weezel (2019, 2020); Witmer et al. (2017). Other related discussions may be found in Abel et al. (2019); Mach et al. (2019); Nordås and Gleditsch (2015); Schleussner et al. (2016); Von Uexkull et al. (2016) and references cited therein. These studies differ from the present paper in that they typically do not consider spatio-temporal dependencies and and/or do not always use a big data perspective of attempting to understand the relationship between temperature anomalies and conflict dynamics globally. Methodologically, some past analyses also used *ad hoc* tools and techniques that are difficult to justify theoretically. By contrast, the Bayesian framework that we propose in this article is capable of modeling big data to elicit large networks of relations both between and within countries, and has strong theoretical foundations.

Climate change is manifesting in many ways across the globe, including through the increased intensity, frequency and duration of temperature- , flood- , and drought-based extreme weather events (Diffenbaugh et al., 2017; Perera et al., 2020; Stott, 2016). While these extreme weather events often go hand-in-hand, we focus in this article on temperature events for three reasons. First, high and anomalous temperature events are among the most closely linked to global climate change—and have implications irrespective of geographic location, proximity to coasts, latitude, or rural-urban context. To this end, the fourth assessment report of the Intergovernmental Panel on Climate Change (IPCC) (Lee, 2007) famously established that between 1950 and 2000 the global average temperature had risen by approximately 1°C. More recently, Diffenbaugh et al. (2017) indicate that changes in global temperature patterns have increased the global chances of exceptionally dry years by as much as 57%. These already ongoing worldwide impacts make temperature deviations from normalcy particularly fitting for our current analysis.

Second, the climatic trends outlined above have also been identified as posing what are perhaps the gravest threats to human societies. As the Stern review (Stern & Stern, 2007) notes in this regard, "[t]he effects of rising temperatures against a background of a growing population are likely to cause changes in the water status of billions of people. According to one study, temperature rises of 2°C will result in 1–4 billion people experiencing growing water shortages, predominantly in Africa, the Middle East, Southern Europe, and parts of South and Central America" (p. 76). Matthew and Hammill (2009) likewise cautioned that climate change and resulting rise in global average temperature would soon outstretch the adaptive abilities of communities across the globe, with implications for social stability, human violence, and conflict. Hence, in addition to deviations of temperature from current averages being among the most direct, widespread, and active aspects of climate change, they are also among of the most threatening to human societies through both direct and indirect pathways.

Third, extant research has established some evidence in favor of a linkage between temperature anomalies and social conflict. Burke et al. (2009) demonstrated that rising temperatures have historically increased civil war incidences in Africa with dire future projections of civil war in the region due to climate change. This line of inquiry was extended by Hsiang et al. (2013) to conclude that a one standard deviation increase in temperature can increase the risk of inter-group conflict by approximately 14%. Bollfrass and Shaver (2015) demonstrated at a global scale that one—albeit not the only—pathway linking such temperature changes to social conflicts operates through diminished agricultural outputs. Landis (2014) offered additional evidence and theory for linking temperature increases to both civil war and low level social conflict across the globe. The theoretical mechanisms proposed in this case complement those of Bollfrass and Shaver (2015) in noting that warmer weather increases the strategic viability of conflict, by (i) enabling conflictual actors to better overcome collective action problems and (ii) enhancing non-state actors' strategic and behavioral incentives to engage in violent conflict. Looking at lower-level forms of social conflict, Yeeles (2015) then finds temperature increases to be associated with urban unrest across a sample of African and Asian cities, albeit more so for lethal rather than non-lethal forms of urban unrest. The above findings and mechanisms accordingly provide us with a basis for examining the relationship between temperature and social conflicts at a global scale, while also underscoring the importance of considering such findings by conflict-type.

However, it is also important to note that not all studies find support for the temperature-conflict pathways outlined above. For instance, Buhaug (2010) critiques Burke et al. (2009) in demonstrating that different data and modeling decisions can yield null findings for temperature's effects on civil conflicts in Africa, whereas follow-up analyses by Burke et al. (2010) continue to provide robust support for temperature-conflict associations albeit with less temporal consistency relative to those of Burke et al. (2009). More recently, BÃühmelt et al. (2014) report an absence of evidence for the role of temperature changes in influencing domestic water conflicts. Finally, while others such as O'Loughlin et al. (2014) find evidence for a temperature effect on conflict in sub-Saharan Africa, they ultimately conclude that "important inconsistencies in the relationship between temperature extremes and conflict are evident in more nuanced relationships than have been previously identified" (p. 16712). In sum, evidence for a direct relation between temperature extremes and social conflicts is far from consistent. This suggests that further analyses, data refinements, and modeling extensions are warranted.

A different kind of focus of studies on climate change and conflicts was brought to attention by Adams et al. (2018), who performed an in-depth review of the related literature prior to 2018. They found that studies on this intersection of topics suffer from the so-called "streetlight effect". That is, many climate-conflict studies suffer from a bias due to the convenience of access to social conflict data in some parts of the world. They highlighted the fact that some studies may be flawed due to sampling based on the dependent variable: oftentimes the focus is on cases where there is conflict whereas independent variables or cases where conflict is largely absent are not sampled properly. The authors also highlighted that research on climate change and conflicts tend to focus on a few accessible regions, and hence are typically reliant on a small number of cases concentrated in relatively small geographic areas. The limited focus of such studies may also lead to misleading and inappropriate stigmatization in its implying that some parts of the world are naturally violent or more prone to climate-induced violence. Related studies, not all uniformly agreeing with the thesis of Adams et al. (2018) may be found in Breckner and Sunde (2019); Butler and KefTord (2018); Ide et al. (2020); Levy (2018); Mach et al. (2019) and elsewhere.

At least some of the inconsistencies and disagreements outlined above are attributable to challenges in modeling the complex spatial and temporal interdependencies that underlie temperature anomalies and social conflicts. Indeed, the estimation of impacts of global warming on conflict is challenging (Scheffran & Battaglini, 2011). A considerable part of the "streetlight effect" discovered by Adams et al. (2018) and discussed elsewhere is due to the fact that many past studies did not consider data on either climate, or conflict, from most parts of the world and hence missed a "big data" perspective. Additionally, such studies tended to focus narrowly on certain kinds of conflicts. In contrast, in this article we discuss both material and verbal conflicts, and consider instances where the actors in such conflicts may represent the government or state, or armed non-state actors, or civilians, and consider data with near-global coverage.

A further aspect of contrast between this article and previous studies is that our Bayesian modeling approach accounts for spatio-temporal dependencies in the data, and is designed to produce consistent statistical inference and probabilistic uncertainty quantification. As discussed above, both temperature anomalies and conflicts exhibit complex temporal and latent spatial dependencies at global and regional levels. Conflict processes are likewise confounded by a great many political, social, economic, and historical factors that in some cases are reinforced by, and in other cases operate distinctly from, climate change. Such conflict is also prone to temporal and spatial spillovers. While many of the above studies of temperature and conflict perform analyses at increasingly fine grained levels of spatial and/or temporal aggregation, they often ignore spatial and temporal interdependencies and consequently suffer from the streetlight effect.

