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Spatiotemporal Patterns of Global Chemical Terrorism: Evidence from Global Terrorism Database (GTD) Between 1970 and Mid-2021

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Abstract

Chemical terrorism poses a persistent global security challenge despite its relatively low frequency. This study examined spatiotemporal patterns and hot spots of global chemical terrorism incidents, as well as associations among operational characteristics recorded in the Global Terrorism Database from 1970 to mid-2021. A total of 357 confirmed chemical terrorism incidents were identified across 62 countries. Although the dataset ends in mid-2021 due to funding cuts, its five-decade coverage provides a valuable historical baseline for examining the understudied geographic evolution of chemical terrorism. Both the linear model ($\beta = 0.2895$, $p < 0.001$) and the Negative Binomial (NB) regression ($\beta = 0.0442$, $p < 0.001$) showed significant positive trends. NB models also further identified significant temporal trends in fatalities and injuries. Comparison of the standard deviational ellipses (SDE) showed an eastward and slight northward shift in the spatial distribution after 2001, with the 2002–mid-2021 distribution becoming more concentrated around the Middle East and South/Southwest Asia. Emerging Hot Spot Analysis identified statistically significant increasing trends in parts of the Middle East and South/Southwest Asia, especially around Iraq, Afghanistan, Pakistan, and neighboring areas. This trend underscores the need for targeted attention to enhanced cross-border intelligence and information sharing, strict control over the production and legitimate use of toxic chemicals, and strengthened emergency-response capacity in these regions.

Keywords: chemical terrorism; global terrorism database; high impact analysis; emerging hot spot; Middle East; South Asia

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1. Introduction

Terrorism has emerged as a major national and global security concern that poses a threat to national sovereignty [1,2]. It has occurred across nearly all regions of the world since the late twentieth and early twenty-first centuries [3]. These incidents cause substantial loss of life and property, leading to public fear and social unrest [4]. It commonly involves the intentional use or threat of violence and fear by non-state actors to coerce a community or government in pursuit of political, ideological, religious, economic, or social goals [5,6].

The tactical short-run goals of terrorism include attracting publicity and media attention, destabilizing political systems, and disrupting economic activity [7,8].

Terrorism is associated with a range of factors, including economic hardship, modernization pressures, institutional order, political shifts, identity crises, global influences, and contagion [8]. Diverse techniques are employed to destabilize economic and political systems, including assassination, armed assault, bombing, explosions, infrastructure sabotage, hijacking, hostage-taking, and unarmed aggression [9]. From a theoretical perspective, routine activity theory suggests that criminal events occur through the convergence of motivated offenders, suitable targets, and the absence of capable guardians [10]. Terrorist attacks would follow similar practices. This framework would help interpret the geographic concentration of chemical terrorism incidents, which share similarities with crime incidents. Beyond its immediate impacts, terrorism can have substantial long-term political and economic consequences, such as governmental instability [8,11]. Weaknesses in disaster response management linked to policy, actors, operations, and technology can cause delays, inadequate coordination, and ineffective responses, increasing casualties and deaths [12].

However, studies on terrorism have profoundly emphasized attack trends, target selection, and spatiotemporal variation, highlighting that terrorist groups employ various methods and targets, and violence against civilians varies across locations and time [13,14]. Among these, the Global Terrorism Database (GTD), an event-based database developed by the National Consortium for the Study of Terrorism and Responses at the University of Maryland, maintains a relatively comprehensive dataset. It records approximately 214,600 domestic and international terrorist incidents. The database includes information on the date, location, attack type, target type, weapon type, and casualties [15]. According to GTD, a terrorist attack refers to the threatened or actual use of illegal force and violence by a non-state actor to achieve a political, economic, religious, or social goal through fear, coercion, or intimidation [5]. Because of its broad temporal coverage, standardized event-level structure, and consistent coding scheme, the GTD has been widely used in terrorism research, including studies of incident fatality rates and regional patterns [16], chemical, biological, radiological, and chemical-terrorism trends [17,18], determinants and causes of terrorism [8,19], domestic and transnational terrorism dynamics [20], group-level escalation behavior [21], weapon and attack patterns [22], target selection analysis [23,24], impact analysis [2], specific weapon type analysis [25,26], hot spot analysis [27], fatality severity [28], and preparedness and training needs [29,30]. Although the dataset's coverage ends in mid-2021 due to funding cuts, its extensive five-decade longitudinal span (1970–2021) provides an essential historical baseline for identifying long-term structural shifts, persistent and emerging hotspots, and macro-level geographic transitions.

The GTD classifies incidents into 13 weapon categories: biological agents, chemicals, explosives/bombs/dynamite, fake weapons, firearms, incendiary devices, melee weapons, nuclear weapons, radiological agents, sabotage equipment, vehicles, other weapons, and unknown weapons [5]. Among these, chemical agents have dual-use characteristics and may be employed for legitimate industrial, agricultural, research, medical, pharmaceutical, protective, certain non-chemical military, and law-enforcement purposes, including domestic riot control, when their types and quantities are consistent with those purposes [31]. In recent years, terrorist groups have used toxic industrial chemicals as well as classical chemical warfare agents to attack general populations [32]. Beyond conventional forms of terrorism, chemical terrorism presents distinct challenges because of its potential to cause mass casualties, expose populations to toxic substances, and necessitate specialized emergency response capabilities. More importantly, the dual-use nature of many chemical substances and technologies further complicates regulatory oversight and preventive efforts [31,32].

Although relatively rare, chemical terrorist attacks have become more frequent over time and have the potential to cause severe casualties [4,32]. The GTD defines a chemical weapon as a toxic chemical contained within a delivery system and dispersed as a liquid, vapor, or aerosol, including through explosive devices [25]. According to U.S. Department of Homeland Security statistics, 239 (56%) of 423 recorded nuclear, biological, and chemical terrorist incidents worldwide from 1950 to 2005 involved chemical agents [4]. DeLuca and colleagues reported that the average annual number of chemical terrorism attacks increased from 5.1 during 1970–2001 to 15.6 during 2001–2017 [29]. Santos and colleagues [25] observed that chemical terrorism occurrences resulted in an average of 51 injuries and 7 fatalities per incident. Tin and colleagues [22] expanded their study to 2018, revealing 347 terrorism-related chemical incidents from 1970 to 2018, which caused 921 deaths and 13,361 nonfatal injuries. On 16 March 1988, Saddam Hussein's forces attacked the Kurdish village with mustard gas and nerve agents, killing about 5000 civilians [33–36]. Aum Shinrikyo released sarin in the Tokyo subway attack on 20 March 1995, causing 13 deaths and 5500 injuries [26,32,37–39]. Between March 2011 and April 2017, at least 1206 people died in chemical attacks in non-state-controlled parts of Syria, 97.6% of whom were civilians [29,40]. The Ghouta attack on 21 August 2013 was the deadliest chemical attack in the Syrian War, killing 897 civilians, 30% of whom were women [40]. Moreover, the Khan Shaykhun chemical attack on April 4, 2017, killed at least 74 people, injured more than 557, and forced over 4.5 million Syrians to flee their homeland [41].

