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Spatial and temporal modeling of conflict related fatality and public health implications in Nigeria

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Fatality resulting from violent conflicts poses a critical public health challenge in Nigeria, straining healthcare systems, disrupting resource allocation, and necessitating targeted interventions to curb the prevalence and strengthen community resilience. According to the Global Organized Crime and Terrorism Indices, Nigeria is ranked among the top countries most impacted by terrorism in 2020. Despite numerous studies on crimes in Nigeria, adequate attention has not been given to quantifying the patterns of fatalities due to conflict events. This work aims to unveil the subtle spatio-temporal pattern of fatality resulting from violent events in Nigeria over a quarter-century. A spatio-temporal mixed model within a Bayesian framework was adopted, and data was sourced from the Armed Conflict Location and Event Data Project. The study found existing temperate seasonality in the pattern of fatalities, with a high fatality impact in Autumn and Winter. Among all the events, sexual violence was the leading cause of fatality in the country. Findings identified spatial and temporal disparities in fatality, with the North-East geopolitical zone being the most exposed region over the years, and uneducated members of poorest households are relatively more at risk of these events. The identified factors and patterns could be relevant for designing sustainable intervention programs or response policies to mitigate violent events in Nigeria.

Keywords Bayesian model, Spatio-temporal model, SPDE, Violent events, Zero-inflated model

Violent events are public health problems that involve physical aggression or forces intended to harm and damage[1]. These can include a wide range of events, such as assaults, riots, acts of terrorism, armed conflict, or interstate and civil wars, which can lead to several fatalities. Despite the global obligation to reduce violent events for the sustenance of development goals, recent reports have observed a surge in battle-related or terrorist attacks, which has become a severe public health concern[2] as survived victims, including women and children are forced to flee their dwellings, experience food insecurity and property damages. According to the 2024 report on the global terrorism index, deaths from terrorist attacks increased by 22% in 2023 and reached a first-time high since 2017[3]. The surge in violent events could be associated with global security challenges, economic and political uncertainty, and weak governance, which provides fertile ground for violence to thrive.

In 2023, Nigeria was ranked among the top 8 countries in the world with high terrorism incidents, fatalities due to violent conflict events, injuries, and hostages[4]. This fact can be attributed to the continuous attack on the Nigerian state by terrorist groups such as Boko Haram, Bandits, and other armed groups. The Boko Haram insurgency has been a major source of fatalities and insecurity, targeting both civilians and security forces. In the northeast region of Nigeria in 2014, the total fatalities per year increased to a first-time high since 2006[5]. To date, terrorist activities by Boko Haram and ISIS-WA have displaced around two million people within Adamawa, Borno, and Yobe states. Additionally, over 300,000 Nigerian refugees have fled to neighboring countries, mainly Cameroon, Chad, and Niger[6–8]. Moreover, the recent surge in farmer-herder conflicts has claimed several lives, and become one of the most security concerns becoming chronic and endemic in the country. In specific regions of the country, various factors such as increasing population density, changes in land use, availability of resources, growing social inequalities, and declining trust among communities have contributed to weakening the effectiveness of traditional dispute resolution methods, ultimately exacerbating conflicts[9]. The impacts of climate change, such as prolonged droughts, and flooding, have heightened competition over limited resources, leading to further strain in relations between farmers and herders. Religious militant groups have

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taken advantage of these inter-communal tensions in different parts of Nigeria to enhance their recruitment efforts[10]. The situation in Nigeria is particularly dire, as the combination of climate-induced resource scarcity and social tensions has created a fertile environment for these groups to thrive, resulting in the intertwining of farmer-herder conflicts with violent extremism, significantly complicating the security landscape in the region.

Additionally, ethnic and religious tensions and political uncertainty have fueled violent conflicts in various parts of the country, further compounding these issues, as periods of electoral tension and disputed results have led to outbreaks of violence in different pockets of regions across the country[11]. The lack of consistent and effective governance in certain regions allows these conflicts to persist, and sometimes intensify, as local power struggles and grievances are left unaddressed. These factors, combined with the activities of criminal groups create a complex and often volatile security landscape in Nigeria. The resultant increase in the fatality rate underscores the urgent need for a comprehensive study of the fatality patterns that is useful for devising sustainable strategies to address these multifaceted challenges.