3 | THE MODEL FRAMEWORK

We use a calendar month as the time unit for the present study, and countries as spatial units. A monthly aggregation is consistent with extant analyses of the conflict event data described below and avoids a number of reporting errors and added noise that would arrive at sub-monthly (e.g., daily) aggregations. Aggregating to monthly temporal units also ensures a degree of smoothing in our measures that helps to reduce measurement-related uncertainties. Alongside the conflict aggregation points mentioned immediately above, this concern is also applicable to our economic controls, for which the monthly aggregation is the minimum level of temporal resolution. We use country-level spatial units due to a lack of reliable sub-national data for many countries, and because economic and social policies are often directed at a nation-state level. The random fields $\{X_{i,t}\}$ and $\{Y_{i,t}\}$ respectively represents the temperature and the count of conflict events for country $i \in \{1, \ldots, L\}$ in time-period $t \in \{1, \ldots, T\}$, where L is the number of countries and T is the number of months. Additionally, let $Z_{i,t} \in \mathbb{R}^{J_1}$ represent the time varying covariates such as trade and economic development that impact likelihood of conflict in a region, with the jth time varying covariate denoted by $Z_{i,t,j}$. Similarly, $W_i \in \mathbb{R}^{J_2}$ represent country specific non-temporal features, with the jth such feature denoted by $W_{i,j}$. Here J_1 and J_2 represent the number of time-varying and not-varying covariates respectively.

Our first step is to estimate and remove seasonality and the long-term trend from the temperature data to create *temperature anomalies* or departures from the regional normal temperature values, after accounting for seasonal variations. For this, for each country $i \in \{1, \ldots, L\}$, we compute and subtract the monthly means from the temperature data, followed by subtraction of a smooth linear trend. The residuals from the above de-seasonalization and de-trending are considered for use as covariates for the conflict-count modeling. We perform separate analysis for the cases where the residuals are positive and where they are negative. More precisely, let the trend and seasonality component in the time series for the ith country be collected together in $\hat{X}_{i,t}$. Then the temperature residuals or anomalies are defined as

$$R_{i,t} = X_{i,t} - \hat{X}_{i,t}, \tag{1}$$

and these are used for further analysis. In Figure 1, we present the data $X_{i,t}$ and the trend and seasonality-based smoothing fits $\hat{X}_{i,t}$ for six illustrative countries, and in Figure 2 we present a global heat map of $|R_{i,t}|$.

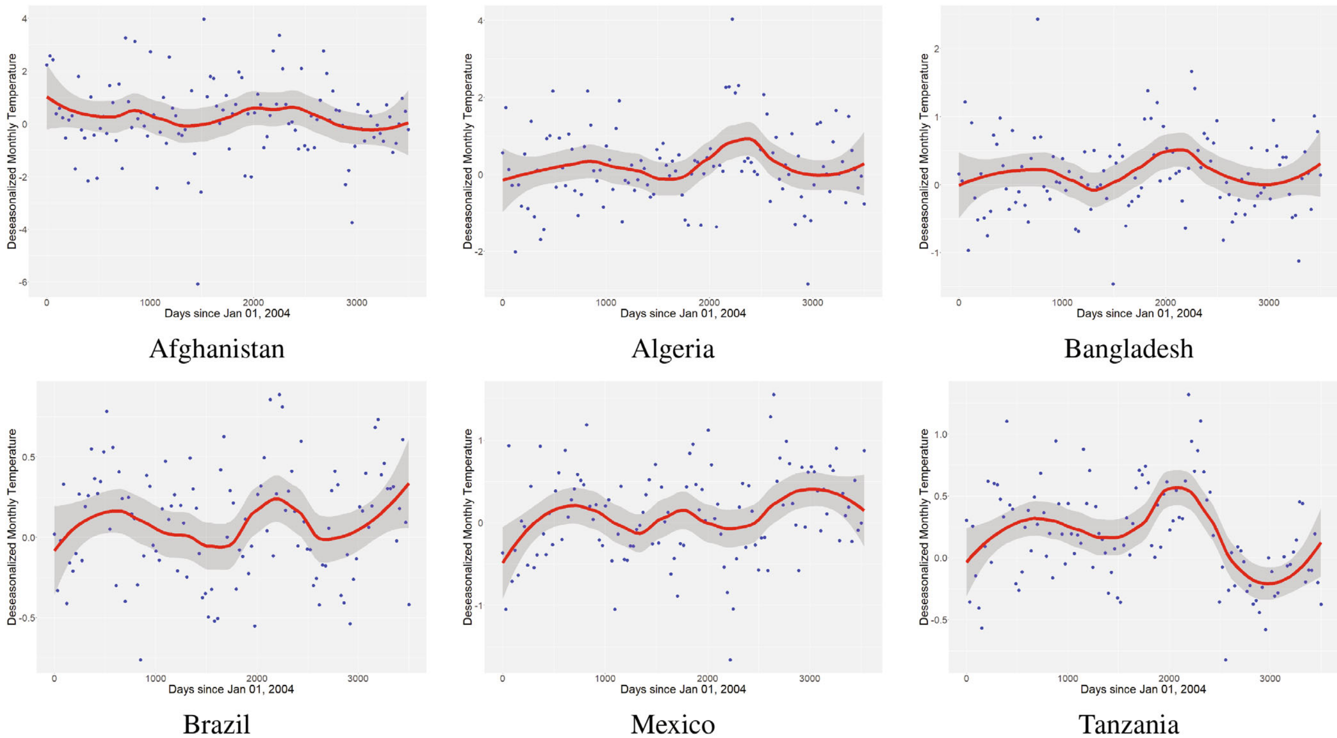

FIGURE 1 Temperature data $X_{i,t}$ and the seasonality and trend adjusted fits $\hat{X}_{i,t}$ for six representative countries.

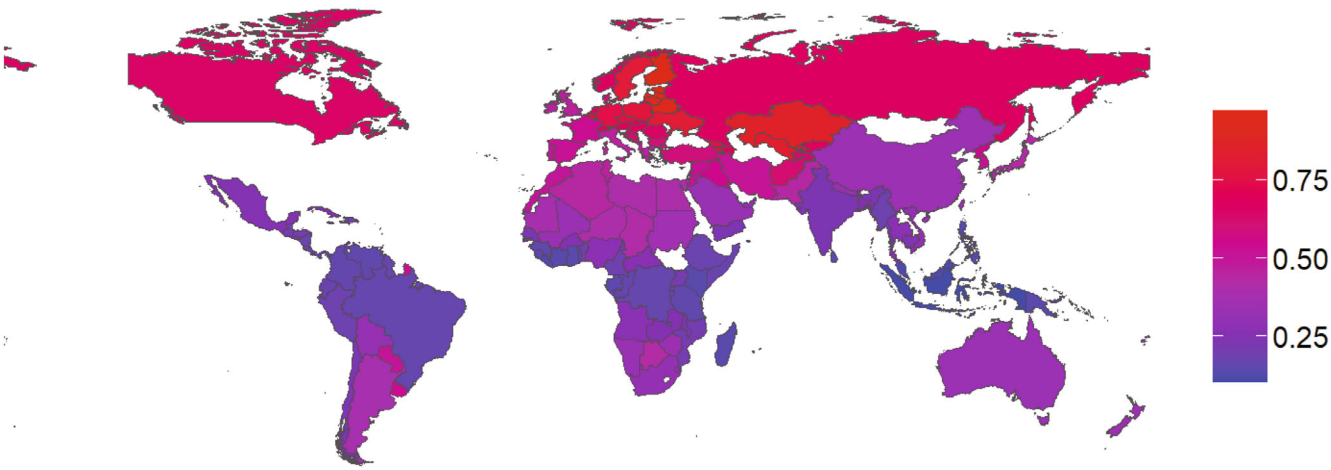

FIGURE 2 Heatmap of the average of the absolute values of temperature anomalies $|R_{i,t}| = \left|X_{i,t} - \hat{X}_{i,t}\right|$ for countries under study.

