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Climate Extremes and Economic Stressors as Predictors of Conflict in Central America Evidence from Monthly Data (2012–2024)

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ABSTRACT

Climate variability shapes economic conditions in Central America, but its short-term political effects remain poorly understood. This paper assembles a high-frequency monthly panel for six Central American countries (2012–2024) by harmonizing multiple conflict datasets (MLP and MLEED), climate indicators (temperature anomalies, precipitation and SPEI-based drought), and an inflation-based measure of economic stress. Using ElasticNet to identify the relevant lag structure for each hazard–outcome pair, and a mediation design to decompose direct and indirect pathways, we examine how climate shocks influence protest and violence through their economic consequences.

The results show a consistent pattern: droughts and temperature shocks generate strong and immediate increases in inflation, indicating rapid pressure on local markets. However, after accounting for this economic channel, the direct effects of climate shocks on protest and violence largely dissipate. Precipitation shocks similarly raise prices but do not translate into systematic changes in conflict outcomes. Across hazards and datasets, the inflation pathway is the most robust mechanism, while political responses remain small, short-lived, and sensitive to specification. Overall, the findings suggest that climate extremes in the region operate primarily through economic stress rather than through direct political destabilization, underscoring the central role of household welfare and market conditions in shaping short-term conflict dynamics.

Keywords: Conflict, Climate extremes, Economic stressors, Central America, MLEED, MLP, EM-DAT, ERA5, SPEI

INTRODUCTION

Central America is widely considered one of the regions most exposed to climate extremes while simultaneously struggling with persistent poverty, weak governance, and recurring violence. Periodic droughts in the "Dry Corridor," hurricanes striking coastal regions, and frequent flooding events have placed enormous pressure on fragile social and political systems. These overlapping stresses raise an enduring question: to what extent do environmental shocks and economic pressures contribute to conflict dynamics in the region?

Scholars have long debated the links between environmental pressures and violent outcomes. Early contributions emphasized the role of scarcity and resource competition as a root cause of instability (Homer-Dixon 1999). Building on these ideas, subsequent empirical studies have investigated how economic and environmental shocks may fuel conflict. For example, Miguel et al. (Miguel et al. 2004a) demonstrated that rainfall variability in Sub-Saharan Africa strongly predicts the outbreak of civil conflict. Similarly, Hendrix and Salehyan (Hendrix and Salehyan 2012a) found that rainfall shocks were associated with social unrest in Africa, providing quantitative evidence that climate variability can exacerbate political instability.

Other researchers have drawn attention to the broader theoretical and methodological challenges in assessing climate–conflict linkages. Gleditsch (Gleditsch 2012) cautioned against deterministic interpretations, noting that the impacts of climate change are mediated by political and institutional contexts. Buhaug (Buhaug 2015) similarly argued that while climate change can matter for conflict, its effects are neither universal nor uniform, highlighting the need for more nuanced and region-specific analyses. Recent re-

views emphasize the diversity of research designs and findings in this field, underscoring the importance of systematic comparison and robust data (Ide 2021).

A growing body of work has also highlighted the role of economic stressors. Rising food prices and volatility, for instance, have been linked to protest and social unrest. Bellemare (Bellemare 2015) shows that spikes in food prices increase the likelihood of political instability, while Smith (Smith 2014) disentangles how food shocks in African cities are associated with sociopolitical unrest. Earlier, Arezki and Brückner (Arezki and Brückner 2011) demonstrated that international food price increases can raise the risk of regime instability, illustrating how global market dynamics can feed into local conflict pressures. Taken together, these studies suggest that climate extremes and economic shocks may interact in mutually reinforcing ways.

For Central America, these dynamics are particularly acute. The Dry Corridor, stretching across Guatemala, Honduras, El Salvador, and Nicaragua, has been described as one of the world's most drought-prone regions (Food and Agriculture Organization of the United Nations 2019). Drought undermines agricultural production and food security, while hurricanes and floods such as those captured in EM-DAT disaster records (EM-DAT: The International Disaster Database 2021) cause devastating losses that erode livelihoods and governance capacity. Meanwhile, broader structural problems, including organized crime and weak state institutions, compound the vulnerability of these societies (Castaneda and Schneider 2017). This combination of environmental extremes, economic hardship, and fragile governance provides fertile ground for protest, organized violence, and broader political instability.

This paper contributes to this debate by examining the interaction between climate extremes and economic pressures in shaping conflict in Central America. Using new monthly data covering 2012–2024, we integrate climate indicators (e.g., drought measures from SPEI, extreme temperature and precipitation from ERA5, and disaster events from EM-DAT), economic indicators (consumer price indices and standardized bean prices), and event-based data on protest and violence (MLEED and MLP). By merging these sources, the study provides a consistent framework to assess whether and how environmental and economic shocks feed into cycles of unrest and conflict. While this work builds on insights from global studies, its focus on Central America addresses a critical gap in the literature, where exposure to climate extremes coincides with persistent poverty and weak governance.

LITTERATURE REVIEW

A large interdisciplinary literature examines how environmental stress and economic shocks shape risks of social unrest and violence. Early theoretical work argued that scarcities of vital resources driven by environmental change, population pressures, or unequal access can erode livelihoods and amplify competition, creating fertile ground for instability (Homer-Dixon 1999). At the same time, comparative politics and peace research caution against deterministic claims: the impacts of climate variability and long-term change are filtered through institutions, governance, and socioeconomic structures (Gleditsch 2012; Buhaug 2015). Recent reviews emphasize that apparent disagreements in "climate–conflict" findings often reflect differences in research design, data, temporal/spatial scales, and outcome definitions rather than a single true effect size (Ide 2021).

Within this broader debate, a prominent empirical strand exploits quasi-exogenous climate variation. Miguel et al. (2004a) show that negative rainfall shocks in Sub-Saharan Africa robustly predict civil conflict onset, a result interpreted through income shocks and state-capacity channels. Subsequent work highlights that climate variability can raise risks of lower-level contention as well: Hendrix and Salehyan (2012a) find that rainfall deviations are associated with social unrest in Africa, while Raleigh and Witmer (2015) underscore that where climate "matters" depends crucially on exposure, sensitivity, and the mediating institutional context. The thrust of this literature is not that climate anomalies uniformly cause conflict, but that they can elevate risk when and where institutional buffers are weak (Gleditsch 2012; Buhaug 2015).

Economic stressors constitute a second major pathway linking environmental shocks to instability. A rich body of evidence documents that food price increases and volatility are associated with a higher likelihood of protests and broader sociopolitical unrest (Bellemare 2015; Smith 2014). At the macro level, exposure to world commodity cycles can transmit instability through domestic political channels: Arezki and Brückner (2011) find that international food price booms are linked to greater regime instability. These findings resonate with arguments that economic grievances and expectations rather than purely climatic triggers

can be the proximate spark for mobilization, especially in urban settings where consumers are net food buyers (Smith 2014). More broadly, weak institutions, limited state capacity, and the presence of organized criminal actors can magnify the political consequences of economic downturns and price shocks (Castaneda and Schneider 2017).

Central America is a compelling regional context where these channels intersect. The "Dry Corridor" spanning Guatemala, Honduras, El Salvador, and Nicaragua is among the world's most drought-prone zones, with recurrent water deficits that undermine agricultural output and household food security (Food and Agriculture Organization of the United Nations 2019). At the other end of the hydro-climate spectrum, tropical cyclones and flood events regularly impose large damages; these shocks are systematically tracked in disaster registries such as EM-DAT (EM-DAT: The International Disaster Database 2021). Early warning work highlights the growing capacity to monitor drought and hydrometeorological extremes in the Americas - tools that can be leveraged to study the conflict implications of shocks on policy-relevant timescales (Funk et al. 2018). The coexistence of recurrent hydro-climatic extremes, structural poverty, and governance challenges in the isthmus suggests that both climate and economic channels are likely to be salient—and potentially mutually reinforcing.

Two cross-cutting issues raised by recent surveys are especially relevant for our design. First, measurement choices matter. Conflict is multi-dimensional: "contentious politics" (e.g., protest) and "organized violence" (lethal or non-lethal) need not respond identically to the same shock (Ide 2021). Similarly, climate indicators capture different physical processes: drought indices such as SPEI (multi-month moisture anomalies), heat extremes (monthly maxima of daily maximum temperature), and extreme precipitation (e.g., monthly max one-day rainfall) represent distinct hazards with distinct timing and pathways to harm. Disaster reports (e.g., EM-DAT: The International Disaster Database 2021) capture realized events that pass reporting thresholds and therefore sit closer to socioeconomic impact. Second, the unit of analysis and frequency shape identification. Monthly country-level panels can trace short-run dynamics and event "surges," complementing annual cross-national studies that focus on onsets/occurrences of civil conflict (Miguel et al. 2004a; Hendrix and Salehyan 2012a). In line with calls for transparent and comparable designs (Ide 2021), we align all sources to a common country–month index and estimate models with country and year fixed effects.

Building on these insights, we treat climate extremes and economic stress as intertwined sources of risk rather than competing explanations. Drought can depress agricultural income, tighten rural labor markets, and raise food prices; heat extremes harm productivity and health; floods and storms damage infrastructure and disrupt markets. These impacts can propagate to urban consumers via price pass-through, raising the salience of economic grievances and potentially shifting repertoires of contention from rural collective action to urban protest (Bellemare 2015; Smith 2014). In settings with weak capacity and the presence of armed non-state actors, the same stressors may also be associated with escalations in violent events, particularly when state responses are perceived as ineffective or biased (Castaneda and Schneider 2017). Yet, as emphasized by Buhaug (2015) and Gleditsch (2012), these are contingent risks: heterogeneity across countries and years is expected.

