Article

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Spatio-Temporal Modeling of Violent Conflict and Fatality in Nigeria: A Point Process Modeling with SPDE Approach

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Abstract: For many decades, Nigeria has been plagued by a consistently high rate of violent events, resulting in countless fatalities and the displacement of citizens. This study aimed to model the spatio-temporal patterns of these events and the associated fatality to gain insight into the chain of events and provide a basis for swift and strategic intervention. To this end, a Cox point process model through the stochastic partial differential equation was adopted, taking into account the location randomness exhibited by violent events occurrence. The data analyzed was derived from the Uppsala Conflict Data Program – Georeferenced Event Dataset (UCDP-GED) version 22. The results revealed that violent events are particularly prevalent in the country's northeast region, with a probability of 0.42 of at least one death occurring per violent event. These findings suggest a need for urgent intervention through informed policymaking, impeding the influx of illegal arms and ammunition in porous borders, and strategically tackling poverty.

Keywords: conflict; fatality; SPDE; Poisson process; Cox process

1 Introduction

In recent years, there has been a spike in communal and sectarian violence, most of which is brutal in nature, involving the use of dangerous weapons and killing in some African countries, including Nigeria (Chinwokwu 2014; Dorff et al. 2020). The direct effect of violence, crime, and social unrest on people has an impact on economic activities in addition to displacing many from their usual place of abode,

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thereby living as displaced persons within or outside their home countries. The impact on healthcare delivery is also enormous as it worsens the fragile health condition of the populace. For instance, due to insurgency and attacks on health workers in northeastern Nigeria, operational challenges have been faced in the provision of malaria intervention services (Omojuyigbe et al. 2023).

Violent crimes and conflict, which are often due to ethnic, regional, and religious factors and largely rooted in territorial identities, are among the major societal problems in Nigeria (Falola 1998; Fry 2014). The post-civil war period in Nigeria has seen an upsurge in violent crimes including rape, murder, armed robbery, sea piracy, cultism, kidnapping, militancy, and terrorism particularly as unleashed by the Boko Haram sect, banditry, farmers-herders clashes and more recently by the indigenous people of Biafra (IPOB) all of which contribute to apparently making most parts of Nigeria relatively insecure. The proliferation of small arms and light weapons in Nigeria, as in many African countries, where over 100 million weapons circulate fuels war, communal clashes, and human rights abuses (John et al. 2007). Regardless of the national policy against the illicit manufacture and trafficking of firearms and ammunition in Nigeria, the smuggling influx of these items into the country is enormous (Mark and Iwebi 2019) and therefore remains gravely disturbing and a threat to national security. Within the first quarter of 2022, an alarming 1,484 persons were abducted, while 2,553 deaths were recorded due to farmer- herder clashes between 2017 and 2020. Since the advent of the Boko Haram sect in 2002, about 35,000 deaths directly linked to the activities of this sect have been reported in the northern part of the country (Council on Foreign Relations 2022). Despite the collective effort of the government to combat violent crime, according to recent data, Nigeria's peace index is still ranked 143rd of 163 around the world, based on a multidimensional report on violence, security, and criminality (Institute for Economics and Peace 2022). Thus, researchers and policymakers have a huge role in bridging the qualitative and quantitative analysis of violent crimes and developing a modernized technique for fighting crime in the country.

Ecological studies of violent crimes are crucial and particularly of interest to criminologists, geographers, public health interventionists, and law enforcement agencies because of the potential to unveil the spatial patterns of crime risks and the risk factors explaining these patterns (Liu and Zhu 2017). However, since the locations and timing of violent events occur in random order, modeling these phenomena requires some complex approaches. In this regard, spatial statistical methods and techniques capable of capturing the random nature of violent events, as adopted in this study, are critical because of their ability to track local variability and identify high-risk locations. This information is useful for driving location-specific policy-making and for strategic planning. Several studies have been directed toward quantifying the spatial heterogeneity of crime occurrence in different places. Groff and La Vigne (2002) extensively reviewed several existing methods for crime prediction, outlining the merits and demerits of each method. For example, the random walk method is sensitive to changes and is advantageous in cities with rapid changes in the pattern of crime. However, the method only depends on the immediate previous month to predict the next month and, therefore does not account for seasonality. Other methods include exponential smoothing, point process models, and artificial neural networks, among others. Mohler et al. (2011) used a nonparametric technique to implement a self-exciting point process model to map residential burglary in Los Angeles. Badiora et al. (2016) conducted a geographical analysis of urban crime in the city of Ile-Ife, Nigeria, and reassured the existence of a spatial heterogeneity of crime occurrence in the city. It was concluded that the spatial patterns depend largely on the type of crime committed. Adeolu (2019) incorporated a geographical information system of the locations of police stations in crime analysis. The author adopted a nearest-neighbor analysis to determine the spatial pattern of the interaction between the locations of police stations and crime spots in Ikeja, Nigeria. Moreover, Madu and Nwankwo (2021) studied the spatial pattern of farmer-herder conflict in Nigeria and found spatial clustering of the frequency of clashes in the Middle Belt of Nigeria. The authors identified climate change as the main factor influencing the clash. Regions with a lesser vulnerability to climatic change were found to suffer more from the clashes. Dorff et al. (2020) developed a statistical model that uses a network-based approach to capture interdependencies between actors. This approach integrates the social relations regression model and the latent factor model to account for the evolving composition of actors within Nigeria's conflict landscape over time. Similarly, Dorff et al. (2023) explores the causes of violence against civilians in civil conflicts using a computational model that accounts for civilians' strategic behavior. It argues that conflicts characterized by high network competition -where clashes between actors are more frequent- result in greater civilian victimization, regardless of overall conflict intensity or the number of actors involved. Cook and Weidmann (2022), addresses the challenges of spatial aggregation in conflict event data while Dorff et al. (2022) emphasizes the role of latent networks in improving spatial predictions of conflict spread. These studies highlight key issues of consideration, including how spatial aggregation may mask fine-grained diffusion patterns or how social networks might influence the spatial spread of conflict. Döring and Mustasilta (2024) highlights the concern of distinguishing between direct spillover effects, where violence spreads across borders, and indirect spillover, where neighboring areas experience violence due to shared risk factors, such as environmental stressors. They emphasize the importance of accounting for both mechanisms when modeling communal violence.