Two cases are considered for analyses, namely where we use as covariates $R_{i,t,+} = \max\{0, R_{i,t}\}$ and $R_{i,t,-} = \max\{0, -R_{i,t}\}$ thus studying "warm/hot" temperature anomalies separately from "cold" anomalies. A further study was performed using $|R_{i,t}|$ as a covariate but not reported here: the finding from this largely aligns with the results were $R_{i,t,+}$ is used as a covariate.

It is reasonable to assume that the baseline values of the climate variables like temperature or precipitation are not drivers of conflicts in any place at any season, but major deviations from the baselines may cause stress and affect societal relations. Thus, we use the residuals $\{R_{i,t}\}$ as input variables to study societal conflicts. This variable, along with other covariates, are used in a Bayesian hierarchical model to study the relationship between the number of occurrences of conflict events and temperature anomalies, controlling for a variety of social, political, and economic features.

Let the expected number of conflicts be given by the latent, unobserved random field $\{\mu_{i,t}\}$. Define, for any $t \in \{1, 2, \ldots, T\}$ the vector $\mu_{*,t} = (\mu_{1,t}, \ldots, \mu_{L,t})$. The framework for this study in terms of this latent process is as follows:

$$[Y_{i,t}|\mu_{i,t}] \sim \text{Negative Binomial } (r_t, p_{i,t}), \tag{2}$$

$$\text{such that } \mathbb{E}Y_{i,t} = \left(1 - p_{i,t}\right)^{-1} p_{i,t} r_t = \mu_{i,t},$$

$$\log(\mu_{*,t}) \sim GP\left(\eta_{*,t}, K_{\kappa,\phi}\right), \tag{3}$$

$$\eta_{*,t} = \beta_0 + \Gamma\left(\log(\mu_{*,t-1}) - \eta_{*,t-1}\right) + \beta_2 R_{i,t} + \sum_{j=1}^{J_1} \beta_{3,j} Z_{i,t,j} + \sum_{j=1}^{J_2} \beta_{4,j} W_{i,j}, \tag{4}$$

$$r_t \overset{i.i.d.}{\sim} \text{Poisson}(R), \tag{5}$$

$$\boldsymbol{\theta} = \left(\beta_0, \Gamma, \beta_2, \beta_{3,1}, \ldots, \beta_{3,J_1}, \beta_{4,1}, \ldots, \beta_{4,J_2}, \kappa, \phi, R\right) \sim \pi(\cdot). \tag{6}$$

In the above, $\boldsymbol{\theta}$ is the collection of all hyperparameters of the system, for which we use a generic notation $\pi(\cdot)$ for the prior distribution in (6). Details about the choice of priors will be specified later. We adopt a Negative Binomial in (2) owing to the presence of overdispersion in the data. The expected count of conflicts has an autoregressive structure, and its mean is a function of exogenous variables $R_{i,t,+}$ (or $R_{i,t,-}$ or $|R_{i,t}|$, the latter case not reported here), $Z_{i,t,j}$'s and $W_{i,j}$'s. The spatial dependencies in the $\{\log(\mu_{i,t})\}$ process is captured through the Gaussian process given in (3) using the mean function $\eta_{*,t}$ and covariance kernel K with hyperparameters κ and ϕ. The details of the the covariance kernel are discussed shortly below. Since spatial dependencies are accounted with the kernel K, we assume that the matrix Γ is diagonal with the ith diagonal element being γ_i.

For the MCMC implementation of (2)–(6), we assign independent priors to several of the parameters as follows

$$\begin{aligned}
\beta_0 &\sim \mathbb{N}(0, \sigma_0^2),\\
\beta_2 &\sim \mathbb{N}(0, \sigma_2^2),\\
\beta_{3,j} &\sim \mathbb{N}(0, \sigma_{j,3}^2)\ \forall j \in \{1, 2, \ldots, J_1\},\\
\beta_{4,k} &\sim \mathbb{N}(0, \sigma_{k,4}^2)\ \forall k \in \{1, 2, \ldots, J_2\},\\
\sigma_0^{-2}, \sigma_2^{-2}, \sigma_{j,3}^{-2}, \sigma_{j,4}^{-2}, R &\sim \text{Gamma}(4, 4).
\end{aligned} \tag{7}$$

For the parameters $\gamma_i = \{1, \ldots, L\}$, we assign a horseshoe regularizing prior (Carvalho et al., 2009) as in Equation (8),

$$\begin{aligned}
\gamma_j &\sim \mathbb{N}(0, \tau^2 \lambda_j^2)\ \forall j \in \{1, \ldots, i-1, i+1, \ldots, L\},\\
\tau &\sim \mathbb{C}^+(0, 1),\\
\lambda_j &\sim \mathbb{C}^+(0, 1),
\end{aligned} \tag{8}$$

where, τ is the global shrinkage parameter, λ_j's are the local shrinkage parameters, and $\mathbb{C}^+(0, 1)$ denotes the half-Cauchy distribution with probability density function given by $f(x) = \frac{2}{\pi}(1 + x^2)^{-1}$ for $x > 0$. While it is important to consider the spatial influence of other regions, especially for countries facing significant ongoing conflicts, which are likely to be major sources of global conflicts, estimating all the parameters for each country without regularization can lead to over fitting of the model. In light of this, we use the regularizing prior to assess the spatial effects of major sources of conflict on other regions.

We have studied the above model using several choices for the kernel K and its associated hyper-parameters for the Gaussian process in (3). The real data analysis results reported below are for the case where a Matérn kernel (see Giorgi and Diggle (2017); Higdon (1998); Stein (1999))

$$K(u; \phi, \kappa) = \frac{\Gamma(\kappa + 1)^{1/2} \kappa^{(\kappa+1)/4} u^{(\kappa-1)/2}}{\pi^{1/2} \Gamma((\kappa + 1)/2) \Gamma(\kappa)^{1/2} (2\kappa^{1/2}\phi)^{(\kappa+1)/2}} \mathcal{K}_\kappa(u/\phi), u > 0, \tag{9}$$

is used. Here, $\mathcal{K}_\kappa(\cdot)$ is the modified Bessel function of the third kind of order κ (Abramowitz & Stegun, 1965). We have used a robust version of the Mahalanobis distance between two points as the metric of choice for the reported results, and obtained the maximum a posteriori estimates $(\kappa, \phi) = 0.75, 0.63$, which we use in the reported analysis. However, on using (κ, ϕ) in a wide interval ($\pm 10\%$ around the above values) produces similar final results, consequently, the results seem to be robust against hyper-parameter values.

In addition, we have conducted the data analysis with numerous other choices of the distance metric, kernel function, and hyperparameters for the kernel functions. In particular, we have experimented with angular distances, Euclidean distances, Euclidean distance after converting the data to directional data, and distance based on principal components, the Laplace and Gaussian kernels with multiple choices of hyperparameters, the linear kernel and the Matérn kernel with various other choices of hyperparameters, and various combinations of the above.