Our empirical framework is tailored to this landscape. We integrate monthly indicators of drought (SPEI-06), heat and rain extremes (ERA5), and realized disasters (EM-DAT); combine them with standardized staple food prices (beans) and an inflation/price pressure index; and link these to event-based measures of protest and violence. The focus on "surge" outcomes acknowledges that event data contain noise and that policy interest often lies in months when activity clearly picks up rather than in single reports. By modeling protests and violence separately, we allow for asymmetric responses across contention types. This design responds directly to the comparative insights in Ide (2021) while retaining the core identification logic from climate-shock studies (Miguel et al. 2004a; Hendrix and Salehyan 2012a; Raleigh and Witmer 2015) and the food-price literature (Bellemare 2015; Smith 2014; Arezki and Brückner 2011).

In sum, prior work suggests three expectations for Central America. First, negative moisture anomalies and heat extremes should be associated with higher probabilities of contentious events, with magnitude moderated by institutions and exposure (Raleigh and Witmer 2015; Buhaug 2015). Second, disasters (storms/floods) may produce short-run spikes in contention or violence through displacement, service disruption, and governance strain (EM-DAT: The International Disaster Database 2021; Funk et al. 2018). Third, economic stress proxied by inflation pressure and staple prices should independently elevate unrest risk and may amplify the

effects of climate shocks, especially in urban areas (Bellemare 2015; Smith 2014; Arezki and Brückner 2011; Castaneda and Schneider 2017). The empirical analysis below is structured to test these hypotheses with a unified monthly panel that centers the region's coupled climate economy dynamics.

DATA DESCRIPTION

We construct a new monthly country panel dataset covering six Central American countries: Guatemala, El Salvador, Honduras, Nicaragua, Costa Rica, and Panama, for the period 2012-2024. The data set integrates environmental, economic and conflict indicators to examine how climate extremes and economic stressors relate to social unrest and violence in the region. Each observation corresponds to one country in one month, resulting in a balanced panel aligned to a common country and month index.

Data for conflict and environmental events come from two complementary sources. The Machine Learning for Peace (MLP) project provides measures of political and social contention derived from more than 120 million online news articles in 60 countries using web scraping and natural language processing. From this dataset, we extract monthly counts of protests and violence, both lethal and non-lethal, and convert them into binary surge indicators equal to one when a country experiences unusually high activity relative to its own historical pattern. The Machine Learning for Environmental Event Detection (MLEED) dataset, which is built from the same underlying text corpus, focuses specifically on environmental issues. It provides two additional outcomes: environmental protests and environmental violence. These are also coded as binary surges. Together, these four outcomes capture both general and environmental forms of social contention.

The environmental conditions are measured using several complementary indicators. Drought is captured using the six-month Standardized Precipitation Evapotranspiration Index (SPEI-06, SPEIbase v2.10, 0.5 degree resolution), aggregated to the national level. Negative values indicate conditions that are drier than usual and months with a SPEI less than or equal to minus one are classified as drought months. Temperature extremes are derived from ERA5-Land monthly reanalysis data using the monthly maximum of daily maximum temperature (txx), expressed as a departure from each country's long-term monthly mean. Extreme precipitation is drawn from ERA5-Land using the maximum one-day rainfall each month (rx1day), after removing the seasonal patterns specific to each country. These indicators capture both slow-onset hazards such as droughts and rapid-onset hazards such as heatwaves and heavy rainfall. A disaster indicator from the EM-DAT International Disaster Database is also included and is coded as one whenever a disaster is reported in a given country and month.

Economic stress is measured using two indicators. The first is an *Economics_Stressor* index constructed from Trading Economics monthly data covering a broad set of inflation and price components. These include inflation expectations, producer price inflation, month-to-month changes in inflation rates, food inflation, core consumer prices, housing and transportation components of the CPI, the overall consumer price index, producer prices and their monthly changes, core inflation rates, harmonised consumer price indices, harmonised inflation rates, rent inflation, and annual inflation. For each of these variables, a standardized score is computed within country using a z-score transformation, so that each series reflects deviations from typical national conditions. The standardized components are then averaged at each country and month to produce a single composite index that summarizes overall inflationary pressure in a format comparable across countries and over time.

The second indicator is an inflation rate series derived from monthly bean prices obtained from the FAO Food Price Monitoring and Analysis tool. Bean prices are standardized within each country to capture deviations from their usual level, and higher values of this indicator represent periods of elevated food-specific inflation. Together, these two measures distinguish between broad macroeconomic pressure and more immediate food-related stress, allowing the analysis to capture the different channels through which economic conditions respond to climate anomalies.

All datasets are harmonized by ISO code, aligned to the first day of each month, and aggregated at the national level. Gridded climate data are averaged using area weights based on consistent national boundaries. Event data are deduplicated before defining surge indicators. Short gaps in the price series are filled using linear interpolation. No extrapolation beyond observed periods is performed. The resulting balanced panel contains one row for each country and each month from 2012 to 2024 and provides an integrated view of climate hazards, economic stress, and social contention across Central America.

To capture the timing of environmental shocks more accurately, all climate indicators used in the study, including SPEI-06, temperature anomalies, and precipitation anomalies, are extended backward to January 2011 even though the analysis period begins in January 2012. Extending the climate series makes it possible to construct a complete set of monthly lags from zero to twelve months for each hazard without introducing missing values at the start of the panel. For each climate variable we generate twelve lagged versions that represent conditions in the previous year. These lagged indicators serve as the basis for the distributed lag analysis that follows.

Because heat and rainfall follow strong seasonal cycles, temperature and precipitation are expressed as anomalies relative to each country's long-term monthly pattern. Monthly observations are deseasonalized so that they reflect unusual conditions rather than predictable seasonal variation. This adjustment facilitates meaningful comparison across months and across countries.

The dataset contains the full set of lagged climate variables, mediators, and outcomes needed for the empirical strategy. Preparing the data in this way allows the analysis to identify which temporal windows are most relevant for each hazard before evaluating possible mediation pathways. The aim is to let the data reveal the timing that matters rather than imposing assumptions in advance.

METHODOLOGY

The empirical strategy is designed to identify how different climate hazards influence episodes of protest and violence across Central America, and to compare the timing and strength of these effects for drought, temperature anomalies, and precipitation deviations. Climate shocks may affect social outcomes immediately or only after several months, so the analysis begins by constructing a complete set of lagged climate variables for each hazard. For each country c and month t, let $X_{c,t-k}$ denote the value of the climate indicator observed k months earlier. For each hazard and each outcome, a sequence of fixed effects regressions is estimated of the form

$$Y_{c,t} = \alpha + \gamma_c + \delta_t + \beta_k X_{c,t-k} + \varepsilon_{c,t}, \tag{1}$$

where $Y_{c,t}$ is one of the four binary surge indicators for protest or violence, γ_c captures country-specific time-invariant factors, and δ_t absorbs common monthly and yearly shocks. This specification follows standard practice in climate–conflict research, where fixed effects are used to isolate within-country variation over time (Miguel et al. 2004b; Hendrix and Salehyan 2012b). Standard errors are clustered at the country level to account for serial correlation.

Since the thirteen lagged versions of each climate variable are highly correlated, including them jointly in an unrestricted regression would lead to multicollinearity and unstable estimates. To avoid imposing an arbitrary lag structure and to allow the data to reveal the most relevant temporal windows, the set of lagged climate variables is screened using an ElasticNet regularization procedure (Zou and Hastie 2005). All climate lags are standardized prior to estimation and residualized with respect to the fixed effects. Let $\widetilde{Y}_{c,t}$ denote the residual from regressing $Y_{c,t}$ on country and time fixed effects, and let $\widetilde{X}_{c,t-k}$ represent the corresponding residuals for the lagged climate variables. The ElasticNet estimator solves

$$\hat{\beta} = \arg\min_{\beta} \left\{ \sum_{c,t} \left(\widetilde{Y}_{c,t} - \sum_{k=0}^{12} \beta_k \widetilde{X}_{c,t-k} \right)^2 + \lambda \left[(1-\alpha) \sum_k \beta_k^2 + \alpha \sum_k |\beta_k| \right] \right\}, \tag{2}$$

which combines the ridge penalty of Hoerl and Kennard (1970) and the LASSO penalty of Tibshirani (1996). The hyperparameters λ and α are selected through cross-validation. The resulting nonzero coefficients identify the subset of lags that exhibit predictive power. Each selected lag is then re-estimated using an unpenalized fixed effects model so that the coefficient and its uncertainty can be interpreted directly.

To investigate whether the effects of climate hazards are transmitted through economic stress, the analysis proceeds with a mediation framework inspired by Baron and Kenny (1986) and commonly used in climate–economy research (e.g., Harari and La Ferrara 2020). Two economic variables serve as potential mediators in the analysis. The first is the *Economics_Stressor* index, which is constructed from a set of monthly indicators that capture short-run macroeconomic pressure. These include inflation expectations, producer

price inflation, month-to-month changes in consumer and producer prices, food inflation, core inflation components, housing and transportation CPI, harmonised price indices, rent inflation, and several related measures. Each component is standardized within country and averaged to form a single composite index that reflects broad economic stress. The second mediator is an inflation rate series derived from monthly bean prices, which captures food-specific inflation affecting household purchasing power. For each climatic lag $X_{c,t-k^*}$ retained in the selection stage, the first step estimates how the mediator responds to the climate shock:

$$M_{c,t} = \alpha_1 + \gamma_c + \delta_t + \lambda X_{c,t-k^*} + u_{c,t}. \tag{3}$$

The second equation introduces both the hazard and the mediator into the outcome model:

$$Y_{c,t} = \alpha_2 + \gamma_c + \delta_t + \theta X_{c,t-k^*} + \phi M_{c,t} + v_{c,t}. \tag{4}$$

The indirect effect of the hazard on the outcome is given by $\lambda\phi$, the direct effect is θ, and the total effect is the sum of the two. This decomposition isolates the economic pathway linking climate anomalies to social unrest and allows comparison across drought, heat, and precipitation shocks. The fixed effects structure is identical across equations, ensuring that all identification comes from within-country changes over time.

All models account for heterogeneity across countries and common shocks across months and years, making the estimates robust to unobserved factors that are constant within countries or that vary uniformly across the region. Complete distributed lag coefficient plots and ElasticNet selection results are reported in the appendix.

