Conflict Victimization Model in Southern Thailand: An Event-Level Analysis Using Multinomial Logistic Regression

Abdunfatah Masamae[1], and Rhysa McNeil[2*] and Mayuening Eso[2]

[1] College of Digital Science, Prince of Songkla University, Songkhla, 90110, Thailand

[2] Faculty of Science and Technology, Prince of Songkla University, Pattani, 94000, Thailand

[*] Correspondence: rhysa.m@psu.ac.th

Abstract: This study investigates the determinants of conflict-related victimization severity in Thailand's southernmost provinces using event-level data from 9,310 southern unrest incidents recorded between 2004 and 2020. Victimization outcomes were classified into three ordered severity categories—safe, injured, and dead—and analyzed using Multinomial Logistic Regression (MLR) to capture differentiated risk mechanisms. The dataset, compiled by the Deep South Coordination Center (DSCC), integrates police, military, and administrative records to provide comprehensive coverage of subnational conflict events. Feature selection was conducted using chi-squared screening followed by backward refinement, yielding nine key predictors encompassing temporal, spatial, contextual, and tactical dimensions. Model estimation was performed under both baseline and imbalance-adjusted weighted specifications, with robustness assessed through cross-validation and sensitivity analyses. Results indicate that non-residential locations, particularly public places, roads, and agricultural areas, substantially increase the likelihood of injury and fatal outcomes. At the same time, rural settings are associated with lower severity risk, and attacks targeting military personnel exhibit markedly elevated injury and fatality odds relative to civilian targets. Shooting attacks emerge as the most lethal modality, with an estimated 15.8-fold increase in fatal risk compared to bombings. Predictive evaluation demonstrates strong discrimination for safe outcomes (AUC = 0.94), with good to moderate performance for injury (AUC = 0.80) and fatal events (AUC = 0.75). The findings highlight the dominant roles of spatial context and attack modality in shaping victimization severity and demonstrate the value of interpretable statistical modeling for informing targeted security planning and conflict-prevention strategies.

Keywords: Multinomial logistic regression; conflict victimization; southern Thailand; imbalanced classification; event-level analysis

1. Introduction

Correctly classifying the outcomes of violent events is an increasingly important operation in conflict analytics and security informatics. Policymakers and practitioners require analytical tools that can distinguish between incidents resulting in no casualties, injuries, and fatalities. These distinctions directly affect emergency preparedness, resource allocation, and long-term planning. From a data science perspective, such problems are typically multiclass and imbalanced, meaning that some outcomes occur far more frequently than others. At the same time, stakeholders often demand interpretability in addition to predictive

ASEAN J. Sci. Tech. Report. **2026**, 29(3), e261780.

2 of 19

accuracy, so that statistical models can both guide immediate decision-making and justify resource allocation transparently. Southern Thailand provides a unique case study for evaluating such models. Since 2004, the southernmost provinces, including Pattani, Yala, Narathiwat, and parts of Songkhla, have experienced more than 7,000 conflict-related deaths linked to protracted insurgency. Unlike many global conflict datasets, the Deep South Coordination Center (DSCC) has consolidated reports from multiple administrative sources, including police, military, and local government. This is resulting in a comprehensive event-level dataset of 9,310 southern unrest incidents covering 2004–2020. This dataset, with its temporal, spatial, and tactical attributes, enables systematic analysis of victimization outcomes at the incident level and represents one of the most complete longitudinal records of subnational violence in Southeast Asia.

To analyze such data, Multinomial Logistic Regression (MLR) offers an interpretable baseline. MLR is widely used in political science, epidemiology, and risk modeling to classify categorical outcomes with more than two categories. Its coefficients, expressed as odds ratios, provide policymakers with interpretable effect sizes that are more transparent than those from many machine learning models. However, MLR is not without limitations: it assumes independence of irrelevant alternatives (IIA), can be sensitive to class imbalance, and may underperform compared to nonparametric classifiers such as decision trees, random forests, or support vector machines. Our approach treats MLR not as a novel methodology, but as an interpretable benchmark against which more complex learners can be evaluated. Prior research in conflict and civil war modeling has employed a variety of approaches to assess event outcomes and risk factors. Competing risks and survival models have been used to examine the duration and escalation dynamics of civil war [1]. More recently, ensemble learning models and spatial econometric approaches have been applied to predict terrorism incidents and conflict clustering [2]. At the same time, a growing literature in data science has emphasized handling imbalanced classification problems through resampling, class weighting, and evaluation metrics beyond simple accuracy. Yet, there remains a gap in systematically applying these imbalanced multiclass methods to subnational conflict event datasets, balancing predictive accuracy with interpretability.

This study addresses that gap by presenting a reproducible data science workflow for multiclass victimization classification. This study focuses on outcomes of southern unrest events in Southern Thailand to demonstrate how transparent preprocessing, model benchmarking, and assumption testing can improve both research credibility and policy relevance. Rather than making causal claims about insurgent strategy, we emphasize the descriptive and predictive utility of our models for real-world decision-support systems.

2. Materials and Methods

2.1 Data Cleaning

The dataset used in this study comprises 9,310 southern unrest events recorded between 2004 and 2020 in Thailand's southernmost provinces, including Pattani, Yala, Narathiwat, and neighboring districts in Songkhla. These records were consolidated and validated by the Deep South Coordination Center (DSCC), Faculty of Science and Technology, Prince of Songkhla University, Pattani Campus, through triangulation from three sources: police, military, and local administrative offices. The original dataset contained 33,312 victim-level observations and 199 variables. To focus on event-level dynamics, several filtering and aggregation steps were applied. First, 7,864 records were excluded as they were associated with self-accidents, criminal disputes, or other non-conflict incidents. Second, since multiple victims could be linked to a single southern unrest incident, 14,083 victim-level records collapsed to avoid duplication, ensuring that each observation represents one unique event. After this process, the final dataset consisted of 9,310 unique southern unrest events, each coded with situational, temporal, and spatial attributes relevant to conflict analysis, as shown in Table 1.

ASEAN J. Sci. Tech. Report. **2026**, *29*(3), e261780.

3 of 19

Table 1. Variable descriptions.

Variable	Definition / Categories	Rationale
Outcome	*Safe* (no casualties), *Injured* (≥1 injury, no deaths), *Dead* (≥1 death)	Defines victimization outcome at the event level.
Month	January–December (categorical)	Captures seasonal/temporal variations in event frequency and severity.
Day	Monday–Sunday	Tests for weekly activity patterns.
Time	morning (06.00–11.59), afternoon (12.00–17.59), evening (18.00–23.59), night (00.00–05.59)	Identifies operational timing of events.
Province	Pattani, Yala, Narathiwat, Songkhla	Captures regional heterogeneity
Zone	residential, public space, road, business, agricultural, military/police base, checkpoint, others	Differentiates exposure risks across everyday and strategic locations.
Area	urban/rural	Reflects differences in density, surveillance, and protection
Target	civilian, civil officer, police, military	Captures differential victimization risk.
Festival	religious holiday, public holiday, none	Explores symbolic timing and crowding effects.
Season	wet/dry	Environmental context for mobility and exposure.
Attack	bombing, shooting, other	Identifies tactical modality of insurgent operations: bombing, gun-shooting, arson, and nail-trapping.

The unit of analysis in this study is therefore a single southern unrest event. Although the original dataset contains victim-level observations, this study's analytical focus is on event-level victimization severity. Because a single southern unrest event may involve multiple victims with different injury outcomes, victim-level information was aggregated into a single event-level outcome using a maximum-severity rule. Specifically, an event was classified as "dead" if at least one fatality occurred; if no fatalities occurred but at least one individual was injured, the event was classified as "injured"; otherwise, the event was classified as "safe." This aggregation strategy prioritizes the most severe consequence for each event and is commonly used in conflict and injury research to avoid double-counting while preserving operational relevance. While this approach may obscure within-event heterogeneity in casualty counts, it enables a consistent and interpretable event-level outcome suitable for multinomial modeling. Of the 199 original variables, 11 were retained based on both empirical relevance and theoretical grounding in insurgent strategy. Temporal factors include the month, day, time of day, season, and whether the event coincided with a festival, capturing possible symbolic timing or the event's operational opportunities. Spatial factors include the province, the specific zone of occurrence (such as residential area, public place, road, or checkpoint), and whether the area was classified as rural or urban, reflecting geographical exposure and risk contexts. Finally, situational and tactical factors include the type of target (civilian, military, police, or civil officer) and the method of attack (such as bombing, shooting, or other tactics; arson and nail-trapping), which represent insurgents' strategic choices to maximize impact or convey political messages. Together, these structured variables form the basis for the multinomial logistic regression analysis, allowing for systematic assessment of how temporal, spatial, and tactical dimensions shape the likelihood of different victimization outcomes.

