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Climate change, temperature extremes, and conflict: Evidence from mainland Southeast Asia

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Abstract

We exploit 0.5°×0.5° raster data for mainland Southeast Asia from 2010 to 2020 to document a non-linear relationship between extreme temperature days and conflict. We show that the occurrence of conflict events increases with extreme *maximum* temperature days, whereas days with extreme *minimum* temperature decrease the occurrence of conflict. Because climate change makes both maximum and minimum temperature extremes more likely, these effects partially offset each other on aggregate. However, our results further suggest that the impact of extreme maximum and minimum temperature days differs for the type of conflict, actors involved and population affected, indicating complex distributional consequences.

Keywords: Climate change; adaptation; conflict; extreme temperature

JEL Codes: Q54; O13; H56; D74; P48.

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1 Introduction

Ongoing climate change implies an increased frequency of extreme weather events, and observed trends are projected to persist in the coming decades (IPCC, 2021). While adaptation to these trends is a private good, so that firms, households and governments could be expected to optimally update their behavior in presence of new extremes, institutional failure and credit constraints have raised concerns that climate change may disproportionately affect the more disadvantaged segments of the population. In particular, a growing literature documents the effects of climate change on instability and violent conflicts, emphasizing that regions heavily reliant on weather-sensitive natural capital and possessing limited capacity to cope with shocks are likely more vulnerable (Von Uexkull et al., 2016; Koubi, 2019; see also Burke et al., 2015).

This paper documents a non-linear effect of weather extremes on conflict incidence (i.e., the probability of a violent conflict occurring during a year, see Hsiang and Meng, 2014; McGuirk and Nunn, 2020). As climate change results in a gradual increase in average temperature, both maximum and minimum daily temperature are also expected to rise. Consequently, the likelihood of days with extreme maximum and minimum temperature will increase. And while extreme maximum temperature can negatively affect livelihoods, notably because of lower agricultural output and increased competition over resources (Breckner and Sunde, 2019), days with extreme high minimum temperature can potentially improve living conditions and increase the opportunity cost of violent conflict.[1] Moreover, failure to control for extreme minimum temperature could bias estimates associated with extreme maximum temperature whenever these two variables are correlated.

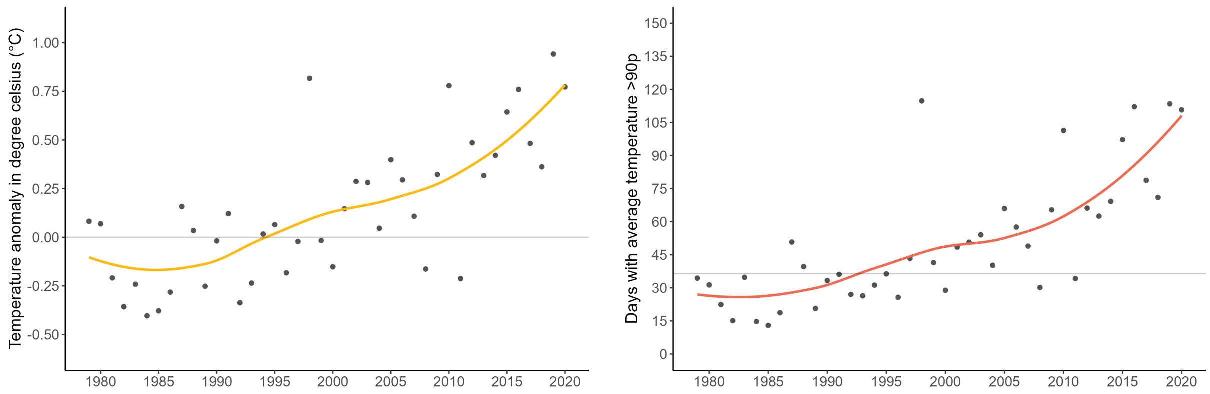
To document the non-linear impact of extreme temperature days on conflict events, we employ data for mainland Southeast Asia covering the period from 2010 to 2020 with sub-national cells of approx. 55 km by 55 km as units of observation.[2] While a wide majority of the existing literature focuses on Africa, Southeast Asia exhibits a number of vulnerability risk factors, such as an important agricultural sector, the presence of ethno-political discrimination and a

[1] For example, Tao et al. (2008) report that higher daily minimum temperature increase rice yields in China, and Nicholls (1997) shows that this effect also applies to wheat in relation to a reduced frost occurrence. The impact of extreme temperature is, however, context dependent (Welch et al., 2010), and we come back to the possibility of an agricultural channel below.

[2] The countries included in our analysis are Cambodia, Laos, Myanmar, Thailand, and Vietnam. As discussed below, we do not consider Malaysia because of data availability issues.

Figure 1: Trends in temperature in mainland Southeast Asia, 1979–2020

(a) Average temperature anomalies (b) Extreme temperature days



Notes: This figure is derived from temperature data for Cambodia, Laos, Myanmar, Thailand, and Vietnam for the period 1979–2020 (source: ECMWF-ERA5, Hersbach et al., 2020). Panel (a) reports difference in average temperature relative to a reference period defined from 1979 to 2009. Panel (b) shows the number of days per year with average daily temperature above the 90^{th} percentile defined on a 1979–2009 sub-monthly climate normal. See Section 2.1 for further details. The curve in each panel is a locally estimated scatterplot smoothing.

history of violence (Collier, 2000; Barnett and Adger, 2007).[3] In addition, observed changes in the local climate has been rapid and significant. This trend is illustrated in Figure 1, which reports temperature anomalies and extreme temperature days from 1979 to 2020. Providing empirical evidence on how climate change affects conflicts in this area is therefore an important contribution of our work.

However, our main contribution is to document the distinct role of extreme maximum and minimum temperature days on the occurrence of conflict events. Specifically, we define two day count indexes at the grid cell level based on reanalysis data from the European Centre for Medium-Range Weather Forecasts (ECMWF-ERA5, Hersbach et al., 2020). The first index is the number of days with maximum daily temperature in the 90^{th} percentile of the 1979–2009 sub-monthly climate normal.[4] We refer to these as days with extreme maximum temperature. The second index is the number of days with minimum daily temperature in the 90^{th} percentile of the 1979–2009 sub-monthly climate normal. We refer to these as days with extreme minimum

[3] For instance, Myanmar and Thailand both exhibit discrimination against Muslim minorities and have recently experienced violence accompanied by military takeovers.

[4] This definition follows guidance on day count index computation by the World Meteorological Organization (Tank et al., 2009), and the 90^{th} percentile is commonly used as a value for extremes (e.g., IPCC, 2021). The 1979–2009 sub-monthly climate normal refers to the distribution of maximum and minimum hourly temperature for a five-day window around each calendar day.

temperature. Importantly, higher values for these two indexes correspond to the occurrence of unusually high temperature, but they separately capture trends in the evolution of each tail of the temperature distribution.

We first use these two indexes to quantify the reduced form impact of annual fluctuations in extreme temperature days on the occurrence of conflict events. Our measure of conflict events is based on geo-referenced data from the Armed Conflict and Location Event Dataset (ACLED Raleigh et al., 2010), which allows us to identify grid cells with at least one conflict event in a given year. The literature on the social and economic impacts of climate change generally suggest that weather fluctuations are exogenous to socio-economic outcomes after conditioning for fixed effects and trends (Burke et al., 2015; Hsiang, 2016; Carleton and Hsiang, 2016).[5] In addition, our empirical approach has several advantages. First, our day count indexes capture short-term episodes of extreme temperature which can be hidden in monthly or yearly averages (Deschênes and Greenstone, 2011). Second, the use of a percentile threshold allows us to detect extreme temperature days in different climate zones, an important feature for the geographical area we consider.[6] Lastly, we employ a measure of grid cell-level climate normal defined on a sub-monthly basis, which allows identifying local temperature shocks throughout the year and not only during the hot season.

We then exploit information about types of conflicts and actors involved available in ACLED and investigate the heterogeneous impacts of extreme maximum and minimum temperature days. Specifically, Seter (2016) suggests that livelihood contraction associated with climate extremes can result in violence against local governments or other local groups when populations do not have sufficient resources to challenge the state. Based on this, we quantify how extreme maximums and minimums differentially affect the occurrence of different types of conflict events: battles between armed forces, violence against civilians, communal violence and state-based conflicts. We further study how extreme maximums and minimums distinctly affect conflict events involving the following pairs of actors: state forces, rebel groups, political militias, identity-based militias, and civilians. Lastly, we provide evidence about the role of vulnerability factors and socioeconomic context to explain climate-conflict linkages. Following

[5] Note that we also control for precipitations as these tend to correlate with temperature and omitting these from the analysis could confound the causal effect of temperature shocks (Auffhammer et al., 2013).

[6] For example, the northern part of Southeast Asia has a warm temperate climate while the south features a tropical climate (Beck et al., 2018).

Von Uexkull et al. (2016), we consider economic development, dependence to agriculture, political discrimination of ethnic groups, as well as the role of demographic pressure (see also Breckner and Sunde, 2019).

Our results suggest that extreme maximum and minimum temperature days have a significant impact on conflict occurrence although these go in opposite direction. In our preferred specification, which includes both cell and country-by-year fixed effects, the contemporaneous effect for an additional day with extreme maximum temperature on conflict incidence is 0.075 percentage points (pp). By contrast, the effect is -0.047 pp for extreme minimum temperature days. This corresponds, respectively, to 0.9% and 0.6% of the unconditional probability of conflict events. In line with these countervailing effects, we find that conflict incidence is on aggregate not affected by anomalies in average temperature. Among an extensive set of robustness checks, we further show that these reduced-form results hold qualitatively when we use a $1° \times 1°$ grid resolution and when we consider average maximum and minimum daily temperature as our variable of interest.

While impacts of extreme maximum and minimum temperature days partially offset each other, our analysis of heterogeneity suggests that the type of conflicts and actors involved differ for extreme maximums and minimums. In particular, the effect of extreme minimums is concentrated on violence against civilians while extreme maximums also affect battles and state-based conflicts. Furthermore, extreme minimum temperature days affect conflict events involving political militias against civilians, whereas extreme maximums trigger conflicts between state forces and civilians, political militias and rebel groups. These results suggest a differential effect of climate change for different groups of affected populations. Nevertheless, we also find that the impact of extreme maximums and minimums are both more pronounced in locations with ethno-political discrimination. By contrast, our data do not indicate a role for other vulnerability factors, namely economic development, local importance of agriculture, and population density.

