Climate and Conflict: Predicting Conflict by Temperature in the Middle East

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Introduction

Over the past two decades, Middle Eastern and North African (MENA) regions have experienced repeated violent conflicts involving insurgent groups and foreign forces (Nordås & Gleditsch, 2014). Increasingly, researchers and policymakers link climate change to these outbreaks, citing the intensification of global temperature rise as a driver of extreme weather in the region. Such extremes exacerbate conditions long associated with conflict, including water scarcity, resource competition, and economic instability (Center for Preventative Action, 2023).

With agriculture and herding forming the backbone of many MENA economies, they are highly vulnerable to drought or other weather extremes. Water shortages not only spark disputes between individuals but also create opportunities for armed groups to seize and weaponize resources, leading to armed extremists demanding allegiance or payment in exchange for access (Nordås & Gleditsch, 2014; Theisen, 2012). These climate pressures compound existing risks: food price spikes, geopolitical tensions, unemployment, and disruptions to education that limit youth opportunity (United Nations, 2020; International Rescue Committee, 2023).

Armed groups can exploit these vulnerabilities either through coercion or strategic aid, thereby strengthening their authority (Akcinaroglu & Tokdemir, 2018). In Yemen, for example, Saudi-led blockades deepened pre-existing water shortages, contributing to one of the world's worst cholera outbreaks between 2016 and 2021 (Center for Preventative Action, 2023). Such crises can also intensify anti-Western sentiment, as armed groups frame climate change as a product of Western excess, further fueling resentment and radicalization (Bourekba, 2021; Ferguson, 2018).

Policymakers argue that mitigating climate change and its effects could help reduce the instability threatening both the MENA region and Western security interests (Center for Preventative Action, 2022). This research focuses on comparing Middle Eastern prediction models to global temperature models. It evaluates the theory that rising temperatures contribute to increased conflict; the research can inform strategies to prevent or mitigate armed conflict both within specified regions and globally. To address these issues, this research examines the following questions:

Q1. Global: Can rising global temperatures predict the total number of global conflicts?
Q2. Middle East: Can regional temperature trends predict the number of conflicts in the Middle East?

Exploratory Data Analysis

UCDP Armed Conflict Data

The armed conflict data was sourced from Uppsala University's Uppsala Conflict Data Program (UCDP), a leading provider of organized violence data. UCDP defines armed conflict as a contested incompatibility involving at least one state actor, resulting in 25 or more battle-related deaths within a calendar year (Davies et al., 2023).

The dataset includes 2,626 conflict-year records from March 1946 to December 2021. Each record corresponds to a conflict active during a year with at least 25 battle-related deaths. Conflicts are assigned unique IDs to track them across years, even if parties or intensity change. Each observation includes region (Europe, Middle East, Asia, Africa, Americas), start and end dates, and detailed conflict attributes.

To create a time series, monthly counts of conflicts were aggregated from March 1946 to December 2021, yielding 910 monthly observations. The global analysis uses all regions (Figure 1), while regional analyses focus on conflicts occurring partially or wholly within specific areas (Figure 2 and 3). The Middle East series includes conflicts in the Middle East alone or combined with Europe, Africa, or the Americas. Similarly, the Africa series covers conflicts in Africa alone or with Europe.

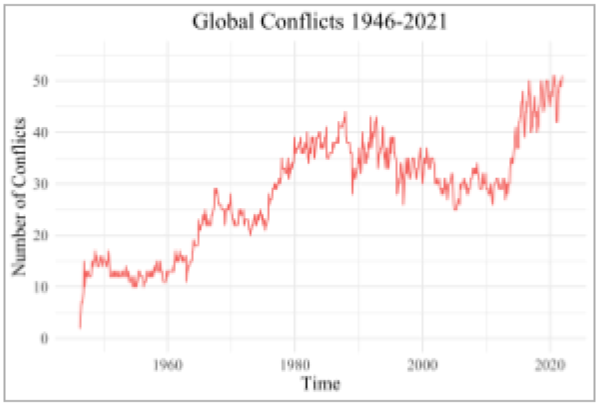


Figure 1. The number of global conflicts from 1946 through 2021 indicates a non-stationary time series.