Numerous studies have delved into the evolution of violent events in Nigeria, shedding light on various aspects of this complex issue. For example, Ukoji and Ukoji[5] analyzed Nigeria's fatality trends by state, year, and event type. Not surprisingly, the study revealed that Borno state had the highest fatality counts in 2021, followed by Lagos, Kaduna, Zamfara, Plateau, and Delta states. In a separate study, Oyewole and Omotola[12] examined the incidence and associated fatality rates of electoral violence during the 2019 general election. The findings indicated that violent events driven by elections were more prevalent in the southern fringe of the country. States such as Rivers, Akwa Ibom, Delta, Benue, Bayelsa, Lagos, Kogi, Ogun, and Kano were identified to have recorded high incidence rates of electoral violence. Furthermore, Egbon et al.[13] developed a Bayesian spatiotemporal model to analyze fatalities resulting from violent events in Western and Central African countries. The research highlighted Nigeria as one of the countries burdened with a high number of violent events and fatalities. Maxwell et al.[14] adopted an auto-regressive integrated moving average model (ARIMA) to predict murder events, estimated to rise during the predicted period. Ajide[15] studied the influence of the economic situation on the violent event rates in Nigeria and highlighted that the government of Nigeria should strive for economic growth and expand job opportunities to ensure that citizens have access to necessities. In a different approach, Fayomi et al.[16] utilized regression modeling to investigate hazardous climate conditions' impact on Nigeria's farmer-herder conflicts from 2014 to 2019. Additionally, Nwozor et al.[17] explored the Nigerian government's failure to effectively address the prevalent farmer-herder conflicts, which have led to alarming fatality rates in the country.

Despite the abundance of studies on crimes and violent events in Nigeria, there has been a noticeable gap in research specifically addressing the fatalities resulting from these incidents. Recently, Egbon et al.[13] developed a spatio-temporal modeling framework to jointly quantify the patterns of fatality resulting from violent events in central and west African countries, including Nigeria. However, the work did not account for the country-specific heterogeneity or cross-boundary spatial effects on fatality across countries; rather, it captured the broad spatial patterns and the factors driving the occurrence in West and Central Africa. The evolution dynamics of fatality due to violent events can be attributed to the interplay of several factors, necessitating a more localized approach, especially for a complex geopolitical landscape like Nigeria. Here, we present the spatiotemporal dynamics of fatality resulting from violent events in Nigeria through Bayesian spatiotemporal statistical models and quantify the factors driving these patterns, which could be relevant in understanding the specific evolution pattern of violent activities and their associated fatality pattern to aid policy response and resource allocation in Nigeria. In addition, we investigated both discrete and continuous spatiotemporal modeling techniques to quantify the effect of reporting bias.

The acquired fatality data are characterized by excessive zeros, which could have stemmed from a complex mechanism generating the fatality counts. For instance, a high number of fatalities could be expected during violent conflicts such as terrorist attacks or banditry in places that are prone to these events. This is not the case in safer regions where less violent events could be characterized by an expected fatality count of zero. Through such a mechanism, structured and unstructured zeroes are compounded giving rise to the excessive zeroes. Based on the acquired data, Fig. 1 shows the bar plot of the number of fatalities due to violent events in Nigeria, indicating evidence of excess zeros. Thus, a standard statistical model could underperform in this scenario. Therefore, the zero-inflated Poisson and Negative Binomial response models were considered for the data. The optimal model was adopted in a Bayesian spatio-temporal statistical modeling approach. A Gaussian random field model in discrete and continuous spatial domain was used to model the spatial component while an order one autoregressive model was used for the temporal pattern of the random fields.

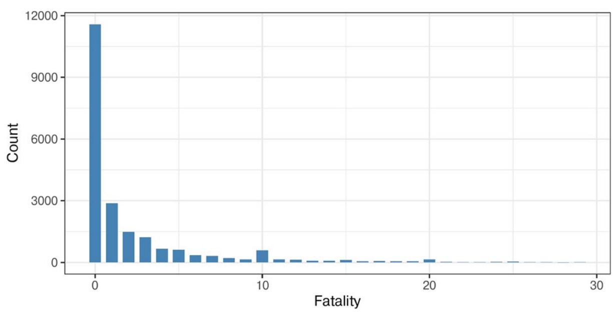

Fig. 1. Bar plot of the number of fatalities per criminal, violent, or non-violent events in Nigeria.