Our work contributes to a large literature on the impact of climate change on conflicts, which so far has predominantly focused on Africa. For example, Burke et al. (2009) find that an increase of average temperature raises the likelihood of civil wars and Harari and La Ferrara (2018) provide geographically disaggregated evidence that droughts increase the occurrence of conflict events (see also Maystadt et al., 2014, on civil conflicts in North and South Sudan). The impact of weather extremes on conflicts is also documented in O'Loughlin et al. (2012) for

East Africa, O'Loughlin et al. (2014) for sub-Saharan Africa, and in Breckner and Sunde (2019) using gridded data for the entire African continent. Our work confirms that extreme weather events have a significant impact on conflict, although our focus on mainland Southeast Asia is important because of a potential sampling bias associated with Africa (Adams et al., 2018). Moreover, relative to these studies, we show that extreme minimums reduce the occurrence of conflicts, thereby emphasizing the importance of non-linear effects in the relationship between climate and conflict.

Our work also contributes to a much smaller number of related studies that focus on Asia. Wischnath and Buhaug (2014) use data for the entire Asian continent and find no consistent evidence that anomalies in average temperature and precipitation have an impact on conflicts. By documenting countervailing effects of extreme maximum and minimum temperature days, we offer a potential explanation for inconclusive results at the average. Closer to our work, Crost et al. (2018) use data for the Philippines to show that the impact of rainfall on conflict is negative during the dry season and positive during the wet season, taking into account the monsoon regime and highlighting agricultural yields as a risk factor (see also Caruso et al., 2016, for Indonesia). By contrast, we show how extreme maximum and minimum temperature differentially impact the type of conflicts, actors involved, and populations affected, so that impacts for local communities do not cancel out.

Finally, we contribute to a literature focusing on the role of context in the relationship between climate change and conflict. For example, Maystadt et al. (2014) show that pastoral and agro-pastoral groups are more strongly affected by temperature shocks in North and South Sudan. Studying the effect of extreme temperature, Breckner and Sunde (2019) finds an amplifying role of demographic pressure on the African continent. Neither Buhaug (2010) nor O'Loughlin et al. (2012) find that economic development and ethno-political discrimination affect the relationship between climate shocks and conflicts in Africa. In Asia, Crost et al. (2018) and Caruso et al. (2016) both focus on the agricultural channel. In the geographical area we consider, our data instead suggest that ethno-political exclusion is a key driver of conflict incidence and significantly amplifies the effect of both extreme maximum and minimum temperature days.

The rest of our paper is organized as follows. Section 2 presents our data and lays out our empirical strategy. Section 3 provides descriptive statistics and delivers our main empirical results. Section 4 reports an extensive set of robustness checks. Finally, in Section 5 we discuss the broader picture emerging from the collective results and briefly conclude.

2 Data and empirical strategy

In this section, we first describe the dataset we assemble to quantify the impact of extreme temperature days on conflict events. Second, we discuss our estimation strategy for our reduced form specification. Third, we present how we extend the analysis to account for heterogeneity in terms of conflict types, actors involved, and vulnerability factors. Lastly, we list a number of robustness checks.

2.1 Main data sources

Our dataset has the structure of a raster and brings together several geo-referenced data sources. We consider grid cells of 0.5° latitude/longitude as our unit of observation, which corresponds to squares of approximately 55 km by 55 km at equator.[7]

Geo-referenced conflict data is taken from ACLED, which documents inter-group conflicts, political violence, demonstrations and politically relevant non-violent events across the world (Raleigh et al., 2010). Each event is defined in terms of type, date, latitude, longitude and actors involved. Data coverage is from 2010 to 2020 and includes Cambodia, Laos, Myanmar, Thailand, and Vietnam.[8] We focus on conflict events corresponding to a common definition from the Uppsala Conflict Data Program (UCDP): "an incident where armed force was used by an organized actor against another organized actor, or against civilians, resulting in at least one direct death" (p.4, Högbladh, 2022). In our analysis of heterogeneous effects, further discussed below, we exploit information about the type of conflict and actors involved.

Climate data are from a high-quality reanalysis dataset of meteorological measurement (ECMWF-ERA5, Hersbach et al., 2020), which combines different sources in a consistent way (including data from weather stations and those from satellites, among other sources). Impor-

[7] In our robustness checks we also consider grid cells of 1° latitude/longitude to alleviate concerns that the choice of grid cell size drive the results. We come back to this below.

[8] Information is collected from local, regional, and national sources such as newspapers, reports from humanitarian agencies, and research publications. As discussed in Harari and La Ferrara (2018) one potential concern with data is selection in reporting, although a systematic correlation with extreme maximum and minimum temperature days is unlikely. Data for Malaysia only starts in 2018, so that we do not include this country in our analysis.

tantly, reanalysis data are less likely to suffer from measurement error that could potentially correlate with unobserved characteristics. Gridded data for temperature are available at an hourly frequency from 1979 onwards and we also retrieve total monthly precipitation in meters of water equivalent for each grid cell. We match a raster containing climate data for grid cells of $0.5°\times0.5°$ to geo-referenced data on individual conflict events.

We use these data to construct our main variables of interest, namely the number of extreme maximum and minimum temperature days for each year and grid cell over the observation period (2010-2020). Following guidelines by the World Meteorological Organization on day count index computation (Tank et al., 2009), we employ data from 1979 to 2009 to determine a sub-monthly climate normal for each grid cell. More specifically, for each calendar day in a year, we consider a five-day window for which we define a distribution of daily maximums and minimums. A given day d during the observation period is then classified as an extreme maximum if its maximum daily temperature is above the 90^{th} percentile of daily maximums observed in the sub-monthly climate normal.[9] Conversely, days with extreme daily minimums are those for which the minimum daily temperature is above the 90^{th} percentile of daily minimum observed in the sub-monthly climate normal. This allows us to measure temperature extremes throughout the year relative to a sub-monthly reference of five days computed over a 30-year period. Our two main variables of interest are then the number of days in a year with extreme daily maximums and extreme daily minimums. We discuss alternative indicators for the climate in the robustness checks below.

2.2 Empirical identification

Our objective is to identify the causal effect of changes in the number of extreme temperature days on the occurrence of conflict events. To do so, we exploit yearly temperature shocks as a set of natural experiments and rely on the idea that the most appropriate counterfactual for a grid cell with an additional extreme maximum / minimum temperature day is the grid cell itself just before or after having undergone the shock (Carleton and Hsiang, 2016). Our empirical strategy therefore leverages repeated observation for each grid cell together with fixed

[9] For instance, the day "January 15, 2015" is classified as an extreme maximum day for a given grid cell if the maximum temperature on that day is higher than the 90^{th} percentile in the distribution of daily maximums for January 13 to 17 observed from 1979 to 2009 in that grid cell (155 observations, i.e., 5 days $\times$ 31 years).

effects. Intuitively, this allows us to control for factors such as culture, history, geography or political institutions that can be assumed to remain constant over the observation period. After conditioning on trends, the literature generally assumes that weather variability is exogenous to social or economic changes and solely determined by random geophysical processes (Hsiang, 2016).

One implication of this identification strategy is that control variables are not necessary. In fact, their inclusion could potentially introduce an endogeneity problem if weather shocks also affect these control variables. One example of a control variable that is endogenous to climatic conditions is income, as GDP has been shown to be affected by yearly fluctuations in the weather (e.g., Dell et al., 2012). However, rainfall is an exemption, as the amount of rain tends to correlate with temperature, and therefore it is necessary to control for precipitation in order to identify the causal impact of temperature extremes (Auffhammer et al., 2013). Furthermore, we follow Burke et al. (2015) by including both contemporaneous and lagged meteorological variables, so as to quantify delayed or persistent impacts.

Formally, the outcome variable *Conflict* is equal to 1 if at least one conflict event occurred in cell i during year t, and the baseline equation we estimate is given by:

$$\begin{aligned} \textit{Conflict}_{i,t} = {} & \beta_1 \cdot \textit{Daily tmax} >\!\textit{90p}_{i,t} + \beta_2 \cdot \textit{Daily tmax} >\!\textit{90p}_{i,t-1} + \\ & \gamma_1 \cdot \textit{Daily tmin} >\!\textit{90p}_{i,t} + \gamma_2 \cdot \textit{Daily tmin} >\!\textit{90p}_{i,t-1} + \\ & \delta_1 \cdot \textit{Precipitation}_{i,t} + \delta_2 \cdot \textit{Precipitation}_{i,t-1} + \alpha_i + \mu_{c,t} + \varepsilon_{i,t} \end{aligned} \tag{1}$$

where *Daily tmax* $>$*90p* and *Daily tmin* $>$*90p* are indexes for days with extreme maximum and minimum temperature, respectively, and *Precipitation* is total yearly rainfall. The parameters β and γ are the coefficients of interest and measure, respectively, the contemporaneous and lagged effect of extreme temperature days. Taken together, these quantify non-linear impacts of extreme maximum and minimum temperature days on conflict events. We control for time-constant unobserved characteristics with cells fixed effects (α_i) and account for time-varying nationwide shocks with country-by-year fixed effects ($\mu_{c,t}$). Finally, ε is an error term.

Equation (1) is a linear probability model and can be estimated with OLS. Following McGuirk and Nunn (2020), we employ two-way cluster standard errors at the cell and climate zone-year level. First, idiosyncratic errors are expected to be serially correlated within a cell whenever unobserved components of conflicts are correlated over time. Second, weather variables are correlated across space, which implies that the error term will be spatially correlated (see Auffhammer et al., 2013).[10] Below we also consider the use of spatial heteroskedastic and autocorrelation consistent estimator (spatial HAC) based on Conley (1999).

While our main objective is to identify the impact of climate change on the occurrence of conflict events, equation (1) quantifies the reduced form impact of weather shocks as a set of natural experiments. This is because we do not measure the climate directly, but only its realizations through the weather.[11] For changes in the weather to be equivalent to changes in the climate, we need to assume that a marginal change in the weather is equivalent to a marginal change in climate, an assumption called marginal treatment comparability (Hsiang, 2016). While this assumption may be more credible when comparing long-run averages (see, e.g., Von Uexkull and Buhaug, 2021, for a critical discussion), it goes against unit comparability that is necessary for causal identification, an issue discussed as the frequency-identification trade-off by Burke et al. (2015). Importantly Hsiang (2016) uses an argument based on the envelope theorem to show that marginal treatment comparability holds when the outcome considered is the solution of a maximization problem. This is supported by existing evidence suggesting that a deterioration in livelihoods and decreased opportunity cost of violence is a key driver of conflict.

2.3 Heterogeneous effects

The literature highlights potential heterogeneity among different types of conflict events and different actors (Seter, 2016; Harari and La Ferrara, 2018), well as the role of potential vulnerability factors (e.g., Von Uexkull et al., 2016; Breckner and Sunde, 2019). In this section we provide an overview of our analysis of heterogeneity to further document the impact of extreme maximum and minimum temperature days.