As shown in Figure 1, the number of global conflicts over time from 1946 through 2021 shows an increasing overall trend, indicating that this is not a stationary time series. The series shows the minimum number of 2 conflicts occurring only in 1946 and the maximum number of 51 conflicts occurring only in 2020 and 2021. The main time periods in which the number of conflicts increased greatly are 1963-1967, 1975-1980, and 2013-2016.

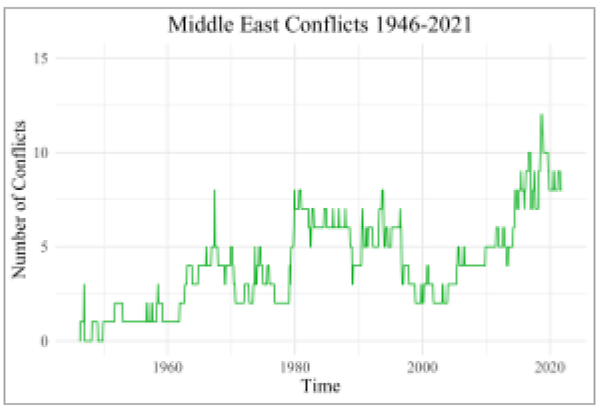


Figure 2. Conflicts in the Middle East from 1946 through 2021 are non-stationary and are in alignment with real-world events.

Figure 2 shows an overall rise in conflicts in the Middle East from 1946 to 2021, with the region averaging 13% of global conflicts. The count ranged from 0 conflicts in 1946–1949 to a peak of 12 in 2018, with major surges in 1962–1967 (Arab–Israeli conflicts), 1979–1980 (Iranian Revolution), and 2004–2019 (post–US invasion of Iraq).

NOAA Temperature Data

Global and MENA land and ocean temperature data was downloaded from the National Oceanic and Atmospheric Administration's (NOAA) National Centers for Environmental Information. The global values are land and ocean temperature anomalies with respect to the 1901-2000 average and the regional values are land and ocean temperature anomalies with respect to the 1910-2000 average. The time series data was readily usable as temperature was reported in Celsius monthly and regionally. The coordinates 27.5ºN, 47.5ºE, located in Saudi Arabia, are used to acquire temperature data for the Middle East region.

Both global and regional temperatures increase during the observed time period. However, the regional areas, Middle East (Figures 4) show much more volatility in temperature compared to the global values (Figure 3).

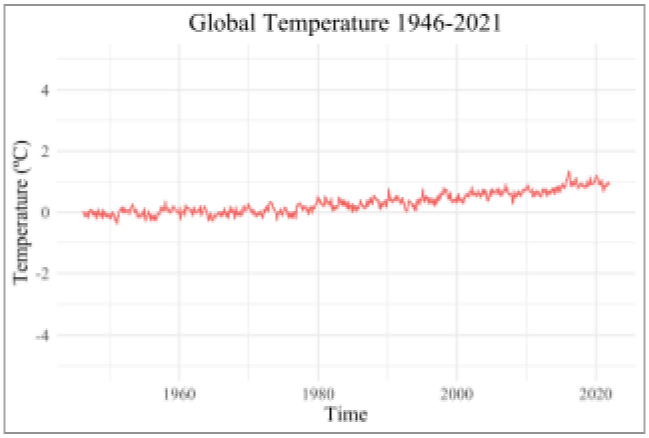


Figure 3. Global temperature from 1946 through 2021 are more consistent than regional temperature changes.

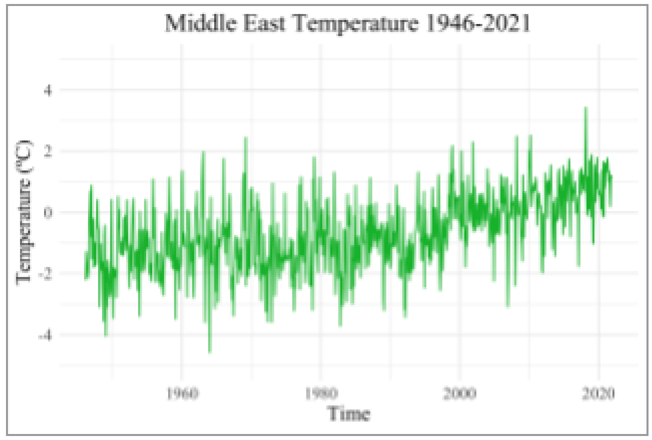


Figure 4. Regional temperatures of the Middle East.