Although chemical terrorism has been widely documented, substantial research gaps remain. Existing studies using data from the Global Terrorism Database have primarily focused on descriptive characteristics of terrorist incidents, including incidence rates, types of chemicals used, casualties, spatial distribution, target types, attack success rates, and temporal patterns [18,25,29]. Unlike prior static assessments, our methodological contribution uniquely integrates a space-time cube framework, iterative outlier detection, and Mann–Kendall trend analysis to dynamically track chemical terrorism's evolution and variation. As an early effort, Castro-Delgado and colleagues analyzed chemical agents, regional distributions, temporal trends, and attack characteristics, but did not apply spatial statistical methods to investigate geographic shifts, multi-scale clustering, or emerging hot spots [18]. However, limited attention has been paid to integrating long-term temporal trends with spatial analytical approaches to assess chemical attacks' severity patterns, geographic transitions, multi-scale clustering, emerging hot spots, county-level severity, and factors associated with chemical attack outcomes. This study provides a spatiotemporal analysis of chemical terrorism incidents recorded in the Global Terrorism Database from 1970 to mid-2021. The study examines trends in incident occurrence, fatalities, and injuries; characterizes the spatial distribution of incidents and their severity; identifies spatial shifts and the emergence of hot spots; and quantifies operational characteristics associated with attack success. This integrated approach provides a more comprehensive understanding by integrating temporal trends, spatial clustering, and attack severity to identify geographic priorities for emergency preparedness.

2. Data and Methods

2.1. Data Source

The Global Terrorism Database (GTD) is an open-source database containing approximately 214,600 global terrorism incidents from 1970 to mid-2021 (except 1993). The GTD is maintained by the National Consortium for the Study of Terrorism and Responses to Terrorism (START) at the University of Maryland and is part of the US Department of Homeland Security Center of Excellence [30]. It is funded by Homeland Security [5] to collect, maintain, and annually publish the relevant information on terrorism attacks world-

wide [2]. It was developed to increase understanding of the characteristics of violence for prevention and effective response. The consortium evaluates media reports to verify if an incident meets the pre-specified eligibility standard [25]. An extensive description of their origin and the data collection methodology can be found in the GTD codebook, which is available on the START website [42]. Additionally, it is worth noting that the 1993 data, which were on hard-copy index cards, were physically lost during an institutional office relocation before START assumed management of the database [5]. Furthermore, GTD lost funding for data collection after partially collecting data for 2021 [5], which explains why our analysis has to end in mid-2021.

2.2. Data Preparation

This study used incident-level data from the Global Terrorism Database (GTD) to examine global patterns of chemical terrorism between 1970 and mid-2021. The GTD provides detailed information on terrorist incidents, including their geographic location, perpetrators, target and weapon types, casualties, nationality, region, sources, and other operational characteristics [5].

Chemical terrorism incidents were identified through a multistage filtering and verification procedure. First, incidents classified as involving chemical weapons under the primary weapon-type variable (weaptype1) were extracted, yielding 351 records. To identify potentially misclassified or additionally relevant incidents, records classified as chemical attacks under secondary weapon-type variables (weaptype2, weaptype3, and weaptype4) were also examined. For incidents involving multiple weapon types, the inclusion criteria were evidence of deliberate use of a chemical agent as part of the attack, rather than just its presence at the scene of the incident. The chemical agent was considered operationally significant if the description of the incident suggested it was used with the intent to cause harm, whether or not deaths or injuries occurred. Incidents where chemical substances were mentioned but their deliberate use as a component of an attack could not be established were excluded. This process identified six additional incidents, which meet the following three criteria: (1) chemical weapons were recorded in at least one secondary weapon field; (2) GTD event descriptions, weapon details, supplementary notes, or available news-source references provided evidence of deliberate chemical-agent use; and (3) the chemical agent was used as an operational component of the attack rather than being incidentally present or merely mentioned. The final event-based dataset therefore comprised 357 (351 + 6 = 357) confirmed incidents across 62 countries between 1970 and mid-2021, representing approximately 0.17% of the 214,600 total GTD incidents.

2.3. Analytical Framework

2.3.1. Temporal Analysis

Temporal patterns of chemical terrorism incidents were examined using the full set of 357 incidents. Annual incident counts were calculated for each year from 1970 to mid-2021, with 1993 having missing data. Ordinary Least Squares (OLS) model was used to model trends in annual incident frequency from 1970 to mid-2021 and for two separate periods: 1970–1992 and 1994–mid-2021, as the 1993 data were lost [5]. For the OLS models, we calculated the slope, coefficient of determination (R^2), and p-value to evaluate the direction and magnitude of temporal trends, goodness of fit, and statistical significance, respectively. In addition, Negative Binomial (NB) regression models were fitted to annual incident, fatality, and injury counts for 1970–2020, excluding 1993 and the incomplete 2021 observations ($N = 50$), to account for overdispersion in the annual count data. Calendar year, centered at 1970, was included as the independent variable to capture temporal trends. The NB model used a log link and estimated an overdispersion parameter to allow for

variation greater than that expected under a Poisson distribution, and was widely used in public safety studies [43–45]. Model results included regression coefficients, standard errors, p-values, 95% confidence intervals, and fit of the model statistics.

2.3.2. Statistical Analysis

Statistical analyses were conducted in Python 3.14 using the pandas, SciPy, and statsmodels libraries. Attack success was defined according to the Success variable in the Global Terrorism Database and was coded as successful or unsuccessful. Descriptive statistics were used to summarize attack outcomes and operational characteristics. Associations between attack success and target type, as well as between attack success and geographic region, were examined using contingency tables and Pearson's chi-square tests of independence. The association between geographic region and target type was also evaluated using Pearson's chi-square test of independence. Expected cell frequencies were examined to assess whether the assumptions of the chi-square tests were satisfied. Perpetrator effectiveness was evaluated by calculating the number and proportion of successful incidents attributed to each perpetrator group. All statistical tests were two-tailed, and statistical significance was set at $p < 0.05$. Additionally, to assess model robustness, for both OLS and NB models, regression coefficients were reported alongside their standard errors, p-values, and 95% confidence intervals. Model fit was evaluated using the log-likelihood, Akaike Information Criterion (AIC), and model-specific R^2, where applicable.

2.3.3. Country-Based Severity Assessment

Country-level impact was evaluated by aggregating incidents across 62 countries using the complete dataset of 357 incidents. To capture both the frequency and severity of attacks, a weighted severity index was constructed based on the Global Terrorism Index–Impact Score (GTI-IS) framework developed by the Institute for Economics & Peace (IEP) and adapted by Singh and Philip [2]. This composite index combines measures with different scales to provide an integrated proxy for the overall impact of terrorist activity. Based on the weighting scheme described in [2], fatalities were assigned a multiplier of 3, whereas incidents and injuries were each assigned a multiplier of 1. This weighting scheme reflects the greater and irreversible societal consequences of fatalities relative to nonfatal injuries and the occurrence of incidents. Countries were subsequently ranked according to their calculated severity scores.

$$Severity = (IncidentFrequency \times 1) + (Fatalities \times 3) + (Injuries \times 1)$$

2.3.4. High-Impact Attack Identification (HIA)

High-impact attacks (HIA) were identified using an iterative outlier detection method applied to casualty-related variables, specifically Fatalities (*nkill*) and Injuries (*nwound*). This approach aimed to detect incidents with unusually high casualties compared to the overall distribution of events. Outliers were determined using the interquartile range (IQR) method [2].

$$\boldsymbol{IQR = Q_3 - Q_1}$$

where

Q_1 represents the first quartile (25th percentile)
Q_3 represents the third quartile (75th percentile)
The upper threshold (T) for identifying high-impact events was calculated as

$$\boldsymbol{T = Q_3 + 1.5 \times IQR}$$

Any incident with a casualty value exceeding this threshold was classified as an outlier:

$$x_i > T$$

Here, x_i denotes the casualty value for incident i.