We start by considering how extreme temperature days affect the occurrence of a number of conflict types as reported in ACLED. The first type is battles, which involve close-range interactions between two organized armed forces and do not involve civilians. The second is violence

[10] Climate zones are identified by the Köppen Climate Classification which divides regions according to precipitation and temperature (Beck et al., 2018). For the area we consider, this gives seven different climate zones.

[11] By definition, the term climate refers to the expected distribution of a set of random variables that characterize the atmosphere and the oceans, whereas the weather refers to realizations of these variables.

against civilians, encompassing all conflict events that involve armed groups against unarmed non-combatant. Third, we consider conflict events of communal violence that exclude government forces. In ACLED this is classified as events involving identity militias, which are organized around values such as religion, ethnicity, or regional affiliation and usually pursue local objectives. Fourth, we document the occurrence of state-based conflicts, which are events involving official forces interacting with an organized armed group.

Next, we focus on conflict events involving specific pairs of actors. Following Harari and La Ferrara (2018), we consider the following actors: (i) the state, including military and police forces; (ii) armed rebels seeking power or separatism; (iii) political militias pursuing political goals; (iv) identity militias (defined above); and (v) civilians. For each pair of actors, the outcome variable is equal to one if at least one conflict event involving a specific pair of actors occurred, zero otherwise.

Lastly, we identify a number of potential vulnerability factors that could affect the relationship between extreme maximum / minimum temperature days and conflict events. These factors are informed by the work of Von Uexkull et al. (2016) and Breckner and Sunde (2019), and we extend our baseline specification (equation 1) as follows:

$$\begin{aligned}
\textit{Conflict}_{i,t} = {} & \beta_1 \cdot \textit{Daily tmax >90p}_{i,t} + \beta_2 \cdot \textit{Daily tmax >90p}_{i,t-1} + \\
& \beta_3 \cdot \textit{Daily tmax >90p}_{i,t} \times Z_i + \beta_4 \cdot \textit{Daily tmax >90p}_{i,t-1} \times Z_i + \\
& \gamma_1 \cdot \textit{Daily tmin >90p}_{i,t} + \gamma_2 \cdot \textit{Daily tmin >90p}_{i,t-1} + \\
& \gamma_3 \cdot \textit{Daily tmin >90p}_{i,t} \times Z_i + \gamma_4 \cdot \textit{Daily tmin >90p}_{i,t-1} \times Z_i + \\
& \delta_1 \cdot \textit{Precipitation}_{i,t} + \delta_2 \cdot \textit{Precipitation}_{i,t-1} + \alpha_i + \mu_{c,t} + \varepsilon_{i,t}
\end{aligned} \tag{2}$$

where Z_i stands for a specific vulnerability factor and is interacted with our day count indexes.[12]

The first vulnerability factor we consider is economic development, which can influence the ability of local populations to adapt. To quantify this, we employ data for 2012 average nighttime light emissions for each grid cell (Elvidge et al., 2021), an approach that has recently

[12] Note that the variable capturing vulnerability factors Z_i is not indexed by time and hence it does not enter the regression as a separate variable. In particular, Z is measured at the beginning of the sample period to mitigate endogeneity concerns, and it is therefore controlled for by the inclusion of cell fixed effects.

gained traction in the economic literature (see Gibson et al., 2021, for a discussion).[13] The second factor is local predominance of agriculture as an economic activity. As crop output may be particularly sensitive to extreme temperature events, agricultural dependence is usually considered to be a risk factor in the relationship between climate and conflict. We define Z_i as 2010 cropland extent at the grid cell level with data from Potapov et al. (2022). The third vulnerability factor is the the presence of ethno-political discrimination, which implies that a share of the population tends to be less supported by the state and potentially targeted by grievances. We employ 2010 data from the Geo-referencing Ethnic Power Relations dataset (Vogt et al., 2015) to construct an indicator variable equal to 1 if a politically marginalized ethnic group resides in a given grid cell, zero otherwise. The last factor is demographic pressure, as dense population may exacerbate pressure on natural resources in the presence of a weather shock (Breckner and Sunde, 2019). For this purpose, we use 2010 data on population density for each grid cell from the Gridded Population of the World V4 (Center for International Earth Science Information Network, 2018). The data supporting our vulnerability analysis is described in more detail in Appendix A.

2.4 Robustness checks

We now turn to robustness checks with respect to several methodological choices. The first is the size of grid cells. While a number of papers in the conflict literature employ grid cells of $0.5^\circ \times 0.5^\circ$ (e.g., Wischnath and Buhaug, 2014; Döring, 2020), others also use a resolution of $1^\circ \times 1^\circ$ (e.g., O'Loughlin et al., 2012; Harari and La Ferrara, 2018). The choice of grid cell size can potentially influence the results, a bias called the modifiable areal unit problem, and our first robustness check replicates our reduced-form results with a 1° grid resolution.

The second robustness check considers alternative measures of temperature shocks, and we re-estimate equation (1) with a the following variables: (i) yearly mean temperature standardized with respect to 1979-2009 climate normal, (ii) average daily minimum and maximum temperature expressed as deviations from the 1979-2009 climate normal, (iii) number of extreme temperature days based on daily mean temperature, and (iv) a standardized precipitation and evapotranspiration index (SPEI) measured in December with a time scale of 12 months.

[13] Data for nighttime light emissions are transformed using an inverse hyperbolic sine to reduce skewness and account for the presence of zeros. See Appendix A.

Following Von Uexkull et al. (2016), we consider both a 12-month SPEI index and a drought indicator equal to 1 if SPEI$\leq$–1, zero otherwise. See Appendix B for further discussions.

The third robustness check replicates reduced-form results using an alternative dataset for conflict events, namely the UCDP Georeferenced Event Dataset (UCDP GED Sundberg and Melander, 2013; Davies et al., 2022). This data source is one of the main providers of conflict data and has been used elsewhere in the literature, including papers that investigate the relationship with climate (e.g., Buhaug, 2010; Fjelde and von Uexkull, 2012; Von Uexkull et al., 2016). Based on these data, we construct an alternative variable measuring conflict events; see Appendix B for a more detailed description of these data in comparison with the ACLED data source.

Lastly, we check for the sensitivity of our results with respect to a surge of violent incidents that occur in western Myanmar since 2017 (commonly known as the Rohingya conflict). In order to mitigate concerns that this local conflict drives the results, we estimate the main specification excluding grid cells that intersect with the Rakhine State of Myanmar in which the conflict takes place.

3 Main empirical results

This section presents the results of our empirical analysis. We start by providing summary statistics for our data. Second, we report reduced-form regression results for the impact of extreme temperature days on conflict events. Third, we report our disaggregated analysis according to the type of conflict, actors involved and potential vulnerability factors.

3.1 Descriptive statistics and spatial representation

In Table 1 we report summary statistics for conflict event occurrence, climate variables, and vulnerability factors. Observations are grid cells of 0.5° latitude/longitude for Cambodia, Laos, Myanmar, Thailand, and Vietnam. Data for climate and conflict cover the period from 2010 to 2020, while vulnerability factors refer to a single year toward the beginning of the observation period.

Starting with conflict data, we observe an average yearly probability of 8.4% that a grid cell experienced at least one conflict event in which the use of armed force resulted in one direct

Table 1: Summary statistics, 2010–2020

Variable	Mean	S.D.	Min.	Max.
Conflict data				
Occurrence of conflict events	0.08	0.28	0	1
By type				
Battles between armed forces	0.05	0.21	0	1
Violence against civilians	0.05	0.22	0	1
Communal violence	0.004	0.06	0	1
State-based conflicts	0.05	0.21	0	1
By actor				
State forces	0.06	0.25	0	1
Rebel groups	0.04	0.20	0	1
Political militias	0.04	0.18	0	1
Identity militias	0.01	0.07	0	1
Civilians	0.06	0.24	0	1
Climate variables				
Daily tmax >90p (days)	82.97	34.51	0	212
Daily tmin >90p (days)	80.78	34.92	5	232
Total precipitation (meters)	8.10	2.80	2.31	28.74
Vulnerability factors				
Nighttime light emissions (2012, IHS)	0.18	0.44	0	4.85
Cropland extent (2010, %)	17.59	24.07	0	88.45
Ethno-political discrimination (2010)	0.09	0.29	0	1
Population density (2010, pop/km^2)	135.83	310.04	0.38	5,412.5

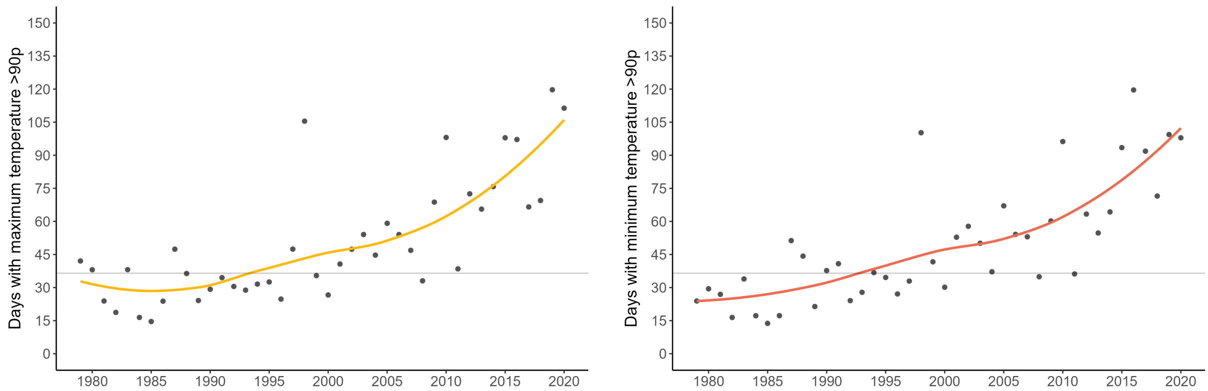
Notes: Summary statistics for climate and conflict data are computed over 8327 observations, which corresponds to 757 cells observed over 11 years (2010–2020). "Daily tmax >90p" and "Daily tmin >90p" are, respectively, the number of days with maximum and minimum daily temperature in the 90th percentile defined on the 1979–2009 sub-monthly climate normal. Data for vulnerability factors refer to grid cell observations for a single year. For nighttime light emissions we apply an inverse hyperbolic sine transformation (IHS).

death or more. Among different types of conflicts, we observe comparable risk of occurrence for battles (4.7%), violence against civilians (5.2%), and state-based conflicts (4.6%), whereas communal violence is less prevalent (0.4%). In line with this, the main actors involved in conflict events are state forces (6.4%), civilians (5.9%) and rebel groups (4.2%), followed by identity militias (0.5%).