Analysis

Global Temperature-Conflict Analysis

To answer Question 1—whether rising global temperatures can predict the total number of global conflicts—the data is subsetted to include only values from March 1946 through December 2015. This allows for the model to be trained on historical data and evaluated on its predictive accuracy through the remainder of the time series (up to December 2021).

Time Series Model: Global Conflict Occurrences by Temperature Trends

A time series model can assess how past temperature fluctuations and conflict patterns influence current conflict frequency. To determine the appropriate model, there is a cross-correlation function (CCF) analysis between detrended and deseasonalized global temperature and conflict series. The CCF results show consistent correlations across lags (Figure 5). This indicates that including lagged temperature values would not improve predictive power, hence why temperature is modeled without lag. The initial global conflict series (Figure 1) reveals both a long-term trend and possible seasonality, prompting the use of first-order differencing. A Seasonal Autoregressive Integrated Moving Average (SARIMA) model is preferred over a standard ARIMA model because seasonality was present but without strong seasonal differencing or random-walk patterns. Using auto.arima with AIC for model selection, the SARIMA(1,1,1)(2,0,0)[12] model was chosen.

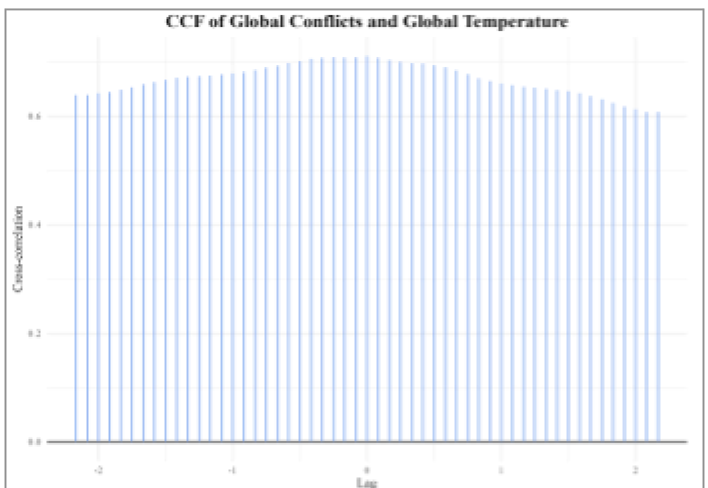
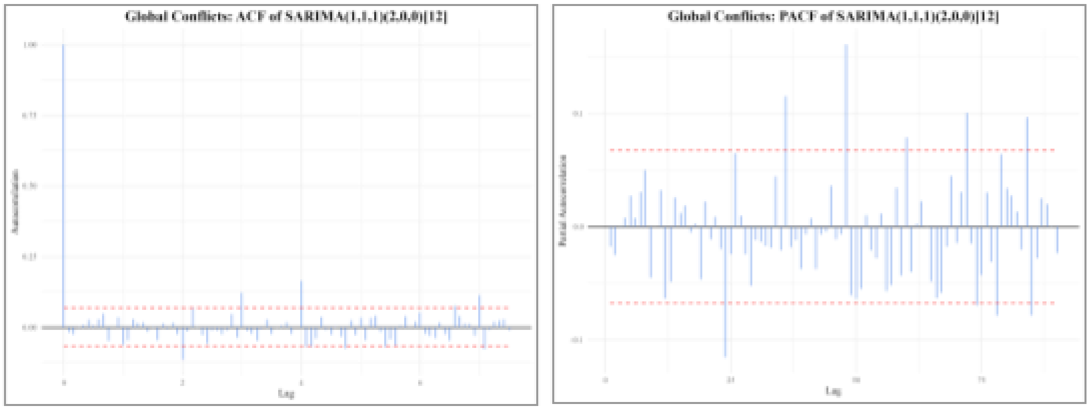


Figure 5. Consistency in correlations across lags in CCF of global temperature and number of global conflicts justify SARIMA model.