2.3.5. Spatial Pattern Analysis

To gain a more thorough understanding of the spatial distribution of chemical terrorism incidents and their temporal variation across space, spatial pattern analyses were conducted using the full dataset of 357 incidents. Each incident was represented as a spatial point using its latitude and longitude coordinates. The incident locations were initially referenced to the World Geodetic System 1984 (WGS 84; EPSG:4326), with geographic coordinates expressed in decimal degrees. For subsequent analyses involving distance and area measurements, we used geodesic calculations to ensure measurement accuracy, following recommendations from Esri and GISCARTA.

(a) Central Tendency

Spatial central tendency was examined in ArcGIS Pro using the Mean Center and Median Center tools. The Mean Center tool calculates the average x- and y-coordinates of all incident locations, identifying the geographic center of the spatial distribution. In contrast, the Median Center tool uses an iterative algorithm to identify the location that minimizes the sum of Euclidean distances to all incident locations. Compared with the Mean Center, the Median Center is less sensitive to spatial outliers and provides a more robust measure of central tendency. The dataset included 357 chemical terrorism incidents represented as point locations. Mean Center analysis was performed for the full study period (1970–mid-2021), pre-2001, and post-2001 periods. Median Center analysis was conducted for the full dataset (1970–mid-2021) because it is less affected by extreme or geographically distant incidents and provides a robust measure of the central location of the distribution.

(b) Standard Deviational Ellipse Analysis

Spatial dispersion and directional trends were analyzed using the Directional Distribution (Standard Deviational Ellipse) tool in ArcGIS Pro 3.7, with the full study period (1970–mid-2021), the pre-2001 period, and the post-2001 period. One Standard Deviation Ellipse (SDE) was generated for each period, providing information on the geographic center, major and minor axes, spatial dispersion, and dominant directional trend. The resulting ellipses were mapped and compared by location, size, and orientation to assess changes in the concentration, extent, and directional distribution of chemical terrorism incidents over time.

(c) Nearest Neighbor Analysis

Spatial clustering was assessed in ArcGIS Pro 3.7 using the Average Nearest Neighbor tool located within the Analyzing Patterns toolset. The 357 incident points were used as the input feature class, and Euclidean distance was applied. The tool calculated the observed and expected mean nearest-neighbor distances, Nearest Neighbor Index, z-score, and p-value. An index below 1 indicated clustering, whereas an index above 1 indicated dispersion.

(d) Ripley's K and L-Function

Clustering across multiple spatial scales was examined in ArcGIS Pro 3.7 using the Multi-Distance Spatial Cluster Analysis (Ripley's K Function) tool. The 357 incident points were analyzed using ten distance bands, a distance increment of 250 km, 999 permutations, and the minimum enclosing rectangle as the study-area method. The 250 km distance was selected following empirical testing of multiple scales. ArcGIS Pro 3.7 generated the final

distance bands from approximately 834.97 km to 8349.75 km based on the spatial extent of the input features and study area. No weight field was applied. A confidence envelope was generated using 999 permutations to evaluate whether the observed spatial pattern differed significantly from complete spatial randomness. Clustering was evaluated by comparing the observed L-function values with the expected values and confidence envelope.

2.3.6. Emerging Hot Spot Analysis

Spatiotemporal patterns of chemical terrorism incidents were examined in ArcGIS Pro 3.7 using the Space Time Pattern Mining toolbox. The incident points were first aggregated into a space–time cube using the Create Space Time Cube by Aggregating Points tool, with 250 km × 250 km spatial bins and 3-year temporal intervals. The 250 km spatial bins and 3-year temporal intervals were selected based on empirical testing of multiple spatial and temporal scales. Given the relatively rare occurrence of chemical terrorism worldwide, finer spatial and temporal resolutions resulted in excessive data sparsity, with many bins containing no incidents. The selected thresholds therefore provided a balance between maintaining sufficient data density for meaningful statistical analysis and preserving the ability to capture regional and temporal variations in incident patterns. Incident counts were summarized for each spatial bin and time step, producing a structured space–time dataset for subsequent analysis. The resulting space–time cube was then analyzed using the Emerging Hot Spot Analysis tool. The Getis–Ord Gi* statistic identified statistically significant hot and cold spots for each time step, while the Mann–Kendall trend test evaluated changes in clustering intensity through time. Based on these results, each spatial bin was classified into an emerging hot or cold spot category, such as new, consecutive, historical, intensifying, diminishing, or no pattern detected. Additionally, as GTD data were unavailable for 1993, Optimized Hot Spot Analysis was conducted as a supplementary sensitivity analysis to assess whether the principal spatial concentrations were broadly consistent when the temporal dimension was excluded.

3. Results

3.1. Temporal Trends of Chemical Terrorism

A total of 357 chemical terrorism incidents were recorded globally between 1970 and mid-2021. The linear trend analysis covered 1970–mid-2021, with 1993 data missing. The highest annual frequency was recorded in 2016 (32 incidents), followed by 2017 (28 incidents) and 2015 (23 incidents). These elevated frequencies clustered within a relatively short period, suggesting a distinct surge in chemical terrorism activity during the mid-2010s (Figure 1). Ordinary Least Squares (OLS) regression indicated a positive and statistically significant overall trend ($\beta = 0.290$, $p < 0.001$, $R^2 = 0.370$), suggesting a gradual increase in chemical terrorism incidents. The moderate R^2 value indicates that time explains 37% of the variance, while additional factors likely contributed to annual fluctuations. The trend during 1970–1992 was small and not statistically significant ($\beta = 0.052$, $p = 0.435$, $R^2 = 0.029$). In contrast, a statistically significant increase was observed during 1994–2020 ($\beta = 0.397$, $p = 0.042$, $R^2 = 0.155$), with more obvious fluctuations, indicating that the overall upward trend may be primarily driven by the later period. We also fitted a Negative Binomial (NB) regression model as a sensitivity analysis, given that chemical terrorism incidents constitute count data. The positive temporal trend in these incidents was further corroborated by the NB model ($\beta = 0.044$, 95% CI: 0.029–0.059, $p < 0.001$). The model yielded an overdispersion parameter of 0.421 and an AIC of 281.80 (Table 1). Notably, the increased variability observed after 1993 may reflect a pivotal shift attributable to both historical and methodological factors. From a tactical perspective, the mid-1990s witnessed the emergence of large-scale chemical attacks by non-state actors, exemplified by Aum Shin-

rikyo's activities in 1994 and1995. From a methodological perspective, the GTD's transition to comprehensive digital open-source intelligence collection in 1998 may have expanded incident coverage and contributed to greater variability in reported frequencies [5].

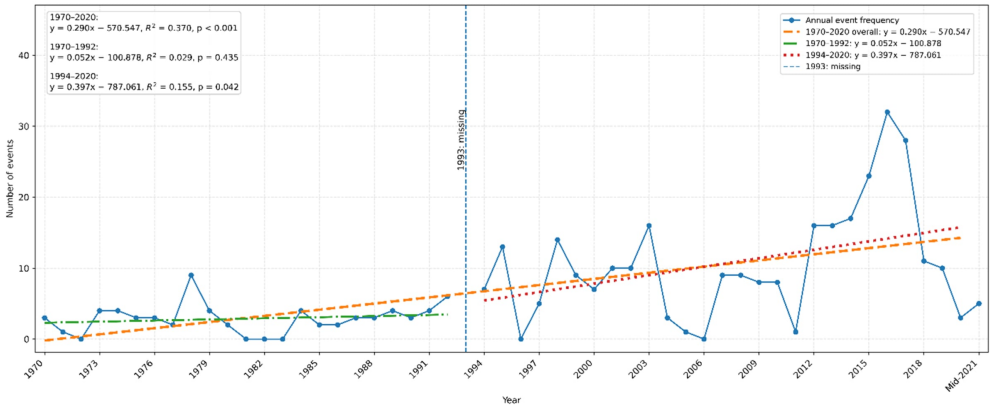


Figure 1. Temporal Analysis of Annual Chemical Terrorism (1970–mid 2021).