The interpretation of the estimated coefficients follows directly from the structure of the models. All climate variables and mediators are standardized within country, which means that the coefficients represent the change in the probability of a surge event associated with a one standard deviation change in the corresponding variable. This standardization facilitates comparison across hazards and outcomes and ensures that effect sizes can be interpreted on a common scale. For lagged specifications, each estimated coefficient reflects the effect of climate conditions observed k months prior to the outcome month, which allows the analysis to trace the temporal profile of the impact of each hazard. In the mediation framework, the indirect effect captures the component of the climate impact that operates through the mediator, computed as the product of the effect of the hazard on the mediator and the effect of the mediator on the outcome. The direct effect represents the remaining influence of the hazard net of the mediation channel. The total effect is the sum of these components. This decomposition clarifies the pathways through which climate anomalies influence protest and violence and allows for a systematic comparison of the mechanisms across the different hazards.

RESULTS

This section presents the empirical results following the structure of our analytical design. We begin by using the ElasticNet procedure to identify the lags of drought, temperature, and precipitation that matter most for monthly conflict outcomes. We then estimate the selected models and decompose each climate effect into its total, direct, and mediated components using economic stress as the key mechanism. The results are presented separately for protest and violence outcomes (both MLP and MLEED), and we refer to the appendix figures when they help clarify the lag structure or the magnitude of the estimated pathways. Throughout, the focus is on understanding whether climate shocks influence conflict directly or primarily through their economic impacts.

Model	Variable	MLP Protest (lag 1)	MLP Protest (lag 8)	MLEED Protest (lag 0)
Mediation	Drought	-0.2429^{***} (0.069)	-0.3002^{***} (0.104)	-0.2394^{***} (0.061)
	MLP Protest	0.1270^{***} (0.039)		
	MLP Violence	-0.1061 (0.129)	-0.1548 (0.106)	
	MLEED Protest			
	MLEED Violence			-0.0708 (0.036)
	Econ. Stressor			
	MLP Disaster	-0.1601 (0.105)	-0.1789 (0.144)	
	MLEED Disaster			-0.1224 (0.097)
	Inflation Rate	0.8389^{***} (0.219)	0.8287^{***} (0.289)	0.8803^{***} (0.261)
Total Effect	Drought	0.0076 (0.026)	-0.0833 (0.014)	0.0123 (0.029)
	MLP Protest			
	MLP Violence	0.0079 (0.017)	0.07382^{***} (0.046)	
	MLEED Protest			
	MLEED Violence			0.0278 (0.021)
	Econ. Stressor		-0.1216^{***} (0.019)	
	MLP Disaster	-0.1216^{***} (0.019)	-0.1770^{***} (0.042)	
	MLEED Disaster			-0.1210^{***} (0.020)
	Inflation Rate	-0.0718 (0.100)	-0.0288 (0.029)	-0.0744 (0.099)
Direct Effect	Drought	0.0099 (0.023)	0.0782 (0.026)	0.0147 (0.028)
	MLP Protest			
	MLP Violence	0.0296^{*} (0.018)	0.0730^{***} (0.047)	
	MLEED Protest			
	MLEED Violence			0.0477 (0.047)
	Econ. Stressor	-0.0209 (0.021)	0.0089 (0.020)	0.0099 (0.011)
	MLP Disaster	-0.1708^{***} (0.040)	-0.1766^{***} (0.044)	
	MLEED Disaster			-0.1197^{***} (0.019)
	Inflation Rate	-0.0798 (0.098)	-0.0740 (0.029)	-0.0831 (0.097)

Table 1: Mediation, Total, and Direct Effect Results for MLP Protest (lags 1 and 8) and MLEED Protest (lag 0)

0.1. *Drought Effects on Protest and Violence*

The results in Table 1 show a consistent pattern linking drought to economic stress and, through that channel, to protest dynamics. For both MLP Protest (lags 1 and 8) and MLEED Environmental Protest (lag 0), the first stage of the mediation design reveals that drought produces a sharp and statistically precise increase in inflation. The coefficients, which range from 0.83 to 0.88 across specifications, reflect a robust rise in prices following moisture deficits. This inflation response is also visible in the mediation plots in Appendix B (Figures 4 and 5), where the inflation pathway clearly stands out as the strongest component of the overall effect.

Although drought shows a negative association with protest in the mediation stage (for example, -0.24 at lag 1 and -0.30 at lag 8 for MLP Protest), these effects lose their significance once the inflation pathway is included. The total effect becomes essentially zero, and the direct effect is equally small. The overall implication is that drought does not directly suppress or stimulate protest in the months identified by the lag-selection procedure. Instead, the relevant movement comes through economic pressure, which drought clearly generates, but which translates only weakly into protest after controlling for other country and time factors. The figures in Appendix A confirm why lags 1 and 8 matter: they correspond to the periods where

the ElasticNet procedure selected non-zero drought coefficients (Figure 1), marking early and mid-horizon responses to dry conditions.

Model	Variable	MLP Violence (lag 0)	MLP Violence (lag 1)	MLP Violence (lag 2)	MLP Violence (lag 4)	MLEED Violence (lag 0)
Mediation	Drought	0.0342	0.0259	−0.2621***	−0.2539***	−0.2440***
		(0.051)	(0.065)	(0.074)	(0.071)	(0.040)
	MLP Protest	0.0973***	0.0970***	0.0126	0.0291	
		(0.045)	(0.056)	(0.074)	(0.064)	
	MLP Disaster	0.0196	0.0199	0.0906	0.0809	
		(0.096)	(0.096)	(0.104)	(0.094)	
	MLEED Protest					0.0821
						(0.127)
	MLEED Violence					
	MLEED Natural Disaster					0.1607
						(0.105)
	Econ. Stressor					
	Inflation Rate	−0.0233	0.8448***	0.9108***	0.7471***	0.7845***
		(0.114)	(0.215)	(0.237)	(0.245)	(0.127)
Total Effect	Drought	0.0342	0.0259	−0.0380	0.0630	0.0376
		(0.051)	(0.065)	(0.061)	(0.024)	(0.043)
	MLP Protest	0.0973***	0.0970***	0.0736*	0.0830	
		(0.045)	(0.056)	(0.038)	(0.044)	
	MLP Disaster	0.0196	0.0199	−0.0226	0.0267	
		(0.096)	(0.096)	(0.122)	(0.122)	
	MLEED Protest					0.0351
						(0.044)
	MLEED Violence					
	MLEED Natural Disaster					0.0046
						(0.023)
	Econ. Stressor					
	Inflation Rate	−0.0233	−0.0195	−0.0270	0.0041	0.0203
		(0.114)	(0.120)	(0.122)	(0.114)	(0.028)
Direct Effect	Drought	0.0272	0.0305	0.0305	0.0562**	0.0461
		(0.057)	(0.015)	(0.016)	(0.021)	(0.045)
	Econ. Stressor	−0.0287*	−0.0266**	−0.0273*	−0.0261**	0.0033
		(0.013)	(0.013)	(0.014)	(0.013)	(0.037)
	MLP Protest	0.0278	0.0278	0.0789*	0.0816*	
		(0.073)	(0.073)	(0.043)	(0.044)	
	MLP Disaster	−0.0475	−0.0475	−0.0245	0.0288	
		(0.027)	(0.027)	(0.027)	(0.048)	
	MLEED Protest					−0.0320
						(0.043)
	MLEED Violence					
	MLEED Natural Disaster					−0.0010
						(0.023)
	Inflation Rate	−0.0222	−0.0112	−0.0012	0.0236	−0.0020
		(0.105)	(0.112)	(0.112)	(0.106)	(0.073)

Table 2: Mediation, Total, and Direct Effect Results for MLP Violence (lags 0, 1, 2, 4) and MLEED Violence (lag 0).

A similar structure appears in Table 2, which reports the results for MLP Violence and MLEED Environmental Violence. As in the protest models, drought produces a sizable increase in inflation, and this pattern holds at all ElasticNet-selected lags (0, 1, 2, and 4). But the direct association between drought and violence is more uneven. At some lags, for instance, lags 2 and 4 for MLP Violence, the mediation-stage coefficients are negative and significant. At others, including the lag 0 specifications for both MLP and MLEED measures, the relationship is small or statistically indistinct.

Once inflation is accounted for, the total effects on violence settle near zero. This reflects the same core mechanism observed in the protest models: drought reliably raises prices, but after absorbing the economic channel, little independent movement remains in the conflict outcomes. The full set of mediation plots in Appendix B (Figures 7 and 6) makes this clearer by showing the strong inflation response and the relatively flat direct pathway.

Taken together, the two tables indicate that drought's main influence in this region operates through economic hardship rather than through immediate conflict responses. The systematic inflation effects suggest rapid pressure on household budgets, but the lag structure and direct–indirect decomposition show that this pressure does not consistently translate into either higher or lower levels of protest and violence once the economic mechanism is fully incorporated into the model.