Figures 6a-b. Global conflict data SARIMA(1,1,1)(2,0,0)[12] plot, ACF and PACF.

However, the diagnostic results from the SARIMA(1,1,1)(2,0,0)[12] model indicate that it is not a well-fitting model for capturing the relationship between global conflict occurrences and temperature (Figure 6). Evidence from the residual diagnostics shows multiple significant spikes in the autocorrelation and partial autocorrelation functions, which suggests that the residuals deviate from the assumptions of white noise. This lack of fit implies that the model fails to adequately capture the underlying temporal dynamics of conflict events. In other words, the relationship between global conflict and temperature cannot sufficiently explain the use of the SARIMA model alone. This result highlights the complexity of the conflict–climate relationship and suggests the need for either an alternative model to better account for the underlying dynamics.

Time Series Regression Model: Number of Global Conflicts by Global Temperature

An Ordinary Least Squares model provides an alternative method to assess the relationship between global temperature and conflict occurrences while controlling for other covariates, which may have been causing the lack of fit in the previous model. To predict the number of global conflicts using global temperature, the following OLS model was fitted: $y_t = \beta_0 + \beta_1 z_t + x_t$ where y_t corresponds to the global conflict time series, z_t corresponds to the global temperature time series, and x_t is some temporally correlated error process. A time series regression with a white noise assumption of x_t error processes yields the following model:

	# of Global Conflicts
Global Temperature	20.122***
Standard Error	21.604***

Significance Codes: ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Table 1. OLS regression of global temperature on the number of global conflicts.

Although Table 1 indicates that global temperature is a significant predictor in the OLS regression model, the residuals reveal clear evidence of trend and potential seasonality (Figure 7), suggesting that the OLS framework fails to capture important temporal dynamics in the conflict data. To address this, a SARIMA model is employed to account for autocorrelation, non-stationarity, and seasonal patterns in time series processes. Following standard procedures, including differencing to address non-stationarity and model selection via AIC, a SARIMA(2,1,1)(2,0,0)[12] model was chosen for the residuals of the regression.

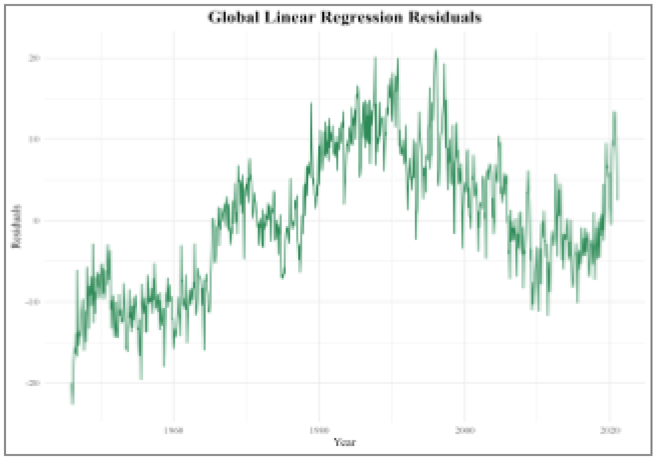


Figure 7. Seasonality in Global OLS regression plot.

When performing diagnostics from this model (regression fitted plot, observed vs. predicted plot, Q-Q plot), it showed an improved overall fit, with a strong correlation between observed and predicted conflict counts. Nevertheless, residual analysis revealed persistent problems: non-normality, significant autocorrelation, and lingering structure inconsistent with white noise. Moreover, model estimates (Table 2) indicate that global temperature is no longer statistically significant when temporal dependencies are taken into account. SARIMA models are inadequate for forecasting conflict trends, and it cannot be meaningfully tested given the lack of predictive power. This addresses Q1 that global temperature alone does not predict the number of global conflicts.