Table 1. Comparison of OLS and Negative Binomial regression results for temporal trends in chemical terrorism incidents, fatalities, and injuries (1970–2020).

Outcome	Model	β	SE	p-Value	95% CI	AIC
Incidents	OLS	0.290	0.055	<0.001	0.180–0.399	318.36
	NB	0.044	0.008	<0.001	0.029–0.059	281.80
Fatalities	OLS	0.521	0.299	0.088	−0.080–1.121	488.50
	NB	0.111	0.034	0.001	0.045–0.177	272.31
Injuries	OLS	11.585	8.867	0.198	−6.244–29.413	827.58
	NB	0.144	0.064	0.024	0.019–0.269	486.71

3.2. Association Between Operational Characteristics

3.2.1. Target Type and Attack Success

A chi-square test indicated a statistically significant association between target type and attack success ($\chi^2 = 73.34$, $p < 0.001$, Cramér's V = 0.45). Higher success rates were observed for attacks targeting police (29 incidents, 93.5% success rate), private citizens and property (88 incidents, 92.6% success rate), and military personnel or facilities (32 incidents, 84.2% success rate). In contrast, attacks targeting general government institutions had a lower success rate at 51.2% for 37 incidents. These findings indicate that attack success varied significantly across target categories.

3.2.2. Regional Variation in Attack Success

A statistically significant association was also observed between geographic region and attack success ($\chi^2 = 64.03$, $p < 0.001$, Cramér's V = 0.42). Higher success rates were recorded in South Asia (91.5%) and the Middle East and North Africa (89.3%), with 86 and 75 successful attacks, respectively. Lower success rates were observed in Australasia and Oceania (20.0%) and Southeast Asia (45.5%). These findings indicate substantial regional variation in attack outcomes.

3.2.3. Perpetrator Group Effectiveness

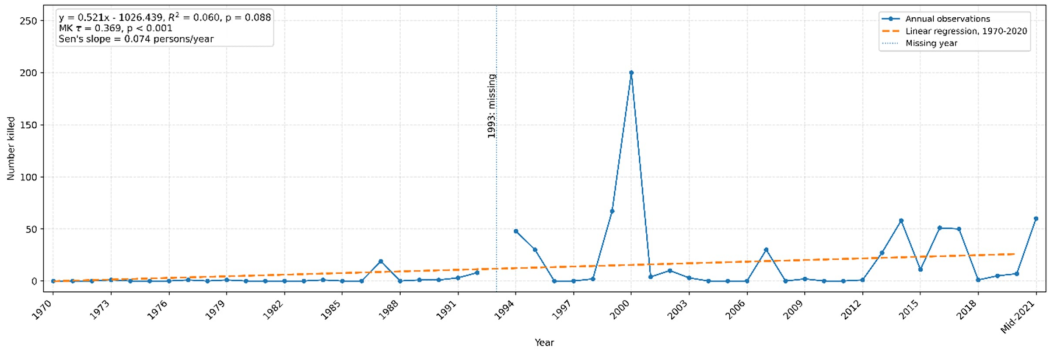
Attack success rates varied across perpetrator groups. According to GTD, among groups, the Islamic State of Iraq and the Levant and the Arab Revolutionary Army recorded success rates of 100%, with 41 and 8 successful attacks, respectively. The Taliban recorded a success rate of 96.4%, with 27 of 28 attacks classified as successful. In comparison, incidents attributed to unknown perpetrators had a success rate of approximately 71.3%, with 127 successful attacks among 178 incidents. These descriptive findings demonstrate variation in recorded success rates across perpetrator categories.

3.2.4. Regional Target Patterns

A statistically significant association was identified between geographic region and target type ($\chi^2 = 625.39$, $p < 0.001$, Cramér's V = 0.40), indicating that target distributions differed across regions. In South Asia, attacks frequently targeted educational institutions and private citizens and property, with 39 and 24 incidents, respectively. In the Middle East and North Africa, military targets and private citizens and property accounted for 24 and 41 incidents, respectively. In Western Europe, attacks more frequently targeted businesses and food-processing, water-treatment, or infrastructure systems, with 7 and 9 incidents, respectively. These findings demonstrate distinct regional differences in target selection.

3.3. Trends in Fatalities and Injuries

Analysis of casualty data revealed distinct temporal patterns in fatalities and injuries associated with chemical terrorism incidents. A total of 703 fatalities and 14,534 injuries were recorded, excluding unknown casualty values. Trend analyses covered 1970–mid-2021, excluding 1993 because of missing data. Fatalities exhibited a positive but not statistically significant linear trend over time ($\beta = 0.521$, $p = 0.088$, $R^2 = 0.060$). Extreme fatality events were sporadic rather than consistently increasing (Figure 2a). Similarly, injuries showed a positive but not statistically significant linear trend ($\beta = 11.584$, $p = 0.198$, $R^2 = 0.034$). Figure 2b reflects the occurrence of sporadic, large-scale incidents (Figure 2b). Furthermore, NB regression analyses indicated significant positive temporal trends in both fatalities ($\beta = 0.111$, 95% CI: 0.045–0.177, $p = 0.001$) and injuries ($\beta = 0.144$, 95% CI: 0.019–0.269, $p = 0.024$), suggesting the NB model outperforms the OLS model in such over-dispersed data (Table 1).



(**a**)

Figure 2. *Cont.*

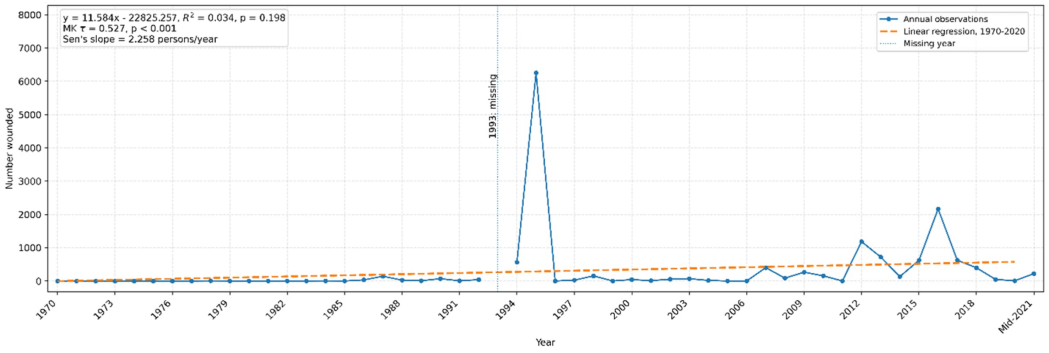


Figure 2. (**a**) Temporal Analysis of Annual Fatalities of Chemical Terrorism (1970–mid 2021). (**b**) Temporal Analysis of Annual Injuries of Chemical Terrorism (1970–mid 2021).

3.4. Country-Level Distribution of Incidents, Fatalities, and Injuries

Country-level analysis revealed substantial variation in the distribution of chemical terrorism incidents, fatalities, and injuries across the 62 affected countries and regions. A small number of countries and regions accounted for a disproportionately large share of both incidents and human casualties, indicating an uneven global pattern. In terms of incident frequency, Afghanistan recorded the highest number of events (67 incidents), followed by Iraq (52 incidents) and the United States (28 incidents). These countries recorded the highest cumulative numbers of chemical terrorism incidents during the study period. A different pattern is observed when examining fatalities. Uganda reported the highest number of deaths (200 fatalities), followed by Iraq (118 fatalities) and Colombia (72 fatalities). Uganda's position is largely driven by a single high-fatality event, whereas Iraq and Colombia reflect more consistent lethal impacts across multiple incidents. In contrast, injuries were most heavily concentrated in Japan, which records the highest number of wounded individuals (6746), followed by Afghanistan (3607) and Iraq (2130). The exceptionally high injury count in Japan is associated with a major high-casualty event, while Afghanistan and Iraq again demonstrate both high incident frequency and substantial human impact (Figures 3–5; Supplementary Tables S1 and S2).

