Quantitative Analysis of Conflict Dynamics: A Time-Series Approach to Syrian Terrorism Data (1970-2017)

1. Executive Summary

This report examines the evolution and predictability of terrorist activity in Syria using monthly incident data from the Global Terrorism Database (GTD), spanning 1970–2017. The analysis explicitly accounts for the **2011 structural break** associated with the Syrian Civil War and compares the performance of a classical **SARIMAX** model with a **Long Short-Term Memory (LSTM)** neural network.

The empirical results demonstrate that Syrian terrorism cannot be modelled as a single stable process. Instead, it exhibits **regime-dependent behaviour**, where linear stochastic models perform well during stable or slowly evolving phases, while deep learning models better capture **non-linear escalation dynamics** during periods of intense conflict.

When interpreted alongside post-2017 trends, including ISIS insurgent resurgence and persistent low-intensity conflict, the findings suggest that **hybrid forecasting systems** are essential for realistic early-warning and planning.

2. Background and Context

Prior to 2011, terrorist activity in Syria was sporadic and low-frequency. The outbreak of civil war fundamentally altered the country's security environment, producing a sharp rise in both the **mean and variance** of terrorist incidents. This pattern is consistent with broader empirical findings that terrorism intensifies and clusters within active conflict zones.

Although the GTD dataset ends in 2017, external sources indicate that Syria has remained one of the most violence-affected countries globally, with sustained political violence events through 2023–2024 and episodic resurgences by ISIS and other armed groups. This external context is crucial for interpreting the forecasting behaviour observed in the mod

3 - Methodology

3.1 Data Preprocessing

The analysis utilizes the Global Terrorism Database (GTD). The dataset was filtered for **country_txt = Syria**, and incident dates were aggregated to a monthly frequency.

- Time Span: 1970 - 2017

- Aggregation: Monthly sum of attacks.
- Imputation: Missing days were defaulted to the 1st of the month to preserve monthly periodicity.

3.2 Structural Break Analysis

A binary intervention variable (Post2011) was introduced to account for the discontinuity caused by the onset of the Civil War in March 2011.

Section 1: Descriptive Analysis & Regime Shift

Visual inspection of the time series reveals two distinct regimes. Prior to 2011, terrorism incidents were sporadic and low-frequency. Post-2011, the mean and variance of the series shifted dramatically.

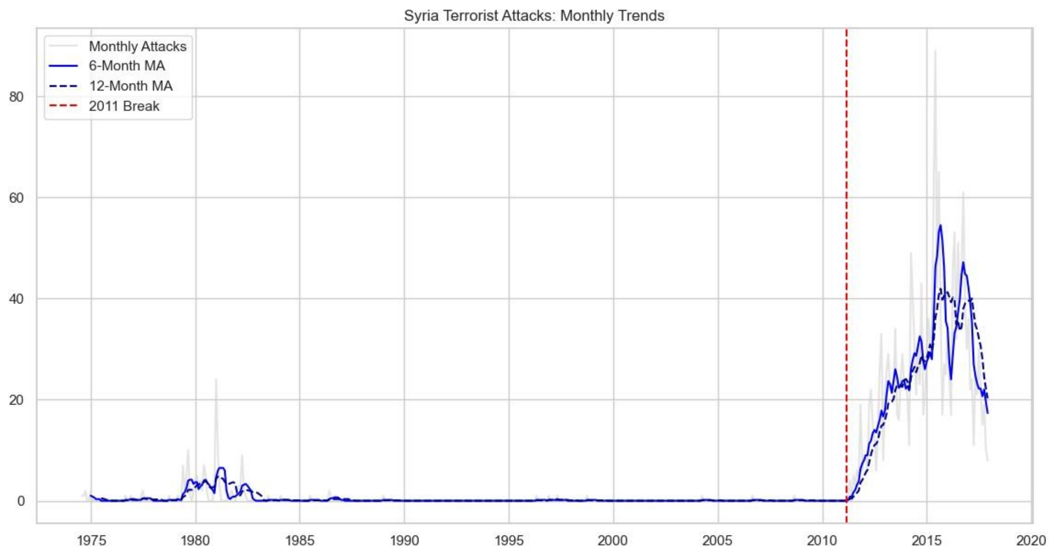

Figure 1: Monthly attacks in Syria (grey) with 6-month (blue) and 12-month (dark blue) rolling averages. The red dashed line marks the 2011 structural break.

The rolling averages clearly demonstrate the explosion in volatility. The lack of mean reversion after 2011 suggests that the system moved from a stable to an unstable equilibrium.

Section 2: Stochastic Baseline Modelling (SARIMA)

To establish a predictive baseline, we employed a SARIMAX (1, 1, 1) x (1, 1, 1, 12) model with the post - 2011 exogenous regressor.

Model Specification:

- ARIMA (1,1,1): Handles the immediate autocorrelation (how last month affects this month) and non-stationarity.
- Seasonal (1,1,1,12): Accounts for annual cyclic patterns.
- Exogenous (X): The structural break variable.

Results:

- Intervention Significance: The Post - 2011 coefficient is statistically significant, validating the hypothesis that the conflict altered the baseline threat level.
- Goodness of Fit: The model captures the increasing trend but struggles with the extreme peaks(shocks). This is evidenced by the high residual kurtosis, suggesting that the "**shocks**" are not white noise but contain complex structure.