2.2 Feature Selection

Depending on the categorical data of the independent variables, filter-based feature selection was performed using the chi-squared test, and the results are summarized in Table 2.

$$\chi^2 = \sum_{i=1}^{r} \sum_{j=1}^{c} \frac{(O_{ij} - E_{ij})^2}{E_{ij}} \tag{1}$$

where *Oij* is the observed frequency, therefore, the actual count in cell *i* and *j* of the contingency table. While *Eij* is the expected frequency, it's the count expected if the variables are independent. This is explained below:

$$E_{ij} = \frac{(Row\ total_i) \times (Column\ total_j)}{N} \tag{2}$$

where *N* is the total of southern unrest, *r* is the number of categories in the predictor, and *c* is the number of outcome classes.

Table 2. Chi-squared features selection

Variable	Chi-squared		
	Degree of freedom	test value	p-value
Month	22	93.39	< 0.001
Day	12	39.11	< 0.001
Time	6	141.81	< 0.001
Province	6	85.33	< 0.001
Zone	12	662.12	< 0.001
Area	2	35.47	< 0.001
Target	6	689.28	< 0.001
Festival	4	62.53	< 0.001
Season	2	17.77	< 0.001
Attack	4	3,309.00	< 0.001

The feature selection results in Table 2 revealed 10 statistically significant independent variables (all $p < 0.05$). Consistent with the model-prediction principle, these variables were excluded because they were not significant ($p > 0.05$). Thus, these eight advanced to the final model analytical process.

2.3 Multinomial Logistic Regression Analysis

The outcome variable in this study was categorical with multiple classes. The MLR was employed as an analytical method. The MLR is specially designed for modeling multiclass categorical outcomes. Let a dependent variable *Y* with *K* classes, and *p* predictor variables, the probability $P(Y = k \mid x)$ that an observation belongs to class *k* is modeled as:

$$P(Y=k|x) = \frac{e^{\beta_0^{(k)} + \beta_1^{(k)} x_1 + \dots + \beta_p^{(k)} x_p}}{\sum_{j=1}^{K} e^{\beta_0^{(j)} + \beta_1^{(j)} x_1 + \dots + \beta_p^{(j)} x_p}} \tag{3}$$

where $\beta_0^{(k)} + \beta_1^{(k)} x_1 + \dots + \beta_p^{(k)} x_p$ is the linear combination of predictors for class *k*, $\beta_0^{(k)}$ is the intercept for class *k* and $\beta_i^{(k)}$ is the coefficient for predictors x_i for class *k*. This was a normalization probability that sums to 1 across all classes. Although the outcome categories (safe, injured, dead) exhibit a natural severity ordering, they were treated as nominal in the MLR framework to avoid imposing the proportional odds assumption required by ordinal models. The connection emerged when it was compared to one class of *k* to the reference class *K*. The ratio of probability is as follows:

$$\frac{P(Y=k|x)}{P(Y=K|x)} = e^{\beta_0^{(k)} + \beta_1^{(k)} x_1 + \dots + \beta_p^{(k)} x_p} \tag{4}$$

Then, this was taken to the natural logarithm to get log-odds:

$$ln\left(\frac{P(Y=k|x)}{P(Y=K|x)}\right) = e^{\beta_0^{(k)} + \beta_1^{(k)} x_1 + \dots + \beta_p^{(k)} x_p} \tag{5}$$

ASEAN J. Sci. Tech. Report. **2026**, *29*(3), e261780.

5 of 19

MLR has been widely applied across diverse studies, including health science, social sciences, and education [3]. Implemented MLR to generate real-time non-invasive vibrotactile feedback signals in operating rooms using field-programmable gate arrays, while [4] employed MLR to analyze electronic medical record audit logs across three clinical groups (primary care, surgical, and non-surgical medical). During the training period, k-fold cross-validation was applied only to the training dataset to assess model stability while preserving temporal separation between training and test data.

2.4 Study Mechanism

This study follows a structured analytical mechanism designed to predict event-level victimization severity while ensuring methodological rigor and preventing information leakage. The mechanism is as follows: Figure 1
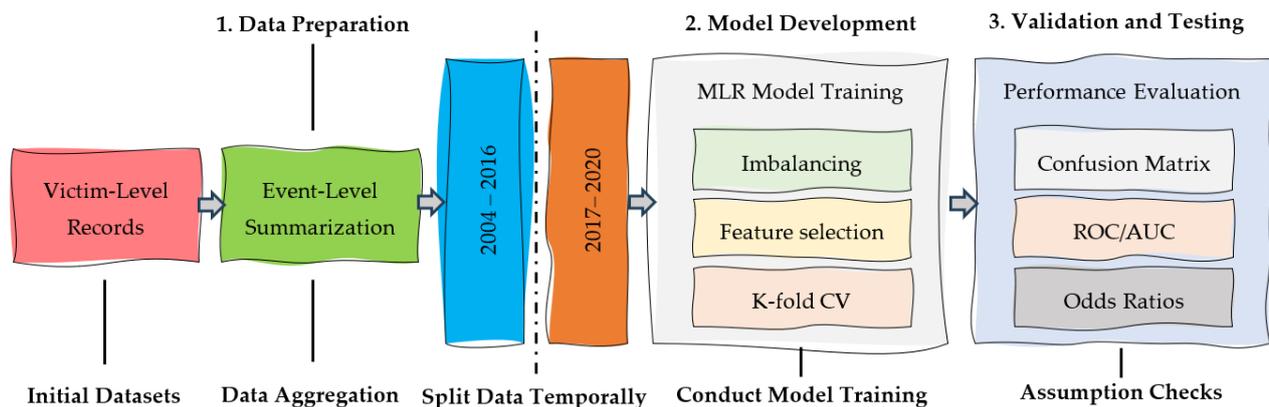
Figure 1. Analytical framework

First, victim-level records were aggregated into event-level outcomes using a maximum-severity rule, yielding three mutually exclusive categories: safe, injured, and dead. The analysis then adopted a temporal validation strategy, with events from 2004–2016 used for model development and events from 2017–2020 reserved for independent testing. Within the training period, class distributions were examined to assess imbalance across outcome categories. To mitigate the influence of class imbalance on parameter estimation and predictive performance, inverse-frequency class weighting was applied during model training. Feature selection was conducted exclusively on the training dataset using univariate screening methods, including chi-square tests for categorical predictors and nonparametric tests for numerical predictors, followed by multivariable model refinement. MLR models were subsequently estimated to examine the associations between temporal, spatial, and contextual predictors and event-level victimization severity. Model stability was evaluated using k-fold cross-validation within the training period, while key model assumptions—particularly the IIA—were assessed using diagnostic tests. Final model performance was evaluated on the held-out test dataset using multiple complementary metrics, including confusion matrices expressed as percentages, macro-averaged performance measures, and one-vs-rest receiver operating characteristic (ROC) curves. Model interpretability was enhanced by estimating odds ratios with 95% confidence intervals and by graphical visualization of effect sizes. Together, this analytical mechanism integrates predictive accuracy, statistical inference, and methodological transparency to support robust interpretation of conflict-related victimization outcomes.

2.5 Validation

2.5.1 Data Splitting

To evaluate the model's ability to generalize to future southern unrest events, a temporal hold-out validation strategy was employed. Specifically, southern unrest events occurring between 2004 and 2016 were used as the training dataset, while events from 2017 to 2020 were reserved as an independent test dataset. This time-based split reflects a realistic prediction setting and prevents information leakage from future events into model estimation.