	AR 1	AR 2	MA 1	Seasonal AR 1	Seasonal AR 2	Global Temp
Coefficient	0.7895	-0.0054	-0.8881	0.2264	0.2626	-0.2369
Standard Error	0.0939	0.0430	0.0905	0.0360	0.0338	0.4026

Table 2. Summary of SARIMA (2,1,1)(2,0,0)[12] time series regression of global temperature on the number of global conflicts.

Middle East Temperature-Conflict Analysis

Similarly, to address Question 2—whether temperature in the Middle East can predict the number of conflicts regionally—conflict in the region is modeled using temperature as the main factor. The data is from March 1946 to December 2015 to test whether the model can capture patterns across the full observed period.

Time Series Model: Middle East Conflict Occurrences by Temperature Trends

To determine the appropriate time series model for Middle East conflict occurrences, a similar CCF plot between the detrended and deseasonalized temperature in the Middle East and number of conflicts in the Middle East is created. Figure 8 reveals the cross-correlations are similar across the lags, so temperature is used with no lag.

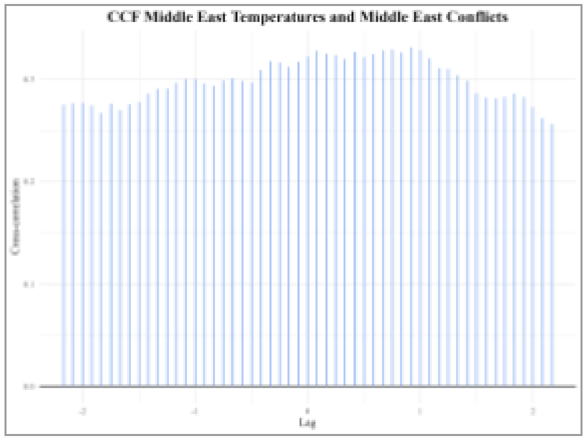
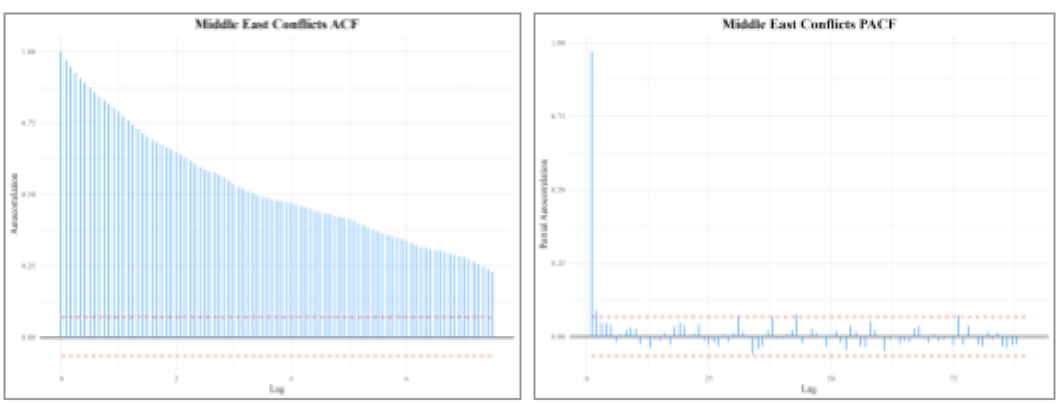


Figure 8. The CCF of temperature in the Middle East and number of conflicts reveals similar cross-correlations across lags.

Conflict trends in the Middle East (Figure 2) show a steady increase over time, while regional temperatures (Figure 4) follow a distinct seasonal cycle, with lower averages in mid-year and higher values at the beginning and end of the year. Additionally, the autocorrelation patterns, with strong correlations across multiple lags in the ACF and a single significant spike in the PACF, led to the use of the SARIMA model with first differencing to model (Figure 9a-b). Using an AIC-based model search, the SARIMA(1,1,2)(0,0,2)[12] model came out to be the best-fitting specification. Residual diagnostics (Figure 12a) confirm stationarity, with no evidence of significant autocorrelation, which means the white noise hypothesis fails to be rejected. This suggests that the model captures the underlying relationship between temperature variation and conflict dynamics in the Middle East.