Though there are numerous studies focusing on Nigeria, little or no specific attention has been given to violent crimes, the resulting fatality, and the underlying spatial dependence. The occurrence of a violent event exhibits spatial dependence, as closer locations are more likely to experience similar patterns of violent crimes, as in the case of the Boko Haram insurgency in Borno and the neighboring states in northeastern Nigeria. Violent events and the associated fatalities are considered to occur at random in the sense that the occurrence of an event does not necessarily signal that another similar event is imminent (King and Jacobson 2017). Thus, this important property needs to be taken into consideration when studying the spatial distributions of violent events, as doing otherwise could result in biased estimates. In this regard, we adopt a spatial point process statistical model to unravel the spatio-temporal patterns of violent events and the associated fatalities in Nigeria by incorporating event location randomness across space and time. We used a Cox process where the log intensity function was linked to a random field, which was modeled efficiently through the stochastic partial differential equation. The integrated nested Laplace approximation was used as leverage to overcome the computational bottleneck of evaluating the integral involved in the likelihood of the process. The proposed spatio-temporal model was compared with a non-homogenous Poisson point process, Strauss point process, and Hawkes point process models. In addition, the fatality counts due to these events were modeled using a standard structural additive mixed model for point-referenced spatial data. The estimated spatio-temporal patterns would identify locations in Nigeria that are relatively more prone to violence. This would assist in localized policymaking, policing, and evaluating the impact of previous interventions over the years.

The remaining part of this work is as follows. Section 2 describes the data and statistical models developed, and Section 3 presents the results from the models. Section 4 presents the discussions of the findings, and Section 5 concludes the work.

2 Materials and Methods

2.1 Data

The conflict data analyzed in this study were derived from the Uppsala Conflict Data Program's Georeferenced Event Dataset (UCDP-GED) version 22.1, the world's main provider of data on organized violence (Sundberg and Melander 2013). The dataset is a project based at the Department of Peace and Conflict Research, Uppsala University. Version 22.1 is a global dataset that covers conflict events occurring around the world between 1989 and the end of 2021. The aim is to put together a tool for the global understanding of subnational conflict patterns and trends. The UCDP-GED defined a conflict event as ”an incident where armed force was used by an organized actor against another organized actor, or civilians, resulting in at least one direct death at a specific location and a specific date" (Högbladh 2022; Sundberg and Melander 2013). The event data are collected from three sets of sources: global newswire reporting, global monitoring and translation of local news performed by the BBC, and other secondary sources such as local media, field reports, and books. The georeferenced data, which specify the Cartesian coordinates of the event, also include information on the specific date of each event, the type of violence (state-based conflict, non-state conflict, or one-sided violence), the actors involved, and the fatalities. The severity of the fatalities, measured by the number of deaths, are presented in different formats depending on the side where it occurred or whether a civilian was involved. For the purpose of our study, the estimates of the total fatalities resulting from an event were analysed to study the space-time patterns of fatalities from conflict events in Nigeria.

In the case of Nigeria, conflict data are available from 1990 to 2021, with many of the early years having only a few cases, as shown in Table 1. Consequently, in order to minimize noise when few data points are available for a particular year and using the earlier years as a benchmark, we grouped the early years' data as follows: 1990–2005, 2006–2010, 2011–2015, while the rest were included in a single year. Beyond the concise presentation of these results, the models based on these groupings demonstrated the lowest bias in the posterior predictive analysis.

Table 1: Frequency count of event and fatality by year.

Year	Event count	Fatality count	Year	Event count	Fatality count
1990	2	89	2006	21	225
1991	4	380	2007	21	153
1992	12	943	2008	27	425
1993	8	1,185	2009	40	530
1994	16	90	2010	91	980
1995	1	1	2011	253	1,830
1996	5	87	2012	406	2,015
1997	20	595	2013	329	3,378
1998	30	337	2014	549	10,324
1999	39	3,519	2015	498	8,848
2000	30	2,104	2016	417	3,828
2001	38	2,414	2017	496	3,545
2002	43	612	2018	524	3,190
2003	61	442	2019	501	2,411
2004	85	2,108	2020	600	3,019
2005	18	116	2021	417	2,368

2.2 Counting Process Model

2.2.1 Model Definition

Let s_i, $i = 1, 2, \ldots, J$ be a spatial location marked by the longitude and latitude within Nigeria's territory $\mathcal{N}$ where the ith violent event occurred in year t ($t = t_1, t_2 \ldots, t_T$). As these locations, $s_1, s_2, \ldots, s_J$ are not predetermined, they are considered random. It is assumed that the occurrence of these events depends on an underlying spatial process we want to estimate. The process is modeled through an intensity function $\lambda(s, t)$, which quantifies the average number of violent events per unit space. This work aimed to model the counting process using the Cox process due to its relative simplicity compared with computationally intensive models for our acquired violent data. The Cox process (Cox 1955) is a generalization of the Poisson process when the process intensity is influenced by an external process such that the intensity function becomes a stochastic process itself. Usually, in the literature, the number of events within a lattice partition is modeled using a Poisson likelihood model conditioned on a linear predictor (Moller and Waagepetersen 2003). However, in this work, we adopted a more efficient approach that does not rely upon lattice counts of events but counts on a mesh triangulation. Weidmann (2016) discussed the concern of reporting bias in conflict event data, particularly how media-based conflict data may be inaccurate due to differential coverage of conflict events, leading to spatial and temporal biases. However, this analysis is based event locations reported from the dataset. Although the data may contain some spatial uncertainty, the mesh triangulation adopted in this work involves grouping spatial locations across the spatial domain in a manner that mitigates the uncertainty associated with geospatial precision, making the estimates more reliable. Moreover, our approach is focused on identifying broader spatial patterns rather than fine-scale diffusion dynamics.