Apart from studying the case where (κ, ϕ) is optimized from the data (thus corresponding to an empirical Bayesian approach), and the case where we have assigned priors on (κ, ϕ), which essentially corresponds to a choice of an infinite mixture of Matérn kernels. A small number of the results from these additional experiments are reported in the supplementary materials for comparison. The overall results, and in many cases the finer details like posterior means, variances and lengths of credible intervals of individual parameters, are singularly consistent across such choice of kernels, hyperparameters and distance metrics, thus exhibiting robustness of the results reported below.

We have primarily used a random walk Metropolis algorithm for the computations reported in this article and in the supplementary materials. However, experiments with other computational approaches, like the use of Integrated Nested Laplace Approximation (INLA) and Gibbs samples (using the JAGS software) have also been conducted. We include some of the results from these computations in the supplementary materials. There are no significant variation in the results or findings using these alternative computational approaches, again exemplifying robustness of the results. The computational speeds differed between softwares and tools used, and it is conceivable that the accuracy of the results may also depend on the approximations used in various algorithms. We found that the computations are considerably extended when we use an infinite mixture of Matérn kernels corresponding to a fully Bayesian hierarchical model. Computations were faster with INLA and with approximate Bayesian computations, but it is not certain that the theoretical foundations of these techniques relate to the statistical framework used in this article. In view of these issues, we adopted a random walk Metropolis algorithm as the main computational technique in this article.

4 | DATA AND VARIABLES

4.1 | Data sources

Our data primarily encompass a series of intrastate conflict-related variables, climate-specific measures, social fragmentation indicators, socio-economic variables, and global trade-related variables.

Our data source for conflicts and political violence is the *Integrated Crisis Early Warning System* (ICEWS)[2]. ICEWS offers disaggregated event data pertaining to a wide array of politically-relevant conflictive and cooperative social interactions. The data are derived from multilingual news (wire) reports via machine coded classification. ICEWS' corresponding events are relational, and encompass international and domestic events involving each and every country in the world aside from purely domestic US-based events. Our focus is on domestic conflictive events within the ICEWS data. For these conflictive events, we follow standard approaches (Chiba & Gleditsch, 2017; Orazio & Yonamine, 2015) in dividing these into material and verbal conflict events. Material conflict encompasses actions such as strikes and protests, destruction of public property, political killings and military assaults, suicide bombings, and government repression. Verbal conflict represents non-physical conflictive interactions such as threats of violence, rejections of cooperation, or accusations of abuse. Each corresponding conflict event is attributed to specific source and target actors. ICEWS' available actor designations are extensive and include information on a given actor's country and socio-political role. We retain three groups of source and target actors for our analysis: citizen actors (abbreviated as *civ*), government actors (abbreviated as *gov*), and armed non-state actors (abbreviated as *reb*). Citizen actors are unarmed domestic actors including references to general populations, civilians, protesters, or mobs, as well as entities such as businesses, non-governmental organizations, and the media. Armed non-state actors include rebels, separatists, insurgents, gangs, and criminals. Government actors include the general government, elected or appointed government officials, the police, the military, and the judiciary. For a given pair of actors, we follow extant research (Bagozzi, 2015; Chiba & Gleditsch, 2017) by aggregating all corresponding

[2] https://dataverse.harvard.edu/dataverse/icews

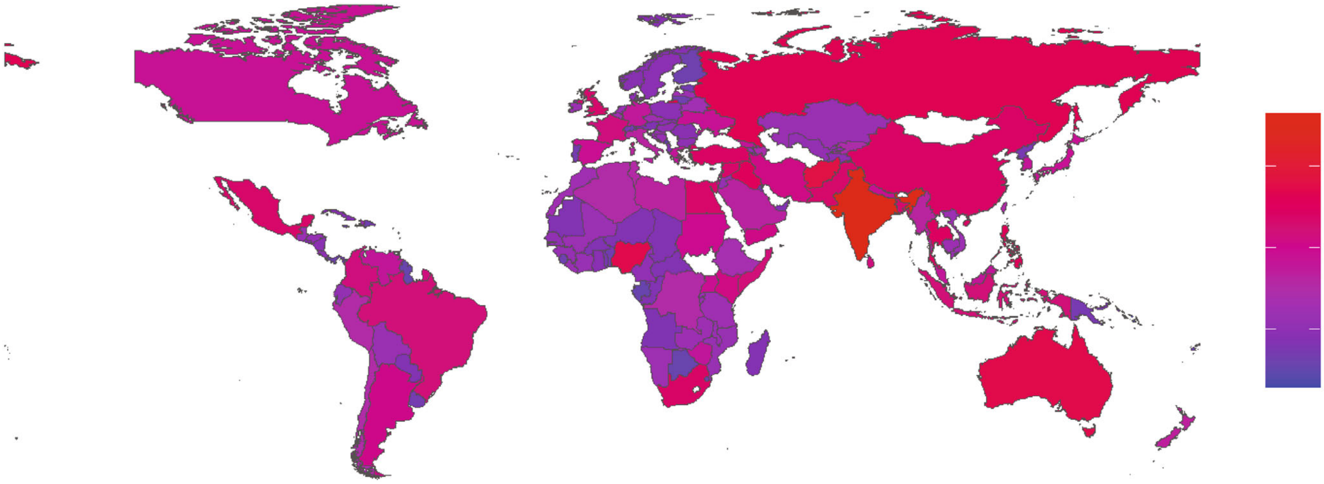

FIGURE 3 Heatmap of natural logarithm of average conflict event counts globally for all years from 2003 to 2013. The country specific values of conflict is computed by dividing the sum total of all the monthly material conflict counts for a country by the total number of months, and then taking a natural logarithm of the resulting average monthly conflict counts.

intrastate conflict events to country-month counts. Altogether, our assembled panel dataset contains 11 years (2003–2013) of observations across 173 countries at a monthly level. Figure 3 presents the sample-period average level of domestic material conflict for most countries (excluding the US) on a global map to provide a visual representation of the spatial variation in this variable. This figure reports the monthly average count of material conflict for each country on a logarithmic scale, computed by dividing the sum total of all material conflict for a country over the entire sample period by the total number of months (132 total months), and then taking a natural logarithm.

We source our data on global temperatures from the Berkeley Earth Surface Temperature (BEST) database[3]. The BEST dataset is constructed from land-based climate station data with various levels of temporal resolution such as daily, weekly, monthly, and yearly levels. For each country, the dataset offers different levels of spatial resolution such as at the individual station level, the major city level, and the country level. The BEST dataset incorporates data from approximately 39,000 earth stations. By contrast, the NOAA and the UK's CRU Hadley center databases includes data from 5000 to 7000 different sources. Therefore, the precision and resolution of the BEST data is considerably higher than several prominent alternatives. We use BEST-derived country-level average temperature data at the monthly aggregation to match the spatial and temporal resolutions of the other datasets discussed below.

We account for three distinct dimensions of social fragmentation (Alesina et al., 2003), which are measured as the probability that a pair of randomly selected people within a given country who do not share a particular social characteristic. We include measures of ethnic, linguistic, and religious fractionalizations respectively denoted by Ethnic_i, Language_i, and Religion_i for country i. These fractionalization measures are often highlighted as important social confounds within extant studies of cross-national civil conflict (Fearon & Laitin, 2003; Janus & Riera-Crichton, 2015). We then account for the overall level of development in country i using the HDI produced by UNDP (2018) in HDI_i. This measure denotes the geometric mean of countries' time-varying levels of living standards, health, and education.