ASEAN J. Sci. Tech. Report. **2026**, 29(3), e261780.

6 of 19

All model development procedures—including feature screening, class imbalance handling, and k-fold cross-validation—were conducted exclusively on the training dataset. The held-out test dataset was used only for final model evaluation.

2.5.2 Model Assessment

Model assessment in this study involved confusion matrices, model accuracy, F1-score, and ROC curves. The confusion matrix for multi-classification is described:

$$CM = \begin{bmatrix} TP_1 & FP_{12} & FP_{13} \\ FP_{21} & TP_2 & FP_{23} \\ FP_{31} & FP_{32} & TP_3 \end{bmatrix} \tag{6}$$

where TP_k is a true positive prediction of class k while FP_{kj} It is a false positive prediction where class j was predicted as k class. Model accuracy was calculated:

$$Accuracy = \frac{\sum_{k=1}^{K} TP_k}{N} \tag{7}$$

where N is the total sample size. Next, the F1-score was calculated:

$$F1_k = 2 \times \frac{Precision_k \times Recall_k}{Precision_k + Recall_k} \tag{8}$$

where

$$Precision_k = \frac{TP_k}{TP_k + \sum_{j \neq k} FP_{jk}} \tag{9}$$

$$Recall_k = \frac{TP_k}{TP_k + \sum_{j \neq k} FN_{jk}} \tag{10}$$

Moreover, the ROC curve was applied to illustrate the fitted model as performed by this equation:

$$TPR_k = \frac{TP_k}{TP_k + FN_k} \quad , \quad FPR_k = \frac{\sum_{j \neq k} FP_{jk}}{\sum_{j \neq k} TN_{jk}} \tag{11}$$

2.6 Statistical Software

All statistical analyses were conducted using R (version 4.5.0). MLR models were estimated with the nnet package, and model evaluation and cross-validation were performed with *caret*. Receiver operating characteristic (ROC) curves and area under the curve (AUC) statistics were computed using the *pROC* package, and data visualization was carried out using *ggplot2*. All analyses were conducted with a fixed random seed to ensure reproducibility.

3. Results and Discussion

3.1 Descriptive Overview

The final dataset comprises 9,310 conflict-related events recorded between 2004 and 2020 in Thailand's southernmost provinces. Event-level victimization severity was classified into three categories: safe, injured, and dead. The distribution of outcomes reveals a pronounced imbalance across severity levels. Of the total recorded incidents, 45.06% resulted in fatalities, 43.15% led to injuries, and only 11.79% were classified as safe events. This distribution indicates that the vast majority of unrest incidents involved human casualties, with fatal outcomes occurring slightly more frequently than injuries. The relatively small proportion of safe events

underscores the high overall severity of conflict episodes in the region and highlights the non-random nature of victimization outcomes. This substantial imbalance in outcomes motivates the use of imbalance-aware modeling strategies in subsequent analyses to ensure reliable estimation and evaluation of severity-specific risk factors. Figure 2 illustrates the distribution of outcome classes over time.

Number of Events per Year
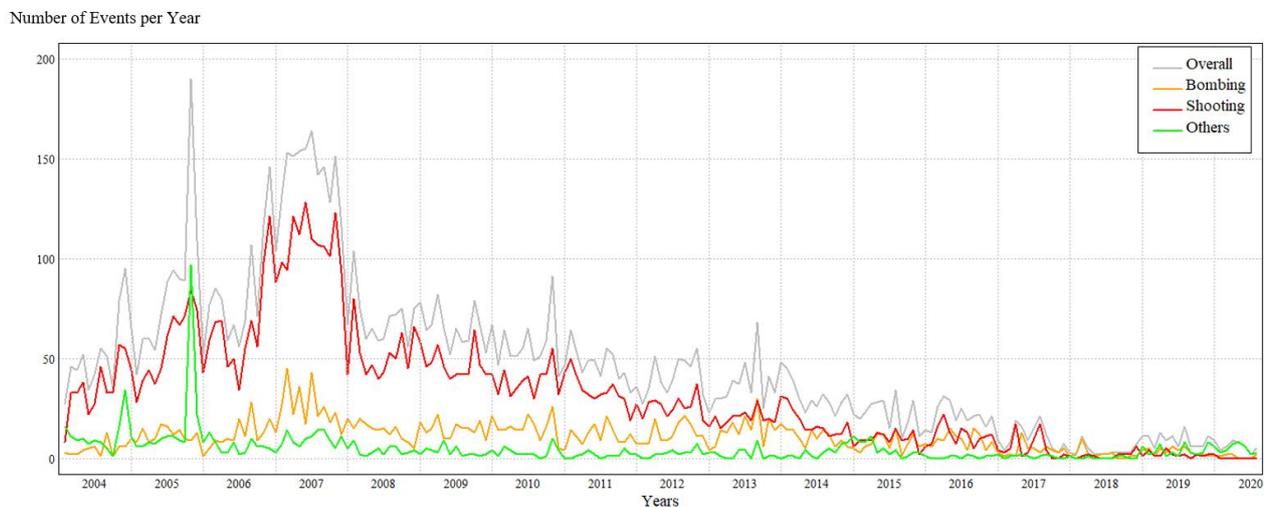
Figure 2. Trends of southern unrest in the southernmost provinces of Thailand

Figure 2 depicts the frequency of southern unrest events in Southern Thailand across different attack types: bombings, shootings, and others over the 17 years. Overall event frequency (gray line) peaked sharply between 2004 and 2007, reflecting the escalation phase of the conflict following its resurgence in early 2004. During this period, shooting incidents (red line) dominated, reaching more than 150 events per year, while bombings (orange line) were comparatively fewer but still frequent. After 2008, all attack types show a gradual, sustained decline, indicating a reduction in large-scale, coordinated violence. By 2015, annual frequencies fell below 20 incidents per year across all categories, suggesting the conflict entered a low-intensity phase. The "other" attack types (green line) include arson, nail trapping, and other weapons. These remained consistently low throughout, rarely exceeding 10 events annually. Overall, this temporal pattern illustrates a high-intensity outbreak phase (2004 – 2007) followed by a steady stabilization and de-escalation trend. The predominance of shootings throughout the period underscores their central role in the conflict's tactical profile, consistent with the model findings that shootings carry the highest lethality odds.

3.2 Model Estimation

Feature selection and model estimation were conducted sequentially using the training dataset to ensure methodological consistency and to prevent information leakage. Candidate predictors were first screened using univariate association tests to identify variables significantly related to event-level victimization severity. These predictors were subsequently refined using backward stepwise selection based on the Akaike Information Criterion (AIC), which balances model goodness-of-fit and model complexity. This procedure yielded a parsimonious set of predictors for multivariable modeling: Month, Day, Time, Province, Zone, Area, Target, Festival, and Attack. Using this final predictor set, multinomial logistic regression models were estimated with the safe outcome specified as the reference category. To assess model adequacy and the impact of outcome imbalance, goodness-of-fit was evaluated using likelihood-based indices, including the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), McFadden's pseudo-R^2, and likelihood ratio tests comparing the fitted models with their corresponding null specifications. The results indicate that the estimated models provide a statistically significant improvement over the null model, as summarized in Table 3.

Table 3. Model estimation

Component	MLR Model
Outcome categories	safe, injured, dead
Selected predictors	Month, Day, Time, Province, Zone, Area, Target, Festival, and Attack
AIC	14,403.96
BIC	14,985.02
McFadden's pseudo-R²	0.18
LR χ² (df)	3,077.65 (df)
LR p-value	< 0.001

       The effects of selected predictors on event-level victimization severity were examined using odds ratios (ORs) with 95% confidence intervals derived from the MLR models. Odds ratios greater than one indicate an increased likelihood of experiencing injury or fatal outcomes relative to the safe reference category, while odds ratios less than one indicate a decreased likelihood. To assess the influence of outcome imbalance on effect estimation, odds ratios derived from the estimated models were examined. Several predictors exhibit heterogeneous effects across outcome categories, indicating that factors associated with injury do not necessarily translate directly into fatal outcomes. This finding underscores the importance of modeling victimization severity using a multinomial framework, rather than collapsing outcomes into a binary specification, as illustrated in Tables 4 and 5.