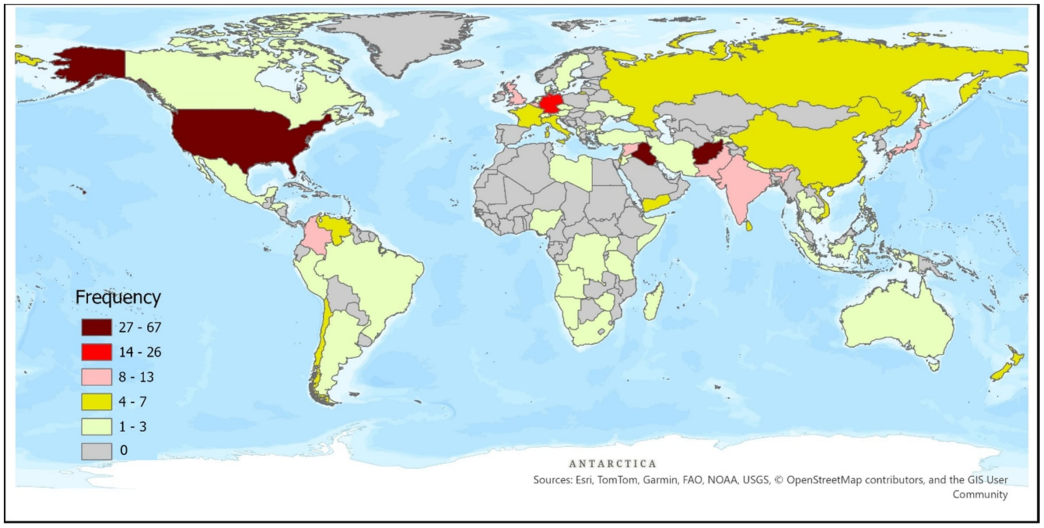


Figure 3. Global Frequency of Chemical Terrorism Incidents, 1970–mid-2021.

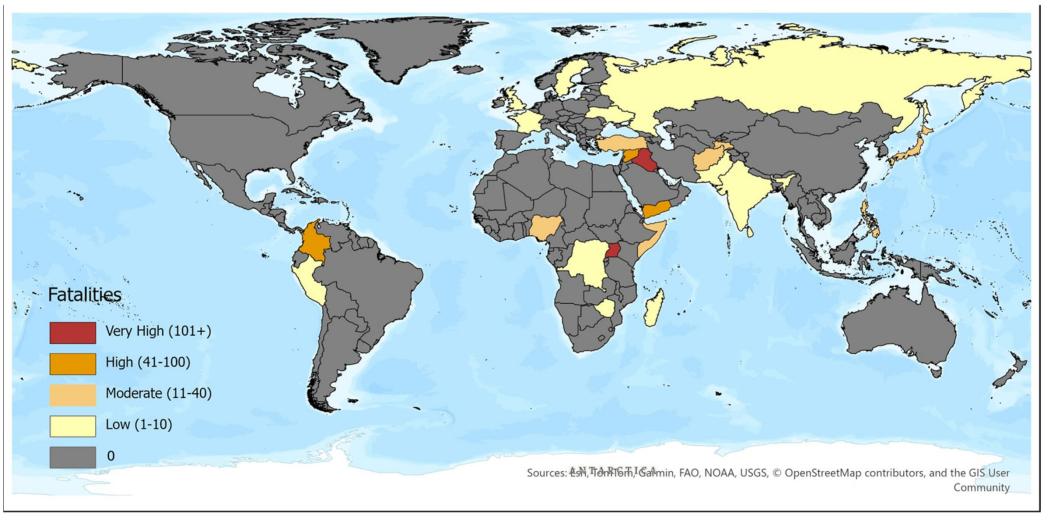


Figure 4. Global Distribution of Fatalities from Chemical Terrorism Incidents, 1970–mid-2021.

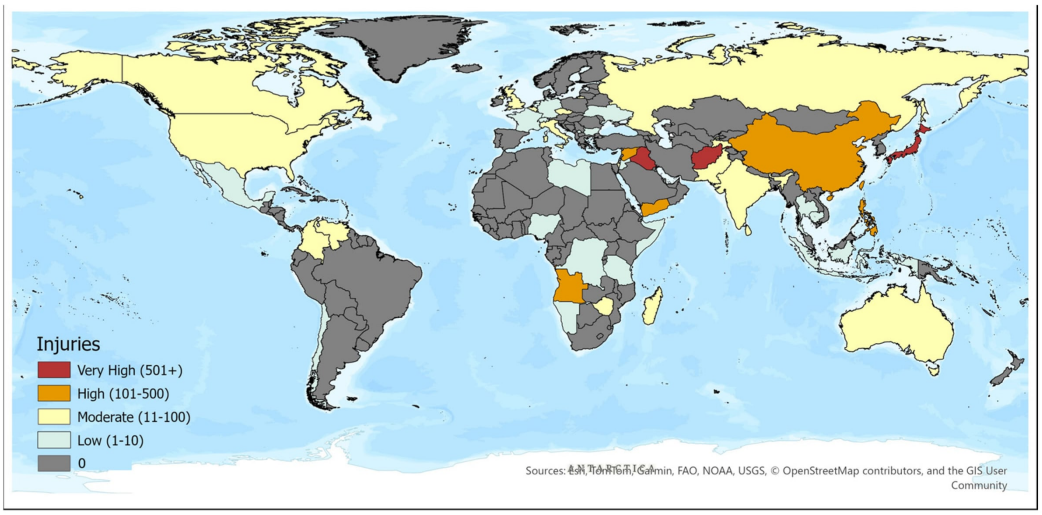


Figure 5. Global Distribution of Injuries from Chemical Terrorism Incidents, 1970–mid-2021.

3.5. Identification of High-Impact Incidents

High-impact attacks (HIAs) were identified using an iterative interquartile range (IQR) outlier detection approach applied separately to fatalities (*nkill*) and injuries (*nwound*). The casualty distributions are highly right-skewed, indicating the presence of extreme events. For fatalities, the dataset (n = 357) shows a low central tendency (mean = 1.97; median = 0), with a maximum of 200 deaths. Initial IQR-based filtering produced an upper bound of 0, identifying 72 outliers. To refine detection, iterative outlier removal was applied, yielding successive thresholds of 33.76, 20.48, and 14.04 deaths. After convergence, 12 events were classified as high-impact based on fatalities. For injuries, the distribution is similarly skewed (mean = 40.71; median = 1; maximum = 5500). Iterative outlier filtering produced thresholds of 446.80, 250.00, and 200.00 injuries, resulting in the identification of 9 high-impact events. These HIAs represent a small fraction of total incidents but account for a disproportionate share of casualties. The most extreme fatality event occurred in Uganda (200 deaths, 2000), followed by Colombia (65 deaths, 1999) and Yemen (45 deaths, 2021). In contrast, injury-based HIAs are dominated by large-scale events in Japan (Tokyo, 1995: 5500 injuries; Yokohama, 1995: 671; Matsumoto, 1994: 500), along with major incidents in Iraq and Afghanistan (Supplementary Tables S3 and S4).