Suppose that $D \subset \mathcal{N}$, where D could represent an administrative division of the country. For a homogeneous Poisson process, it is assumed that the number of violent events that occur in any partition D is Poisson distributed with constant intensity λ, the number of events in D and $D^{'} \subset \mathcal{N}, D \cap D^{'} = \varnothing$ are independent random variables, and the events are uniform within each partition. However, this work adopted the inhomogeneous Poisson process (Weinberg et al. 2007), commonly referred to as the log-Gaussian Cox process (Krainski et al. 2018), which allows the intensity of the process to vary across space and time, unlike the homogeneous process. The expected number of violent events within partition D at time t is given as

$$\mathbb{E}(D \mid t) = \int_D \lambda(s, t) \mathrm{d}s, \;\; s \in D, \tag{1}$$

where $\lambda(s, t)$ is an intensity process at location s in time t. Given the intensity surface and a set of observed point pattern $\mathcal{Y}_t$ at time t, the log-likelihood is given as (Baddeley and Turner 1998):

$$\log f(\mathcal{Y}_t \mid \lambda) = |\mathcal{N}| - \int_{\mathcal{N}} \lambda(s,t)\mathrm{d}s + \sum_{s \in \mathcal{Y}_t} \log \lambda(s,t), \tag{2}$$

which is analytically intractable as it contains an integral of a spatial process over the whole spatial domain. Here, $|\mathcal{N}|$ is the total area covered by $\mathcal{N}$, and $\mathcal{Y}_t$ is the collection of all point processes at time t, which we considered in this work as a single year or group of consecutive years. The log-likelihood consists of two main terms: the stochastic integral and the evaluation of the intensity at the data points. The intensity is modeled as a realization of a random field defined as

$$\lambda(s,t) = \exp\left(\beta_0 + \mathbf{c}_{st}^T \boldsymbol{\gamma} + u(s,t)\right), \tag{3}$$

where $u(s, t)$ is a spatio-temporal process, β_0 is the constant parameter over $\mathcal{N}$, and $\mathbf{c}_{st}^T \boldsymbol{\gamma}$ is a linear combination of dummy coded variables in vector $\mathbf{c}$ to adjust for the violence type (state-based conflict, non-state conflict, or one-sided violence), and $\boldsymbol{\gamma}$ is the corresponding regression coefficient. Thus, the counting variation across space is assumed to be due to an underlying process $u(s, t)$. The stochastic nature of the intensity in (3) further complicates the likelihood function. Moreover, the occurrence of violent conflicts at a particular location may trigger a conflict at a nearby location which indicates the presence of strong spatial association. Thus, we proposed the use of the Stochastic Partial Differential Equation (SPDE), which efficiently evaluates the intensity in (3) and additionally, incorporates spatiotemporal dependencies of the point process to account for spatial patterns in the data over time. The theoretical details of the formulation using the SPDE approach are included in the supplementary material (Lindgren et al. 2011; Simpson et al. 2016).

Consider the illustration of the point pattern in a dual mesh shown in Figure 1, constructed using the finite element method of the R-INLA package. From our dataset, the red points indicate the locations where violent events took place, and each polygon represents a sub-region of $\mathcal{N}$. Let s_i represent the location where the ith violent event occurred and $\tilde{s}_i$ be the centroid of a polygon within the dual mesh (see Equation (5) in the supplementary material). The idea of using the SPDE approach through the `R-INLA` as a way to estimate the spatial point pattern is simply to construct a data augmentation (Krainski et al. 2018). In this manner, the Poisson likelihood can then be easily adopted. The pseudo-observation is constructed as a binary response $\mathbf{y}$, with one representing the occurrence of a violent event and 0 representing the non-occurrence. To estimate the smooth surface spatiotemporal pattern in R-INLA, construct $y(s_l, t)$ at time t such that

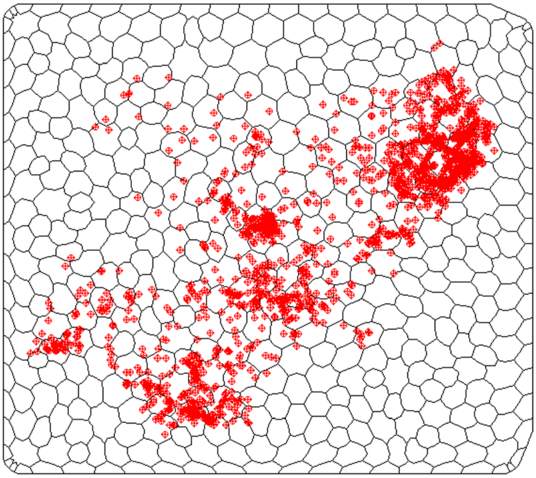

Figure 1: A dual mesh representing the Nigeria domain $\mathcal{N}$. Each partition of the region is a polygon whose centroid is s and each red point is the location s_i where a violent event occurred.

$$y(s_l, t) = \begin{cases} 1 & \text{if } s_l \in \{s_i\}_{i=1}^{J}, \\ 0 & \text{if } s_l \in \{\tilde{s}_i\}_{i=1}^{p}, \end{cases}$$

where p is the total number of polygons in the dual mesh. In other words, the length of the vector $\mathbf{y}$ is the sum of the length of the observed data and the total number of polygons. To account for the impact of differences in exposure, the area of the polygons is computed and used as weights in the regression model. Thus, the corresponding log of the weight w is then given as

$$w(s_l, t) = \begin{cases} 0 & \text{if } s_l \in \{s_i\}_{i=1}^{J}, \\ area(s_l) & \text{if } s_l \in \{\tilde{s}_i\}_{i=1}^{p}. \end{cases}$$

where area(s_l) is the area of the polygon whose centroid is $\tilde{s}_l$. The idea is that the area of a location (single point) where an event occurred is zero. In Poisson regression, w is commonly referred to as the offset variable.

Suppose the location s_l is taken to be the location of the observed events for $l > p$ and the centroid of the polygons for $l \le p$. A $(p + J) \times n$ projection matrix $\mathbf{A}$ is created using a suitable `R` function within the package (See `R` code). The matrix is obtained by concatenating the $J \times n$ observed projection matrix $\mathbf{A}_{data}$ and identity matrix $\mathbf{A}_{polygone}$ of size p. That is, $\mathbf{A}$ = columnstack($\mathbf{A}_{\text{polygone}}$, $\mathbf{A}_{\text{data}}$). This only makes sense if we choose $n = p$. The $\mathbf{A}_{data}$ is obtained based on the dual mesh and the locations of observed violent events. Given the weights and the pseudo-observation, the `R-INLa` can be easily applied to estimate the intensity. Deriving the projection matrices using linearly independent deterministic piecewise linear functions $\{\varphi_j(s, t)\}_{j=1}^{n}$, the intensity function can then be written as

$$\lambda(s,t) = \exp\left(\beta_0 + \mathbf{c}_{st}^T \boldsymbol{\gamma} + \sum_{j=1}^{n} \theta_{tj} \varphi_j(s,t)\right) \tag{4}$$

where θ_{tj} is the coefficient of the piecewise. Let $\boldsymbol{\theta}_t = (\theta_{11}, \theta_{12} \ldots, \theta_{tn})^\top$, we assume an autoregressive temporal model for $\boldsymbol{\theta}_t$, such that each $\boldsymbol{\theta}_t$ is temporally correlated with $\boldsymbol{\theta}_{t-1}$ by an amount $\rho \in [-1, 1]$, modeled as $\boldsymbol{\theta}_t = \rho\boldsymbol{\theta}_{t-1} + \boldsymbol{\epsilon}_t$, where ϵ_t is the error term. A positive value of ρ indicates that event occurrence at a given year is positively correlated to events in the previous years. Several works have described the Bayesian estimation steps through the R-INLA package (Blangiardo et al. 2013; Egbon et al. 2021; Schrödle and Held 2011). For technical details, see Rue et al. (2009), Martins et al. (2013), and the supplementary material.