Model	Variable	MLP Protest (lag 0)	MLP Protest (lag 1)	MLP Protest (lag 2)	MLP Protest (lag 4)	MLEED Protest (lag 5)	MLEED Protest (lag 8)
Mediation	Temperature	−0.0084	−0.0153	−0.0161	−0.0258	−0.0352	−0.0552
		(0.048)	(0.052)	(0.056)	(0.060)	(0.065)	(0.069)
	MLP Violence	−0.1502**	−0.1509**	−0.1516**	−0.1471**		
		(0.071)	(0.073)	(0.074)	(0.067)		
	MLP Disaster	−0.1140	−0.1112	−0.1113	−0.1160	−0.0995	−0.0763
		(0.098)	(0.098)	(0.098)	(0.099)	(0.103)	(0.100)
	MLEED Violence					0.1569**	0.1623**
						(0.059)	(0.065)
	Econ. Stressor					0.7898***	0.7614***
						(0.274)	(0.278)
	Inflation Rate	0.8161***	0.8191***	0.8174***	0.7972***	0.7998***	0.7614***
		(0.265)	(0.260)	(0.262)	(0.276)	(0.274)	(0.278)
Total Effect	Temperature	−0.0304***	−0.0235**	−0.0134	−0.0082	−0.0116	0.0154
		(0.006)	(0.010)	(0.010)	(0.008)	(0.010)	(0.011)
	MLP Violence	0.0816	0.0788	0.0782	0.0799		
		(0.047)	(0.047)	(0.046)	(0.044)		
	MLP Disaster	−0.1211***	−0.1168***	−0.1191***	−0.1203***	−0.0200	−0.0151
		(0.020)	(0.020)	(0.023)	(0.019)	(0.021)	(0.023)
	MLEED Violence					0.0473	0.0407
						(0.024)	(0.020)
	Econ. Stressor						
	Inflation Rate	−0.0736	−0.0677	−0.0707	−0.0774	0.0453	0.0664
		(0.097)	(0.096)	(0.099)	(0.104)	(0.054)	(0.060)
Direct Effect	Temperature	−0.0303***	−0.0233**	−0.0133	−0.0079	−0.0112	0.0143
		(0.006)	(0.010)	(0.011)	(0.024)	(0.010)	(0.012)
	Econ. Stressor		0.0083	0.0084	0.0085	0.0132	0.0147
			(0.011)	(0.011)	(0.015)	(0.039)	(0.044)
	MLP Violence	0.0289	0.0280	0.0344*	0.0812*	0.0341	0.0347
		(0.048)	(0.048)	(0.047)	(0.044)	(0.040)	(0.042)
	MLP Disaster	−0.1193***	−0.1180***	−0.1182***	−0.1139***	−0.0060	−0.0139
		(0.018)	(0.018)	(0.019)	(0.024)	(0.021)	(0.023)
	MLEED Violence					0.0341	0.0347
						(0.040)	(0.042)
	Inflation Rate	−0.0805	−0.0745	−0.0776	−0.0841	0.0349	0.0551
		(0.096)	(0.095)	(0.097)	(0.104)	(0.047)	(0.055)

Table 3: Mediation, Total, and Direct Effects of Temperature on Protest (lags 0–4 for MLP, lags 5 and 8 for MLEED).

TEMPERATURE RESULTS

The results in Table 3 show a clear pattern in how temperature shocks shape protest activity. Across the lags selected by the ElasticNet procedure (lags 0 to 4 for MLP Protest and lags 5 and 8 for MLEED Protest), the estimates indicate that higher temperatures reduce protest activity in the short run. These negative coefficients typically fall between −0.02 and −0.03 and are statistically significant in several specifications, especially at lags 1 and 2.

At the same time, temperature shocks generate a strong and highly consistent increase in inflation. The inflation coefficients, which range from about 0.79 to 0.83, are remarkably stable across all models. This shows that temperature spikes reliably translate into higher consumer prices. The mediation plots in Appendix B (Figures 8 and 9) illustrate this pattern clearly, with the inflation pathway standing out as the dominant channel.

Once inflation is added to the model, the direct effect of temperature on protest becomes weaker and often loses statistical precision. Although the total effect of temperature on protest remains negative, its magnitude becomes small relative to the inflation pathway. Taken together, these results suggest that while temperature shocks create economic stress through rising prices, this pressure does not consistently spill over into increased protest after controlling for country and time factors.

Model	Variable	MLP Violence (lag 2)	MLP Violence (lag 4)	MLP Violence (lag 12)	MLEED Violence (lag 4)	MLEED Violence (lag 5)
Mediation	Temperature	0.0149	−0.0209	0.0123	−0.0297	−0.0335
		(0.058)	(0.061)	(0.062)	(0.063)	(0.065)
	MLP Protest	0.0304	0.0306	0.0240		
		(0.055)	(0.058)	(0.058)		
	MLP Disaster	−0.1332	−0.1019	−0.0729		
		(0.089)	(0.101)	(0.100)		
	MLEED Protest				0.0838	0.0598
					(0.042)	(0.129)
	MLEED Natural Disaster				0.1653	0.1623
					(0.101)	(0.101)
	Inflation Rate	0.8226***	0.7999***	0.8234***	0.7031**	0.7064**
		(0.259)	(0.271)	(0.253)	(0.297)	(0.294)
	Economic Stressor					
Total Effect	Temperature	−0.0041	0.0241	0.0175	0.0180**	0.0108
		(0.012)	(0.014)	(0.010)	(0.007)	(0.012)
	MLP Protest	0.0798	0.0823**	0.0816**		
		(0.044)	(0.042)	(0.045)		
	MLP Disaster	−0.0290	−0.0273	−0.0269		
		(0.029)	(0.030)	(0.030)		
	MLEED Protest				0.0838	0.0730
					(0.042)	(0.042)
	MLEED Natural Disaster				0.0043	0.0043
					(0.023)	(0.023)
	Inflation Rate	−0.0141	0.0043	−0.0144	0.0247	0.0402
		(0.113)	(0.104)	(0.111)	(0.066)	(0.071)
	Economic Stressor					
Direct Effect	Temperature	−0.0046	0.0233*	0.0148	0.0190**	0.0118
		(0.010)	(0.013)	(0.010)	(0.007)	(0.011)
	Economic Stressor	0.0310	−0.0301**	−0.0295**	−0.0299**	0.0285***
		(0.014)	(0.013)	(0.014)	(0.016)	(0.016)
	MLP Protest	0.0832	0.0823**	0.0823**		
		(0.027)	(0.042)	(0.043)		
	MLP Disaster	−0.0278	−0.0268	−0.0268		
		(0.027)	(0.028)	(0.028)		
	MLEED Protest				0.0838	0.0832
					(0.042)	(0.042)
	MLEED Natural Disaster				−0.0006	−0.0080
					(0.022)	(0.022)
	Inflation Rate	0.0115	0.0284	0.0099	0.0247	0.0178
		(0.104)	(0.098)	(0.102)	(0.067)	(0.073)

Table 4: Mediation, Total, and Direct Effects of Temperature on MLP and MLEED Violence (Various Lags).

Table **??** reports the corresponding results for temperature and violence. The first stage again shows a strong rise in inflation at all selected lags (lags 2, 4, and 12 for MLP Violence and lags 4 and 5 for MLEED Violence). In contrast, the direct temperature–violence relationship is weak and unstable. Some coefficients are slightly positive, others are close to zero, and none remain significant once inflation is included. The full set of mediation figures in Appendix B (Figures 10 and 11) show the same pattern, with a strong inflation response but little consistent movement in the violence outcomes.

Overall, the temperature results indicate that the main immediate consequence of temperature anomalies in this region is economic rather than political. Temperature shocks reliably raise prices, but once this inflation channel is accounted for, there is no systematic evidence that hotter months lead to more or less protest or violence. Unlike drought, which produces clearer lagged responses, the temperature effects are more variable and do not generate stable conflict outcomes after incorporating the mediation structure.

Model	Variable	MLP Protest (lag 12)	MLEED Protest (lag 0)	MLP Violence (lag 6)	MLEED Violence (lag 4)
Mediation	Precipitation	0.0123 (0.062)	-0.2394^{***} (0.061)	0.0071^{***} (0.002)	0.0064^{***} (0.001)
	MLP Protest			0.0304 (0.060)	
	MLP Violence	0.0240 (0.058)			
	MLP Disaster	−0.0729 (0.100)		−0.1089 (0.097)	−0.1100 (0.099)
	MLEED Protest				0.0157^{***} (0.053)
	MLEED Violence		−0.0708 (0.036)		
	Econ. Stressor				
	MLEED Disaster		−0.1224 (0.097)		
	Inflation Rate	0.8234^{***} (0.253)	0.8803^{***} (0.261)	0.8244^{***} (0.255)	0.7588^{***} (0.260)
Total Effect	Precipitation	0.0175^{*} (0.010)	0.0123 (0.029)	−0.0046 (0.002)	−0.0008 (0.001)
	MLP Protest			0.0085 (0.045)	
	MLP Violence	0.0787 (0.046)			
	MLP Disaster	−0.0269 (0.030)		−0.0146 (0.114)	−0.0331 (0.038)
	MLEED Protest				0.0383 (0.040)
	MLEED Violence		0.0278 (0.021)		
	Econ. Stressor				
	MLEED Disaster		-0.1210^{***} (0.020)		
	Inflation Rate	−0.0144 (0.111)	−0.0744 (0.099)	−0.0146 (0.114)	0.0527 (0.072)
Direct Effect	Precipitation	0.0148 (0.010)	0.0147 (0.028)	-0.0061^{*} (0.002)	−0.0005 (0.001)
	MLP Protest			0.0213 (0.062)	
	MLP Violence	0.0470 (0.047)			
	MLP Disaster	−0.1204 (0.020)		−0.0833 (0.090)	−0.0307 (0.042)
	MLEED Protest				0.0360 (0.039)
	MLEED Violence		0.0337 (0.039)		
	Econ. Stressor	0.0087 (0.012)	0.0098 (0.011)	0.0087 (0.012)	0.0283 (0.073)
	MLEED Disaster		-0.1197^{***} (0.019)		
	Inflation Rate	−0.0783 (0.097)	−0.0831 (0.097)	0.0087 (0.116)	0.0288 (0.073)

Table 5: Mediation, Total, and Direct Effects of Temperature and Precipitation on MLP/MLEED Protest and Violence.

Table 5 reports the mediation results for precipitation using the ElasticNet-selected lags: lag 12 for MLP Protest, lag 0 for MLEED Environmental Protest, lag 6 for MLP Violence, and lag 4 for MLEED Environmental Violence. Across all four outcomes, the first stage of the mediation design shows a consistent pattern. Higher precipitation leads to a strong and statistically precise increase in inflation, with coefficients ranging from about 0.82 to 0.88. This suggests that wet months in the region place meaningful pressure on local prices, possibly through short-term disruptions to markets, transportation, or agricultural supply.

For the protest outcomes (left side of the table), the direct relationship between precipitation and unrest is weak. In the MLP Protest model (lag 12), the precipitation coefficient is small and statistically indistinguishable from zero. In the MLEED Environmental Protest model (lag 0), the coefficient is negative, but the effect disappears entirely once inflation is included in the model. As a result, the total effects for both protest measures remain close to zero. The mediation figures in Appendix B (Figures 12 and 13) clearly show the same pattern: precipitation raises inflation, but this increase does not produce a meaningful change in protest activity.