Socio-economic drivers like trade and overall levels of development are also known to be associated with social conflicts (Calì & Mulabdic, 2017; Janus & Riera-Crichton, 2015; Kim & Conceição, 2010). To control for these potential economic confounds, we first use data on country-level exports for different sectors such as commodity exports, agricultural exports, and manufacturing exports from the World Bank's multi-country economic time series[4]. Economic growth on the one hand can improve the resources available in a country and reduce conflict. On the other hand, increases in economic activities such as commodity production and manufacturing are associated with acquisition of land and other resources, and sometimes displacements of populations leading to conflicts. For these reasons, accounting for exports as a time varying control is important. Our export and trade related covariates are $Commodity\_Exports_{i,t}$,

[3] https://climatedataguide.ucar.edu/climate-data/global-surface-temperatures-best-berkeley-earth-surface-temperatures
[4] https://microdata.worldbank.org/index.php/home

Agriculture_Exports$_{i,t}$, and *Manufacturing_Exports*$_{i,t}$, which are respectively the total commodity exports, agricultural produce exports and manufactured product exports of country i in time period t.

4.2 | Data analysis schemes

We estimated several models to investigate the relation between temperature anomalies and intrastate conflicts. At the top level we analyze the relation between temperature deviations and either (*i*) material conflict or (*ii*) verbal conflict. At the next level we analyze the relation between temperature deviations and material conflict between different pairs of actors, namely *gov-civ*, *gov-reb*, and *civ-reb*. Then, we study whether there is a difference between which actor (*government, civilian, rebel*) initiates a conflict under a given set of conditions.

Accordingly, we first analyze the response variables Material_conflict$_{i,t}$ and Verbal_conflict$_{i,t}$, which are the monthly counts of all material and verbal conflicts in country i during month t between all pairs of actors. We constructed these variables from the ICEWS data by aggregating 6 measures from the corresponding conflict types involving the following non-directed actor pairings: (i) *gov-reb*, (ii) *gov-civ*, and (iii) *reb-civ*. Next, we complement this analysis by disaggregating by actor and conflict type. We also study which actors are more likely to initiate conflicts. In this article, we present the disaggregated actor models for material conflict only. Verbal conflicts within our disaggregated actor framework entail higher levels of sparsity as compared to our actor-disaggregated material conflict models, but result in no statistical challenges and produce substantially similar insights to those reported presently in our article. For brevity, for the disaggregated studies we only report results for the case where positive temperature anomalies $R_{i,t,+}$ is used.

The software code for this study, as well as a synthetic data product that closely imitates the original (partially embargoed) data, is available here: https://github.com/Ujjal-Mukherjee/Temperature-Anomaly-Conflict-Code.git.

5 | MODEL ESTIMATION RESULTS

5.1 | Model estimation results for material conflict

We begin by presenting the results for material conflicts in Tables 1 and 2, using positive ($R_{i,t,+}$) and negative ($R_{i,t,-}$) temperature anomalies respectively. In both tables, we report the posterior mean, standard deviation, 2.5% quantile, the median and the 97.5% quantile for the parameters of interest, along with the posterior probability that the parameter takes a value at or below zero. This last quantity may be used to compute the depth of zero in the posterior distribution, and values close to zero or one denote that true parameter value is extremely unlikely to be zero. Thus, these probabilities help in evaluating the importance of retaining a covariate and its corresponding parameter in the model framework. For example, if zero was within the 95% credible interval given by the 2.5% and 97.5% quantiles of the posterior, then the corresponding probability in the last column of Table 1 (or Table 2) would be in the range $(0.025, 0.975)$.

TABLE 1 Results from MCMC computations when using positive temperature anomalies on the material conflict data.

Variables	Post. mean	Std. dev.	Q (2.5%)	Median	Q (97.5%)	$\mathbb{P}$ (Par.≤ 0)
(Intercept)	1.18	0.05	1.15	1.15	1.33	0.00
Language	0.38	0.07	0.34	0.35	0.62	0.00
Religion	−0.11	0.02	−0.16	−0.11	−0.11	1.00
Ethnicity	−0.07	0.04	−0.08	−0.08	0.07	0.93
HDI	−0.99	0.06	−1.19	−0.96	−0.96	1.00
Agriculture exports	0.11	0.01	0.09	0.10	0.14	0.00
Manufacturing exports	0.08	0.04	0.01	0.10	0.10	0.02
Commodity exports	0.12	0.01	0.09	0.13	0.13	0.00
Pos. temp. anomaly	0.39	0.03	0.37	0.37	0.47	0.00

TABLE 2 Results from MCMC computation when using negative temperature anomalies on the material conflict data.

Variables	Post. mean	Std. dev.	Q (2.5%)	Median	Q (97.5%)	$\mathbb{P}$ (Par.$\leq$ 0)
(Intercept)	1.24	0.04	1.16	1.22	1.32	0.00
Language	0.03	0.13	−0.15	0.02	0.50	0.22
Religion	0.25	0.06	0.22	0.23	0.36	0.01
Ethnicity	−0.21	0.09	−0.46	−0.19	−0.03	0.98
HDI	−0.21	0.21	−0.88	−0.12	−0.09	1.00
Agriculture exports	−0.07	0.04	−0.22	−0.07	−0.03	0.98
Manufacturing exports	−0.16	0.06	−0.18	−0.18	0.01	0.97
Commodity exports	0.19	0.04	0.09	0.21	0.25	0.00
Neg. temp. anomaly	−0.11	0.06	−0.18	−0.11	0.10	0.95

We find that essentially all the variables of interest are significant in this study, but there are important differences between the cases where a warm place gets warmer (a unit increase in positive temperature anomalies $R_{i,t,+}$, illustrated in Table 1) compared to when a cold place gets colder (illustrated in Table 2). Significantly, we find that a warm temperature anomaly has a significant positive contribution towards increasing material conflicts, even after accounting for seasonality, trend, social, economic and other variables. For negative temperature anomalies, we find that a unit reduction of temperature is associated with decreased number of conflicts. Religious and ethnic diversity, as well as improvements in wellbeing conditions measured by the HDI tend to bring down material conflict counts.

This analysis offers evidence consistent with Burke et al. (2009), Hsiang et al. (2013), Bollfrass and Shaver (2015), Landis (2014) and others in demonstrating that temperature deviations do indeed increase social conflict at a global scale—even after accounting for a variety of potential confounds and associated spatial-temporal dynamics. When juxtaposed against this result, our finding that a country's HDI instead reduces material conflict within this same global sample provides a critical sanity check for our framework: it stands to reason that with greater economic, health, and educational developments there are fewer societal grievances and stronger institutions for managing those grievances that do arise. This rationale, and our HDI-based finding overall, again aligns well with the extant literature (e.g., Kim & Conceição, 2010).