Figures 9a-b. The ACF and PACF of temperature in the Middle East.

Time Series Regression Model: Number of Middle East Conflicts by Regional Temperature

Knowing that the time series model is able to capture temperature variation and conflict dynamics in the Middle East, a time series regression can be used to assess how strong this relationship is while controlling for other covariates. The model $y_t = \beta_0 + \beta_1 z_t + x_t$ is used where y_t corresponds to the Middle East conflict time series, z_t corresponds to the Middle East temperature time series, and x_t is some temporally correlated error process. A time series regression with a white noise assumption of x_t error processes yields the following model:

	# of Conflicts in the Middle East
Middle East Temperature	0.2850***
Standard Error	3.8500***

Significance Codes: '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Table 3. OLS regression of temperature in the Middle East on the number of conflicts in the Middle East.

An initial regression assuming white-noise errors (Table 3) indicates that temperature is significant. However, residual trends in the ACF and PACF suggest no seasonality, hence why the error process should be modeled with ARIMA. An AIC-guided search identified ARIMA(3,1,2) as the best specification, with first differencing applied due to non-stationarity.

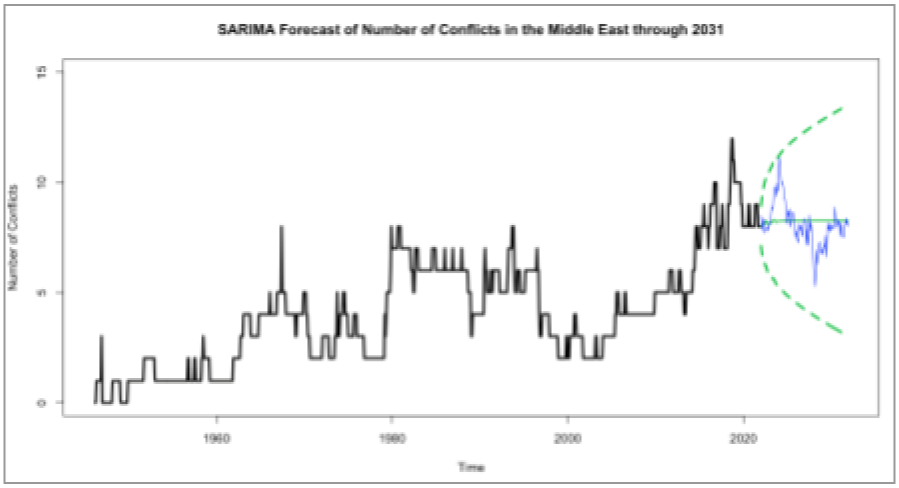
	AR 1	AR 2	AR 3	MA 1	MA 2	ME Temp
Coefficient	0.7067	-0.0048	-0.0217	-0.8454	0.0536	-0.0055
Standard Error	0.6439	0.2876	0.0514	0.6454	0.3689	0.0145

Table 4. Summary of ARIMA (3,1,2) time series regression of temperature in the Middle East on the number of conflicts in the Middle East.

Diagnostic checks for this model show high kurtosis in the Q-Q plot and minor autocorrelation in the PACF, though the model visually tracked the observed data well. Despite the initial significance of temperature, it becomes non-significant in the ARIMA-corrected model (Table 4), while the residual patterns are similar to those of the SARIMA model used to model conflict alone. Given these results, including temperature in the regression does not meaningfully improve the model. Therefore, the initial SARIMA(1,1,2)(0,0,2)[12] model alone is sufficient for forecasting conflict in the Middle East.

Middle East Number of Conflicts Forecast

The first SARIMA forecast evaluates how well the model predicts Middle East conflicts from 2016 to 2021 by comparing predicted values with actual observations. The model captures the overall trend, with most observed values falling within the confidence intervals, though notable spikes in 2019 and 2020 fall outside the model's expected range (Figure 10)). The forecast highlights that conflicts are overall steadily increasing with fluctuations year to year. The confidence interval is quite large, suggesting that the SARIMA forecast can vary unpredictably.



Figures 10. Number of conflicts in the Middle East ten-year forecast from 2021 through 2031.