3.6. Spatial Pattern Analysis Results

Mean center and standard deviational ellipse (SDE) analyses were conducted for three periods (1970–2001, 2002–mid-2021, and the full study period, 1970–mid-2021) to examine temporal changes in the geographic center, spatial dispersion, and orientation of chemical terrorism incidents (Figure 6). Across the full study period, the overall mean center was located near Egypt and the eastern Mediterranean region (approximately 27.96° N, 32.66° E), whereas the median center was situated farther east, in Iraq (approximately 34.80° N, 43.34° E). As the median center is less sensitive to extreme spatial outliers, this difference suggests that the overall geographic distribution is influenced by the broad dispersion of incidents across North Africa, Europe, and the Middle East. Comparison of the two subperiods further reveals a pronounced eastward shift in the mean center. Before 2001, the mean center was located in North Africa (approximately 27.25° N, 7.99° E), whereas after 2001, it shifted eastward toward the Iraq–Saudi Arabia region (approximately 28.33° N, 45.30° E). This displacement suggests a geographical reorientation of chemical terrorism activity after 2001, with a greater concentration of incidents in the Middle East and adjacent parts of South Asia.

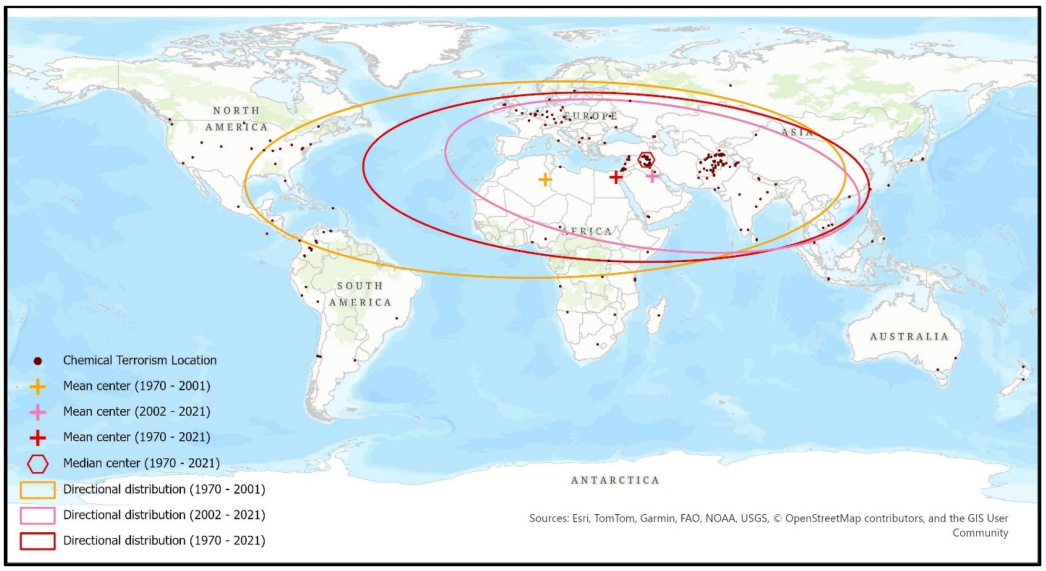


Figure 6. Mean and Median Centers and SDEs of Chemical Terrorism Incidents, 1970–mid-2021.

For the full period 1970–2021, the ellipse is centered at approximately 27.97° N, 32.66° E, with an X standard distance of 9825.02 km and a Y standard distance of 3252.04 km, indicating a broad east–west pattern extending from the Americas through Europe, Africa, and Asia (Figure 6). The pre-2001 ellipse is the largest, with an X standard distance of 11,645.40 km, a Y standard distance of 3799.38 km, and an area of 138,993,749.37 km^2, suggesting that earlier events were more widely dispersed across the Atlantic, Europe, Africa, and Asia. After 2001, the ellipse decreases in size, with an X standard distance of 8095.55 km, a Y standard distance of 2800.87 km, and an area of 71,230,737.59 km^2, showing a more concentrated distribution around Europe, North Africa, the Middle East, and South Asia, particularly near the India–Pakistan-Afghanistan region. Overall, the pattern shifted from a wider pre-2001 distribution across the Americas, Europe, Africa, and Asia to a more concentrated post-2001 cluster across Europe, North Africa, the Middle East, and South Asia.

The Average Nearest Neighbor analysis revealed a statistically significant clustered spatial pattern of chemical terrorism incidents. The observed mean nearest-neighbor distance was 136,088.87 m, substantially shorter than the expected mean distance of 508,524.75 m

under a random spatial distribution. This yielded a Nearest Neighbor Ratio (NNR) of 0.27, indicating that incidents were considerably closer to one another than would be expected by chance. The strongly negative z-score (−26.47) and p-value ($p < 0.001$) further confirmed the statistical significance of this clustering pattern. Collectively, these findings indicate that chemical terrorism incidents are not randomly distributed but instead exhibit a pronounced tendency to cluster in specific geographic areas, especially the Middle East and South Asia (Figure 6).

The Multi-Distance Spatial Cluster Analysis revealed statistically significant clustering of chemical terrorism incidents across all distance bands examined, ranging from approximately 834.97 km to 8349.75 km. The observed L(d) values consistently exceeded the upper confidence envelope, indicating a significant departure from complete spatial randomness across the analyzed spatial scales. At the first evaluated distance band (approximately 834.97 km), the observed L(d) value was 3,338,933.37, substantially exceeding the upper confidence limit of 909,307.80 and demonstrating statistically significant clustering at this scale. This finding suggests pronounced regional clustering, with incidents concentrated within relatively close geographic areas. Although the difference between the observed and expected values decreased as distance increased, the observed L(d) values remained above the upper confidence envelope up to approximately 8349.75 km. Collectively, these findings indicate that chemical terrorism incidents were neither randomly nor evenly distributed globally but instead exhibited substantial spatial concentration across both regional and broader transcontinental scales.

3.7. Emerging Hot Spot of Chemical Terrorism

The Emerging Hot Spot Analysis, conducted using 250 km spatial bins and 3-year temporal intervals, showed that most spatial locations were classified as No Pattern Detected, indicating that most analyzed areas did not exhibit a statistically significant emerging hot or cold-spot pattern during 1970–2021. The main hot spot patterns were concentrated in two regions: the Middle East, centered broadly on Iraq and adjacent areas, and South/Southwest Asia, particularly the Afghanistan–Pakistan region. The significant locations were classified as consecutive hot spots, indicating an uninterrupted sequence of statistically significant hot-spot conditions during the most recent time intervals (Figure 7).

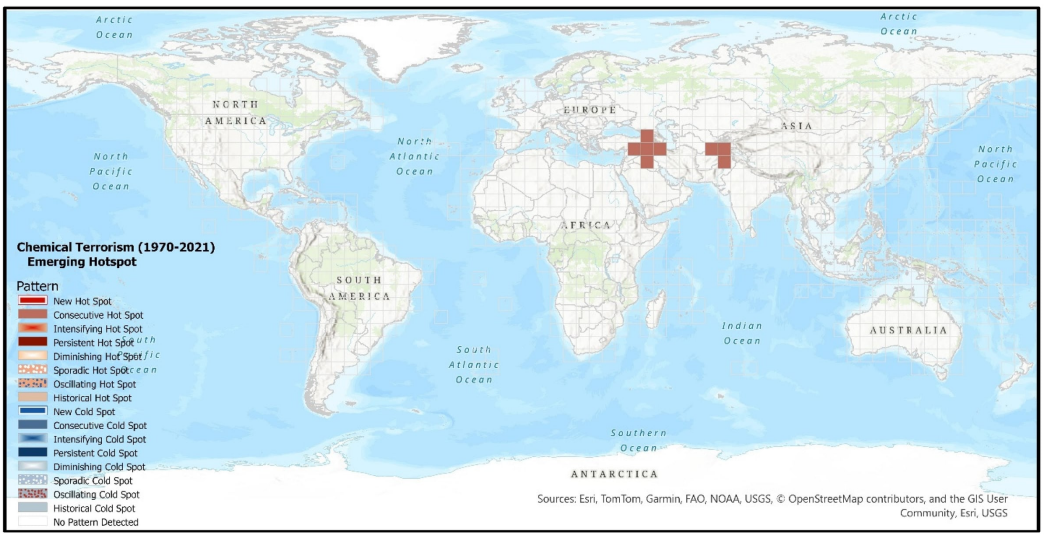


Figure 7. Emerging Hot Spot Analysis of Chemical Terrorism Incidents, 1970–mid-2021.