The remainder of the article is structured as follows. Section "Method" describes the data and the theory of the statistical method adopted, sections "Result" and "Discussion" present the results and discussion respectively while section "Conclusion" concluded the paper.

Method

Data

In this work, the dataset used to study the variability of fatalities due to these violent events was acquired from the Armed Conflict Location and Event Data Project (ACLED). ACLED is a data collection, analysis, and crisis mapping project that collates data on violent events across the world including the type, the actors, time of occurrence, locations, and fatalities. For Nigeria, we extracted violent-related events and fatalities from the year 1997 to 2021. The sample size is 21,777. We considered fatality counts per event as the target (response) variable, and the covariates are the *types of events*, *temperate season*, and *spatial location*. Our interest is to understand the spatio-temporal dynamics of fatalities resulting from these events across Nigerian states, which could be useful for policy-making in the country. We obtained the population data of each state from the National Bureau of Statistics (https://www.nigerianstat.gov.ng/), which is used as an offset in comparing fatality across different states. Nigeria is made up of thirty-six (36) administrative states and a Federal Capital Territory (FCT). These states and the FCT are further subdivided into local government areas (LGAs), bringing the total number of LGAs across the country to 774. Each local government area experiences varying levels of violent incidents, leading to differences in the frequency and severity of fatalities resulting from such events.

The descriptive statistics of the acquired dataset are illustrated in Fig. 2 and Table 1. Figure 2a displays the pattern of violent event counts per 100,000 population from 1997 to 2021, while Fig. 2b showcases the corresponding spatial distribution of violent event count per 100,000 population. Additionally, Fig. 2c depicts the fatality count per 100,000 population, and Fig. 2d presents the corresponding spatial distribution of fatality count per 100,000 population. The descriptive plots reveal that the violent event count surged between 2010 and 2021, likewise the corresponding fatality for these events. Overall, the pattern shows that the event and fatality counts are non-linear with time. Table 1 shows the total event count, fatality count, and the ratio of fatality count to event count.