Results

The analysis for the global conflicts suggests that neither the SARIMA(1,1,1)(2,0,0)[12] model nor the SARIMA(2,1,1)(2,0,0)[12] time series regression adequately capture the complex dynamics, indicating that global temperature alone may not be a significant predictor of global conflicts, thereby refuting the question that global temperatures predict number of conflicts.

Based on the analysis conducted for the Middle East region, regional temperatures in the Middle East may have predictive power for the number of conflicts in the region. The selected SARIMA(1,1,2)(0,0,2)[12] model demonstrates a significant association between Middle East temperature and conflict dynamics. While the analysis does not directly address the impact of global warming on conflict trends, there is evidence that regional temperature fluctuations are linked to conflict dynamics in the Middle East.

In both the global and regional analyses, the SARIMA forecasts quickly lose predictive power, with confidence intervals widening ("trumpeting") and point forecasts flattening to a constant value after just a year or two (Figure 10). Residuals also deviate from normality, showing heavy tails, which raises concerns about the accuracy of forecast intervals. While the models behave reasonably in simulation and offer some insight, their wide confidence intervals highlight both the complex nature of conflict and the limits of linear time series methods in capturing the data-generating process.

Limitations & Future Recommendations

In examining the relationship between UCDP armed conflict data and global temperatures, several limitations affect the direct causal link between climate change and conflict. Confounding variables such as power distribution among groups, food and water scarcity, and socioeconomic inequalities can strongly influence conflict dynamics. Correlations between temperature and conflict may partly reflect these indirect pathways rather than a direct climate-to-conflict mechanism.

This complexity highlights the need for future research to examine how environmental stress interacts with political, social, and economic structures to escalate conflict. Mapping these mechanisms, as illustrated in Figure 11, can identify points where intervention is most effective for prevention and resolution. Understanding how climate pressures intersect with societal power dynamics and livelihood insecurity is critical for designing strategies that address both environmental stressors and the conditions that enable violence. By doing so, future work can better clarify the role of climate change in conflict and inform sustainable peacebuilding efforts.

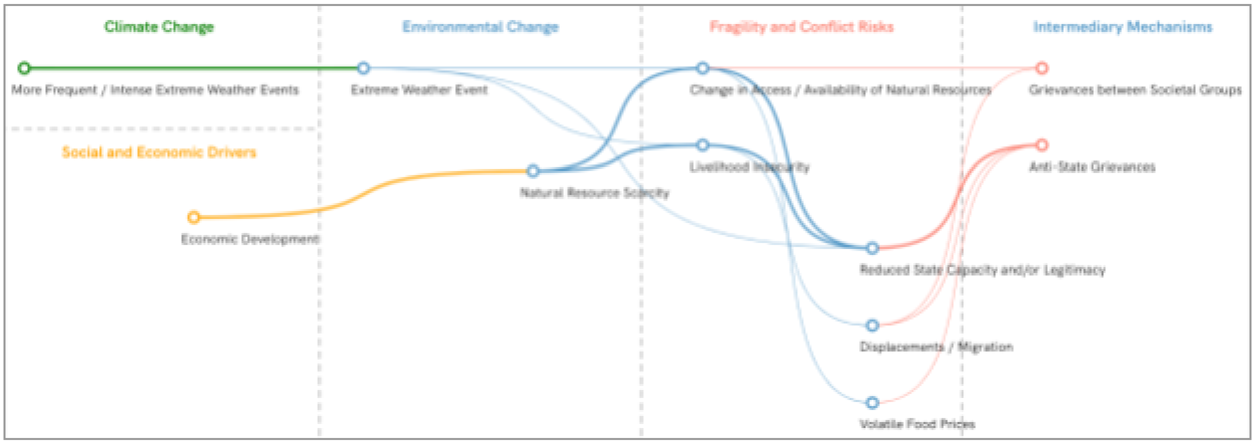


Figure 11: Conceptual Map of Causal Pathways Between Climate Change and Conflict (Syrian Civil War, n.d.)