The violence outcomes (right side of the table) show a similar structure. In the MLP Violence model (lag 6) and in the MLEED Environmental Violence model (lag 4), precipitation has only a weak and unstable direct association with violent events. Some coefficients are slightly positive, others slightly negative, but none remain significant once inflation is added to the model. The total effects cluster around zero, indicating that precipitation does not have a consistent independent influence on violence. The mediation figures in

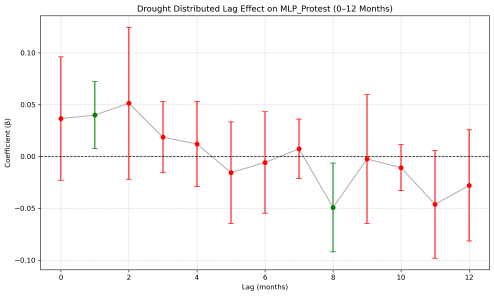
Appendix B (Figures 14 and 15) reinforce this, showing a strong inflation response but little direct movement in conflict outcomes.

Taken together, the precipitation results point to a coherent conclusion. Rainfall shocks produce strong and reliable increases in inflation, yet these economic pressures do not translate into meaningful or persistent changes in either protest or violence after accounting for country and time fixed effects. Unlike drought, which displays more distinct lagged patterns, or temperature, where the inflation channel is similarly strong, precipitation does not generate systematic political or social responses in the models. In short, precipitation matters economically, but its effects on conflict outcomes remain limited once the inflation pathway is fully incorporated.

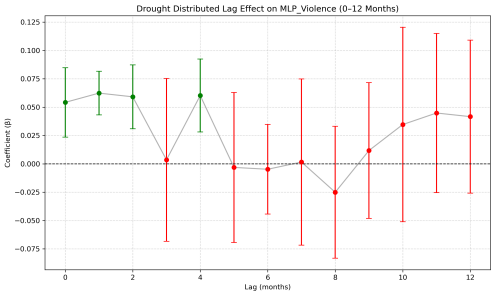
APPENDIX

A. APPENDIX A. ELASTICNET LAG SELECTION RESULTS

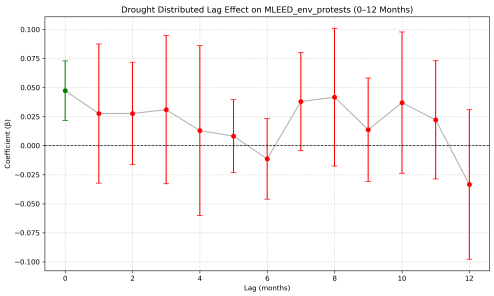
A1. DROUGHT



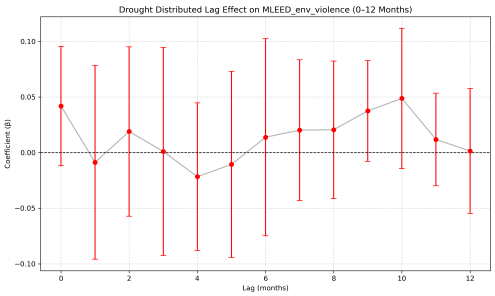
(a) MLP Protest



(b) MLP Violence



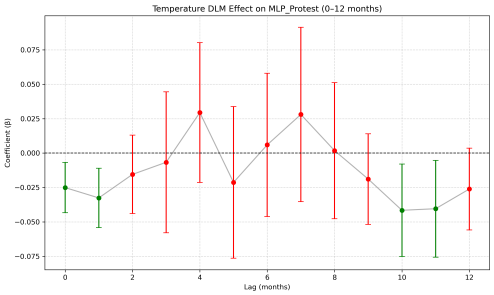
(c) MLEED Environmental Protest



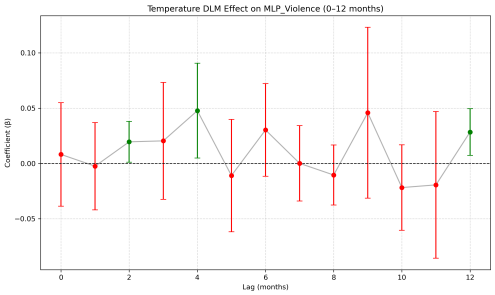
(d) MLEED Environmental Violence

Figure 1: ElasticNet-selected lags for drought across conflict outcomes.

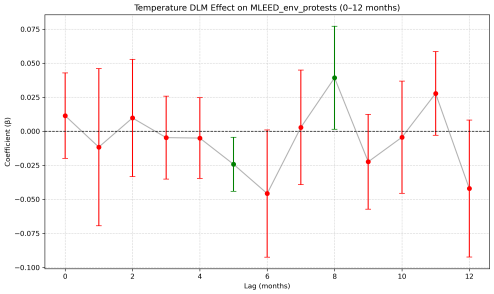
A2. TEMPERATURE



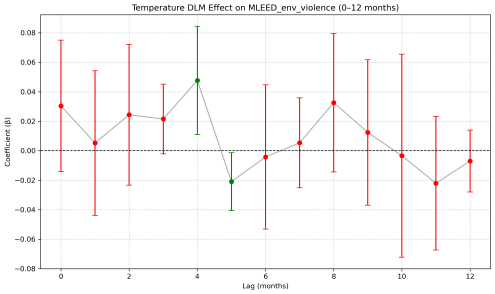
(a) MLP Protest



(b) MLP Violence



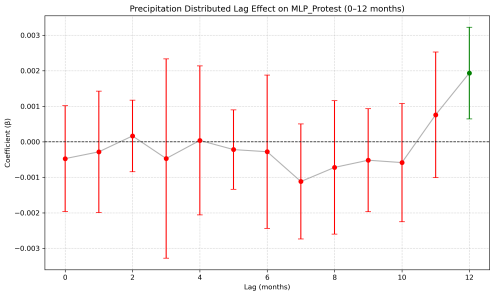
(c) MLEED Environmental Protest



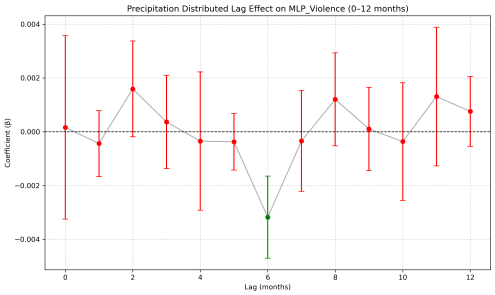
(d) MLEED Environmental Violence

Figure 2: ElasticNet-selected lags for temperature across conflict outcomes.

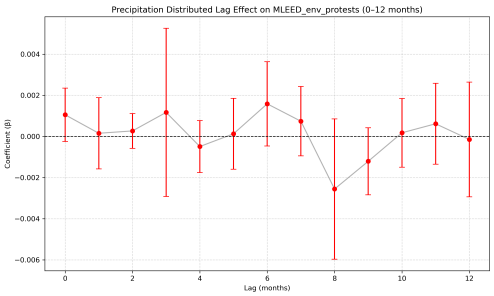
A3. PRECIPITATION



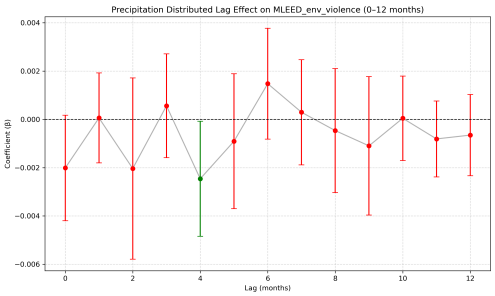
(a) MLP Protest



(b) MLP Violence



(c) MLEED Environmental Protest



(d) MLEED Environmental Violence

Figure 3: ElasticNet-selected lags for precipitation across conflict outcomes.

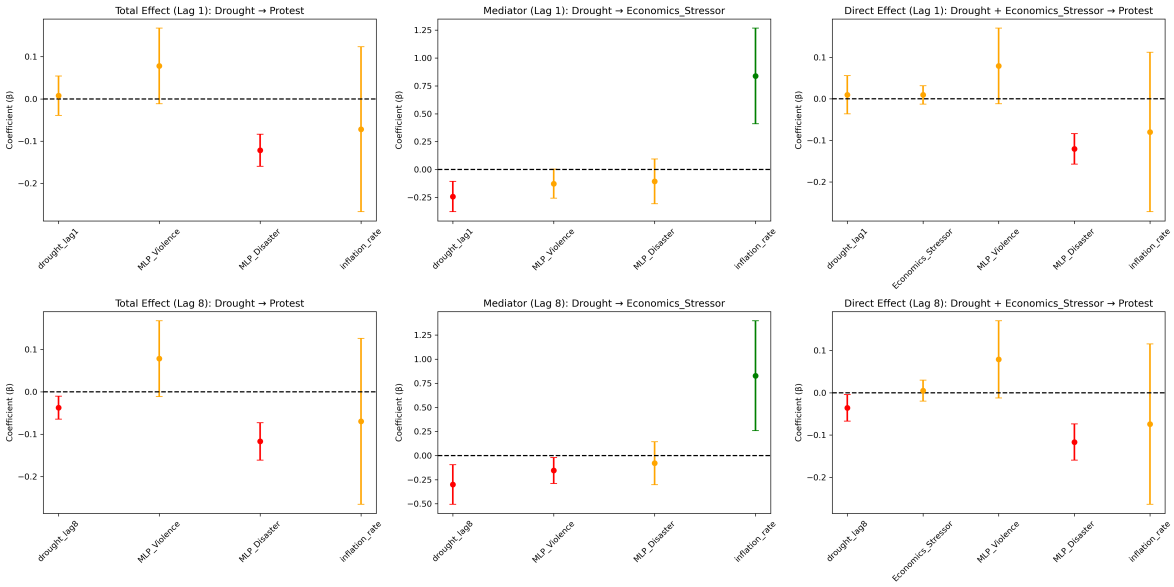


Figure 4: Mediation results: Drought → MLP Protest (lags 1 and 8).