Climate variables suggest a significant increase in extreme temperature days relative to the sub-monthly climate normal measured from 1979 to 2009. The variable *Daily tmax >90p*, an index for the number of days with maximum daily temperature in the 90th percentile of the 1979–2009 sub-monthly climate normal, is around 83 on average. The corresponding number for extreme minimum temperature days, measured by the variable *Daily tmin >90p*, is around

Figure 2: Trends in extreme temperature days for mainland Southeast Asia, 1979–2020

(a) Daily tmax >90p (days) (b) Daily tmin >90p (days)



Notes: This figure is derived from temperature data for Cambodia, Laos, Myanmar, Thailand, and Vietnam for the period 1979–2020 (source: ECMWF-ERA5, Hersbach et al., 2020). In Panel (a) "Daily tmax >90p" is the number of days with maximum daily temperature in the 90^{th} percentile defined on the 1979–2009 sub-monthly climate normal. In Panel (b) "Daily tmin >90p" is the number of days with minimum daily temperature in the 90^{th} percentile defined on the 1979–2009 sub-monthly climate normal. The curve in each panel is a locally estimated scatterplot smoothing.

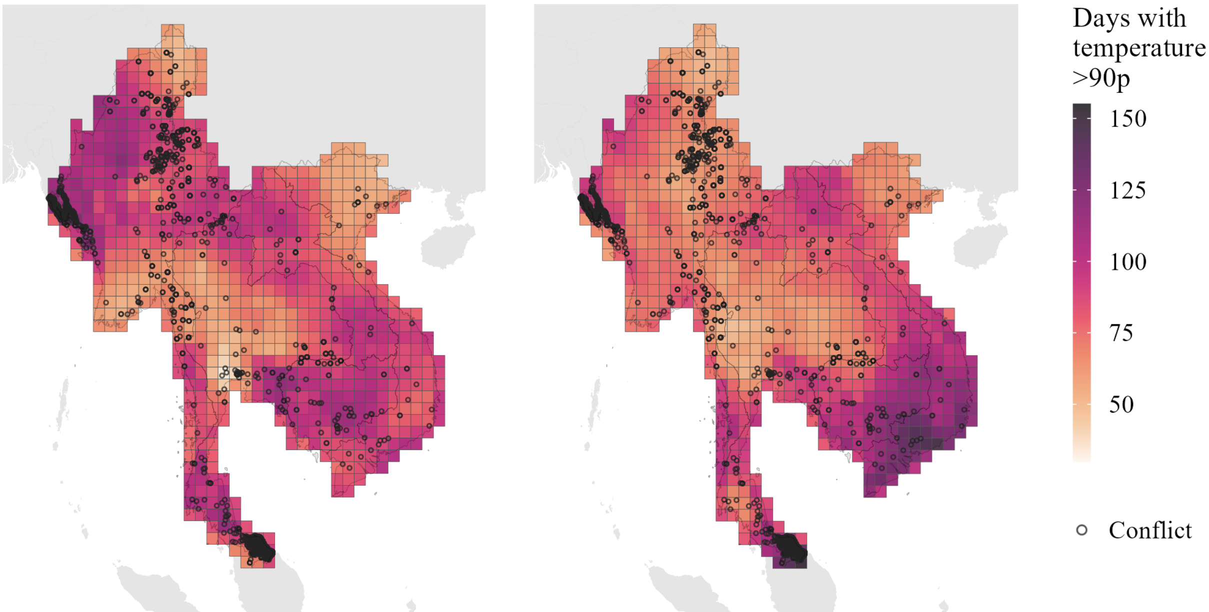
81. This represents an increase of around 45 days relative to the reference period in which the number of days with extreme maximums and minimums is around 36.5 by construction. This increasing trend for the occurrence of extreme daily maximums and minimums temperature is further illustrated in Figure 2.

The spatial distribution of conflict events and extreme temperature days is mapped in Figure 3. Specifically, we display average yearly number of extreme temperature days at the grid cell level for 2010-2020 and overlay the occurrence of conflict events for that period. Panel (a) reports extreme daily maximums and panel (b) focuses on extreme daily minimums.

A comparison of panels (a) and (b) suggests important heterogeneity in how daily maximums and minimums are distributed across space. In particular, days with extreme maximum temperature (panel a) are more likely to occur in western Myanmar, southern Thailand, and in southeastern part an area that encompasses Cambodia and Vietnam. We also observe a relatively high count of extreme maximums in an area encompassing Myanmar, Thailand, and northern Laos. By contrast, days with extreme minimum temperature (panel b) are mostly confined to the southern portion of a region spanning Cambodia, Thailand and Vietnam. Therefore, while regional occurrence of extreme temperature days tends to be correlated, the two types of extremes have a very distinct pattern of spatial occurrence.

Figure 3: Extreme temperature days and conflict events in mainland Southeast Asia

(a) Extreme maximum temperature (b) Extreme minimum temperature



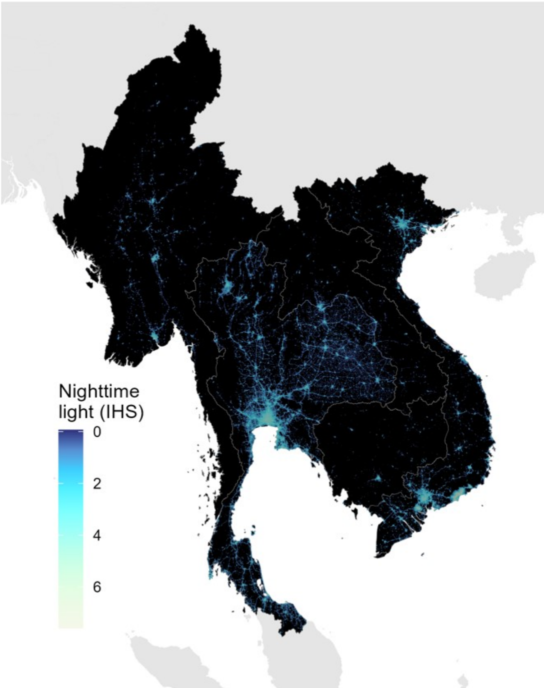
Notes: This figure shows the spatial distribution for the average number of extreme temperature days for 2010-2020, with overlaid conflict events occurring during that period. Panel (a) reports the average number of days with extreme maximum daily temperature in the 90^{th} percentile defined on the 1979–2009 sub-monthly climate normal, while panel (b) instead focuses on daily minimums.

Figure 3 further shows some geographical clustering of conflict events. First, the western part of Myanmar (Rakhine/Chin) is associated with the long-standing Rohingya conflict, characterized by violence and persecution against a Muslim minority. A second cluster of conflict events is in the northeastern part of Myanmar (Kachin/Shan), where multiple armed groups with insurgent claims clash with local state forces. The third cluster is in the southern provinces of Thailand (Narathiwat, Pattani, and Yala), where violence is ongoing between Muslim separatists and the Buddhist majority government. Grid cells in other areas of the map exhibit a more dispersed pattern of conflict, with relatively fewer events reported in Laos and Vietnam.

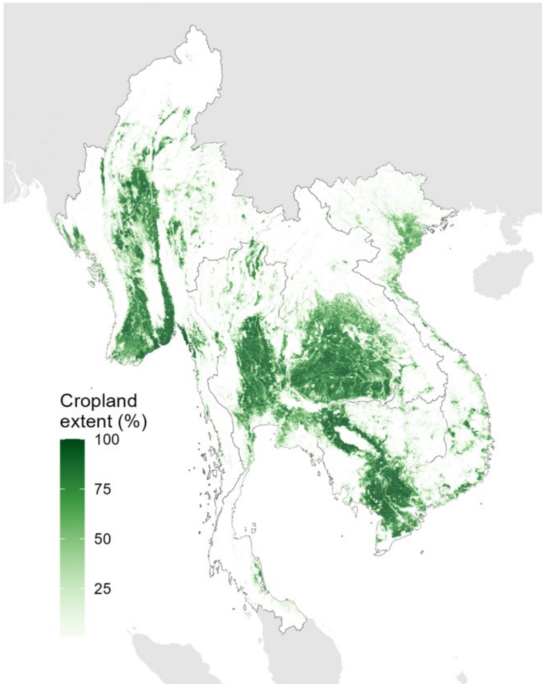
Turning to vulnerability factors discussed in Section 2.3 and reported at the bottom of Table 1, our data suggests significant variability, with spatial heterogeneity illustrated in Figure 4. Specifically, we map nighttime light emissions in panel (a), cropland extent in panel (b), politically discriminated ethnic groups in panel (c) and population density in panel (d). These data refer to the beginning of the observation period (2010), except for nighttime light emissions for which the earliest observation is 2012 (see Appendix A for further details).

Figure 4: Spatial distribution of vulnerability factors

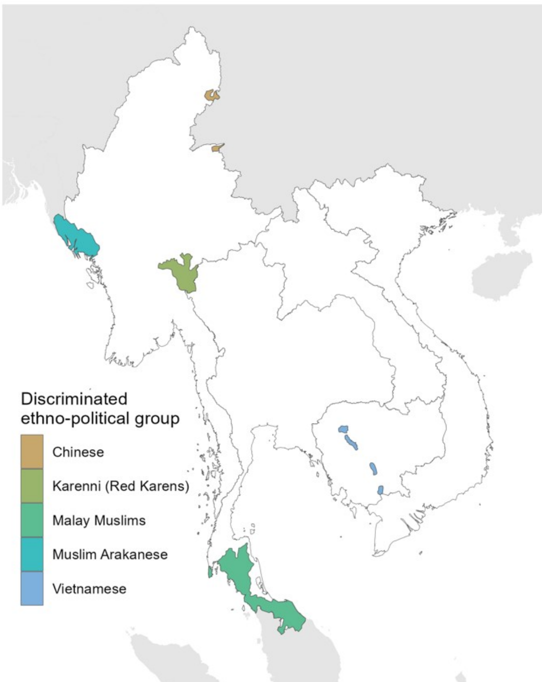
(a) Nighttime light emissions



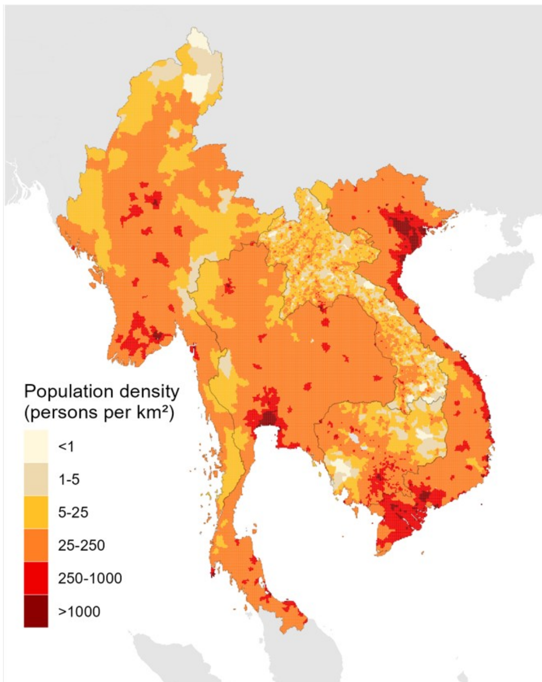
(b) Cropland extent



(c) Ethno-political discrimination



(d) Population density



Notes: This figure shows the spatial distribution of the vulnerability factors employed in the analysis. Panel (a) reports 2012 nighttime light emissions with an inverse hyperbolic sine (IHS) transformation applied. Panel (b) shows 2010 cropland extent (coverage percentage). Panel (c) is 2010 location of politically discriminated ethnic groups. Panel (d) is 2010 population density (persons per square kilometer). See Appendix A for further definitions and data sources.