Final Takeaways

The results of this research highlights the complex relationship between temperature and armed conflict. For Q1, which asks whether global temperature can predict global conflicts, both the time series and regression models did not support the hypothesis that rising global temperatures are associated with increased conflict. Contrary to initial expectations, there is no significant link between global warming and global conflict levels. In contrast, the Middle East analysis suggests that regional temperature fluctuations may provide predictive insight into conflict dynamics, supporting the proposition that local temperature variations are tied to conflict occurrences. However, issues such as multicollinearity and indirect causal pathways likely limited the reliability of the models. These findings emphasize the complexity of conflict and the critical role that environmental degradation, alongside broader social and political factors, plays in shaping patterns of violence.

References

Akcinaroglu, S., & Tokdemir, E. (2018). To instill fear or love: Terrorist groups and the strategy of building reputation. *Conflict Management and Peace Science*, *35*(4), 355–377. https://www.jstor.org/stable/26959403

Bourekba, M. (2021). Climate change and violent extremism in North Africa.

Center for Preventative Action. (2022, November). *Climate Change and Conflict in the Sahel*. Council on Foreign Relations. https://www.cfr.org/report/climate-change-and-conflict-sahel

Center for Preventative Action. (2023, October). *Climate Change and Regional Instability in the Middle East*. Council on Foreign Relations. https://www.cfr.org/report/climate-change-and-regional-instability-middle-east

Davies, Shawn, Therese Pettersson & Magnus Öberg (2023). Organized violence 1989-2022, and the return of conflict between states. *Journal of Peace Research* 60(4).

Ferguson, J. (2018, March 7). *As climate change parches Somalia, frequent drought comes with conflict over fertile land*. PBS NewsHour. https://www.pbs.org/newshour/show/as-climate-change-parches-somalia-frequent-drought-comes-with-conflict-over-fertile-land

Gleditsch, Nils Petter; Peter Wallensteen, Mikael Eriksson, Margareta Sollenberg & Håvard Strand (2002) Armed Conflict 1946–2001: A New Dataset. *Journal of Peace Research* 39(5): 615–637.

Hodler R, Lechner M, Raschky PA. Institutions and the resource curse: New insights from causal machine learning. PLoS One. 2023 Jun 1;18(6):e0284968. doi: 10.1371/journal.pone.0284968. PMID: 37262065; PMCID: PMC10234542.

International Rescue Committee. (2023, August 17). *The Central Sahel: How conflict and climate change drive crisis | International Rescue Committee (IRC)*. https://www.rescue.org/article/central-sahel-how-conflict-and-climate-change-drive-crisis

Lange, M. A. (2019). Impacts of climate change on the Eastern Mediterranean and the Middle East and North Africa region and the water–energy nexus. *Atmosphere*, *10*(8), 455.

May, J. F., Guengant, J. P., & Barras, V. (2017). Demographic challenges of the Sahel countries. *Africa's Population: In Search of a Demographic Dividend*, 165-177.

Merrill, Ryan K., Anthony W. Orlando, Oil at risk: Political violence and accelerated carbon extraction in the Middle East and North Africa, *Energy Economics*, Volume 92, 2020, 104935, ISSN 0140-9883, https://doi.org/10.1016/j.eneco.2020.104935.

Nordås, R., & Gleditsch, N. P. (2014). Climate change and conflict. In *Competition and conflicts on resource use* (pp. 21-38). Cham: Springer International Publishing.

Pettersson, Therese (2023) UCDP/PRIO Armed Conflict Dataset Codebook v 23.1 (https://ucdp.uu.se/downloads/).

Theisen, O. M. (2012). Climate clashes? Weather variability, land pressure, and organized violence in Kenya, 1989–2004. *Journal of peace research*, *49*(1), 81-96.

United Nations. (2020, July 24). *Climate Change Exacerbates Existing Conflict Risks, Likely to Create New Ones, Assistant Secretary-General Warns Security Council | Meetings Coverage and Press Releases*. United Nations Meetings Coverage and Press Releases. https://press.un.org/en/2020/sc14260.doc.htm

United Nations. (n.d.). Bringing dry land in the sahel back to life | UN news. United Nations. https://news.un.org/en/story/2022/01/1110322.