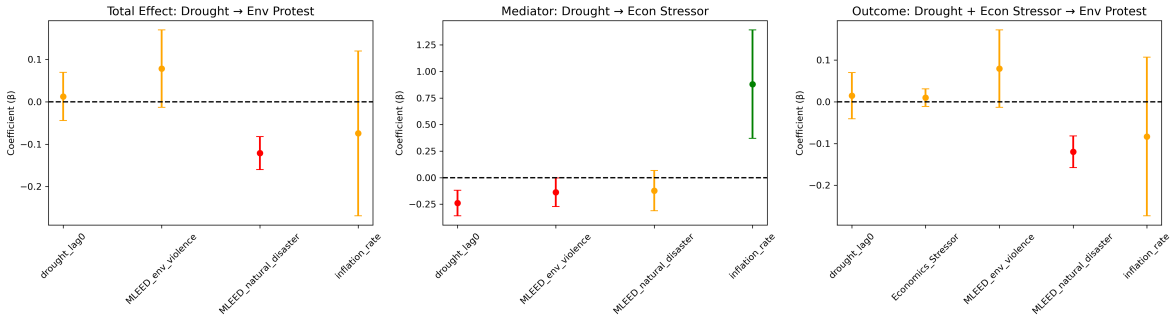


Figure 5: Mediation results: Drought → MLEED Environmental Protest (lag 0).

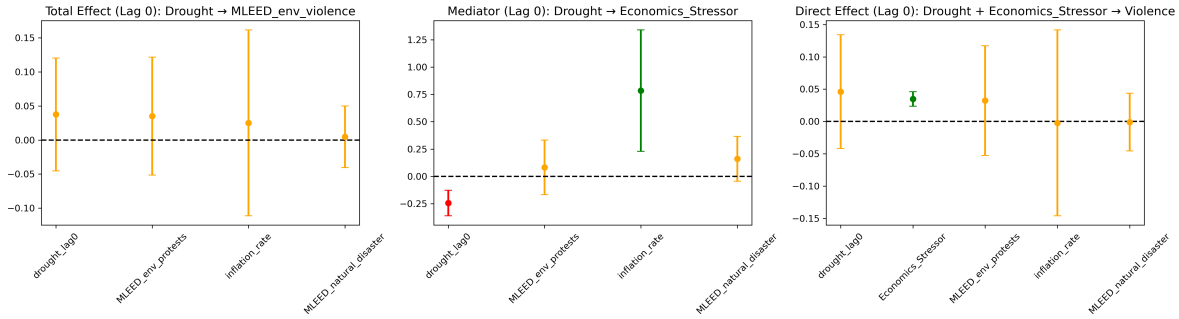


Figure 6: Mediation results: Drought → MLEED Environmental Violence (lag 0).

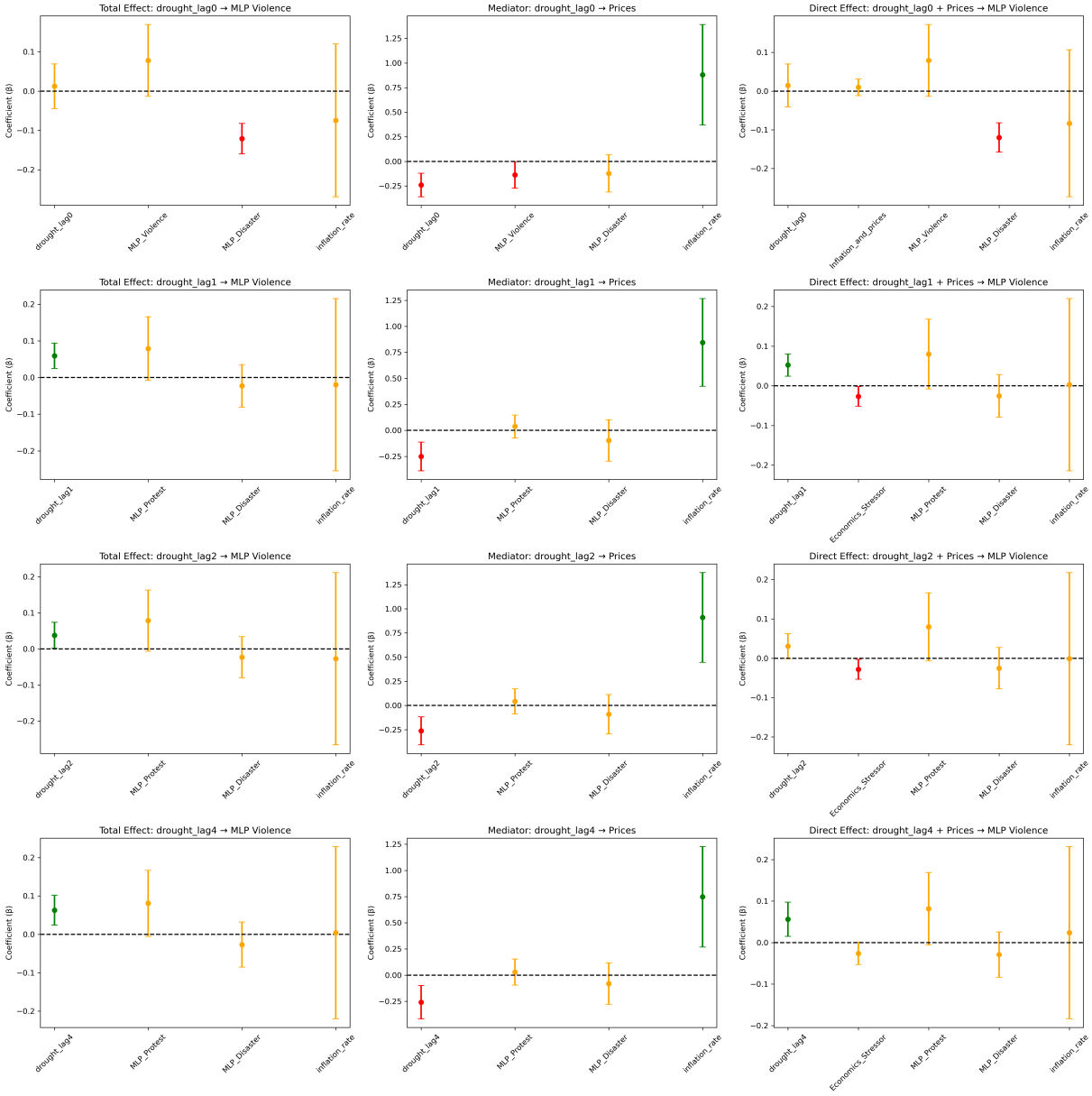


Figure 7: Mediation results: Drought → MLP Violence (lags 0, 1, 2, 4).

APPENDIX C. TEMPERATURE MEDIATION RESULTS

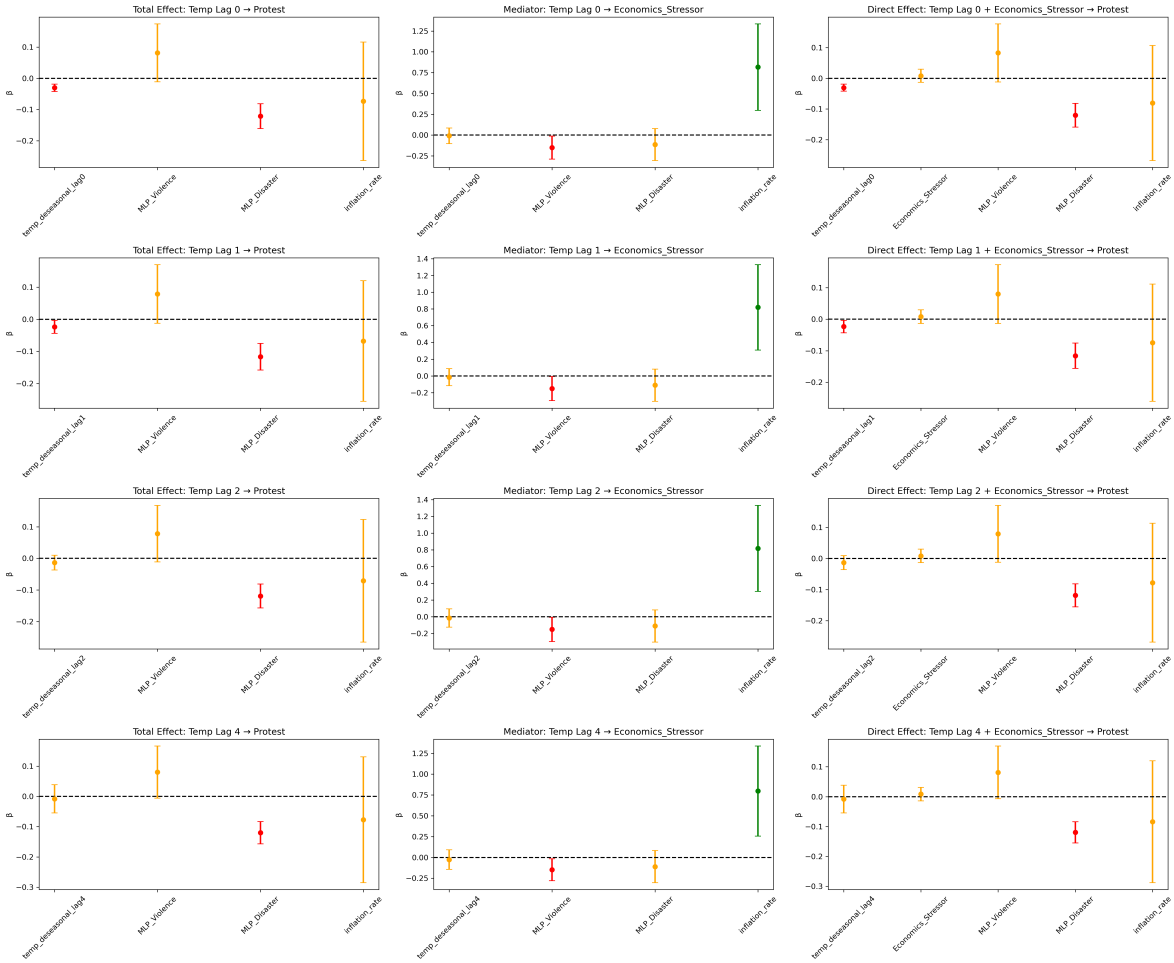


Figure 8: Mediation results: Temperature → MLP Protest (lags 0, 1, 2, 4).