To account for differences in the spatial patterns of various types of violence (state-based conflict, non-state conflict, or one-sided violence), we include violence type as a covariate in the regression model, allowing us to adjust for these variations while analyzing overall violence occurrence.

2.2.2 Residual Analysis for the Point Process

Let Δ be the vector of the parameters of the point process to be estimated from the data, and $\widehat{\Delta}(Y)$ be the corresponding Bayes estimate (e.g. the posterior mean). The raw residuals are calculated as (Baddeley et al. 2005)

$$I_\Delta(B) = n(B) - \int_B \lambda_\Delta(u, Y)\mathrm{d}u, \tag{5}$$

where B is a subregion of $\mathcal{N}$, which could represent a partition, $\lambda_\Delta(u, Y)$ is the true intensity of the spatial point process, and $n(B)$ is the number of the point process within region B. Theoretically, $\mathbb{E}(I_\Delta(B)) = 0$, which is similar to the error term in classical linear regression. However, (5) is not observable. We approximate the residual using

$$R_{\widehat{\Delta}}^{(k)} = n(B_k) - \int_{B_k} \widehat{\lambda}(u, Y)\mathrm{d}u, \tag{6}$$

where $B_k \subset \mathcal{N}$ is the kth polygon of the dual mesh shown in Figure 1, and $\widehat{\lambda}(u, Y)$ is the plugin estimator of the process intensity. This implies that the closer to zero $R_{\widehat{\Delta}}^{(k)}$ is, the more adequate the adopted model.

To further analyze the performance of the model, we adopted the Stoyan-Grabarnik diagnostic criterion (Stoyan and Grabarnik 1991; Baddeley et al. 2005). Let $m_i = 1/\lambda(s_i, Y)$ be the weight of the observed point process at s_i. Then the total weight for all points that fall in polygon $B \subset \mathcal{N}$ is given by

$$M(B) = \sum_{s_i \in B} m_i, \tag{7}$$

with expected value $\mathbb{E}(M(B)) = |B|$, where $|B|$ is the area of B. To compute $M(B)$ from the observed data, the plugin estimate of the intensity was used. That is, $\widehat{m}_i = 1/\widehat{\lambda}(s_i, Y)$ and $\widehat{M}(B) = \sum_{s_i \in B} \widehat{m}_i$. According to Baddeley et al. (2005), polygon B with an extreme value of $\widehat{M}(B) - |B|$ may indicate a region with irregularities.

2.3 Fatality Model

Beyond the spatial point process, this work is interested in unraveling the pattern of the fatality rate caused by the occurrence of violent events in Nigeria. Hence, a spatio-temporal model was adopted. Moreover, it was assumed that the locations where a fatality occurred were not random in this scenario. In this case, model transformation is unnecessary to adopt the `R-INLA` approach for parameter estimation. The frequency distribution of the observed fatality is shown in the supplementary material.

Let $Z(s_l, t)$ represents the total number of deaths at location s_l and at time t for any type of violent event (state-based conflict, non-state conflict, or one-sided violence). Then, $Z(s_l, t)$ is a random variable with a probability distribution P. That is,

$$Z(s_l, t) \mid \mu_{lt} \sim P, \ l = 1, 2, \ldots, J\,; t = 1, 2, \ldots, T. \tag{8}$$

where μ_{lt} denotes the parameter of P, which represents the fatality rate. Conditioning on the spatial latent variable u and intercept through the linear predictor, to be defined in Equation (10), three competing models were examined for P. These include the Poisson, Generalized Poisson, and Negative Binomial distributions. With the observed data, we computed the Watanabe-Akaike information criterion (WAIC) to determine the best probability mass function. The results of the comparison are shown in the supplementary material. Based on the results, the generalized Poisson distribution outperformed the other competing models. Thus, we utilized the Consul and Jain (1973) and Zamani and Ismail (2012) parameterization of the generalized Poisson probability distribution given as

$$P(Z(s_l, t) = z \mid \mu_{lt}, \delta) = \frac{\mu_{lt}(\mu_{lt} + \delta z)^{z-1}}{(1+\delta)^z z!} \exp\left(-\frac{\mu_{lt} + \delta z}{1 + \delta}\right), z = 0, 1, 2, .., \delta \geq 0, \tag{9}$$

with mean μ_{lt} and variance $\mu_{lt}(1 + \delta)^2$, and δ accounts for over-dispersion in the data.

Particularly for the fatality occurrence, the expected fatality count (mean) μ_{lt} in location s_l at time t is linked to a structural linear predictor given as

$$\mu_{lt} = \exp(\beta + \mathbf{c}_{lt}^T \boldsymbol{\gamma} + \nu(s_l, t) + \log E_{s_l, t}), l = 1, 2, \ldots, J; t = 1, 2, \ldots, T, \tag{10}$$

where $E_{s_l,t}$ is the offset variable defined as the population size of the administrative state where location s_l belongs at year t, and $\mathbf{c}_{lt}^T\boldsymbol{\gamma}$ is as previously defined, which is used to adjust for violence type. $v(s_l, t)$ is a spatio-temporal latent effect. The dispersion parameter δ was assumed constant, and a fixed global regression intercept β_0. Given the complete model in Equations (9) and (10), the SPDE model was again adopted for the spatial pattern. That is, for $\mathbf{s}_t = (s_{1t}, s_{2t}, \ldots, s_{Jt})$, then $u(\mathbf{s}_t) = \mathbf{A}_t\boldsymbol{\vartheta}_t$, where $\mathbf{A}_t$ is the projection matrix based on all the locations where violent events occurred at time t and $\boldsymbol{\vartheta}_t$ is the corresponding spatial field parameter.