Data for nighttime light emissions displayed in panel (a) suggest higher economic activities in Thailand and in Vietnam, which coincides with higher GDP figures by the World Bank for these two countries. Cropland extent (panel b) indicates that Thailand, parts of central Myanmar, Cambodia, and the lower part of Vietnam have the largest area devoted to agriculture. This is consistent with FAO data showing that these countries are among the largest producers of paddy rice in the world. Panel (c) shows that the spatial distribution of politically discriminated ethnic communities aligns with that of conflict events discussed above, especially in Myanmar (the Rohingyas) and in Thailand (the Malay Muslims). No groups are reported in Laos or Vietnam. Lastly, data for population density in panel (d) highlights a number of major cities such as Bangkok, Hanoi, Ho Chi Minh and Yangon, and is lowest in Laos, Cambodia and parts of Myanmar.

Taken together, the descriptive analysis suggests ample grid cell variability in the variables we consider. The spatial distribution of conflicts shows clusters in western Myanmar and southern Thailand, which coincide with ethno-political discrimination. We also observe a significant shift in the distribution of extreme temperature days, with an increase in the occurrence of extreme daily maximums and minimums, and that the location of these extremes differs for maximums and minimums. Importantly, however, while differences in averages are interesting in their own right, our empirical analysis features grid cell fixed effects and country-level trends to break cross-sectional correlation and instead focuses on within grid cell variability. The results of this causal analysis are what we discuss next.

3.2 Reduced-form results: extreme temperature days and conflict events

Table 2 reports baseline estimates for equation (1), where the outcome is an indicator variable equal to 1 if a grid cell experienced at least one conflict event in a year, zero otherwise. Estimates associated with the variable *Daily tmax >90p* and its lag represent the percentage point variation (pp) in the occurrence of conflict events caused by an additional day with extreme maximum temperature. Symmetrically, the coefficients estimates for the variable *Daily tmin >90p* and its lag represent the pp change in conflict events associated with an additional extreme minimum temperature day. In column 1 we report results for a specification with cell fixed effects as the only control. In column 2 we further control for total precipitation, and in column 3 we add year fixed effects. Lastly, column 4 replaces year fixed effects with country-by-year fixed effects. Two-

Table 2: Reduced-form regression results for the impact of extreme temperature days on conflict

	Dependent variable: Indicator for conflict events			
	(1)	(2)	(3)	(4)
Daily tmax >90p	0.061***	0.063***	0.073***	0.075***
	(0.019)	(0.019)	(0.020)	(0.023)
Daily tmax >90p, t-1	0.017	0.033	0.034	0.023
	(0.017)	(0.020)	(0.021)	(0.027)
Daily tmin >90p	-0.059***	-0.054***	-0.044**	-0.047**
	(0.017)	(0.016)	(0.019)	(0.022)
Daily tmin >90p, t-1	-0.020*	-0.027**	-0.043***	-0.028
	(0.011)	(0.013)	(0.015)	(0.020)
Observations	8,327	8,327	8,327	8,327
Total precipitation		X	X	X
Year FE			X	
Country x year FE				X
Cell FE	X	X	X	X

Notes: All regressions are estimated using OLS. Observations correspond to 757 cells observed over 11 years (2010–2020). The outcome is a dummy equal to 1 if a conflict event occurred in a cell during a year, zero otherwise. "Daily tmax >90p" and "Daily tmin >90p" are, respectively, the number of days with maximum and minimum daily temperature in the 90^{th} percentile defined on the 1979–2009 sub-monthly climate normal. All estimates are multiplied by 100 for ease of interpretation and represent changes in percentage point. Standard errors are two-way clustered at the cell and climate zone-year level and are reported in parentheses. *, ** and *** denote statistical significance at 10%, 5% and 1% respectively.

way clustered standard errors at the cell and climate zone-year level are reported in parentheses throughout.[14]

The results show that a marginal increase in days with extreme maximum temperature leads to higher occurrence of conflicts events in that same year. Conversely, the contemporaneous impact of days with extreme minimum temperature is negative, so that the occurrence of conflict declines when the number of days with extreme minimum temperature increases. The non-linear impact of extreme maximum and minimum days are consistent across columns, although the impact of extreme maximums tends to increase with additional controls whereas the impact of extreme minimums gets closer to zero. Coefficients for the lags of *tmax* and *tmin* have

[14] In Appendix C we show that statistical inference is similar if we use spatial heteroskedastic and autocorrelation consistent estimator (spatial HAC) based on Conley (1999), which allows for a correlation of errors among cells whose centroid is at or below a certain distance. This approach to statistical inference is more computationally intensive and does not guarantee a positive definite variance-covariance matrix, and given similar results we employ two-way clustered standard errors in the subsequent results (see also Hsiang, 2016).

consistent signs, but these are smaller in magnitude and are less precisely estimated.

Quantitatively, our preferred specification in column 4 suggests that one additional day with extreme daily maximum increases the probability of conflict events by 0.075 pp (p-val.$<$0.01). At the mean of the sample, this corresponds to an increase of about 0.9% in the unconditional probability of conflict events. By contrast, an additional day with extreme minimum temperature reduces the probability of conflict by 0.047 pp (p-val.$<$0.05), or about 0.6% of the unconditional average. Given observed changes in the number of extreme temperature days relative to the reference period discussed in Section 3.1, which is around 45 days per year, these impacts are significant.

3.3 Heterogeneity: types of conflict events

Table 3 provides evidence about the impact of extreme temperature days on the occurrence of different types of conflict events. In column 1 we consider battles between organized armed forces, excluding civilians. In column 2 we focus on conflict events against civilians. Column 3 considers events of communal violence involving an identity militia but excluding government forces. Lastly, column 4 documents state-based conflicts involving government forces and armed organized groups. In each column we control for total precipitation and its lag, cell fixed effects and country-by-year fixed effects. Two-way clustered standard errors are reported in parentheses throughout.

Results confirm countervailing impacts of days with extreme maximum temperature and of those with extreme minimum temperature, but with different incidence by types of conflict events. Columns 1 and 4 indicate that days with extreme maximum temperature increase the probability of experiencing events categorized as battle by armed groups (by 0.059 pp in the same year, p-val.$<$0.01, and by 0.037 pp in the following year, p-val.$<$0.05) and state-based violence (0.064 pp in the same year, p-val.$<$0.01, and by 0.038 pp in the following year, p-val.$<$0.05). Contemporaneous marginal effects represent around 1.2% of the unconditional probability of battles between armed forces (lagged effect: 0.7%) and 1.4% for state-based conflicts. For these types of conflicts, coefficients for days with extreme minimum temperature have a negative sign but are small in magnitude and not precisely estimated.

For conflict events involving violence against civilians, we find that extreme maximum temperature days increase the contemporaneous occurrence of conflicts by 0.041 pp (p-val.$<$0.05)

Table 3: Impact of extreme temperature days on alternative types of conflict

	Dependent variable: Indicator for conflict events			
	Battles between armed forces (1)	Violence against civilians (2)	Communal violence (3)	State-based conflicts (4)
Daily tmax >90p	0.059***	0.041**	-0.004	0.064***
	(0.015)	(0.019)	(0.005)	(0.017)
Daily tmax >90p, t-1	0.037**	0.004	-0.008	0.038**
	(0.018)	(0.026)	(0.006)	(0.017)
Daily tmin >90p	-0.006	-0.035**	-0.008	-0.009
	(0.015)	(0.017)	(0.005)	(0.014)
Daily tmin >90p, t-1	-0.011	-0.023	-0.0002	-0.014
	(0.016)	(0.017)	(0.004)	(0.016)
Observations	8,327	8,327	8,327	8,327
Total precipitation	X	X	X	X
Country x year FE	X	X	X	X
Cell FE	X	X	X	X

Notes: All regressions are estimated using OLS. Observations correspond to 757 cells observed over 11 years (2010–2020). The outcome is a dummy equal to 1 if the corresponding type of conflict event occurred in a cell during a year, zero otherwise. "Daily tmax >90p" and "Daily tmin >90p" are, respectively, the number of days with maximum and minimum daily temperature in the 90^{th} percentile defined on the 1979–2009 sub-monthly climate normal. All estimates are multiplied by 100 for ease of interpretation and represent changes in percentage point. Standard errors are two-way clustered at the cell and climate zone-year level and are reported in parentheses. *, ** and *** denote statistical significance at 10%, 5% and 1% respectively.

while extreme minimum temperature days decrease it by 0.035 pp (p-val.<0.05). This is respectively 0.8% and 0.7% of the unconditional probability of violence against civilians. Lagged effects associated with violence against civilians have consistent signs but are not statistically significantly different from zero. We do not find evidence that communal violence is affected by extreme temperature days.

3.4 Heterogeneity: actors involved in conflict events

We now consider how extreme temperature days affect conflict events involving alternative pairs of actors. Table 4, panel (a), presents results for equation (1) where the outcome is an indicator variable equal to one for conflict events involving state forces against the following actor: state forces (column 1), rebel groups (column 2), political militias (column 3), identity militias (column 4), and civilians (column 5). Panels (b) repeats the analysis for conflict events involving rebel groups, panel (c) for political militias, and panel (d) for identity militias.[15] Each column includes total precipitation and its lag, as well as cell and country-by-year fixed effects. Two-way clustered standard errors are reported in parentheses throughout.

Results in panel (a) indicate that days with extreme maximum temperature have a positive impact on the occurrence of conflict events involving state forces and rebel groups, with point estimates of 0.052 pp in the same year (p-val.$<$0.01) and 0.040 pp in the year after (p-val.$<$0.05). We also observe a positive and statistically significant effect of extreme maximums on conflict events involving state forces against political militias (lagged effect of 0.022 pp, p-val.$<$0.05) and against civilians (contemporaneous effect of 0.035 pp, p-val.$<$0.05). We do not find an effect of extreme temperature days for events involving state forces against state forces or against identity militias.