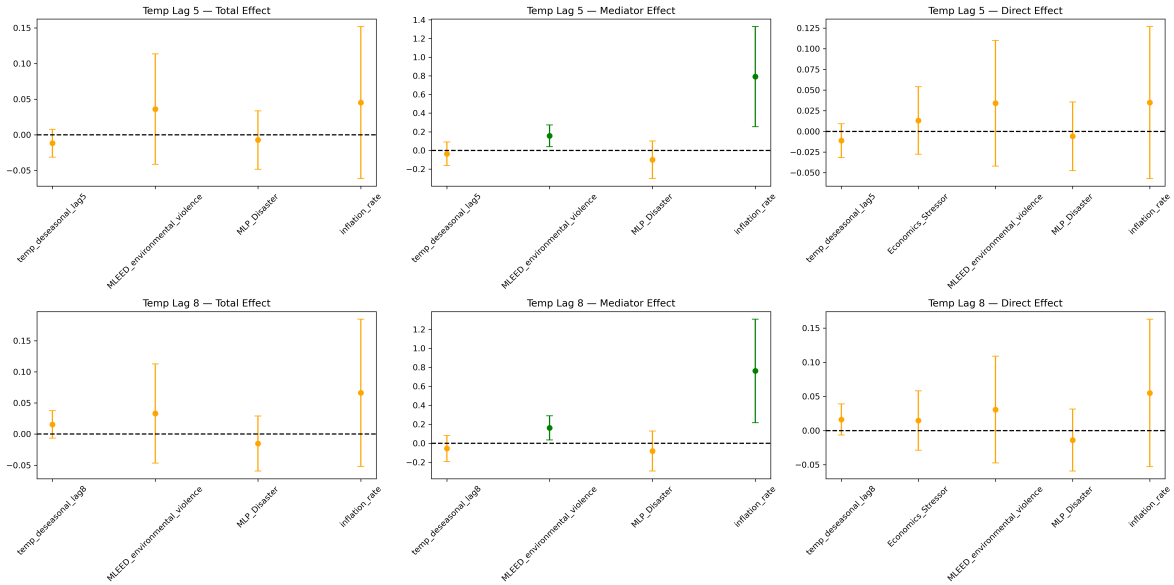


Figure 9: Mediation results: Temperature → MLEED Environmental Protest (lags 5, 8).

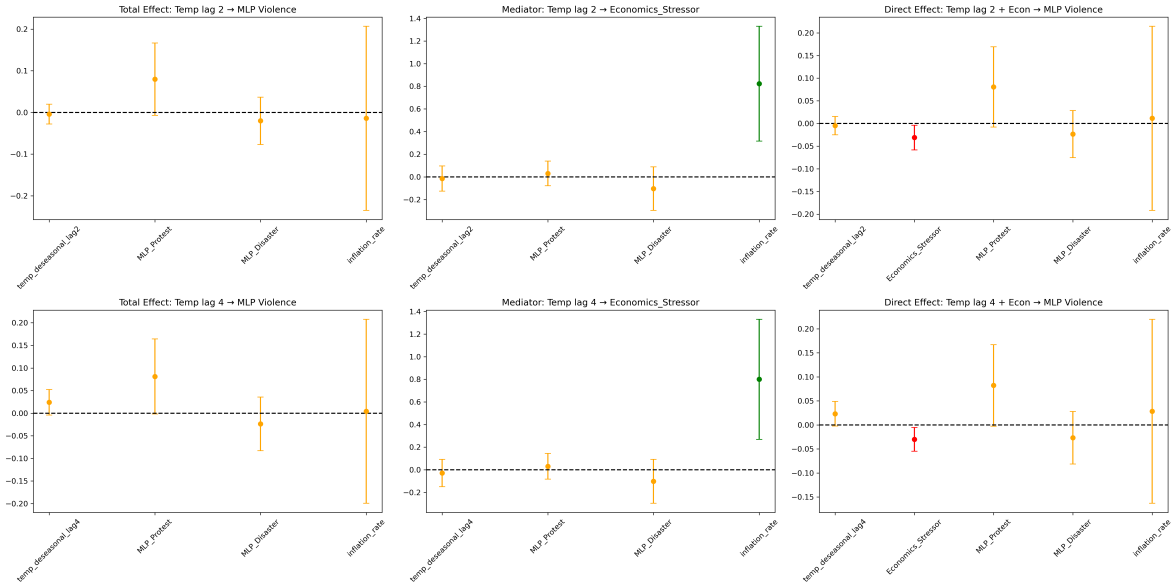


Figure 10: Mediation results: Temperature → MLP Violence (lags 2, 4).

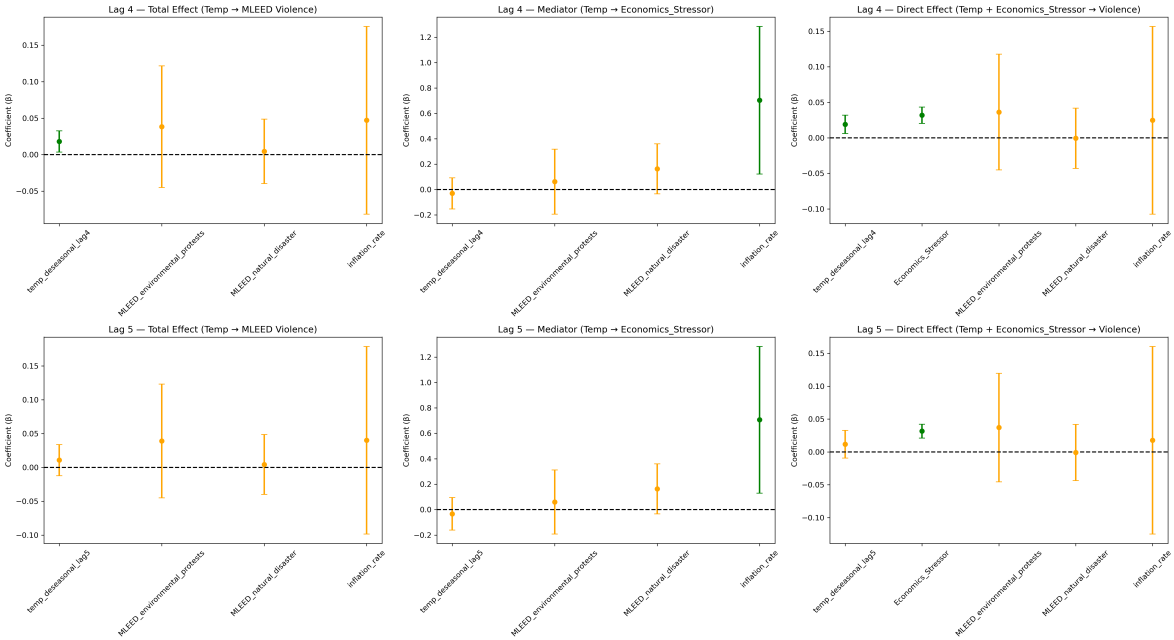


Figure 11: Mediation results: Temperature → MLEED Environmental Violence (lags 4, 5).

APPENDIX D. PRECIPITATION MEDIATION RESULTS

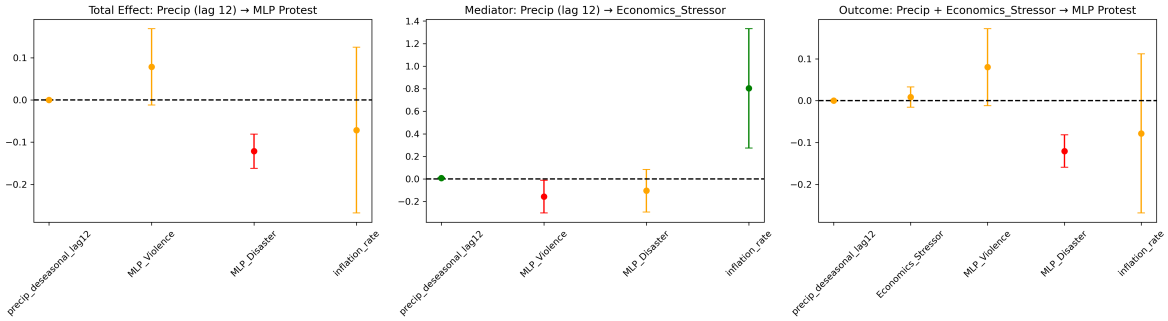


Figure 12: Mediation results: Precipitation → MLP Protest (lag 12).

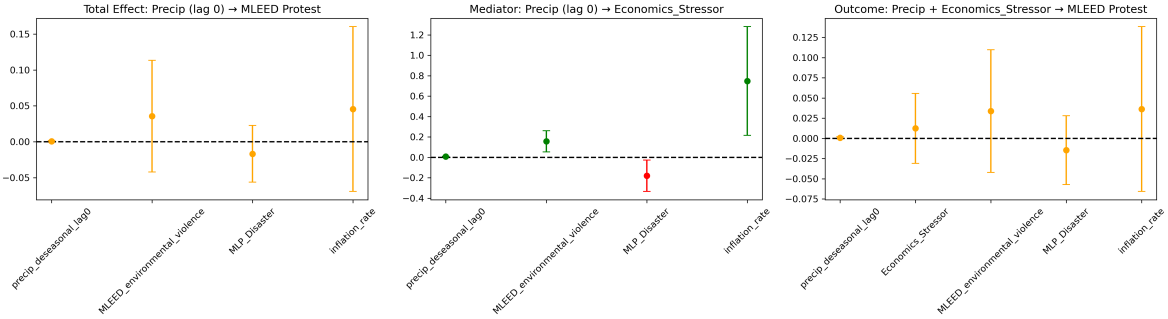


Figure 13: Mediation results: Precipitation → MLEED Environmental Protest (lag 0).