2.4 Posterior Uncertainty

A benefit of the Bayesian technique is its ability to quantify uncertainties in the model parameters. The technique requires assigning prior probability distributions to the model parameters. For this analysis, the prior distributions assumed are described in the supplementary material. We utilized the posterior distributions to compute exceedance posterior probabilities. Let $\pi(\beta_0, \boldsymbol{\theta} \mid \mathcal{D})$ and $\pi(\beta, \boldsymbol{\vartheta}, \delta \mid \mathcal{D})$ be the joint posterior distribution trained on the observed data $\mathcal{D}$. Then we computed the posterior predictive probabilities given as

$$\begin{aligned} P(y(s_l,t)=1 \mid \mathcal{D}) &= \int P_p(y(s_l,t)=1 \mid \beta_0, \boldsymbol{\gamma}, \boldsymbol{\theta})\pi(\beta_0, \boldsymbol{\gamma}, \boldsymbol{\theta} \mid \mathcal{D})d(\beta_0, \boldsymbol{\gamma}, \boldsymbol{\theta}) \\ P(Z(s_l,t) \geq 1 \mid \mathcal{D}) &= \int P_{gp}(Z(s_l,t) \geq 1 \mid \beta, \boldsymbol{\gamma}, \boldsymbol{\vartheta}, \delta)\pi(\beta, \boldsymbol{\gamma}, \boldsymbol{\vartheta}, \delta \mid \mathcal{D})d(\beta, \boldsymbol{\gamma}, \boldsymbol{\vartheta}, \delta), \end{aligned} \tag{11}$$

where P_p and P_{gp} are the Poisson distribution for the point process and generalized Poisson distributions for the fatality counts respectively. `R-INLA` package provides `R` functions to draw samples from the posterior distributions making it easy to approximate the integrals in Equation (11) efficiently. The marginal posterior densities of the predictions were first obtained from the package, from where the quantile probabilities were computed.

3 Results

Figure 2 presents the plots of the count of conflict events and fatalities based on the six geographical zones of Nigeria. As evident, beginning in 1990, the case counts were relatively low in all the zones, but a slight rise was noticed in the South-South zone around 1998, but this quickly reduced thereafter. Around 2003 and 2004, there were observed rising cases in the South-South and North Central zones

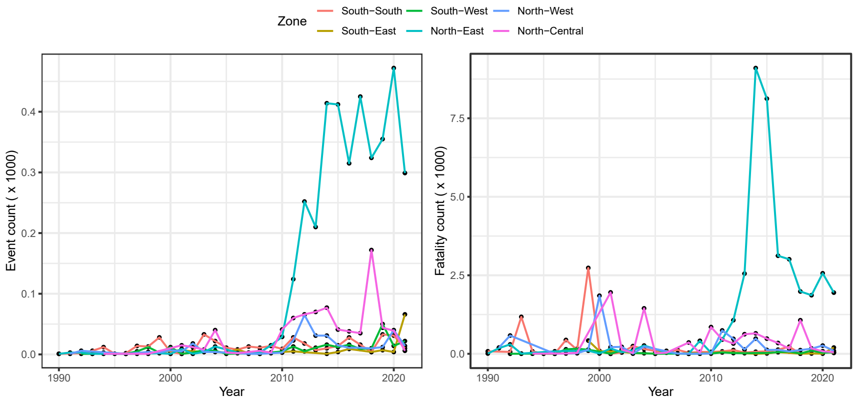

Figure 2: Event and fatality counts based on the six geopolitical zones of Nigeria.

respectively, which again reduced immediately after those years. Beginning in 2010, the number of reported cases surged in the northeast part of the country, exceeding what was obtained in any other part of the country, and this continued for the rest of the years. The South-South region also experienced rising cases of violent events around that time but not as experienced in the North-East. As for the fatality, between 1990 and 2000, the South-South zone recorded the highest number of fatalities, while between 1998 and around 2004, fatalities were high in the North-West and North-Central parts of the country. Beginning in 2010, as may be expected, the Northeast region recorded the highest number of fatalities, peaked in the year 2004, and gradually reduced but still higher than the reported fatalities in the other zones.

3.1 Residual Analysis

For comparative purposes, we also fitted a non-homogeneous Strauss point process and Hawkes point process models on our data using the ppm function in spatstat package and fit_stelfi function in stelfi package respectively (Baddeley et al. 2015; Jones-Todd and van Helsdingen 2023). In addition, we fitted a non-homogenous Poisson point process. These models are briefly described in the supplementary material. Using a cross-validation technique for the Strauss process, the interaction (irregular) parameter was chosen to be 0.5, and the other parameters were estimated from the data. For every k polygon in the dual mesh, the residuals in (6) were computed for the four models and are shown in Figures 3 and 4. Figure 3a, b, c, and

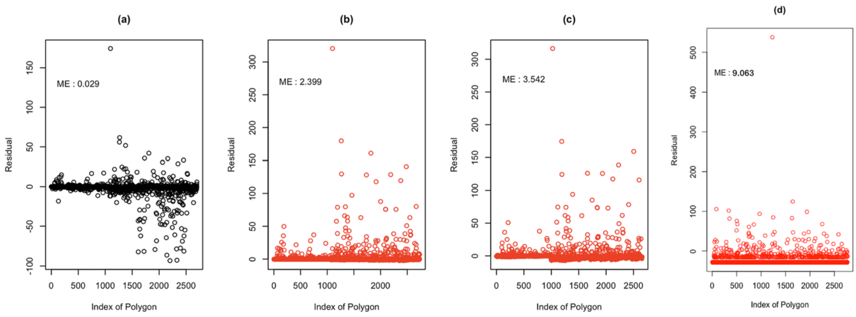

Figure 3: Raw residuals $R_{\Delta}^{(k)}$ computed for all polygons in the dual mesh: (a) Proposed model, (b) non-homogeneous Poisson point process model, (c) Non-homogeneous Strauss point process model, and (d) Hawkes point process model. The text "ME" is the average of the residuals.