Our findings for ethnic and religious fractionalization are not always consistent with extant (null) findings for these variables within the literature. That being said, most extant investigations into these variables focus only on civil conflict and/or civil war, which represent a small subset of the conflicts considered in our study. Likewise, most extant studies do not model multiple fractionalization measures simultaneously, which complicates their individual interpretations in light of their respective correlations. In Table 1 the trade-related variables are each reliably associated with the global incidence of material conflict. This is a contrary result to common jurisprudence that economic development through external trade should be associated with overall a reduction in conflicts. It is still likely the case that trade and economic development in the long run does reduce risk of conflicts, as indicated by our HDI finding. However, in the short run, trade can exacerbate conflicts. This in part may be due to the higher exposure that it creates for some countries in relation to trade shocks and trade volatility, which have been linked to due to various forms of social conflict (Calì & Mulabdic, 2017; Janus & Riera-Crichton, 2015). This may also be due to pressures on resource reallocation and redistribution between different sectors such as those of agricultural, commodity, and industry, and corresponding implications for jobs and wages within these sectors. Examples of conflicts arising due to the latter dynamics are provided by Fox (2015); Allen (2017); Herrera and Martinez-Alvarez (2022).

For the above analysis, the Markov chain Monte Carlo (MCMC) computations were run with a burn-in of 2000 steps, and results were collected for 25,000 iterations using a thinning parameter of 5. We implement several tests to validate the convergence of the MCMC algorithm. In Figure 4, we provide auto-correlation plots for some of the parameters. We can observe from these auto-correlation plots that the MCMC chains do not exhibit much long-term correlation, indicating good convergence. These figures and other diagnostic studies we carried out indicate that the posterior convergence of the MCMC estimate is acceptable. In Figure 5, we plot the observed versus predicted values of conflict on a logarithmic scale when using positive temperature anomalies.

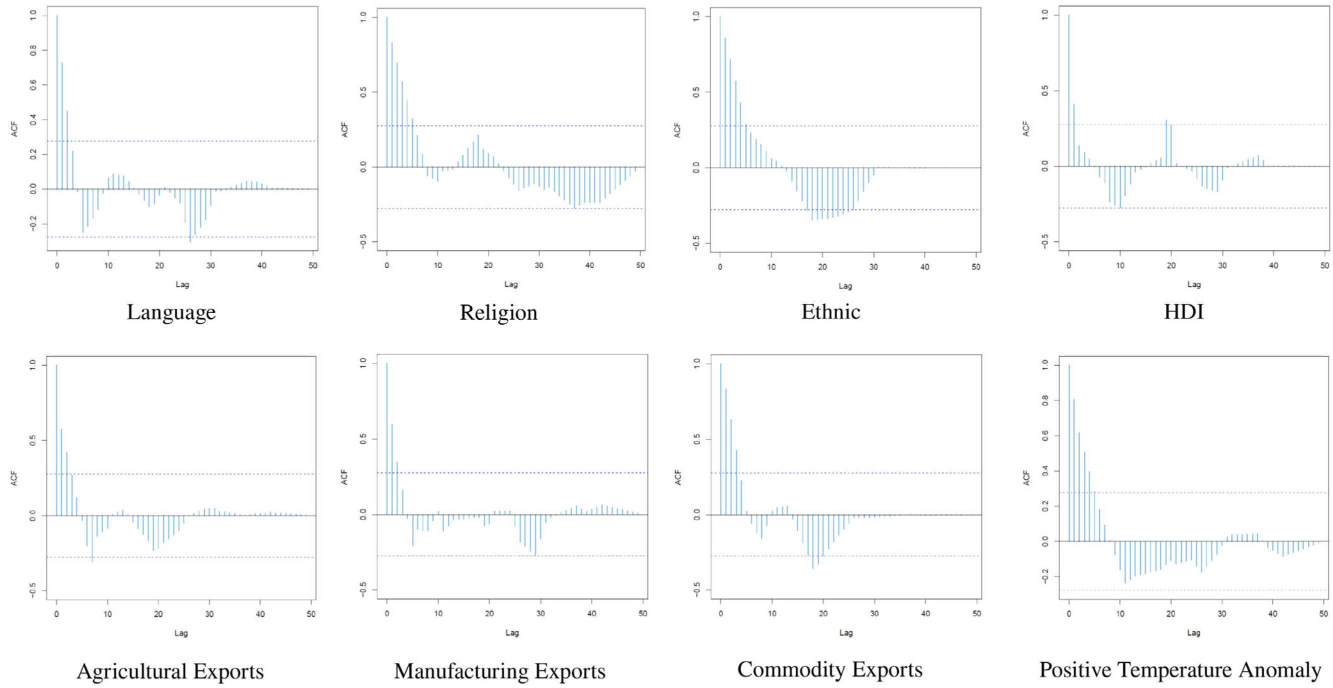

FIGURE 4 Auto-correlation plots for the MCMC computations on material conflict (corresponding to Table 1).

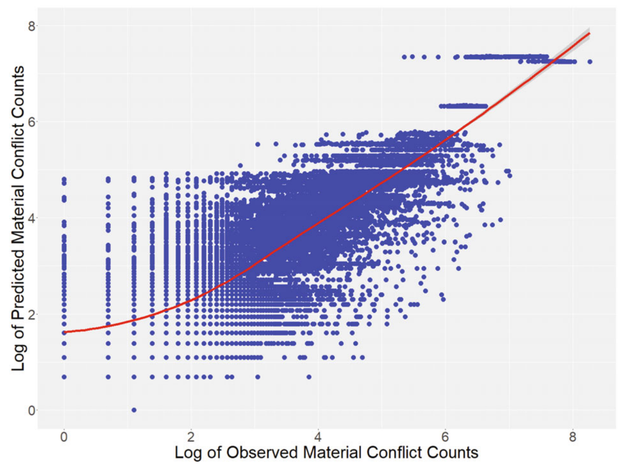

FIGURE 5 Scatterplot of observed versus predicted values of conflict from the final model.

5.2 | Model estimation results for verbal conflict

In Tables 3 and 4, we present the results for the case of verbal conflicts for positive and negative temperature anomalies respectively. Some of the control variables, like HDI and commodity exports when using positive anomalies and several others when using negative anomalies, are not significant. Most importantly for our assessment, however, we find that positive temperature anomalies continue to increase this alternate form of social conflict.

The above findings continue to reinforce our earlier conclusions regarding the positive (i.e., conflict inducing) relationship between positive temperature anomalies and social conflict. Our findings for verbal conflict furthermore suggest that the significant associations between temperature anomalies and verbal threats, accusations, and ultimatums may serve as an important leading indicator for temperature's relationship with material conflicts, given the past role of verbal conflict as an input for material conflict forecasting efforts (Orazio & Yonamine, 2015). At the same time, our Table 4 findings also suggest that temperature's effect may be stronger for material conflicts than for verbal conflicts. The latter

TABLE 3 Results from MCMC computations when using positive temperature anomalies on the verbal conflict data.

Variables	Post. mean	Std. dev.	L.95.C.I.	Median	U.95.C.I	ℙ (Par.≤ 0)
(Intercept)	1.71	0.09	1.30	1.75	1.75	0.00
Language	0.16	0.14	−0.02	0.14	0.70	0.06
Religion	−0.19	0.13	−0.26	−0.26	0.22	0.88
Ethnicity	−0.19	0.18	−0.75	−0.14	0.10	0.97
HDI	−0.03	0.32	−1.30	0.10	0.10	0.20
Agriculture exports	−0.08	0.05	−0.18	−0.09	0.10	0.92
Manufacturing exports	0.03	0.06	0.00	0.00	0.18	0.01
Commodity exports	0.05	0.13	−0.30	0.11	0.11	0.17
Pos. temp. anomaly	0.05	0.06	0.02	0.02	0.19	0.00

TABLE 4 Results from MCMC computation when using negative temperature anomalies on the verbal conflict data.