Panels (b) to (d) show that, for pairs of actors not involving state forces, extreme maximum days do not significantly impact the occurrence of conflict events. Instead, we find evidence that days with extreme minimum temperature tend to reduce the occurrence of conflict events involving political militias and civilians (lagged effect of -0.028 pp, p-val.$<$0.05) and rebel groups against rebel groups (contemporaneous effect of -0.009 pp, p-val.$<$0.1). For other pairs of actors the sign associated with extreme minimum is predominantly negative but the associated estimates are not precisely estimated.

3.5 Heterogeneity: local vulnerability factors

Results for equation (2) are reported in Table 5. In each column, we interact count indexes for extreme temperature days and their respective lag with a variable Z_i quantifying local vulnerability factors. In column 1 we consider the role of economic development and use nighttime light emissions as a proxy for local economic activities. Column 2 documents the role of agricultural dependence by using cropland extent as an interaction. Column 3 uses an indicator variable for the presence of ethno-political discrimination. Lastly, in column 4 we use population density as

[15] Note that our data do not allow us to identify an initiator among the two actors. Estimates are therefore symmetrical with respect to the diagonal and omitted for simplicity. The only exception is conflict events involving civilians, as civilians are unarmed and therefore always victims of conflict events.

Table 4: Impact of extreme temperature days on conflict events with alternative pairs of actors

	Dependent variable: Indicator for conflict events				
Actor:	State forces (1)	Rebel groups (2)	Political militias (3)	Identity militias (4)	Civilians (5)
Panel a: State forces vs.					
Daily tmax >90p	0.004	0.052***	0.010	0.003	0.035**
	(0.003)	(0.016)	(0.010)	(0.003)	(0.016)
Daily tmax >90p, t-1	-0.006	0.040**	0.022**	0.002	-0.009
	(0.004)	(0.018)	(0.011)	(0.003)	(0.020)
Daily tmin >90p	0.0007	-0.004	-0.006	0.002	-0.008
	(0.004)	(0.014)	(0.007)	(0.003)	(0.015)
Daily tmin >90p, t-1	0.002	0.0008	-0.014	-0.005	7.39×10^{-5}
	(0.003)	(0.015)	(0.010)	(0.003)	(0.013)
Panel b: Rebel groups vs.					
Daily tmax >90p	–	0.007	-0.0009	-0.0003	0.010
		(0.004)	(0.003)	(0.0009)	(0.009)
Daily tmax >90p, t-1	–	-0.009	0.003	-0.0007	0.011
		(0.007)	(0.002)	(0.002)	(0.008)
Daily tmin >90p	–	-0.009*	0.002	-0.0007	-0.010
		(0.005)	(0.003)	(0.0007)	(0.007)
Daily tmin >90p, t-1	–	-0.003	-0.0007	-0.001	-0.004
		(0.005)	(0.001)	(0.0009)	(0.007)
Panel c: Political militias vs.					
Daily tmax >90p	–	–	0.003	0.0008	0.023
			(0.002)	(0.0006)	(0.016)
Daily tmax >90p, t-1	–	–	0.002	0.001	0.019
			(0.001)	(0.001)	(0.019)
Daily tmin >90p	–	–	-0.002	-0.0005	-0.015
			(0.002)	(0.0005)	(0.012)
Daily tmin >90p, t-1	–	–	0.0001	-0.0003	-0.028**
			(0.001)	(0.0003)	(0.014)
Panel d: Identity militias vs.					
Daily tmax >90p	–	–	–	-0.004	-0.003
				(0.003)	(0.004)
Daily tmax >90p, t-1	–	–	–	-0.004	-0.005
				(0.003)	(0.004)
Daily tmin >90p	–	–	–	-0.003	-0.006
				(0.002)	(0.004)
Daily tmin >90p, t-1	–	–	–	-0.002	0.003
				(0.003)	(0.004)

Notes: Each panel and column displays the results of an OLS regression where the outcome is a dummy equal to 1 if a conflict event occurred between two specific actors in a cell during a year. “Daily tmax >90p” and “Daily tmin >90p” are, respectively, the number of days with maximum and minimum daily temperature in the 90^{th} percentile defined on the 1979–2009 sub-monthly climate normal. All estimates are multiplied by 100 for ease of interpretation and represent changes in percentage point. Each regression is estimated on 8,327 grid cell by year observations and includes total precipitation (and its lag) as control variables as well as cell fixed effects and country by year fixed effects. Standard errors are two-way clustered at the cell and climate zone-year level and are reported in parentheses. *, ** and *** denote statistical significance at 10%, 5% and 1% respectively.

Table 5: Impact of extreme temperature days on conflict for alternative vulnerability factors

	Dependent variable: Indicator for conflict events			
Variable Z:	Economic development (1)	Agricultural dependence (2)	Ethno-political discrimination (3)	Demographic pressure (4)
Daily tmax >90p	0.059**	0.083***	0.056***	0.066***
	(0.024)	(0.025)	(0.020)	(0.023)
Daily tmax >90p × Z	-0.021	-0.0003	0.160*	6.71×10^{-5}
	(0.053)	(0.0007)	(0.082)	(8.79×10^{-5})
Daily tmax >90p, t-1	0.022	0.040	0.006	0.024
	(0.029)	(0.030)	(0.025)	(0.031)
Daily tmax >90p, t-1 × Z	0.019	-0.0010	0.162***	-1.03×10^{-5}
	(0.042)	(0.0007)	(0.051)	(0.0001)
Daily tmin >90p	-0.038	-0.037	-0.032	-0.031
	(0.024)	(0.023)	(0.021)	(0.024)
Daily tmin >90p × Z	0.002	-0.0006	-0.099*	-0.0001
	(0.052)	(0.0007)	(0.059)	(9.32×10^{-5})
Daily tmin >90p, t-1	-0.028	-0.040*	-0.007	-0.033
	(0.019)	(0.022)	(0.017)	(0.021)
Daily tmin >90p, t-1 × Z	-0.002	0.001	-0.142**	4.02×10^{-5}
	(0.030)	(0.0008)	(0.054)	(8.84×10^{-5})
Observations	6,813	8,327	8,327	8,327
Total precipitation	X	X	X	X
Country x year FE	X	X	X	X
Cell FE	X	X	X	X

Notes: All regressions are estimated with OLS using cell by year observations. The outcome is a dummy equal to 1 if a conflict event occurred in a cell during a year, zero otherwise. "Daily tmax >90p" and "Daily tmin >90p" are, respectively, the number of days with maximum and minimum daily temperature in the 90^{th} percentile defined on the 1979–2009 sub-monthly climate normal. The variable Z corresponds to a specific vulnerability factor: economic development (column 1), agricultural dependence (column 2), ethno-political discrimination (column 3), and demographic pressure (column 4). All estimates are multiplied by 100 for ease of interpretation and represent changes in percentage point. Standard errors are two-way clustered at the cell and climate zone-year level and are reported in parentheses. *, ** and *** denote statistical significance at 10%, 5% and 1% respectively.

a measure of demographic pressure.[16] For each regression we control for total precipitation and its lag, cell fixed effects and country-by-year fixed effects. Two-way clustered standard errors are reported in parentheses.

Overall, results provide little evidence that economic development, agricultural dependence and demographic pressure act as vulnerability factors, as none of the coefficients associated with interaction terms in columns 1, 2 and 4 are statistically significant at the usual confidence levels. The only factor that is found to affect the relationship between extreme temperature days and

[16] As mentioned previously, vulnerability factors are measured at the beginning of the observation periods to mitigate concerns of endogeneity. This corresponds to 2010, except for nighttime light emissions which are only available from 2012. For this variable, the number of observation decreases to 6,813 observations (column 1) since we drop 2010 and 2011 data.

conflict events is ethno-political discrimination (column 3). In particular, when discrimination is present in a grid cell, the positive impact of extreme maximum temperature days on conflict incidence is 0.16 pp higher both contemporaneously (p-val.$<$0.1) and with a lag (p-val.$<$0.01). Conversely, ethno-political discrimination reinforces the mitigating impact of days with extreme minimum temperature on the occurrence of conflict events. Specifically, in cells experiencing ethno-political discrimination the marginal effect of an additional extreme minimum temperature day is 0.1 pp lower contemporaneously (p-val.$<$0.1) and declines by 0.142 pp with a lag (p-val.$<$0.05).

Taken together, these results indicate that ethno-political discrimination reinforces the impact of extreme temperature days by a factor of two to three relative to what we measure at the average of the sample.

4 Results for robustness checks

This section reports the results of our robustness checks. First, we provide results for $1^\circ \times 1^\circ$ grid resolution. Second, we employ alternative measures of temperature-driven weather shocks. Third, we replicate the analysis using UCDP GED as an alternative source of conflict data. Lastly, we exclude grid cells affected by the Rohingya conflict in Myanmar.

4.1 Robustness: grid resolution

Results reported in Table 6 replicate baseline regression results with grid cells of 1° latitude/longitude. Following the reporting in Table 2, we gradually add control variables and fixed effects from columns 1 to 4. We report two-way clustered standard errors in parentheses.

Relative to baseline reduced form results, estimates for the contemporaneous effect of extreme maximum temperature days are larger. Similarly, coefficients for extreme minimum temperature days tend to be more negative than baseline counterparts, although point estimates in column 4 are almost identical. Estimates for lagged effects tend to be consistent with baseline results and are not precisely estimated. In fact, estimated standard errors tend to be larger throughout, which suggests that a lower grid cell resolution primarily affects accuracy rather than our qualitative findings.

Table 6: Reduced-form results with a 1° latitude/longitude spatial resolution

	Dependent variable: Indicator for conflict events			
	(1)	(2)	(3)	(4)
Daily tmax >90p	0.128***	0.137***	0.149***	0.129**
	(0.040)	(0.043)	(0.048)	(0.058)
Daily tmax >90p, t-1	0.026	0.052	0.071	-0.013
	(0.035)	(0.042)	(0.049)	(0.064)
Daily tmin >90p	-0.117***	-0.109**	-0.077*	-0.053
	(0.040)	(0.041)	(0.045)	(0.058)
Daily tmin >90p, t-1	-0.035	-0.051	-0.058	0.046
	(0.029)	(0.033)	(0.037)	(0.054)
Observations	2,222	2,222	2,222	2,222
Total precipitation		X	X	X
Year FE			X	
Country x year FE				X
Cell FE	X	X	X	X

Notes: All regressions are estimated using OLS. Observations correspond to 202 cells observed over 11 years (2010–2020). The outcome is a dummy equal to 1 if a conflict event occurred in a cell during a year, zero otherwise. "Daily tmax >90p" and "Daily tmin >90p" are, respectively, the number of days with maximum and minimum daily temperature in the 90^{th} percentile defined on the 1979–2009 sub-monthly climate normal. All estimates are multiplied by 100 for ease of interpretation and represent changes in percentage point. Standard errors are two-way clustered at the cell and climate zone-year level and are reported in parentheses. *, ** and *** denote statistical significance at 10%, 5% and 1% respectively.