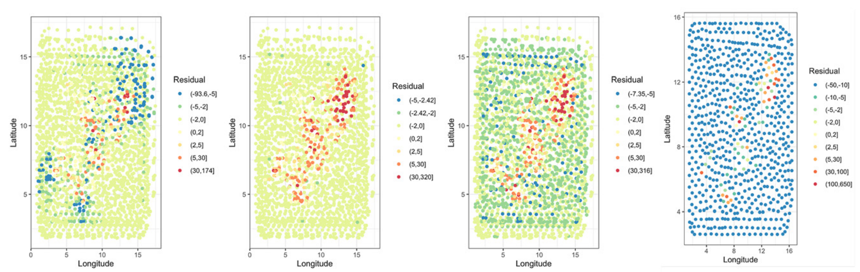

Figure 4: Raw residuals $R_{\Delta}^{(k)}$ computed for all polygons in the dual mesh and plotted with respect to the coordinates of the polygons' centroids: (a) Proposed model, (b) Non-homogeneous Poisson point process model, (c) Non-homogeneous Strauss point process model, and (d) Hawkes point process model.

d show the raw residuals against the indexes of the polygons for the proposed model, non-homogeneous Poisson process model, non-homogeneous Strauss process, and Hawkes point process model, respectively. The text within the plot "ME" indicates the average absolute value of the raw residuals. That is ME $= p^{-1}\sum_{k=1}^{p} \mid R_{\Delta}^{(k)} \mid$, where p is the total number of polygons in a dual mesh similar to Figure 1. The result shows that the non-homogeneous Poisson process model performed less adequately compared with the proposed model and the non-homogenous Strauss point process model. Similarly, the Hawkes process model relatively underperforms compared with the proposed model. The model overestimated the point process, especially in polygons containing no observed event count, indicating that the data might not have strictly supported the self-exciting nature of the Hawkes process. Figure 4 shows the same residuals but plotted with respect to the spatial locations of the centroids of the polygons. The colors on the plots are indicative of the residual values, and a model with residuals closer to zero is considered to have outperformed the others. The result indicates that the proposed model performed considerably better than the other models.

Figure 5 (left) shows the values of $\widehat{M}(B) - |B|$, as described in Section 3.1, for the proposed model against the index of non-empty polygons B. The distinct (red) points are the polygons whose $\widehat{M}(B) - |B|$ is higher than the 97 % quantile. The locations of these polygons are shown in Figure 5 (right). The points are majorly located in the northwest region of the country. This finding agrees with empirical evidence that indicated a surge of armed conflicts in these regions in the most recent years, unlike before.

Table 2 shows the posterior means and 95 % credible intervals for the hyperparameters of the models considered. From the point process model, the result of the temporal correlation parameter ($\rho = 0.662$) shows a strong positive correlation in the occurrence of violent events in successive years. For the fatality model, the estimate ($\rho = 0.895$) shows a stronger temporal correlation in successive years compared with the value obtained for event occurrence. The estimates of the spatial range r and standard deviation σ show that the spatial extent of fatality occurrence is significantly higher compared with event occurrence. Particularly, the posterior mean of the range for the fatality count is $r = 2.840$, which implies that the spatial correlation is strong for locations within approximately 231.54 km (2.08 $\times$ 111.32 km), and it is negligible beyond this distance assuming one-degree latitude is 111.32 km. Similarly, for the point process, the spatial correlation is negligible beyond 99.63 km. The posterior estimate of $\delta = 5.340$ indicates a high marginal variance in the fatality counts across the country. Figure 6 presents the posterior mean of the log intensity of the spatio-temporal point process model. The findings indicate that during the period 1990–2005, the cases of violent events were more prominent in the southern part of the country, particularly everywhere in the neighboring oil-rich states of Delta,

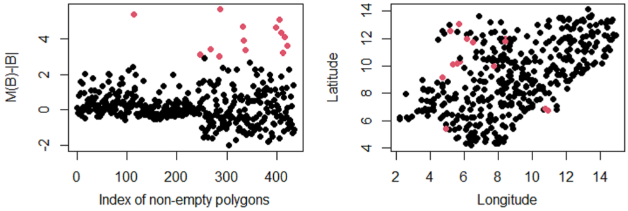

Figure 5: Stoyan-Grabarnik diagnostic.

Table 2: Posterior estimates of hyperparameters.

		Mean	2.5 %	97.5 %
Point process	ρ	0.662	0.609	0.713
	r	0.895	0.894	0.896
	σ	1.600	1.170	2.190
Fatality	ρ	0.895	0.894	0.896
	δ	5.340	5.319	5.356
	r	2.840	2.147	3.818
	σ	1.292	1.131	1.486

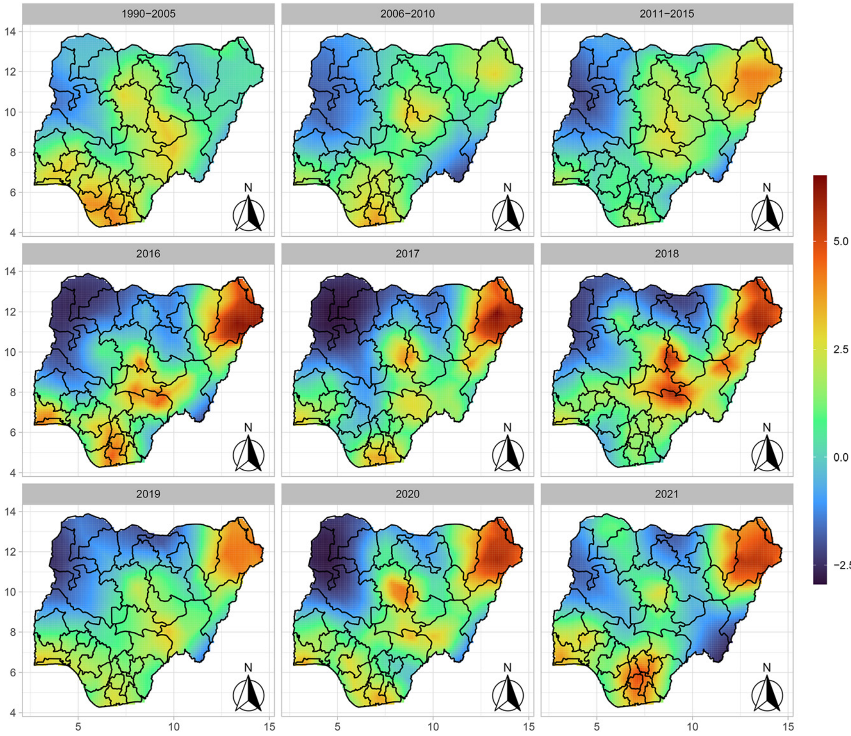

Figure 6: Posterior mean of the log intensity (log $\lambda(s, t)$) for the point process of violent event.