Variables	Post. mean	Std. dev.	L.95.C.I.	Median	U.95.C.I	ℙ (Par.≤ 0)
(Intercept)	0.73	0.10	0.65	0.77	1.01	0.00
Language	0.10	0.07	0.06	0.06	0.29	0.00
Religion	−0.02	0.08	−0.09	−0.01	0.28	0.88
Ethnicity	−0.22	0.06	−0.46	−0.19	−0.11	1.00
HDI	−0.26	0.10	−0.55	−0.23	−0.20	1.00
Agriculture exports	−0.01	0.10	−0.07	−0.01	0.30	0.86
Manufacturing exports	0.08	0.03	0.01	0.08	0.08	0.02
Commodity exports	0.12	0.10	−0.18	0.08	0.21	0.08
Neg. temp. anomaly	0.04	0.07	−0.07	−0.01	0.22	0.52

distinction, though nuanced, aligns well with Yeeles (2015), who finds temperature anomalies to be more reliably associated with lethal rather than non-lethal forms of urban social unrest. Further assessments of the interrelated associations of temperature anomalies with both verbal and material conflict thus is an important avenue for future research.

5.3 | Exploring different types of material conflict

The results presented above are based on the case where conflicts among the different actors (i.e., government, armed nonstate actors, and civilians) are aggregated together. In this section, we instead provide separate estimates for material conflicts between the different actors discussed above. This allows us to better evaluate whether positive temperature anomalies and related control variables exhibit distinct relationships with conflicts arising between different societal actors. Such disaggregated analyses thereby enable us to further evaluate the actor-contingent effects of our earlier temperature-based findings, which is consistent with the climate-conflict literature's recent emphasis on the identification of contingent and/or complex causal pathways underpinning the effects of climate variability upon social conflict (von Uexkull & Buhaug, 2021).

In Tables 5–7 we provide estimates for the rate of material conflict between different combinations of our adversarial actors, when positive temperature anomalies are considered. While temperature anomalies exhibit a positive effect on material conflict for government-civilian and government-rebel actors, we do not find that temperatures reliably induce conflict among rebel and civilian actors. This suggests that the conflict-inducing effects of temperature deviations primarily operate through civilian/rebel-government conflict (e.g., protests, rebel attacks on government resources, or state repression) rather than through increased rates of rebel violence against civilians. This latter finding that material conflicts between citizens and armed non-state actors are not reliably affected by temperatures anomalies is contrary to at least

TABLE 5 Results from MCMC computation when using positive temperature anomalies on the material conflicts between government and citizen actors.

Variables	Post. mean	Std. dev.	L.95.C.I.	Median	U.95.C.I	ℙ (Par.≤ 0)
(Intercept)	0.49	0.15	0.42	0.42	0.91	0.00
Language	−0.20	0.15	−0.30	−0.22	0.41	0.94
Religion	0.07	0.07	0.02	0.06	0.33	0.02
Ethnicity	0.06	0.05	−0.02	0.06	0.16	0.15
HDI	−0.31	0.22	−1.28	−0.24	−0.19	1.00
Agriculture exports	−0.10	0.06	−0.20	−0.09	0.03	0.92
Manufacturing exports	−0.12	0.13	−0.47	−0.06	0.10	0.94
Commodity exports	0.31	0.12	0.17	0.26	0.57	0.01
Pos. temp. anomaly	0.07	0.02	0.02	0.08	0.22	0.02

TABLE 6 Results from MCMC computation when using positive temperature anomalies on material conflict between government and rebel actors.

Variables	Post. mean	Std. dev.	L.95.C.I.	Median	U.95.C.I	ℙ (Par.≤ 0)
(Intercept)	2.44	0.17	1.88	2.46	2.61	0.00
Language	0.21	0.09	0.00	0.23	0.53	0.01
Religion	0.10	0.06	−0.15	0.11	0.18	0.04
Ethnic	−0.20	0.06	−0.23	−0.23	−0.09	1.00
HDI	−0.21	0.27	−1.19	−0.13	−0.08	1.00
Agriculture exports	0.35	0.08	0.12	0.37	0.51	0.00
Manufacturing exports	0.05	0.05	−0.09	0.05	0.14	0.05
Commodity exports	−0.40	0.09	−0.56	−0.44	−0.07	0.99
Pos. temp. anomaly	0.09	0.10	0.06	0.06	0.51	0.00

TABLE 7 Results from MCMC computation when using positive temperature anomalies on material conflict data between citizen and rebel actors.

Variables	Post. mean	Std. dev.	L.95.C.I.	Median	U.95.C.I	ℙ (Par.≤ 0)
(Intercept)	3.29	0.42	2.05	3.42	3.62	0.00
Language	0.08	0.12	−0.17	0.08	0.30	0.31
Religion	0.06	0.09	−0.18	0.10	0.17	0.16
Ethnicity	−0.30	0.19	−0.73	−0.35	−0.06	0.99
HDI	−0.48	0.28	−1.15	−0.36	−0.20	1.00
Agriculture exports	0.06	0.16	−0.15	0.05	0.30	0.43
Manufacturing exports	0.84	0.22	0.20	0.89	1.09	0.00
Commodity exports	−0.90	0.23	−1.18	−0.86	−0.29	0.98
Pos. temp. anomaly	0.23	0.15	−0.01	0.24	0.44	0.09

some past research regarding the effects of droughts on rebel violence against civilians (e.g., Bagozzi et al., 2017). Rather, temperature deviations appear instead to be more directly and reliably associated with lower level forms of social conflict involving rebel-government and civilian-government interactions. This aligns well with the literature. For example, our positive and reliable finding concerning temperature's relation with civilian-government material conflict is consistent with research suggesting that temperature variability spurs aggression, food insecurities, and low level conflict (e.g., protests) directed towards governments by citizens in urban contexts (e.g., Bellemare, 2015; Koren et al., 2021; Yeeles, 2015). Illustrative examples likewise suggest that these dynamics can also arise in rural settings, such as in the case of recent violent farmer protests in India in 2021–2022 (Levien, 2018).

5.4 | Who initiates temperature-induced conflict?

An interesting aspect of the ICEWS conflict data—and our resultant material and verbal conflict measures—is that it is classified by which actor initiates each conflict. For example, the variable *govreb_matconf* indicates the count of material conflicts that governmental actors initiated against rebel actors. In this section, we present the results of material conflicts after disaggregating these conflicts by each initiating actor. Tables 8–10 represents the results of the association between positive temperature anomalies and other covariates on material conflicts that were initiated by government, citizen, and rebel actors respectively. From the results, we find that all actors tend to increase their intensity of conflict initiation as a result of positive temperature anomalies. However, interestingly, we find that the strongest association is for rebel actors. For rebel actors, the posterior mean for the slope parameter corresponding to positive temperature anomalies is 0.07 with a 95% confidence band of [0.01, 0.15]. The fraction of the posterior samples less than zero in this case is 0.03. Following

TABLE 8 Results from MCMC computation when using positive temperature anomalies on material conflict initiated by government actors.