Table 4. MLR model ref. safe vs. injured

	Estimate	SE	OR	CI Lower	CI Upper	p-value
Constant	-60.608	0.000	0.000	0.000	0.000	< 0.001
Month						
January*	0.326	0.041	1.386	1.278	1.503	< 0.001
February	0.274	0.040	1.316	1.215	1.424	< 0.001
March	-0.049	0.041	0.953	0.879	1.032	0.234
April	0.000	-	-	-	-	-
May	0.077	0.042	1.080	0.996	1.172	0.063
June	-0.011	0.041	0.989	0.912	1.072	0.782
July	0.177	0.040	1.194	1.104	1.291	< 0.001
August	0.036	0.040	1.037	0.960	1.120	0.358
September	0.240	0.040	1.271	1.174	1.376	< 0.001
October	-0.188	0.038	0.829	0.769	0.893	< 0.001
November	-0.142	0.039	0.868	0.804	0.937	< 0.001
December	-0.104	0.043	0.901	0.829	0.981	0.016
Day						
Sunday*	0.000	-	-	-	-	-
Monday	-0.049	0.029	0.952	0.900	1.008	0.090
Tuesday	0.087	0.029	1.091	1.031	1.155	0.003
Wednesday	-0.234	0.029	0.791	0.748	0.837	< 0.001
Thursday	0.138	0.029	1.148	1.085	1.216	< 0.001
Friday	0.152	0.031	1.165	1.097	1.236	< 0.001
Saturday	0.103	0.030	1.109	1.045	1.176	0.001

ASEAN J. Sci. Tech. Report. **2026**, *29*(3), e261780.

9 of 19

Table 4. MLR model ref. safe vs. injured (continus)

	Estimate	SE	OR	CI Lower	CI Upper	p-value
Time						
morning*	0.000	-	-	-	-	-
afternoon	-0.009	0.028	0.991	0.938	1.048	0.756
evening	0.096	0.028	1.101	1.042	1.163	0.001
night	-0.202	0.015	0.817	0.794	0.842	< 0.001
Province						
Pattani*	0.000	1.000	-	-	-	-
Narathiwat	0.179	0.029	1.196	1.131	1.265	< 0.001
Yala	0.096	0.031	1.100	1.036	1.168	0.002
Songkhla	-0.326	0.006	0.722	0.713	0.730	< 0.001
Zone						
resident*	0.000	-	-	-	-	-
bases and checkpoints	1.396	0.004	4.040	4.012	4.069	< 0.001
public places	1.613	0.035	5.018	4.683	5.378	< 0.001
road	1.319	0.023	3.738	3.572	3.912	< 0.001
business	0.829	0.039	2.292	2.123	2.474	< 0.001
agriculture	0.520	0.008	1.682	1.657	1.707	< 0.001
others	2.061	0.036	7.850	7.312	8.428	< 0.001
Area						
urban*	0.000	-	-	-	-	-
rural	-0.422	0.035	0.655	0.612	0.702	< 0.001
Target						
civil*	0.000	-	-	-	-	-
civil officer	-0.006	0.031	0.994	0.935	1.057	0.850
police	0.321	0.045	1.378	1.262	1.506	< 0.001
military	1.521	0.038	4.578	4.246	4.936	< 0.001
Festival						
religious*	0.000	-	-	-	-	-
public holiday	0.375	0.015	1.455	1.413	1.498	< 0.001
general	0.486	0.034	1.626	1.520	1.738	< 0.001
Attack						
bombing*	0.000	-	-	-	-	-
shooting	0.719	0.029	2.052	1.939	2.170	< 0.001
others	-2.180	0.018	0.113	0.109	0.117	< 0.001

The multinomial logistic regression results in Table 4 indicate that the likelihood of injury, relative to safe outcomes, varies systematically across temporal, spatial, and contextual factors. Several months, particularly January, February, July, and September, are associated with significantly higher odds of injury compared to April, while October through December show reduced injury risk, suggesting seasonal variation in event severity. Day-of-week effects further reveal that incidents later in the week are more likely to result in injury, whereas Wednesday and nighttime events are associated with lower odds of injury. Together, these temporal patterns indicate that injury severity is not uniformly distributed across calendar or daily cycles. Spatial and situational characteristics exert stronger and more consistent effects. Events occurring in

ASEAN J. Sci. Tech. Report. **2026**, *29*(3), e261780.

10 of 19

Narathiwat and Yala provinces are more likely to result in injury than those in Pattani, while Songkhla exhibits a substantially lower risk. Incidents in non-residential zones—particularly public places, roads, business areas, and security-related locations—are associated with markedly higher injury odds, highlighting the heightened vulnerability of these settings. Attacks targeting police and military personnel also display substantially elevated injury risk relative to civilian targets. In addition, shooting incidents are associated with more than twice the odds of injury compared to bombings, whereas other attack types are linked to significantly lower injury likelihood. Overall, the results underscore the importance of considering contextual and tactical heterogeneity when modeling victimization severity, reinforcing the suitability of a multinomial framework for capturing differentiated outcome patterns. On the other hand, the likelihood of death, which is related to safe outcomes, is presented in Table 5.

Table 5. MLR model ref. safe vs. dead

	Estimate	SE	OR	CI Lower	CI Upper	p-value
Constant	-189.767	0.000	0.000	0.000	0.000	< 0.001
Month						
January	0.596	0.041	1.816	1.674	1.969	< 0.001
February	0.425	0.040	1.529	1.414	1.653	< 0.001
March	0.175	0.040	1.191	1.100	1.289	< 0.001
April*	0.000	-	-	-	-	-
May	0.378	0.041	1.459	1.346	1.582	< 0.001
June	0.434	0.041	1.544	1.425	1.673	< 0.001
July	0.443	0.039	1.558	1.442	1.683	< 0.001
August	0.408	0.039	1.505	1.393	1.625	< 0.001
September	0.420	0.040	1.521	1.406	1.646	< 0.001
October	-0.004	0.038	0.996	0.925	1.072	0.918
November	0.117	0.039	1.124	1.041	1.214	0.003
December	0.185	0.043	1.203	1.107	1.309	< 0.001
Day						
Sunday*	0.000	-	-	-	-	-
Monday	-0.093	0.029	0.911	0.861	0.963	0.001
Tuesday	0.227	0.029	1.255	1.186	1.328	< 0.001
Wednesday	-0.134	0.028	0.875	0.827	0.925	< 0.001
Thursday	0.049	0.029	1.050	0.993	1.111	0.086
Friday	0.148	0.030	1.159	1.093	1.230	< 0.001
Saturday	0.135	0.030	1.145	1.080	1.214	< 0.001
Time						
morning*	0.000	-	-	-	-	-
afternoon	-0.137	0.028	0.872	0.825	0.922	< 0.001
evening	-0.252	0.028	0.777	0.736	0.820	< 0.001
night	-0.449	0.015	0.638	0.620	0.658	< 0.001
Province						
Pattani*	0.000	1.000	-	-	-	-
Narathiwat	0.108	0.028	1.114	1.054	1.177	< 0.001
Yala	0.061	0.031	1.063	1.001	1.129	0.047
Songkhla	-0.460	0.006	0.631	0.624	0.639	< 0.001

Table 5. MLR model ref. safe vs. dead (continus)

	Estimate	SE	OR	CI Lower	CI Upper	p-value
Zone						
resident*	0.000	-	-	-	-	-
bases and checkpoints	0.551	0.004	1.735	1.723	1.747	< 0.001
public places	1.535	0.035	4.642	4.338	4.966	< 0.001
road	1.058	0.023	2.880	2.752	3.013	< 0.001
business	0.822	0.036	2.275	2.120	2.441	< 0.001
agriculture	0.938	0.009	2.556	2.512	2.600	< 0.001
others	1.540	0.035	4.663	4.355	4.992	< 0.001
Area						
urban*	0.000	-	-	-	-	-
rural	-0.270	0.034	0.763	0.714	0.815	< 0.001
Target						
civil*	0.000	-	-	-	-	-
civil officer	0.169	0.032	1.184	1.112	1.261	< 0.001
police	-0.115	0.041	0.891	0.823	0.965	0.005
military	0.908	0.036	2.480	2.309	2.664	< 0.001
Festival						
religious*	0.000	-	-	-	-	-
public holiday	0.183	0.014	1.201	1.168	1.235	< 0.001
general	0.381	0.034	1.463	1.370	1.562	< 0.001
Attack						
bombing*	0.000	-	-	-	-	-
shooting	2.762	0.028	15.826	14.988	16.710	< 0.001
others	-0.446	0.020	0.640	0.615	0.666	< 0.001