The trend-bin results further showed statistically significant increasing trends in these regions. The strongest increasing trends were observed in the Afghanistan–Pakistan region

and the Middle East, with several bins significant at the 95% and 99% confidence levels (Figure 8). Additional increasing trends at the 90% confidence level were observed in scattered areas of Europe, eastern Africa, and South Asia. In contrast, statistically significant decreasing trends were observed in scattered parts of North America, Central America, South America, Europe, and North Africa. Overall, the results indicate that consecutive hot spots and the strongest upward trends were concentrated primarily in the Middle East and the Afghanistan–Pakistan region. In contrast, decreasing trends were more geographically dispersed (Figures 7 and 8). Identifying these two consecutive hot spots is important because each exhibited a single uninterrupted run of at least two statistically significant hot spot bins during the final time-step intervals, despite never having been identified as a statistically significant hot spot in any earlier time step. These newly emerging hot spots in the most recent year are consistent with the eastward-moving trend shown in Figure 6. Such emerging hot spots indicate a statistically significant, sustained upward trajectory in the spatial concentration of chemical attacks over time, pinpointing regions where non-state actors have systematically escalated and sustained their chemical capabilities rather than conducting isolated strikes.

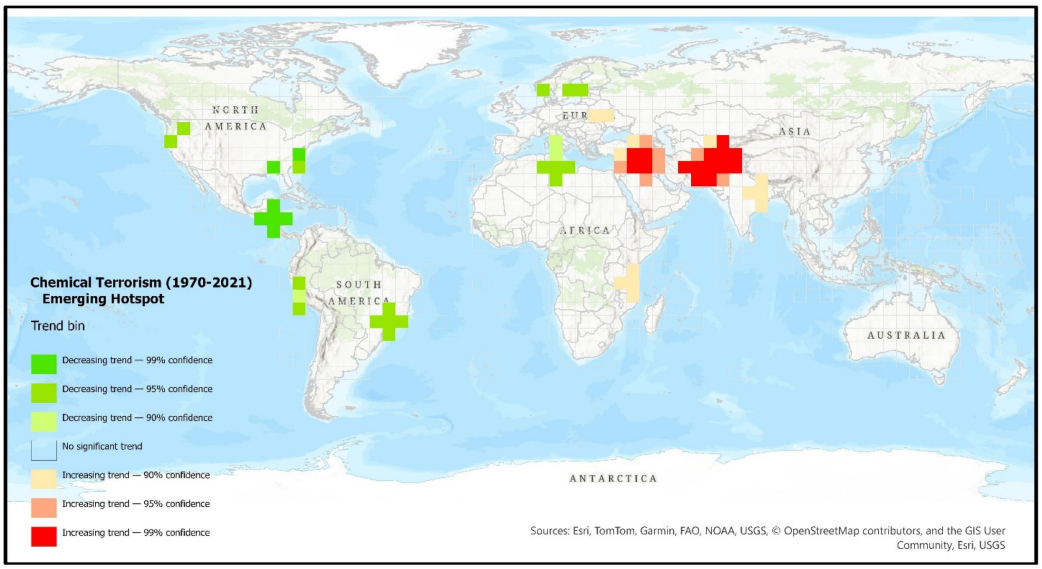


Figure 8. Trend Bin Count of Emerging Chemical Terrorism Hot Spots, 1970–2021.

A supplementary Optimized Hot Spot Analysis was conducted to compare overall spatial concentrations with those identified by Emerging Hot Spot Analysis. Significant hot spots occurred mainly in the Middle East and South and Southwest Asia, particularly around Iraq, Afghanistan, Pakistan, and neighboring areas. Most other regions showed no statistically significant pattern (Supplementary Figure S1). These findings align well with Figures 6 and 7.

4. Discussion

Although chemical terrorism remained relatively sparse in the broader terrorism context, our study found a statistically significant increase in the frequency of these incidents over the period. For example, a previous study identified 292 chemical terrorism incidents, representing 0.19% of all GTD events between 1970 and 2015 [25]. Another study reported that chemical attacks constituted 0.21% of GTD incidents from 1970 to 2017 [29], while their mean annual frequency increased from 6.0 in 1970–2011 to 24.9 in 2011–2017, possibly due to conflicts in Afghanistan (2012, 2015), Syria, and Iraq (2016). Consistent with our findings, a previous study found that chemical incidents increased sharply after 2011 and

peaked at 32 in 2016, and then declined to 3 to 5 cases annually by 2020–2021. Although COVID-19 restrictions may have contributed, the decline had already started before the pandemic [18]. The greater variability after 1993 may reflect both changes in attack patterns and differences in data collection practices. Large-scale attacks, including those by Aum Shinrikyo in 1994–1995, and changes in reporting coverage may have contributed to the observed fluctuations, though this study did not assess their respective contributions. Despite their rarity, these incidents can have disproportionate human, psychological, and public health consequences [32]. Public perceptions of risk can also intensify these effects, creating fear disproportionate to the actual risk of harm [46]. Furthermore, the occurrence of 357 incidents across 62 countries, together with the substantial casualties and persistent regional hot spots, highlights the importance of preparedness for chemical terrorism. The marked increase in chemical terrorism incidents over time (Figures 1 and 2), along with the emergence and clustering of hot spots in the Middle East and the Afghanistan–Pakistan region (Figures 6–8), underscores the need to strengthen surveillance and emergency response capabilities in these regions. Both the ordinary least squares (OLS) and negative binomial (NB) regression models supported an upward temporal trend in chemical terrorism incidents. The NB model provided a good fit to the over-dispersed annual incident counts, whereas OLS served as an interpretable linear baseline. Meanwhile, the findings suggest that an increase in the frequency of chemical terrorism incidents does not necessarily correspond to a proportional or consistent increase in the number of casualties per attack.