Variables	Post. mean	Std. dev.	L.95.C.I.	Median	U.95.C.I	$\mathbb{P}$ (Par.$\leq$ 0)
(Intercept)	0.98	0.10	0.90	0.90	1.24	0.00
Language	0.50	0.09	0.24	0.55	0.56	0.00
Religion	−0.18	0.08	−0.31	−0.24	−0.04	1.00
Ethnicity	−0.26	0.11	−0.33	−0.32	0.03	0.97
HDI	−0.09	0.25	−0.71	−0.15	0.27	0.68
Agriculture exports	−0.07	0.07	−0.11	−0.11	0.10	0.89
Manufacturing exports	0.13	0.09	0.04	0.10	0.42	0.00
Commodity exports	0.05	0.06	−0.12	0.05	0.15	0.12
Pos. temp. anomaly	0.00	0.07	−0.10	−0.00	0.09	0.73

TABLE 9 Results from MCMC computation when using positive temperature anomalies on material conflict initiated by citizen actors.

Variables	Post. mean	Std. dev.	L.95.C.I.	Median	U.95.C.I	$\mathbb{P}$ (Par.$\leq$ 0)
(Intercept)	1.94	0.14	1.53	2.01	2.05	0.00
Language	0.37	0.08	0.28	0.34	0.70	0.00
Religion	−0.14	0.03	−0.18	−0.14	−0.06	0.99
Ethnicity	−0.18	0.11	−0.38	−0.15	0.10	0.94
HDI	0.03	0.28	−1.02	0.15	0.16	0.22
Agriculture exports	−0.15	0.14	−0.34	−0.19	0.17	0.83
Manufacturing exports	0.18	0.17	−0.23	0.29	0.29	0.26
Commodity exports	0.11	0.07	−0.01	0.12	0.31	0.03
Pos. temp. anomaly	0.03	0.02	−0.02	0.04	0.10	0.14

TABLE 10 Results from MCMC computation when using positive temperature anomalies on material conflict initiated by rebel actors.

Variables	Post. mean	Std. dev.	L.95.C.I.	Median	U.95.C.I	$\mathbb{P}$ (Par.$\leq$ 0)
(Intercept)	2.48	0.29	1.41	2.53	2.67	0.00
Language	−0.14	0.14	−0.28	−0.17	0.52	0.92
Religion	0.01	0.11	−0.24	0.04	0.18	0.43
Ethnicity	0.02	0.04	−0.02	0.02	0.12	0.31
HDI	−0.32	0.19	−1.12	−0.25	−0.24	1.00
Agriculture exports	0.09	0.06	−0.16	0.09	0.12	0.07
Manufacturing exports	0.04	0.09	−0.02	0.01	0.32	0.12
Commodity exports	−0.02	0.09	−0.14	−0.03	0.17	0.79
Pos. temp. anomaly	0.07	0.04	0.01	0.05	0.15	0.03

rebel actors, citizen actors exhibit the next strongest relation. Yet, in this case, the posterior mean of the slope parameter corresponding to positive temperature anomalies is 0.03, with a 95% confidence band of $[-0.02, 0.10]$ and only a 0.14 fraction of the posterior samples falling on the negative side of the real line. By contrast, and not surprisingly, government actors only respond to conflicts that are initiated by other actors as a result of temperature anomalies. Indeed, 72% of the conflicts involving rebels are initiated by rebels. By comparison, the same quantities for citizen and government actors are 65% and 35% respectively.

6 | CONCLUSION

Our study is predicated upon understanding the relation between temperature anomalies and social conflicts of different kinds among different groups of actors like government forces, armed non-state individuals and groups, and unarmed civilians. We have developed a Bayesian framework that is designed to address spatio-temporal dependencies in the different variables under study including temperature measurements and conflict counts, and can handle data from all parts of the world under a unified framework.

Two of the strongest criticisms one may make of the current literature on understanding the relation between climate change and social conflicts are that these studies suffer from a sampling bias due to dependent-variable sampling and "the streetlight effect" (Adams et al., 2018), and do not address the spatio-temporal dependencies in the data. In this study, we have proposed a framework that addresses both these criticisms. While not all forms of sampling bias are eliminated by considering data at the global scale and by considering both cases of violence and a lack of violence, clearly our study does not involve dependent-variable sampling. Our model also clearly involves spatio-temporal dependencies along with both endogenous and exogenous covariates.

In terms of statistical methodological development, future studies may focus on explicitly modeling the sampling bias in the data. We have used a separable framework where temporal dependence is modeled with an autoregression and spatial dependence is modeled with a Gaussian process. A smaller study that we carried out, not reported here, suggests that using a non-separable model does not result in significant difference in the findings. However, further studies on this topic are clearly needed. We engaged in in-depth robustness analysis using different distance metrics, kernels for Gaussian process and choice of kernel hyper-parameters. These results strongly suggest that the reported findings of this article are not artefacts of the modeling paradigm or choice of constants or priors, but are reflective of what the data tells us.

We have considered temperature anomalies as the main climate driver in this study, owing to its supreme importance, its presence in the existing literature and the availability of reliable data on temperature globally. Future research may additionally consider precipitation, intensity-duration-frequency of droughts, tropical storms or other climatic events, and various climate related indices like the Palmer drought index, tele-connections like the El-Nino Southern Oscillation (ENSO) and so on. Methodologically, inclusion of such additional climate-related variables in the model does not create any new challenges, however, availability of high quality data on many such variables worldwide remains a challenge. Similarly, additional control variables may also be included in our study as and when they are available. Our model could likewise be applied in future studies to evaluate the relationships between subnational social conflict data and subnational measures of climate change—an area of inquiry that is increasingly becoming an important compliment to country-level climate-conflict research (Bollfrass & Shaver, 2015; Koubi, 2019, 349)

Substantively, we find that temperature deviations are associated with material conflict, as well as with verbal conflict and with material conflicts specifically involving government and nonstate adversaries. By comparison, we do not find consistent evidence for temperature's impacts on material conflict between armed nonstate actors (e.g., rebels) and civilians. These countervailing results directly contribute to research on the role of climate change in social conflicts. Early studies in this area often reported contradictory results regarding climate variability's impacts on conflict (Buhaug, 2010; Burke et al., 2009, 2010; Hsiang et al., 2013; Koubi et al., 2012). More recent work has sought to bridge this divide by calling for research into the contingent and otherwise more complex effects of climate change on conflict (Koubi, 2019; von Uexkull & Buhaug, 2021). Our article has taken a step in this direction through its detailed modeling and analysis of temperature's effects on both material and verbal conflict, and of temperature's effects on different actor-specific subsets of material conflict events.

More generally, our results provide new insights into the complex relationship between climatic change, climate variability, and human societies. In doing so, we have identified a set of refined findings pertaining to which conflict processes, specifically, may be more and less exacerbated by temperature anomalies. These findings accordingly stand to improve environmental management and environmental cooperation efforts by clarifying the consequences of temperature deviations for social conflict. Our Bayesian modelling framework can likewise serve to facilitate future investigations by both researchers and practitioners into these and additional nuances. Together these contributions accordingly help to advance scientific understandings of two complex domains, and to shed new light on the current and potential future contributions of climate change to societal conflict.

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