Bayelsa, Rivers, Imo, and Abia. The estimates also indicate high cases in parts of Lagos, Ogun, and Osun states, and another cluster around Kaduna, Plateau, and parts of Taraba and Benue states. Between 2006 and 2010, the cases of violent events were still higher in states around the oil-rich South-South region, particularly in Rivers and Imo states; in parts of Kaduna, Plateau, and Bauchi states; and in neighboring

Borno and Yobe states. During the period spanning 2011–2015, the cases of violent events occurred more in Borno, spreading through many of the contiguous states in the northern part of the country except those in the northwest region, where cases remained low. By 2016, there were high concentrations in Borno, spreading slightly to parts of the neighbouring Adamawa and Yobe states. There were other clusters in some other neighbouring locations, particularly around Nasarawa, Benue, Taraba, and the southern part of Kaduna; in Rivers, Bayelsa, Abia, and Anambra, spreading to parts of Delta; and also in Lagos and Ogun states.

For the rest of the years under consideration, the estimates show that reported cases of violent events continued intensely in Borno state and sometimes spreading to parts of neighbouring Adamawa and Yobe states. Again, similar to the previous years, the same locations in the southern and north-central regions continued to have reported cases of violent events, though with less intensity in some years, for example, in 2019. However, by the year 2020 and particularly in 2021, the findings indicate a gradual spread of conflict events around Sokoto, Zamfara, and Katsina states.

Turning to the estimates of the reported fatality, Figure 7 shows the posterior predictive of the log expected fatality counts per violent event. The findings show a high intensity of fatality in most parts of the country during the period 1990–2005. The few places with low estimates are Kwara, Kebbi, Sokoto, Ekiti, parts of Oyo, and Niger states. During the period 2006–2010, the spread of places with high estimates of fatality reduced substantially, concentrating mainly in Borno and most parts of Kaduna, spreading to neighboring locations in Bauchi and Plateau states. By the years 2011–2015, the clusters appear to be closing up around Borno and Kaduna states extending to neighboring locations of the two places. The estimates for years 2016, 2017, and 2018 follow closely that of 2011–2015, though the intensity of the estimates fades with time. In the years 2019 through 2021, the estimates show that the fatalities were concentrated around neighboring Borno and Yobe and also in Kaduna, spreading toward the states of Zamfara and Sokoto.

Figure 8a shows the probability of observing violent events per administrative state in the country, computed using Equation (11). A higher value indicates a higher chance of a violent event occurring in a given state. The figure shows that the northeast and the south-south geopolitical regions are more at risk of these events. Similarly, Figure 8b shows the posterior predictive probability of at least one death per violent event in an administrative state. Consistent with the previous results, the probability of fatality per violent event is higher than 0.42 in the northeast region and part of north central and south-south geopolitical regions in the country. This result indicates that for any violent event that occurred during the period under consideration, it is expected that there would be at least one death with 0.42 probability in

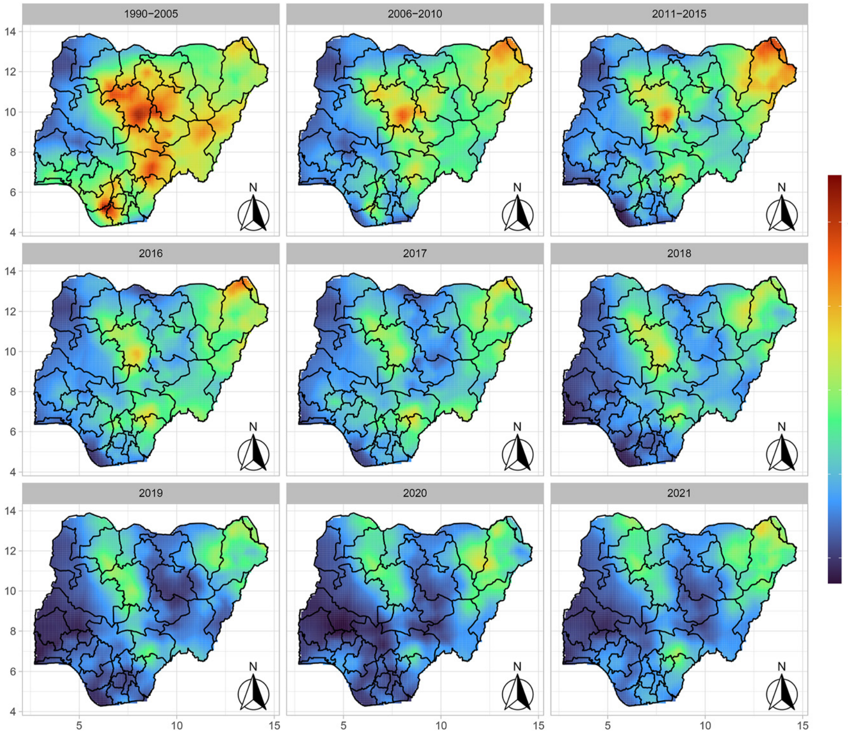

Figure 7: Posterior predictive of the log expected fatality counts (log μ) per violent event.

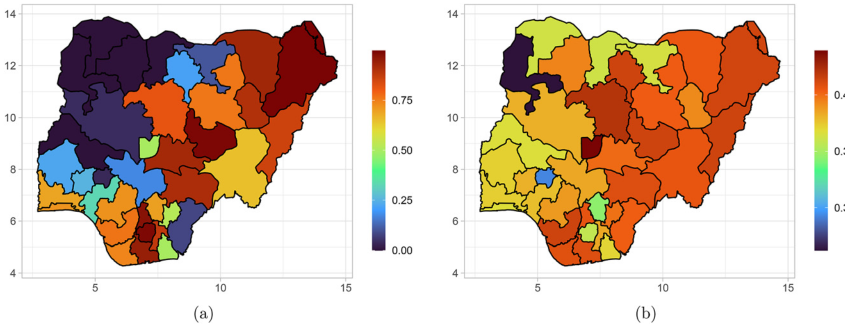

Figure 8: Posterior predictive probabilities of at least (a) one violent event per administrative state and (b) one fatality occurring per violent event per administrative state.

high-intensity states that include Borno, Adamawa, FCT, Plateau, Kaduna, Kano, Delta, Bayelsa, and Rivers. States with a probability lower than 0.36 include Ekiti, Enugu, and Imo.

4 Discussion

This study considered a point process modeling technique for estimating the spatio-temporal patterns of violent events and their associated fatalities in Nigeria. A Cox process was adopted where the expected event intensity was considered to vary with space. The SPDE model was used to quantify the spatial intensity and to make projections across the spatial domain. The findings reveal hotspots whose impact, in most cases, cut across a wide landscape involving various administrative states at different times. In addition, the results reveal a high spatial correlation between violent events and the resulting fatalities in successive years across Nigeria. The high correlations imply similar spatial patterns for each of the violent events and fatalities across Nigerian states over time.