Moreover, the high proportion of successful attacks targeting private citizens and property (92.6%) highlights the importance of preparedness in civilian settings. Civilian and educational sites may be easier to attack because they are open and inadequately protected. Such visibility may also increase publicity and fear [47]. Moreover, terrorist operational success largely depends on terrorist resources and target vulnerability, while successful negotiations depend on the relative strengths of the terrorist actors and bargaining position [48]. Stakeholders' responses should remain targeted and proportionate to avoid strengthening violent groups [49,50]. About half of all attacks were attributed to unknown perpetrators, and of these attacks, approximately 71% were successful. Unknown groups refer to the attribution and data limitation of insufficient evidence linking terrorist groups or individuals. The Syrian civil war and the rise of the Islamic State of Iraq and the Levant (ISIL) have both contributed to regional instability and increased the operational space for extremist groups [51–53]. Terrorist groups in this region reportedly used chlorine, sulfur mustard, and other toxic agents, demonstrating tactical adaptation and the exploitation of weak regulatory and security systems [51,53,54]. Moreover, persistent terrorist violence in Iraq stems from the institutional collapse, sectarian polarization, and insurgency that followed the 2003 Iraq War, including the rise of Al-Qaeda-linked groups [55,56]. Conflict environments have enabled armed groups to acquire toxic industrial chemicals and incorporate chemical agents into insurgent and terrorist operations [29,32]. There have been growing calls for enhanced international cooperation on security matters among all countries, while respecting the sovereignty and territorial integrity of each state. Such cooperation can help mitigate transnational threats and promote regional and international peace and stability [57]. Additionally, the consecutive hot spots (Figure 8) indicate persistent spatial clustering in the Middle East and South/Southwest Asia, highlighting areas that may benefit from sustained monitoring and preparedness. In practical terms, this suggests that in regions such as the Afghanistan–Pakistan border area and Iraq, terrorist networks did not merely carry out isolated chemical attacks but developed, maintained, and adapted their chemical deployment capabilities over successive periods. Although our spatial analyses empirically identify geographic clustering, institutional instability, links to

armed conflict, and cross-border dynamics are discussed as contextual explanations drawn from the literature rather than as causal mechanisms directly tested in this study.

Furthermore, incident frequency, fatalities, and injuries varied across countries in our study. Figure 6 illustrates an eastward shift in the geographic distribution of chemical terrorism incidents after 2001, accompanied by a reduction in spatial dispersion. Unlike emerging hot spot analysis, which identifies localized concentrations of incidents, this analysis captures broader shifts in their global geographic distribution over time. This pattern is consistent with the increasing concentration of terrorism in conflict-affected regions, particularly the Middle East and North Africa (MENA), which accounted for 36.1% of global attacks and 49.3% of terrorism-related deaths during 2002–2018, largely driven by civil conflicts [20,58]. The concentration of incidents in Afghanistan and Pakistan may reflect decades of armed conflict and political instability that weakened Afghan state institutions and governance [59]. The porous and mountainous Afghanistan–Pakistan border also facilitated militant movement and logistical support in areas with limited state control [60]. Therefore, the overlap of consecutive hot spots and statistically significant increasing trends in the Afghanistan–Pakistan border area and Iraq indicates persistent spatial clustering and a sustained increase in incident frequency over time. These findings identify geographic priorities for preparedness rather than serve as predictions of future attacks. They also highlight the need to strengthen cross-border cooperation, intelligence sharing, border governance, and institutional capacity to mitigate chemical terrorism risks in these regions. Furthermore, country-specific preparedness measures are urgently needed, including chemical-event surveillance, hospital surge capacity, decontamination capabilities, and mass-casualty response training. Additionally, the substantial numbers of casualties reported in Japan and Uganda underscore the importance of maintaining the capacity to respond to mass-casualty events beyond the identified hot-spot regions.

Apparently, there are significant regional differences in chemical attacks, with the highest success rates in South Asia, the Middle East, and North Africa. Similarly, Demir and colleagues found that region and target or victim type in such regions were significant predictors of successful terrorist incidents [61]. Weak state capacity also creates operational opportunities for terrorist groups [62]. Also, the threat of Chemical, Biological, Radiological, and Nuclear (CBRN) attacks has escalated in recent years because of advancements in technology and terrorist willingness to utilize unconventional weaponry [63]. In South Asia, terrorist attacks have been associated with political instability, ethnic conflict, sectarian violence, extremism, and insurgency [64]. In contrast, terrorism in the Middle East and North Africa (MENA) has been linked to deficiencies in political, educational, and financial capacity, as well as demographic vulnerabilities [65]. Governments in MENA should strengthen CBRN planning, training, and regional cooperation [66]. Prolonged conflict in Syria and Iraq enabled terrorist groups, particularly the Islamic State, to develop and deploy chemical agents [32,51]. These regional differences underscore the need for context-specific preparedness strategies, with particular attention to educational institutions in South Asia and civilian and military facilities in MENA, which represent the most frequently targeted settings in their respective regions. Nevertheless, the Tokyo subway sarin attack is an example of an event that raised public awareness of the threat of chemical terrorism in non-active war zones, reporting 13 deaths and 5500 injuries, along with long-term physical and psychological effects among survivors [26,37,38]. The high proportion of successful attacks targeting private citizens and property (92.6%), together with the substantial number of injuries recorded in Japan (6746), highlights the need to strengthen preparedness for chemical incidents in civilian settings, including outside conflict-affected regions. By integrating spatial clustering patterns with casualty severity, this study demonstrates that regions with high incident frequencies do not necessarily experience the greatest casualty burdens, as

illustrated by Japan and Uganda (Figures 3–8). These findings underscore the importance of prioritizing surveillance in persistent hot spots while maintaining mass-casualty response capacity in regions beyond these areas.

This study has several limitations. First, the Global Terrorism Database (GTD) dataset relies primarily on media reports, which may be subject to inaccuracies and reporting biases. The GTD documentation also acknowledges limitations arising from restricted reporting, limited independent corroboration, and insufficient transparency in some government sources, potentially resulting in selection bias, underreporting, and unverified incident details [5]. Furthermore, the absence of data for 1993 creates a gap in the temporal analysis, while the GTD's focus on attacks committed by subnational actors excludes attacks attributed to state actors, such as national governments [5]. Second, the availability and quality of incident-level information in GTD vary considerably, with potential coding errors, missing geospatial data, incomplete perpetrator and casualty information, and changes in data-collection methods over time, all of which may affect the reliability and comparability of the spatial and temporal findings. Third, due to data and resource limitations, the global spatial statistical methods employed in this study (e.g., Average Nearest Neighbor and Ripley's K) assessed clustering relative to complete spatial randomness but did not account for potentially important covariates, such as uneven population density, conflict exposure, and reporting biases. Consequently, the identified spatial patterns should not be interpreted as evidence of underlying causal mechanisms. Future research should consider employing risk-adjusted spatial analytical frameworks to account for these factors and better investigate the potential drivers of observed patterns, when such data are available. Finally, data limitations prevented an assessment of seasonal variations across regional contexts, including potential differences between summer and winter in the Northern and Southern Hemispheres. Future studies incorporating more comprehensive temporal data could further investigate seasonal patterns and their regional variations.

5. Conclusions

Overall, this study examined the spatiotemporal patterns, severity, and operational characteristics of global chemical terrorism incidents recorded in the Global Terrorism Database (GTD) between 1970 and mid-2021. Both ordinary least squares (OLS) and negative binomial (NB) regression models indicated a statistically significant increase in the frequency of chemical terrorism incidents over time, while the NB models also identified significant temporal trends in fatalities and injuries. Spatial analyses revealed increasing concentrations of incidents in South Asia and the Middle East, particularly in conflict-affected regions, alongside declining trends in parts of the Americas, Europe, and North Africa. These findings highlight the need for targeted surveillance, strengthened emergency-response capacity, and enhanced cross-border cooperation in persistent hot spots, while maintaining mass-casualty preparedness in other regions given the potential severity of isolated attacks. Furthermore, governments should strengthen regulatory controls over the production, storage, transportation, and legitimate use of toxic chemicals. Improved perpetrator-identification systems, cross-border investigations, and effective enforcement of national and international counterterrorism laws are also essential to mitigating chemical terrorism risks.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/ijgi15120535/s1, Figure S1: Optimized Hot Spot Analysis Results; Table S1: Country-level distribution of chemical terrorism incidents, fatalities, injuries, and severity scores; Table S2: Country label harmonization used in the analysis; Table S3: High-impact attacks based on fatalities; Table S4: High-impact attacks based on injuries.

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