Table 5 presents the multinomial logistic regression results comparing fatal versus safe outcomes, with safe events specified as the reference category. Strong and consistent temporal patterns are evident. Relative to April, almost all months are associated with significantly higher odds of fatal outcomes, particularly during the first three quarters of the year, indicating a pronounced seasonal escalation in lethality. Day-of-week effects further reveal elevated fatal risk for incidents occurring on Tuesdays, Fridays, and Saturdays, whereas Mondays and Wednesdays are associated with reduced odds of death. Time-of-day effects show a clear gradient, with incidents occurring in the afternoon, evening, and especially at night exhibiting substantially lower odds of fatality compared to morning events, suggesting that the most lethal incidents tend to occur earlier in the day. Spatial and situational factors emerge as the dominant determinants of fatal outcomes. Compared to Pattani province, events in Narathiwat and Yala show modestly higher odds of death, while Songkhla consistently exhibits substantially lower fatal risk. Incidents occurring outside residential areas are markedly more lethal: public places, roads, business areas, agricultural zones, and security-related locations such as bases and checkpoints all demonstrate dramatically elevated odds of death relative to residential settings, with effect sizes far exceeding those observed for injury outcomes. Rural areas are associated with lower fatal risk than urban areas, highlighting important contextual differences in escalation dynamics. Target characteristics further differentiate severity, with attacks against military targets showing more than double the odds of fatality compared to civilian targets, while police targets exhibit slightly lower fatality risk. Finally, attack modality displays the strongest effect in the model: shooting incidents are associated with an exceptionally large increase in the odds of death relative to bombings, underscoring the extreme lethality of

direct-fire tactics. Collectively, these findings indicate that fatal outcomes are driven primarily by location, target type, and attack modality, reinforcing the importance of modeling severity as a multinomial process rather than collapsing outcomes into a binary framework.

Taken together, the results from Tables 4 and 5 reveal several common structural patterns governing both injury and fatal outcomes, albeit with differing magnitudes. Across both severity levels, victimization risk exhibits clear temporal regularities, with elevated odds concentrated in specific months and on particular days of the week, indicating that conflict severity is shaped by recurring patterns of activity and exposure rather than random occurrence. While temporal effects are more pronounced for fatal outcomes, both models consistently demonstrate that severity varies across calendar cycles, reflecting systematic shifts in operational intensity over time. This temporal factor finding aligns with Summer et al. [5], who found that successful incidents were more likely to be perpetrated by individuals living more than 100 miles from the target location. Most notably, spatial and situational factors emerge as the dominant shared determinants of injury and fatal outcomes. In both models, incidents occurring in non-residential environments—such as public places, roads, business districts, agricultural zones, and security-related locations—are associated with substantially higher odds of harm relative to residential areas. These settings often involve greater population exposure and a higher potential for property damage, particularly during large-scale or coordinated attacks, which, in turn, increases the likelihood of casualties [6]. Spatial patterns also converge across provinces, with events in Narathiwat and Yala consistently exhibiting higher severity risk than those in Pattani, while Songkhla demonstrates a persistently lower risk, suggesting important regional differences in conflict dynamics and security control.