Findings from the result indicate a concentration of violent events and crimes across different parts of Nigeria, especially in the north east region can be attributed to a number of factors such as population density, unemployment, access to quality education, migration, family disruption and addiction with some of the factors reported to be location-dependent (Adeyemi et al. 2021; Akpan et al. 2022; Egbon et al. 2024). For instance, the influx of unskilled Nigerians from the northern part of the country and other illegal migrants from the neighboring African countries particularly the Sahel areas into Lagos has increased the myriad of security issues and crime (Akpan et al. 2022). This could be attributed to why the estimated intensity of violent events in the southern part of the country is relatively higher in recent years. This corroborates the estimated probability of fatality in these regions.

The persistent high spatial clustering of violent crimes around northeastern Nigeria, particularly in Borno and its contiguous states, is majorly a result of the activities of the Boko Haram sect, which have been terrorizing this part of the country since around 2009 (Iyekekpolo 2020). Consequently, the associated fatality counts due to these events are relatively higher compared with other regions of the country. The sect is opposed to Western education and culture and all institutions and agencies that represent them, including government institutions. They perceive these to be at variance with the beliefs, values, and customs of the Muslim religion that is predominant in northern Nigeria (Adeolu 2019). According to Adesoji (2010), the religious sensitivity of the Nigerian populace provides a fertile breeding ground for the sec,t and this was equally aided by the economic dislocation in the country, the desperation of politicians for political power, and the ambivalence of some vocal armed Islamic leaders. The sect violently bombed churches, mosques, police and military formations, and other government institutions. They engage in suicide bombing, kidnapping of people,e particularly women and students, shooting of victims at close range, throat-slitting, and daylight and nocturnal attacks (Akinbi 2015; Iyekekpolo 2020).

The relatively high estimated pattern in the central region of the country spanning to some northern fringe could be attributed to the clash between farmers and headers that has become intense from around the year 2015. The conflict often leads to fatality and wanton destruction of properties and livestock. Factors such as climate change leading to recurrent drought with the attendant competition for freshwater; land acquisition by large-scale farmers and urbanization, leading to increased competition for land resources by herders and crop farmers; increased in livestock numbers and blockage of cattle grazing routes by crop farmers have been implicated as the cause of clashes between the farmers and the herders (Madu and Nwankwo 2021; Nnaji 2022; Onah et al. 2020; Usman and Nichol 2022). The recurrent conflict has detrimental consequences on the livelihood of both parties, including loss of yield and income, which aggravate low income, poverty, and food insecurity, thereby increasing the people's tendency to engage in more crime and violent events (Nnaji 2022).

The estimated violent event patterns seen in the southern region of the country could be linked to events associated with exploration and exploitation of crude oil in the Niger Delta belt of the country, which is the crude oil-bearing region of Nigeria. There has been several records of an unprecedented spate of violent conflicts that started around 1997 (Ifedi and Anyu 2011; Ikelegbe 2005). This is a sequel to the exploration and exploitation of crude oil that led to environmental degradation, soil impoverishment, pollution, biodiversity, and loss of aquatic life without concrete efforts to mitigate these consequences by the governments of Nigeria and the multinational companies who embarked on the exploration (Omofonmwan and Odia 2009). Furthermore, the exploration, which is done with capital-intensive technologies, generates high-wage employment for a few workers who are mostly drawn from outside the region. Thus, conflicts in the region started as community agitation, which underwent several transformations over time. The agitation against the multinational companies was extended to the Nigerian state and later, from a pure developmental issue, political demands such as resource control, federal restructuring, and a demand for the resolution of national issues through a conference of ethnic nationalities were all brought in. The entrance of youths into the agitation brought another dimension with the springing up of youth militancy with volatile demand and enhancement in the scale of confrontations and violence (Ikelegbe 2006; Nwankwo 2015). The activism and militancy of these youths become associated with an aggressive tide of abductions, hostage and ransom taking, and other economic crimes such as piracy, pipeline vandalization, and oil pilferage (Ikelegbe 2005). However, recent interventions by the Federal Government of Nigeria through an amnesty program have brought a reduction in the spate of crises in the region (Oluwaniyi 2011).

It is noteworthy that the spatio-temporal maps for the fatality provide evidence of a reduction in the spate of killings from violent events across the country except for a few locations, particularly around the Borno axis where the activities of the Boko Haram sect have not been fully brought under control and in the northwestern part of the country, especially in the neighboring Kaduna, Zamfara, and Sokoto states. The devastating acts of armed banditry due to the proliferation of arms, porous borders, high level of illiteracy, and the poor socio-economic status of the majority of the people have posed a security threat to this part of the country (Abdullahi and Mukhtar 2022). The worrisome manner in which the bandits operate increases the spree of kidnapping and hostage-taking, including seizing of school children, outright killing and maiming of people, population displacement, loss of means of livelihood, particularly livestock, and disruption of economic activities (Olapeju and Peter 2021). The Government of Nigeria, therefore, needs to adopt strategies to address the root cause of the crises as this may be more efficient than engaging in confrontational acts using the military as this would, among other things, expose innocent citizens to more dangers.

Despite the robustness of the analytical approach, it has certain limitations. Specifically, the adopted model does not account for reporting bias related to the location of violent events. Additionally, the analysis does not consider violence-specific spatial processes. Future work can integrate these aspects into the modeling framework to enhance model applicability.

5 Conclusions

This work adopted a Cox process model through the stochastic partial differential equation as implemented in the R-INLA package to uncover the spatial patterns of violent events and the associated fataltiesin Nigeria. The model accounts for location randomness, which is essential for understanding the nature of occurrence. Findings showed that violent events are highly prevalent in the northeast region of the country, with the probability that at least one death would occur for any violent event estimated to be around 0.42. The findings from this work indicate the need for swift and strategic intervention through policy reform, training, and retraining of law enforcement officers in the country, especially in the pocket of regions with estimated high violence intensity and associated fatalities. The government could resuscitate border policies in collaboration with neighboring countries, particularly the north east border to impede the influx of illegal arms and ammunition. Doing so could help to ensure the safety of citizens, improve food security, lower spending on fighting insurgency, and create a more secure environment, which consequently attracts foreign investors. The map produced in this work could be used to study the impact of previous policies, intervention planning, and formulation of local-specific policies.

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