4.2 Robustness: alternative measures of weather shocks

In Table 7 we reproduce baseline estimation with alternative temperature-driven measures of weather shocks. In column 1, we report results for mean temperature standardized relative to local 1979-2009 climate normal. In column 2, we use mean daily maximum and minimum temperature expressed as deviations from their 1979-2009 climate normal. In column 3, we examine the effect of extreme temperature days identified with the daily average. Finally, we introduce a 12-month SPEI either as an index (column 4) or to indicate the occurrence of a drought (column 5). These variables are described in more detail in Appendix B. In columns 1 to 3 we control for total precipitation and its lag, and all columns include cell fixed effects and country-by-year fixed effects. Two-way clustered standard errors are reported in parentheses.

Overall, the only temperature-based measure that has a consistent effect on conflict events is average maximum and minimum daily temperature (column 2). Specifically, a one standard

Table 7: Reduced-form results with alternative measures of weather shocks

	Dependent variable: Indicator for conflict events				
	(1)	(2)	(3)	(4)	(5)
Mean temperature	0.464				
	(0.596)				
Mean temperature, t-1	-0.070				
	(0.625)				
Maximum temperature		1.79***			
		(0.628)			
Maximum temperature, t-1		1.23			
		(0.863)			
Minimum temperature		-1.46*			
		(0.778)			
Minimum temperature, t-1		-1.02			
		(0.726)			
Daily temperature >90p			0.022		
			(0.019)		
Daily temperature >90p, t-1			-0.010		
			(0.022)		
SPEI-12				-0.111	
				(0.565)	
SPEI-12, t-1				0.777	
				(0.537)	
SPEI-Drought					-0.999
					(0.892)
SPEI-Drought, t-1					-1.35
					(1.27)
Observations	8,327	8,327	8,327	8,327	8,327
Total precipitation	X	X	X		
Country x year FE	X	X	X	X	X
Cell FE	X	X	X	X	X

Notes: All regressions are estimated using OLS. Observations correspond to 757 cells observed over 11 years (2010–2020). The outcome is a dummy equal to 1 if a conflict event occurred in a cell during a year, zero otherwise. Independent variables capture alternative measures of temperature-driven weather shocks and are described in Appendix B. All estimates are multiplied by 100 for ease of interpretation and represent changes in percentage point. Standard errors are two-way clustered at the cell and climate zone-year level and are reported in parentheses. *, ** and *** denote statistical significance at 10%, 5% and 1% respectively.

deviation increase in maximum temperature is associated with a 1.79 percentage point (pp) increase in the contemporaneous occurrence of conflict events (p-value <0.01). Conversely, a one standard deviation increase in minimum temperature is associated with a 1.46 percentage point (pp) decrease in the contemporaneous occurrence of conflict events (p-value <0.1). While lagged effects have consistent signs, these are not statistically significant at conventional levels.

Other measures of weather shocks do not suggest an impact on the occurrence of conflict

Table 8: Reduced-form regression results with alternative conflict data (UCDP GED)

	Dependent variable: Indicator for conflict events			
	(1)	(2)	(3)	(4)
Daily tmax >90p	0.016	0.014	0.018	0.025
	(0.012)	(0.014)	(0.016)	(0.016)
Daily tmax >90p, t-1	0.011	0.016	0.020	0.025
	(0.013)	(0.013)	(0.016)	(0.016)
Daily tmin >90p	-0.038***	-0.036***	-0.025	-0.026
	(0.012)	(0.011)	(0.016)	(0.016)
Daily tmin >90p, t-1	-0.009	-0.010	-0.019	-0.021
	(0.012)	(0.012)	(0.015)	(0.017)
Observations	8,327	8,327	8,327	8,327
Total precipitation		X	X	X
Year FE			X	
Country x year FE				X
Cell FE	X	X	X	X

Notes: All regressions are estimated using OLS. Observations correspond to 757 cells observed over 11 years (2010–2020). The outcome is a dummy equal to 1 if a conflict event occurred in a cell during a year, zero otherwise, and is derived from the Uppsala Conflict Data Program Georeferenced Event Dataset (UCDP GED, V.22.1). See Appendix B for further details. "Daily tmax >90p" and "Daily tmin >90p" are, respectively,the number of days with maximum and minimum daily temperature in the 90^{th} percentile defined on the 1979–2009 sub-monthly climate normal. All estimates are multiplied by 100 for ease of interpretation and represent changes in percentage point. Standard errors are two-way clustered at the cell and climate zone-year level and are reported in parentheses. *, ** and *** denote statistical significance at 10%, 5% and 1% respectively.

events, which supports the relevance of extreme temperature as a trigger for conflict events. In particular, the fact that mean temperature does not affect the occurrence of conflict events can be linked to the countervailing impacts of maximum and minimum temperature shocks.

4.3 Robustness: alternative conflict data

In Table 8 we replicate baseline regression results using the UCDP GED as an alternative source of data (see Appendix B for further details and a comparison with ACLED data). We follow the presentation in Table 2 and gradually add control variables and fixed effects from columns 1 to 4. We report two-way clustered standard errors in parentheses.

Results show that the coefficients associated with extreme temperature days are of similar sign throughout, for both contemporaneous and lagged effects. Point estimates are, however, smaller in magnitude, and in our preferred specification (column 4) these do not reach statistical significance at conventional levels. Therefore, while the results provide confidence in the validity of the effect reported in our baseline analysis, we are not able to confirm effect sizes using UCDP GED. One explanation for these inconclusive results is the more restrictive definition of conflict events used in UCDP GED (see Harari and La Ferrara, 2018, for a similar result for Africa). This implies lower variability in the outcome, and Figure B1 in Appendix B shows that UCDP GED features no conflict events in Vietnam and Laos for 2010–2020 whereas ACLED suggest a much more detailed picture.

4.4 Robustness: Rohingya conflict in Myanmar

Our last robustness checks consider the potential role of the Rohingya conflict in Myanmar for our results. Table 9 reports baseline reduced form estimation focusing only on grid cells that do not overlap with Rakhine State. We follow the presentation of Table 2 and gradually add control variables and fixed effects from columns 1 to 4. Two-way clustered standard errors are reported in parentheses.

Results suggest that the Rohingya conflict has a limited impact on the magnitude of our baseline results. Specifically, excluding cells overlapping with the Rakhine State suggests a slightly lower contemporaneous impact of extreme maximum days, whereas the contemporaneous impact of extreme minimum temperature days is somewhat more negative. The precision of our estimates remains very similar.

5 Discussion and conclusion

This paper has studied the impact of extreme temperature days on conflict events in mainland Southeast Asia. While climate change has implied a steady increase in average temperature from 1979, our data indicate that the yearly number of days with maximum temperature above the 90^{th} percentile of the sub-monthly climate normal has more than doubled. Estimation results from our preferred specification suggest that an additional day with extreme maximum temperature increases the unconditional probability of conflict events by about 0.9% on average, which confirms evidence from the existing literature. More interestingly, we show that the number of days with extreme minimum temperature also increased by a factor of more than two, suggesting that the shift in both tails of the temperature distribution follow a similar trend. In our

Table 9: Reduced-form results excluding Rakhine State in Myanmar

	Dependent variable: Indicator for conflict events			
	(1)	(2)	(3)	(4)
Daily tmax >90p	0.049***	0.048***	0.062***	0.061***
	(0.016)	(0.016)	(0.019)	(0.020)
Daily tmax >90p, t-1	0.006	0.015	0.017	-0.005
	(0.013)	(0.017)	(0.020)	(0.022)
Daily tmin >90p	-0.058***	-0.055***	-0.046**	-0.051**
	(0.016)	(0.017)	(0.019)	(0.022)
Daily tmin >90p, t-1	-0.013	-0.017	-0.025*	-0.013
	(0.012)	(0.015)	(0.015)	(0.018)
Observations	8,008	8,008	8,008	8,008
Total precipitation		X	X	X
Year FE			X	
Country x year FE				X
Cell FE	X	X	X	X

Notes: All regressions are estimated using OLS. Observations correspond to 728 cells observed over 11 years (2010–2020). The outcome is a dummy equal to 1 if a conflict event occurred in a cell during a year, zero otherwise. "Daily tmax >90p" and "Daily tmin >90p" are, respectively, the number of days with maximum and minimum daily temperature in the 90^{th} percentile defined on the 1979–2009 sub-monthly climate normal. All estimates are multiplied by 100 for ease of interpretation and represent changes in percentage point. Standard errors are two-way clustered at the cell and climate zone-year level and are reported in parentheses. *, ** and *** denote statistical significance at 10%, 5% and 1% respectively.

preferred specification, an additional day with minimum temperature above the 90^{th} percentile reduces the unconditional probability of conflict events by about 0.6% on average.

While the impact of extreme maximum and minimum temperature days have opposite signs, both results can be rationalized by the theory of opportunity cost. As documented in the literature (Ranson, 2014; Breckner and Sunde, 2019), days with extreme maximum temperature decrease the opportunity cost of participating in violence and stimulate tensions between groups due to relative deprivation. Conversely, the occurrence of extreme minimum temperature can improve livelihood conditions of local populations, and therefore decrease incentives for civilians and rebel groups to take part in conflicts or fight over resources.

Taken together, non-linearities in how conflict events respond to climate change imply that a shift in the distribution of temperature lead to compensating effects on aggregate. Importantly, however, our data shows that the geographical localization of extreme maximum and minimum temperature shocks is distinct, and we find that the type of conflict and population affected by extreme maximums and minimums are not the same. Specifically, extreme maximums have been shown to be associated with specific types of conflicts: battles by armed groups, state-based violence, as well as violence against civilians. Moreover, events triggered by extreme maximum temperature days involve state forces and include violence against rebel groups, political militias and civilians. By contrast, the reduction of conflict events associated with extreme minimum temperature days predominantly involves civilians, and includes interactions with political militia and rebel groups, but not governmental forces.