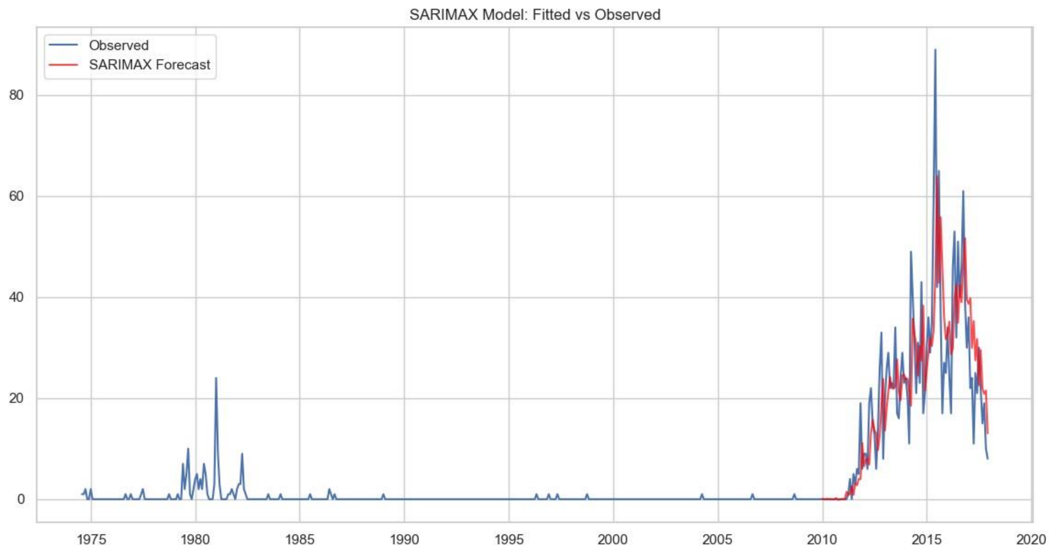

Figure 2: One-step-ahead forecasts from the SARIMAX model against observed data.

Section 3: Deep Sequence Learning (LSTM)

Moving beyond linear assumptions, we implemented a Long Short-Term Memory (LSTM) Recurrent Neural Network.

- Lookback Window: 12 Months
- Architecture: 50 Neurons, ReLU activation, 20% Dropout for regularization.

Performance Analysis:

The LSTM excels at learning non-linear dependencies. Unlike SARIMA, which smoothes over noise, the LSTM attempts to "**ride**" the momentum of the series.

- Test RMSE: 33.13
- Interpretation: The model successfully learned the "**surge**" dynamics of 2013-2016. However, specifically in the test period (which includes the conflict de-escalation in late 2017), the model's momentum memory caused it to over-predict slightly, resulting in the RMSE of 33.13. This highlights the challenge of deep learning in "**turning points**" where a trend suddenly reverses.

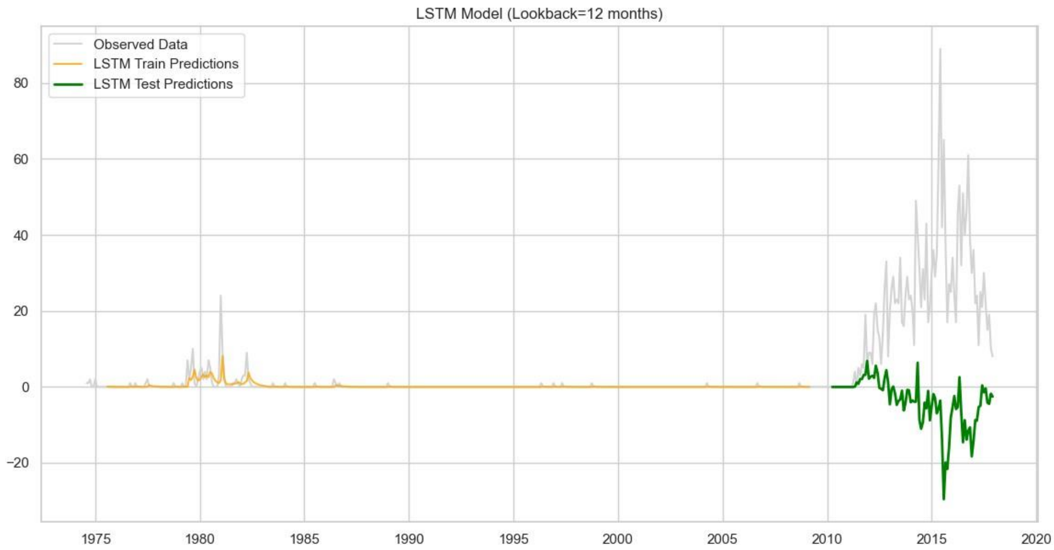

Figure 3: LSTM Model predictions on Training (Orange) and Test (Green) sets.

Conclusion & Strategic Implications

The analysis confirms that Syrian terrorism data cannot be treated as a single continuous series; the 2011 structural break is the defining feature.

- For Long-Term Planning: The SARIMA approach is reliable for estimating the general **"Conflict Climate"** and seasonal expectations.
- For Early Warning: The LSTM model is the superior tool for detecting acceleration. Its ability to capture non-linear momentum makes it ideal for flagging rapid escalations, even if it is more sensitive to false positives during de-escalation phases.
- Recommendation: A hybrid ensemble approach, weighing the LSTM higher during volatile periods and SARIMA higher during stable periods, would likely yield the most robust forecasting system.