Target characteristics further reinforce shared escalation mechanisms. Attacks directed at military targets are consistently associated with elevated odds of both injury and fatal outcomes compared to civilian targets, reflecting the inherently confrontational nature of engagements involving security forces as represented in [7, 8]. While bombing attacks frequently result in substantial property damage and widespread disruption, their association with human casualties is more moderate relative to shooting incidents, which emerge as the most severe attack modality across both models. Shooting attacks significantly increase the likelihood of injury and, more strongly, fatal outcomes, highlighting the heightened lethality of direct-fire methods and their shared risk determinants across attack modalities and temporal patterns [9]. Collectively, these shared findings indicate that while injury and fatal outcomes differ in intensity, they are driven by a largely overlapping set of contextual, target-specific, and tactical factors, reinforcing the importance of modeling victimization severity using a multinomial framework that captures both common escalation pathways and outcome-specific effects. Next, Figures 3 and 4 present a log-scale forest plot of odds ratios with confidence intervals, facilitating comparison of effect magnitude and statistical uncertainty across predictors and outcome contrasts.
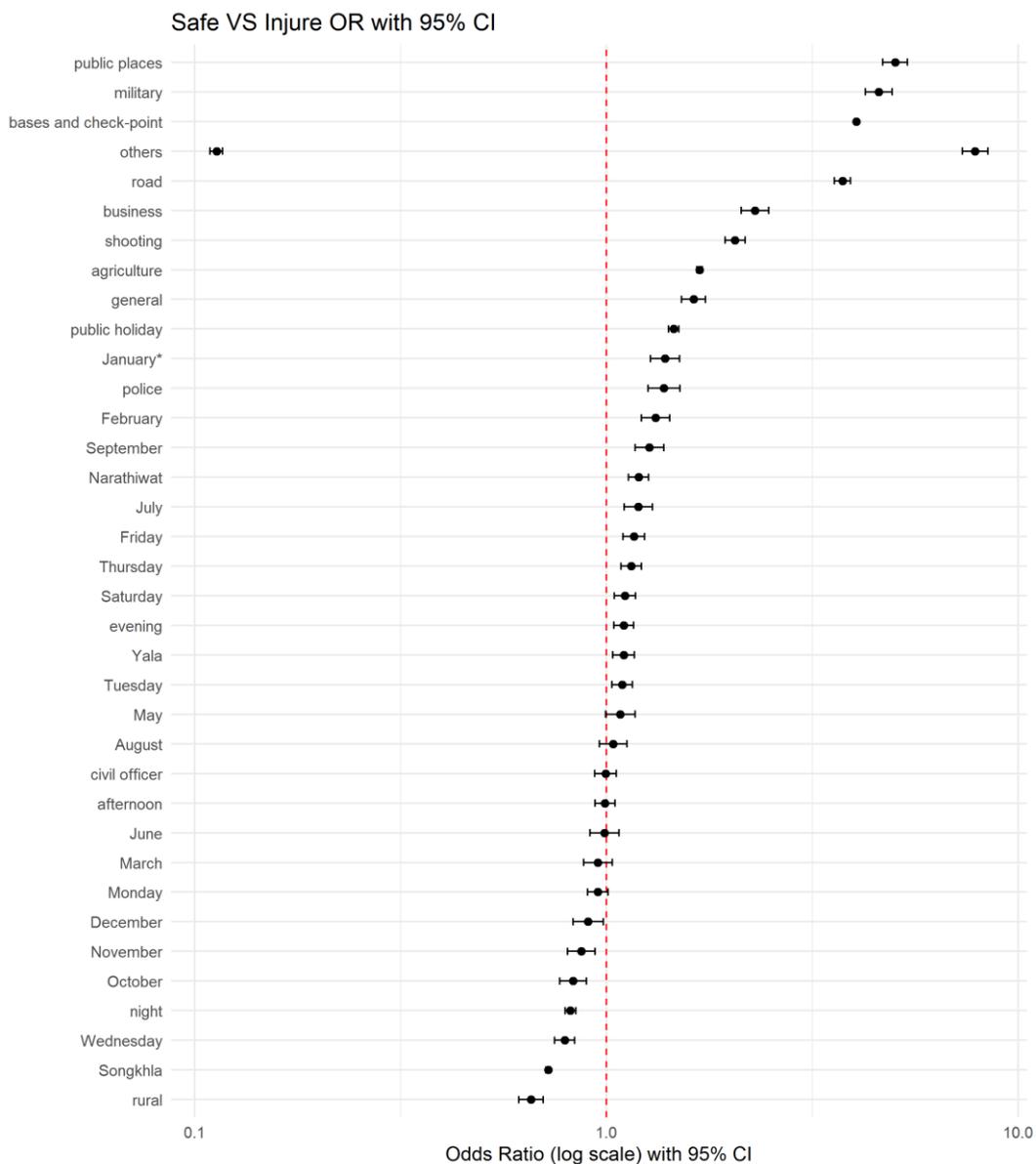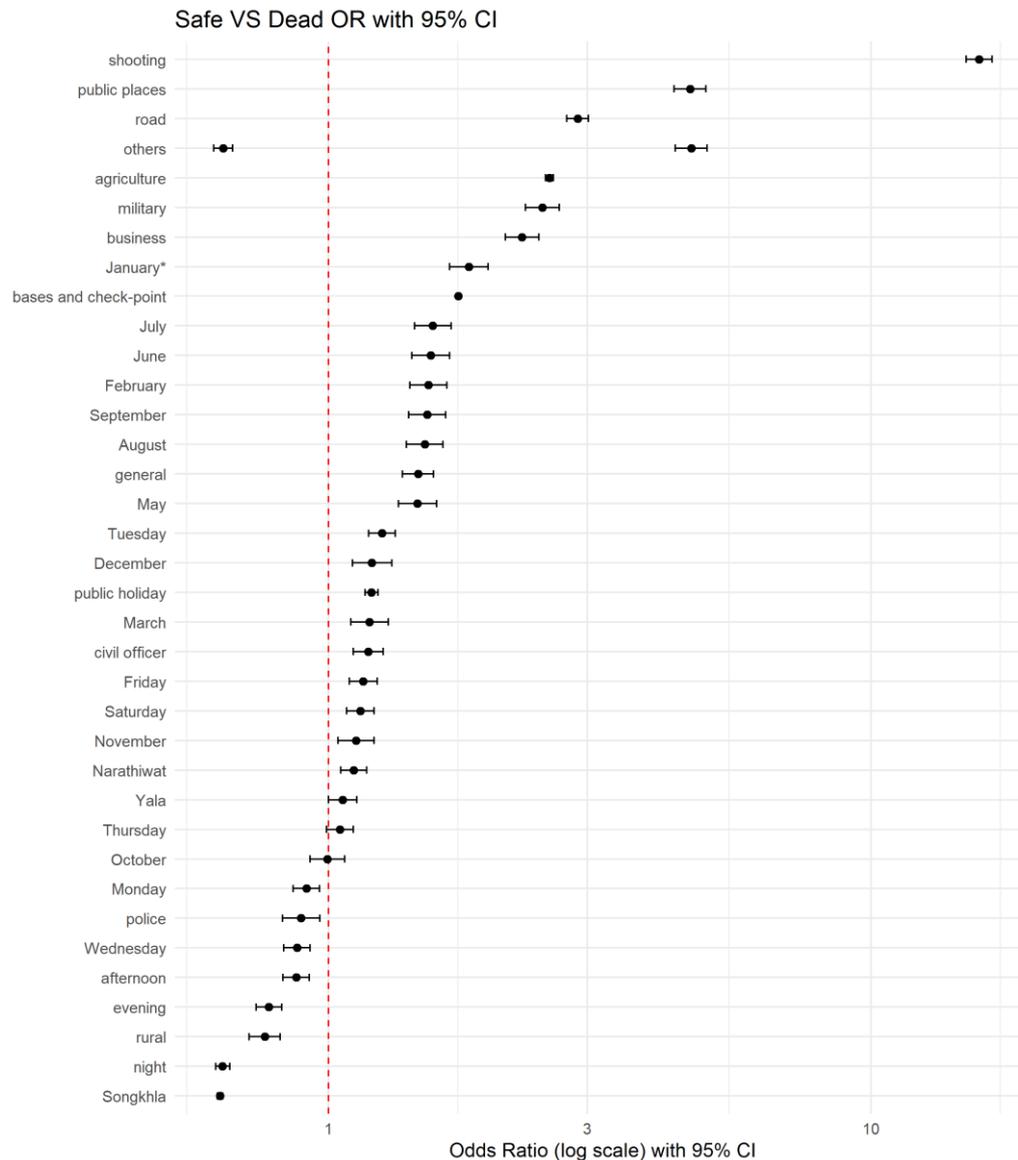
Figure 3. The 95% CI plot of Safe vs Injured

Figure 3 presents a log-scale forest plot of odds ratios with 95% confidence intervals for the injured versus safe comparison. Predictors with confidence intervals entirely above one indicate an increased likelihood of injury relative to safe outcomes, while those with intervals below one are associated with reduced injury risk. The plot shows that location- and target-related factors, particularly incidents in non-residential zones and attacks against security forces, exhibit the strongest positive associations with injury. In contrast, several temporal factors and rural settings are associated with a lower likelihood of injury. The width of some confidence intervals reflects uncertainty arising from data sparsity and outcome imbalance, but the overall pattern reinforces the importance of situational and contextual determinants in shaping injury severity.

Figure 4. The 95% CI plot of Safe vs Dead

The dead versus safe comparison, Figure 4, indicates that fatal outcomes are driven primarily by situational and tactical factors, with the largest increases in odds observed for shooting incidents, non-residential locations (particularly public places and roads), and security-related targets. These effects are substantially stronger than those observed for injury outcomes, highlighting a clear escalation mechanism associated with attack modality and location. In contrast, several temporal factors, rural settings, and specific provinces exhibit odds ratios below one, indicating reduced likelihood of fatal outcomes relative to safe events. Although some confidence intervals are wide—reflecting the rarity of fatal events—the overall pattern demonstrates that lethality is dominated by where and how attacks occur, rather than by timing alone.

3.3 Performance Evaluation

The predictive performance of the multinomial logistic regression models was evaluated using classification-based metrics, with particular attention to outcome imbalance across severity categories. Model discrimination was assessed using receiver operating characteristic (ROC) curves and the corresponding area under the curve (AUC), computed separately for each outcome category as presented in Figure 5. In addition, confusion matrices expressed as row-wise percentages were used to evaluate classification accuracy conditional on the true outcome class, providing an interpretable assessment of model performance under imbalanced class distributions.
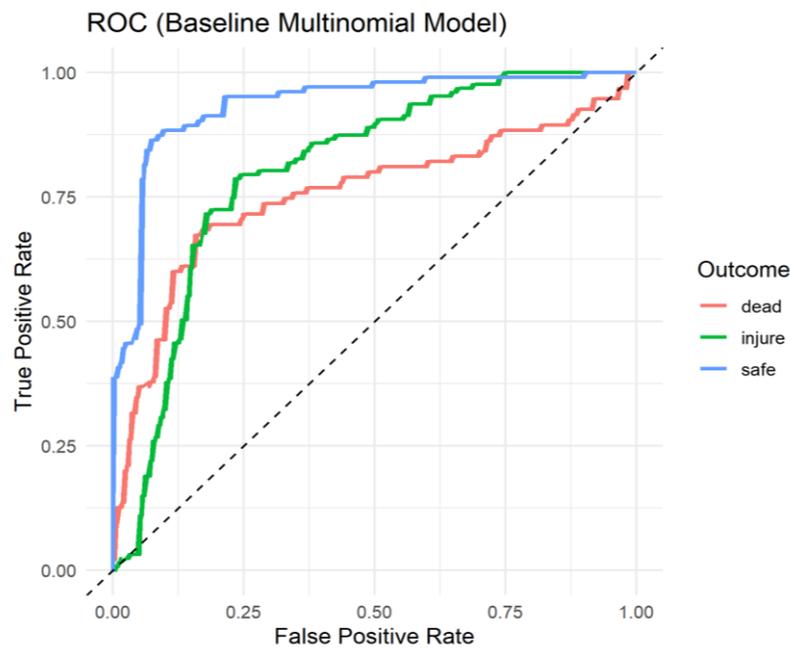
Figure 5. ROC curve model discrimination