Despite these differences, an important common feature of conflict events affected by changes in extreme maximum and minimum temperature is that they are more likely to occur in the presence of ethno-political discrimination. Areas that feature politically marginalized ethnic groups are therefore more responsive to changes in the climate and the occurrence of new extremes, although the effect of climate change can also benefit the local population. Because conflicts represent a specific adaptation response which is outside of traditional market-based adaptation, institutions and policies can reallocate resources in order to shelter civilian populations from some but not all types of climate extremes (i.e., extreme maximums).

We close by emphasizing that Southeast Asia remains an under-studied region in the climate change literature seeking to quantify socio-economic impacts, and we offer two avenues open for research. First, while we employ highly disaggregated data, micro-level studies on behavior by vulnerable population remains important. In particular, Southeast Asia is an important rice growing area, and a more detailed account of precipitation and variability induced by local monsoon regime is an important area for future research. Second, migration is another adaptation margin to climate shocks, which can itself cause tensions and trigger conflicts. A better understanding of such displacement effects in relation to climate change is much needed.

Appendix A Additional data for heterogeneous effects

This Appendix discusses data for vulnerability factors identified in Section 2.3. We measure economic development in each grid cell with 2012 data on average nighttime light emissions provided by the Earth Observation Group, Visible and Infrared Imaging Suite (Elvidge et al., 2021).[17] We select the masked average radiance with "background, biomass burning, and aurora zeroed out." The data is available with a 15 arc second in nW/cm2/sr and averaged for each grid cell. We apply an inverse hyperbolic sine transformation to mitigate skewness and accommodate the presence of zeros.

To proxy agricultural dependence, we employ the extent of cropland coverage in each cell. This data is from Potapov et al. (2022). Specifically, based on satellite measurements, the authors provide global maps at a resolution of 0.025 pixels from 2000 to 2019, every four years. Their definition of croplands is "land used for annual and perennial herbaceous crops for human consumption, forage (including hay) and biofuel" which is "largely consistent with the arable land category reported by the Food and Agriculture Organization" (Potapov et al., 2022, p. 19). For each grid cell, we compute average coverage based on data for 2010.

The metric of ethno-political discrimination is the presence of a politically excluded ethnic group in a cell. To identify such groups, we rely on the 2021 Ethnic Power Relations Dataset (Vogt et al., 2015). This data is based on expert surveys and reports on politically relevant ethnic groups worldwide and their access to power from 1946 to 2021, whereby a community may dominate, share authority, or be excluded from it. We retain those groups whom the state seeks to keep out of power and which are targets of discrimination. We then combine these data with geo-referenced Ethnic Power Relations Dataset to locate these groups spatially and retain only the status in 2010. For each cell, we code an indicator variable equal to 1 if a politically marginalized ethnic group resides there, zero otherwise.

Lastly, we measure demographic pressure with data on population density from the Gridded Population of the World V4 (Center for International Earth Science Information Network, 2018). This dataset relies on national censuses and population registers to model the global spatial

[17] This data is only available from 2012 onwards. An alternative data source available for the estimation period is the Defense Meteorological Satellite Program (1992–2013). However, concerns have been raised as to its reliability for low-density rural areas (Gibson et al., 2021), which may be particularly problematic for the countries we consider.

distribution for every five years from 2000 to 2020 and at a resolution of up to 30 arc seconds. For each grid cell, we compute the mean density based on data for 2010.

Appendix B Additional data for robustness checks

This Appendix discusses data used in the robustest checks laid out in Section 2.4. In particular, we consider a number of alternatives to extreme temperature days. First, we compute mean temperature in each grid cell and year, standardized based on the 1979-2009 climate normal. Second, we use daily maximum and minimum values to compute the respective averages for each grid cell and year, and standardize it with respect to average maximum and minimum computed for the 1979-2009 climate normal. Third, we compute an index for the number of extreme temperature days based on daily averages, representing days in the 90^{th} percentile of the 1979–2009 climate normal. Fourth, we consider a SPEI retrieved from SPEIbase v.2.7 (Vicente-Serrano et al., 2010). The SPEI combines temperature, precipitation, latitude, wind speed, and sunshine exposure to assess soil moisture conditions. The index is based on inputs from the Climatic Research Unit of the University of East Anglia and is expressed as standard deviations from the average. We use the measure from December with a 12-month time scale, which reflects the situation during the whole year.

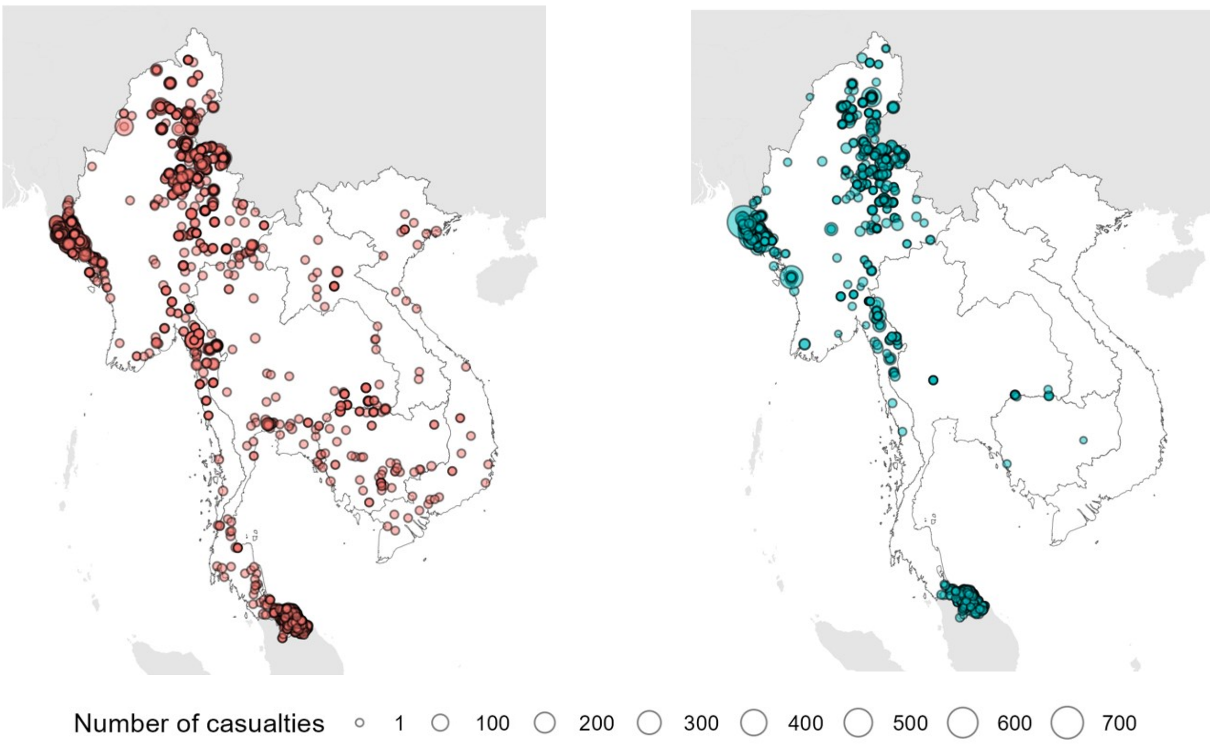
In the robustness checks we also consider an alternative source of data on conflict events and derive our outcome variable from the Uppsala Conflict Data Program Georeferenced Event Dataset (UCDP GED), version 22.1 (Sundberg and Melander, 2013; Davies et al., 2022). These data cover organized violence across the world from 1989 to 2021. The coding strategy differs from ACLED in two ways. First, it only considers events that are part of a large-scale conflict resulting in at least 25 deaths within a year. Second, UCDP GED only includes "incident where armed force was used by an organized actor against another organized actor, or against civilians, resulting in at least 1 direct death" (Högbladh, 2022, p. 4). For each cell by year observation, our outcome variable is equal to one if at least one conflict event as defined above occurred, zero otherwise.

As compared to UCDP GED, ACLED features a broader definition of conflicts and is not constrained by a minimum number of deaths over the year. A comparison of the spatial distribution of conflict events is reported in Figure B1.

Figure B1: Alternative data on conflict events in mainland Southeast Asia

(a) ACLED dataset

(b) UCDP GED dataset



Notes: This figure shows the spatial distribution of conflict events for 2010-2020 defined as "an incident where armed force was used by an organized actor against another organized actor, or against civilians, resulting in at least 1 direct death" (p. 4 Högbladh, 2022). Panel (a) reports data from the Armed Conflict Location & Event Data Project (ACLED). Panel (b) shows data from the Uppsala Conflict Data Program Georeferenced Event Dataset (UCDP GED). Each circle represents an event and size of the circle is proportional to the number of victims.

Appendix C Baseline results with spatial heteroskedastic and autocorrelation consistent standard errors

In Table C1 we test for the sensitivity of our baseline reduced-form results with respect to the use of spatial heteroskedastic and autocorrelation consistent standard errors (spatial HAC Conley, 1999). We vary the cutoff of spatial dependence in the error term from 0 (column 1) to 600 kilometers (column 5), which corresponds to approx. 0 and 10 cells in each direction, respectively. Estimated standard errors are reported below each coefficient and suggest that they remain very similar to our baseline results reported in Table 2.

Table C1: Reduced-form results with alternative cutoff distance for spatial HAC standard errors

	Dependent variable: Indicator for conflict events				
Cutoff distance (km) :	0 (1)	150 (2)	300 (3)	450 (4)	600 (5)
Daily tmax >90p	0.075***	0.075***	0.075***	0.075***	0.075***
	(0.018)	(0.020)	(0.020)	(0.020)	(0.020)
Daily tmax >90p, t-1	0.022	0.022	0.022	0.022	0.022
	(0.019)	(0.020)	(0.021)	(0.021)	(0.022)
Daily tmin >90p	-0.047***	-0.047**	-0.047**	-0.047**	-0.047**
	(0.018)	(0.020)	(0.021)	(0.020)	(0.020)
Daily tmin >90p, t-1	-0.028	-0.028	-0.028	-0.028	-0.028
	(0.017)	(0.018)	(0.019)	(0.020)	(0.020)
Observations	8,327	8,327	8,327	8,327	8,327
Control (total precipitation)	X	X	X	X	X
Country x year FE	X	X	X	X	X
Cell FE	X	X	X	X	X

Notes: All regressions are estimated using OLS. Observations correspond to 757 cells observed over 11 years (2010–2020). The outcome is a dummy equal to 1 if a conflict event occurred in a cell during a year, zero otherwise. "Daily tmax >90p" and "Daily tmin >90p" are, respectively, the number of days with maximum and minimum daily temperature in the 90^{th} percentile defined on the 1979–2009 sub-monthly climate normal. All estimates are multiplied by 100 for ease of interpretation and represent changes in percentage point. *, ** and *** denote statistical significance at 10%, 5% and 1% respectively.

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