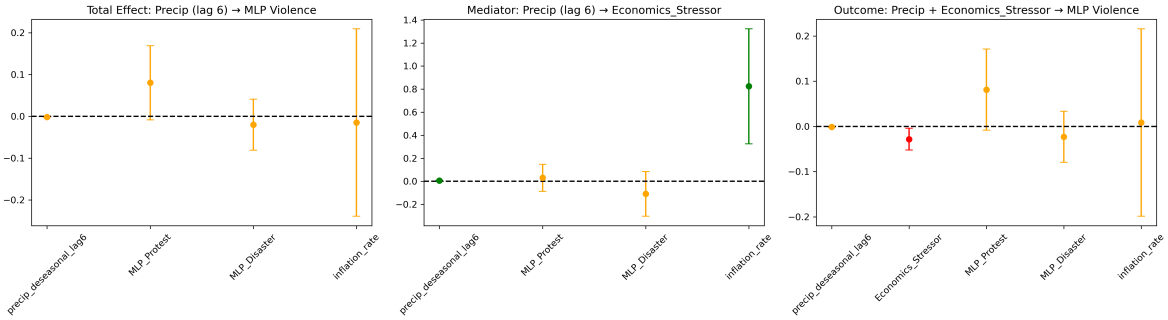


Figure 14: Mediation results: Precipitation → MLP Violence (lag 6).

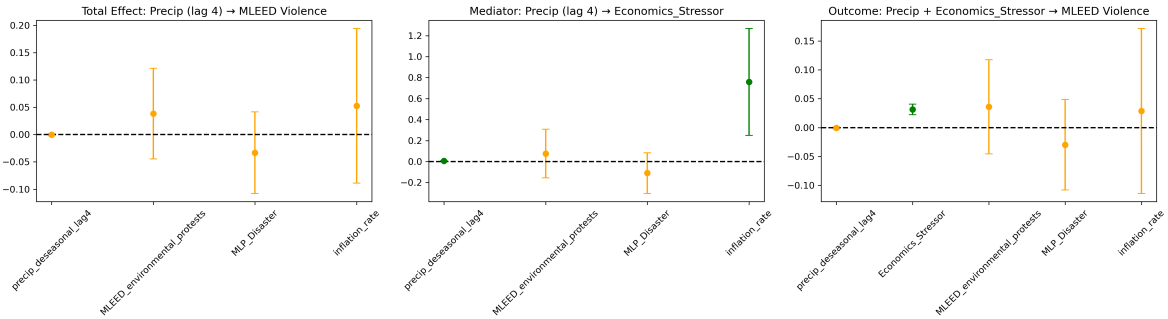


Figure 15: Mediation results: Precipitation → MLEED Environmental Violence (lag 4).

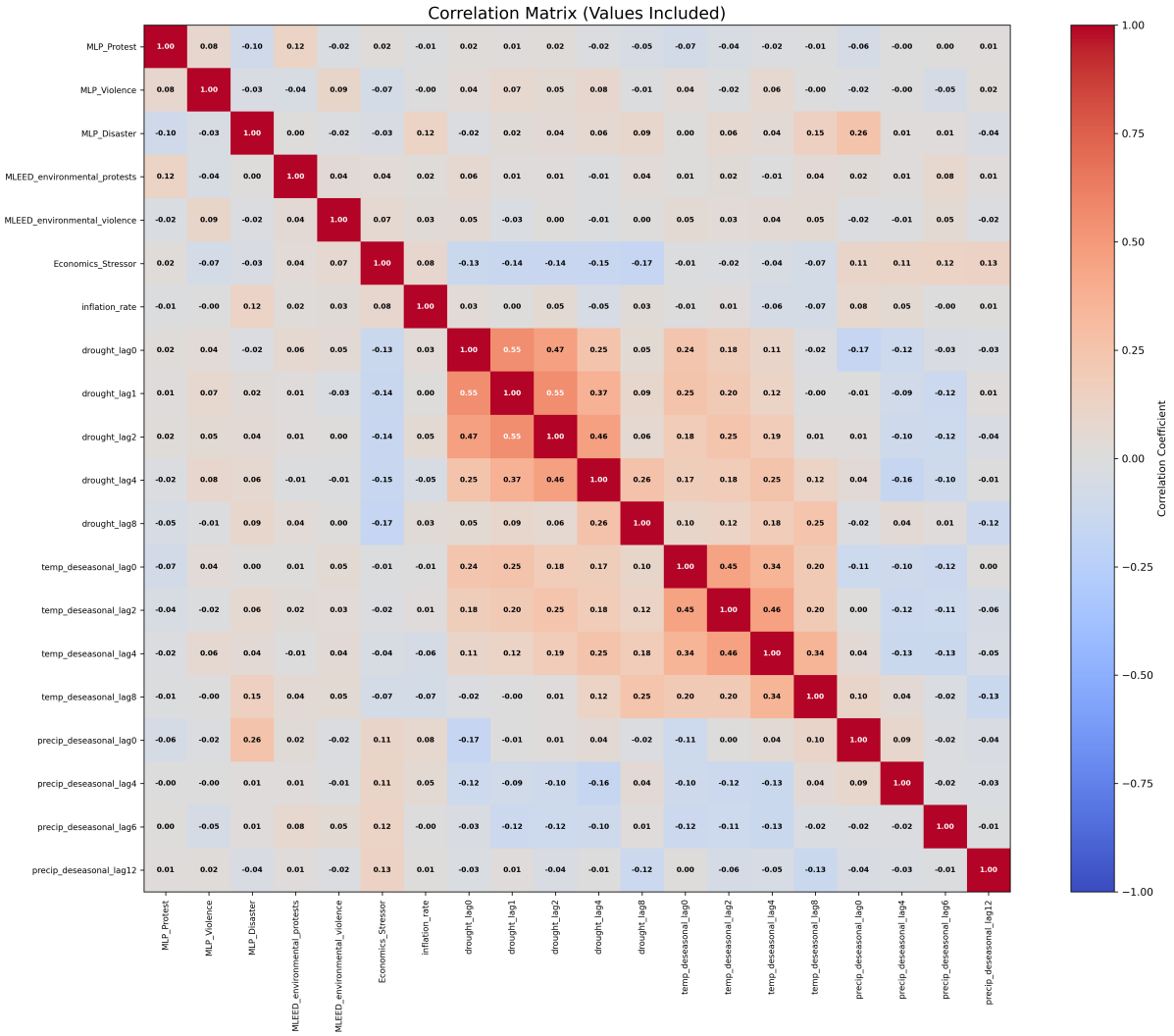


Figure 16: Correlation matrix of climate, economic, and conflict variables.

Arezki, R. and Brückner, M. (2011). Food prices and political instability. *IMF Working Papers*, (WP/11/62):1–30.

Baron, R. M. and Kenny, D. A. (1986). The moderator mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology*, 51(6):1173–1182.

Bellemare, M. F. (2015). Rising food prices, food price volatility, and social unrest. *American Journal of Agricultural Economics*, 97(1):1–21.

Buhaug, H. (2015). Climate-conflict research: Some reflections on the way forward. *Wiley Interdisciplinary Reviews: Climate Change*, 6(3):269–275.

Castaneda, J. and Schneider, B. R. (2017). Organized crime, weak states, and violence in latin america. *World Politics*, 69(1):118–161.

EM-DAT: The International Disaster Database (2021). Natural disasters 2020. https://public.emdat.be/.

Food and Agriculture Organization of the United Nations (2019). El salvador, guatemala, honduras, and nicaragua: Dry corridor food security outlook. FAO Report.

Funk, C., Nicholson, S. E., Landsfeld, M., and Michaelsen, J. (2018). Drought early warning in the americas. *Bulletin of the American Meteorological Society*, 99(4):705–717.

Gleditsch, N. P. (2012). Whither the weather? climate change and conflict. *Journal of Peace Research*, 49(1):3–9.

Harari, M. and La Ferrara, E. (2020). Climate change and economic activity: Evidence from u.s. counties. *Econometrica*, 88(6):2369–2409.

Hendrix, C. and Salehyan, I. (2012a). Climate change, rainfall, and social conflict in africa. *Journal of Peace Research*, 49(1):35–50.

Hendrix, C. S. and Salehyan, I. (2012b). Climate change, rainfall, and social conflict in africa. *Journal of Peace Research*, 49(1):35–50.

Hoerl, A. E. and Kennard, R. W. (1970). Ridge regression: Biased estimation for nonorthogonal problems. *Technometrics*, 12(1):55–67.

Homer-Dixon, T. (1999). *Environment, Scarcity, and Violence*. Princeton University Press.

Ide, T. (2021). Climate change and conflict: A systematic comparison of research designs, data, and results. *Current Climate Change Reports*, 7(3):91–102.

Miguel, E., Satyanath, S., and Sergenti, E. (2004a). Economic shocks and civil conflict: An instrumental variables approach. *Journal of Political Economy*, 112(4):725–753.

Miguel, E., Satyanath, S., and Sergenti, E. (2004b). Economic shocks and civil conflict: An instrumental variables approach. *Journal of Political Economy*, 112(4):725–753.

Raleigh, C. and Witmer, F. (2015). Where does climate change matter? *Conflict Management and Peace Science*, 32(2):134–158.

Smith, T. G. (2014). Feeding unrest: Disentangling the causal relationship between food price shocks and sociopolitical conflict in urban africa. *Journal of Peace Research*, 51(6):679–695.

Tibshirani, R. (1996). Regression shrinkage and selection via the lasso. *Journal of the Royal Statistical Society Series B: Statistical Methodology*, 58(1):267–288.

Zou, H. and Hastie, T. (2005). Regularization and variable selection via the elastic net. *Journal of the Royal Statistical Society Series B: Statistical Methodology*, 67(2):301–320.