The area under the ROC curve (AUC) values in Figure 2 indicate that the baseline multinomial logistic regression model demonstrates strong overall discriminatory ability, with performance varying across outcome categories. The model achieves an AUC of 94% for the safe outcome, indicating excellent discrimination and indicating that safe events are identified with high accuracy. This result is expected given that safe cases constitute the majority of observations and exhibit more stable patterns. For the injured outcome, the AUC of 80% suggests good discrimination, indicating that the model can reasonably distinguish injury events from other outcome categories. While performance is lower than for safe outcomes, the AUC remains well above conventional thresholds for acceptable classification, demonstrating that the model meaningfully captures injury-related patterns. The dead outcome yields an AUC of 75%, representing moderate but informative discrimination. This comparatively lower value reflects the inherent difficulty of predicting rare, heterogeneous fatal events. Importantly, the AUC remains substantially above the random classification benchmark (0.5), indicating that the model retains predictive value even for the most severe outcome category. Overall, the decreasing AUC values across severity levels reveal a clear severity gradient in predictive performance, with the strongest discrimination for non-severe outcomes and reduced—but still meaningful—performance for fatal events. This pattern underscores both the challenges posed by class imbalance and the necessity of complementary evaluation using weighted models and additional performance metrics. Next, the confusion matrix results further reveal that misclassification primarily occurs between adjacent severity categories, with fewer extreme errors between safe and fatal outcomes. This suggests that while prediction uncertainty remains—especially for rare fatal events—the model captures meaningful structure in severity differentiation. Collectively, these findings indicate that the weighted multinomial model provides a balanced and robust predictive framework for modeling event-level victimization severity in the presence of substantial class imbalance.
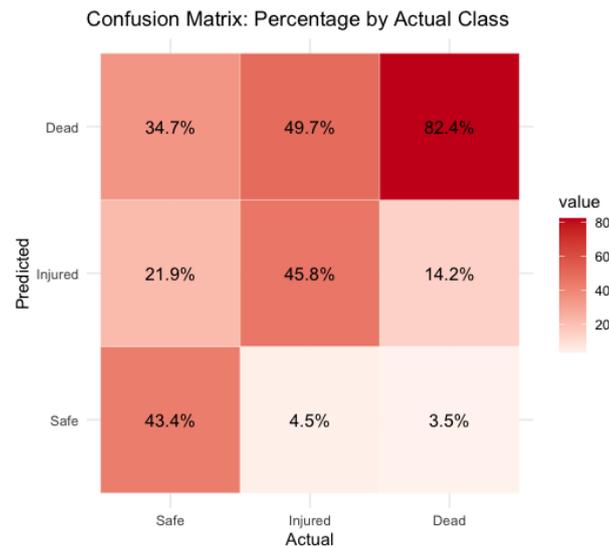
Figure 6. Confusion matrix of southern unrest victimization

The confusion matrix in Figure 6 reveals significant variation in the model's ability to classify outcomes across the three categories of southern unrest victimization: safe, injured, and dead. For dead, the model demonstrates strong performance with a recall of 82.4%, indicating it successfully identifies over 80% of actual fatalities. However, its precision for dead is moderate (59.3%), meaning that nearly 40% of predicted "dead" cases were false alarms (misclassified as safe or injured). This suggests the model errs on the side of caution for fatalities, which could be critical for emergency response but may strain resources due to overprediction. For Injured, precision was the highest among all classes (68.8%), showing that when the model predicts an injury, it is correct ~69% of the time. However, its recall is notably lower (45.8%), revealing that over half of actual injuries are missed (often misclassified as Dead). This gap signals a need to improve sensitivity to injury cases, possibly by addressing class imbalance or refining feature selection. The Safe category performs poorly across both metrics, with the lowest recall (43.4%) and modest precision (59.4%). This means the model fails to detect more than half of truly safe cases (mislabeling them as injured/dead) and incorrectly predicts safety in ~40% of cases.

Such errors could undermine trust in the system, especially if used for risk assessment. A series of sensitivity analyses was conducted to assess the robustness of the estimated effects and predictive performance. First, to evaluate the impact of outcome imbalance, all analyses were performed using both a baseline multinomial logistic regression model and an imbalance-adjusted weighted specification. While the weighted model yielded improved sensitivity for injury and fatal outcomes, the overall direction and relative magnitude of estimated effects remained consistent across model specifications, indicating that the weighting strategy does not drive the substantive conclusions. Second, the IIA assumption underlying the multinomial framework was examined using the Hausman–McFadden test. As commonly observed in imbalanced outcome settings, the test produced numerically unstable statistics, limiting definitive inference regarding strict adherence to IIA. To mitigate this limitation, additional robustness checks were conducted, including alternative predictor specifications and comparison with an ordinal logistic regression model. The consistency of results across these analyses suggests that potential deviations from the IIA assumption do not materially affect the study's conclusions. Third, model stability was assessed using k-fold cross-validation, with performance metrics averaged across folds. The cross-validated results demonstrate stable discrimination across outcome categories, with only modest fold-to-fold variability, supporting the generalizability of the fitted models. Collectively, these robustness checks indicate that the findings are stable across alternative modeling choices and are not sensitive to specific assumptions or estimation procedures.

ASEAN J. Sci. Tech. Report. **2026**, 29(3), e261780.

17 of 19

3.3 Discussion and Limitation

Beyond the empirical findings, this study contributes methodologically and contextually to the understanding of victimization severity in subnational conflict settings. The application of multinomial logistic regression (MLR) enables explicit differentiation between safe, injured, and fatal outcomes, allowing severity-specific risk mechanisms to be examined without collapsing heterogeneous outcomes into a binary framework. While ensemble machine learning approaches such as Random Forests or Support Vector Machines have been widely applied in terrorism and conflict risk modeling [2, 10]. MLR offers a distinct advantage in terms of interpretability, providing transparent estimates of effect size and direction that can be clearly communicated to policymakers. This transparency is particularly important in conflict-affected regions, where security decisions require justification and accountability. From a behavioral perspective, the heightened vulnerability of military personnel to both injury and fatal outcomes likely reflects the symbolic and strategic value of such targets to insurgent groups. This finding aligns with theories in the civil war literature that conceptualize selective violence as a form of strategic communication intended to undermine state authority or morale [11]. The distinction between the elevated injury risk for police personnel and the lack of a corresponding increase in fatality risk further suggests differentiated targeting logics, potentially influenced by perceived threat levels, engagement rules, or operational constraints [12].

The spatial dynamics observed in this study also resonate with geographic theories of conflict vulnerability. Incidents occurring in public places, roads, business districts, and agricultural areas exhibit substantially higher odds of severe victimization, reflecting increased exposure, population flow, and limited protective infrastructure. Such environments are also more prone to property damage, particularly during coordinated or high-impact attacks. Prior research on African civil wars has similarly documented that violence often clusters in accessible, high-traffic locations where territorial control is contested or shifts frequently [13]. These findings underscore the importance of geographically targeted intervention strategies, including infrastructural reinforcement and surveillance in transit corridors and economic zones. Temporal variations further reveal meaningful escalation patterns. The finding that nighttime attacks are significantly less lethal suggests constraints related to tactical visibility, logistics, or coordination after dark. This pattern is consistent with evidence from other conflict regions, where nighttime engagement tends to be lower due to operational limitations and heightened detection risk [14]. Counterinsurgency planning and public safety operations could therefore be optimized by aligning patrol intensity and surveillance resources with time-specific risk profiles, particularly during morning and daytime periods when fatal outcomes are more likely. Despite these contributions, several limitations should be acknowledged. First, the analysis relies on event-level aggregation using a maximum-severity rule, in which the most severe observed outcome is used to classify each incident. While this approach preserves operational relevance and aligns with common practice in conflict event analysis, it necessarily obscures within-event variation in casualty counts and injury severity. Future research could extend this framework using count-based, ordinal, or hierarchical models to capture casualty intensity more granularly while retaining event-level interpretability.

Second, although multinomial logistic regression provides a flexible and interpretable framework, it relies on the independence of irrelevant alternatives (IIA) assumption. Formal diagnostic testing yielded numerically unstable results, a known limitation in imbalanced multiclass conflict data. To address this concern, robustness checks using alternative model specifications, including ordinal logistic regression, were conducted and yielded substantively consistent findings. Nonetheless, future studies may consider modeling approaches that explicitly relax the IIA assumption, such as nested or mixed logit models, where data availability permits. Third, the dataset exhibits substantial imbalance in outcomes, with injury and fatal events accounting for the majority of observations. Although imbalance-aware modeling strategies were implemented and predictive performance was evaluated using multiple metrics, including ROC curves and confusion matrices, classification performance for rare and heterogeneous outcomes—particularly fatal events—remains constrained by data sparsity. Expanding the temporal scope or integrating additional conflict datasets may further enhance model stability and predictive accuracy. Finally, while this study focuses on incident-level characteristics, future research should incorporate demographic risk factors, such as age, gender, and occupation, to better understand which groups are most vulnerable. Reports from global conflict

ASEAN J. Sci. Tech. Report. **2026**, *29*(3), e261780.

18 of 19

databases, including the Geneva Declaration Secretariat and the Uppsala Conflict Data Program, have highlighted the uneven burden of violence among civilian populations, which may be masked in aggregate models [15]. Integrating such disaggregated information would enhance humanitarian targeting and resource allocation. Taken together, these contextual and methodological discussions extend the policy relevance of the findings and position this study as both an interpretable predictive tool and a framework for deeper causal inquiry into subnational conflict dynamics.

4. Conclusions

This study examined the determinants of conflict-related victimization severity in Thailand's southernmost provinces using event-level data from 9,310 unrest incidents recorded between 2004 and 2020. By applying multinomial logistic regression, the analysis explicitly differentiated between safe, injured, and fatal outcomes, allowing severity-specific risk mechanisms to be identified without collapsing heterogeneous outcomes into a binary framework. The results demonstrate that victimization severity is shaped primarily by spatial context, target type, and attack modality, with temporal factors playing a secondary but consistent role. Incidents occurring in non-residential locations—particularly public places, roads, agricultural areas, and security-related zones—are associated with substantially elevated risks of both injury and fatality. Attacks targeting military personnel exhibit markedly higher odds of severe outcomes, reflecting the confrontational nature and strategic salience of such targets. Among attack modalities, shooting incidents emerge as the most lethal, exhibiting an order-of-magnitude increase in fatal risk compared to bombings, underscoring the extreme lethality of direct-fire tactics. From a predictive perspective, the multinomial framework demonstrates strong discrimination for safe events and moderate but informative performance for injury and fatal outcomes, despite substantial class imbalance. Sensitivity analyses confirm that the substantive findings are robust across baseline and weighted model specifications, alternative predictor sets, and validation strategies. Although formal testing of the independence of irrelevant alternatives (IIA) assumption yielded unstable results— common in imbalanced multiclass settings—comparative analyses indicate that potential deviations do not materially affect the study's conclusions. Methodologically, this study reinforces the value of multinomial logistic regression as an interpretable benchmark for conflict analytics. While more complex machine learning models may achieve higher predictive accuracy, the transparency of odds ratios and confidence intervals provides policymakers with actionable insights for resource allocation, patrol planning, and civilian protection. The proposed analytical workflow—combining transparent preprocessing, imbalance-aware modeling, and comprehensive performance evaluation—offers a reproducible framework applicable to other subnational conflict settings. Several limitations warrant acknowledgment. Aggregating victimization-level records into event-level outcomes using a maximum-severity rule prioritizes operational relevance but obscures within-event variation in casualties. Future research could extend this framework using hierarchical, count-based, or ordinal models to capture casualty intensity more granularly. Additionally, integrating real-time geospatial data, demographic attributes, and dynamic conflict indicators may further enhance predictive performance and policy relevance. Overall, this study provides empirical evidence and methodological guidance for modeling conflict related to victimization severity. By demonstrating how interpretable statistical models can capture differentiated escalation pathways, the findings support the integration of data-driven analytics into evidence-based security planning and early-warning systems in conflict-affected regions.

5. Acknowledgements

Author Contributions: Conceptualization, A.M., R.M., and M.E.; Methodology, A.M., R.M., and M.E.; Formal analysis and investigation, A.M., R.M., and M.E.; Writing–original draft preparation, A.M. and R.M.; Writing–

References

[1] Brandt, P. T.; Mason, T. D.; Gurses, M.; Petrovsky, N.; Radin, D. *When and How the Fighting Stops: Explaining the Duration and Outcome of Civil Wars. Def. Peace Econ.* **2008**, *19*(6), 415–434. https://doi.org/10.1080/10242690701823267

[2] Olabanjo, O. A.; Aribisala, B. S.; Mazzara, M.; Wusu, A. S. *An Ensemble Learning Model for the Prediction of Danger Zones: Towards a Global Counter-Terrorism. J. Soft Comput. Lett.* **2021**, *3*, 1–6. https://doi.org/10.1016/j.socl.2021.100020

[3] Erbas, I.; Vargas, D. A.; Guclu, B. *FPGA Implementation of Multinomial Logistic Regression for Vibrotactile Feedback in a Robotic Hand.* In *2020 International Conference on e-Health and Bioengineering (EHB)*; IEEE, 2020; pp 1–4. https://doi.org/10.1109/EHB50910.2020.9280239

[4] Wilkinson, K.; Seo, K.; Pierce, R.; Tonellato, P.; Kim, J. H.; Myers, D. *Electronic Medical Record Specialty Group Comparison by Multinomial Logistic Regression.* In *2021 IEEE 9th International Conference on Healthcare Informatics (ICHI)*; IEEE, 2021; pp 415–421. https://doi.org/10.1109/ICHI52183.2021.00067

[5] Summer, J.; Ratcliff, K.; Smith, B. *Spatial Analysis of U.S. Terrorism Incidents.* National Consortium for the Study of Terrorism and Responses to Terrorism (START), 2017. 1-4.

[6] Miller, E. *Use of Firearms in Terrorist Attacks in the United States, 1970–2014.* START, 2015. http://www.start.umd.edu/pubs/START_FirearmsinTerrorism_BackgroundReport_July2015.pdf

[7] Boonthep, N.; Intharachat, S.; Iemsomboon, T. *Factors Influencing Injury Severity Score Regarding Thai Military Personnel Injured in Mass Casualty Incident April 10, 2010: Lessons Learned from Armed Conflict Casualties: A Retrospective Study. BMC Emerg. Med.* **2012**, *12*(1), 1-7. https://doi.org/10.1186/1471-227X-12-1

[8] Eso, M.; McNeil, R.; Masamae, A. *Factors Associated with Severe Violent Events in the Southernmost Provinces of Thailand. Adv. Appl. Stat.* **2020**, *63*(1), 59–74. https://doi.org/10.17654/AS063010059

[9] Stelmach, J.; Moch, N. *Time in Responding to Terrorist Attacks in Cities. Sustainability* **2022**, *14* (21), 1-19. https://doi.org/10.3390/su142416643

[10] Peng, A. *An Integrated Machine Learning Approach to Studying Terrorism.* B.S. Thesis, Department of Computer Science, Yale University, New Haven, CT, 2018.

[11] Kalyvas, S. N. *The Logic of Violence in Civil War*; Cambridge University Press: Cambridge, 2006. https://doi.org/10.1017/CBO9780511818462

[12] Shapiro, J.; Siegel, D. A. *Coordination and Security: How Mobile Communications Affect Insurgency. J. Peace Res.* **2015**, *52* (3), 312–322. https://doi.org/10.1177/0022343314559624

[13] Buhaug, H.; Rod, J. K. *Local Determinants of African Civil Wars, 1970–2001. Polit. Geogr.* **2006**, *25*(3), 315–335. https://doi.org/10.1016/j.polgeo.2006.02.005

[14] Lafree, G.; Dugan, L. *Introducing the Global Terrorism Database. Terror. Polit. Violence* **2007**, *19*(2), 181–204. https://doi.org/10.1080/09546550701246817

[15] Geneva Declaration Secretariat. *Global Burden of Armed Violence.* September 2008. https://www.refworld.org/reference/research/gds/2008/en/64390