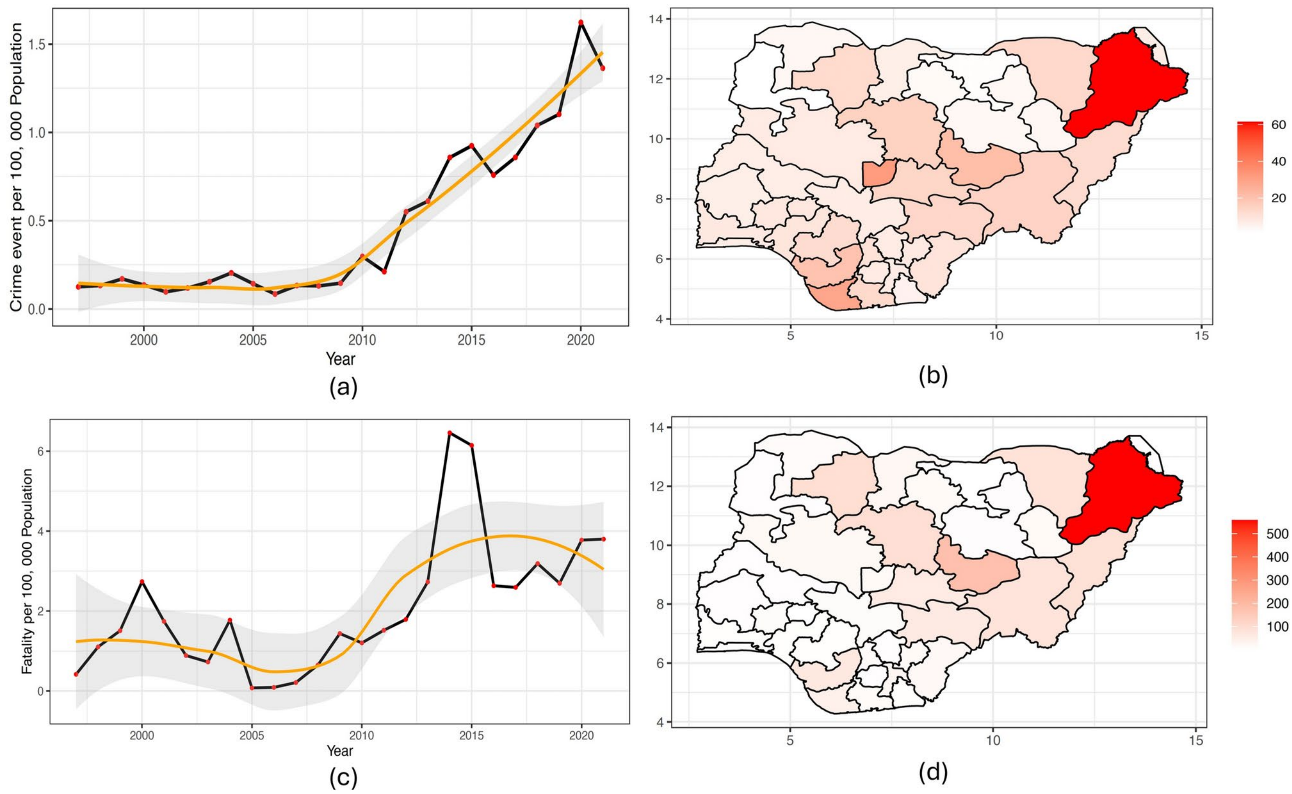

Fig. 2. Descriptive statistics of (**a**) the number of violent-related events per 100,000 population across years, (**b**) the number of violent-related events per 100,000 population across administrative states, (**c**) the number of fatalities per 100,000 population across years, and (**d**) the number of fatalities per 100,000 population across administrative states. The figures were generated by the authors using the ggplot2 (version 3.5.1) package in R version 4.4.1.

Event type	Total event count	Total fatality count	Fatality/event
Air/drone strike	452	5325	11.781
Armed clash	5315	33,502	6.303
Attack	5731	32,567	5.683
Government regains territory	293	1949	6.652
Grenade	12	27	2.250
Mob violence	1065	2850	2.676
Non-state actor overtakes territory	54	919	17.019
Remote explosive/landmine/IED	462	3149	6.816
Sexual violence	53	800	15.094
Shelling/artillery/missile attack	62	291.000	4.694
Suicide bomb	267	3524	13.199
Violent demonstration	1184	905	0.764

Table 1. Summary of event type's fatality count and count per violent event.

Statistical method

Let $Y_{it} \in \mathbb{N}$ be a discrete random variable denoting fatality counts in violent events and y_{it} be the observed fatality counts during event $i = 1, 2, ..., n$ in year $t = 1997, 1998, ..., 2021$. We assume that Y_{it} is governed by some probability distribution $P(. \mid \boldsymbol{\mu})$ with parameter $\boldsymbol{\mu}$. Our interest is to model the fatality count based on a subset of the parameter vector $\boldsymbol{\mu}$ through a canonical link function *g* on covariates influencing the fatality counts. However, the data we wish to model contains excess zeros, meaning that the number of zeros observed is far higher than expected; thus, a standard count model *P*, such as Poisson, Negative Binomial, and Generalized Poisson distributions, may underperform due to the influence of these zeros. Hence, we adopt a zero-inflated model $P_0(. \mid \boldsymbol{\mu})$ defined as the mixture

$$P_0(Y_{it} = y_{it} \mid \boldsymbol{\mu}, \pi_{it}) = \pi_{it}\mathbb{I}_{(y_{it}=0)} + (1-\pi_{it})P(Y_{it} = y_{it} \mid \boldsymbol{\mu})\mathbb{I}_{(y_{it}\geq 0)},\ y_{it} = 0, 1, 2..., \tag{1}$$

where π is the probability of a structured zero, and $\mathbb{I}_{(a=b)}$ is an indicator function that is one if $a = b$ and zero otherwise. For example, some events, such as a peaceful protest or demonstration, are not expected to lead to a fatality. Such type of zero fatality is said to be structured zero, and it is modeled by the first expression in Eq. 1 with a logistic link function. However, there are criminal or other violent events where by chance, no fatality is recorded. Such zero fatality type is called unstructured zero, which is modeled as part of the second expression of Eq. 1. We compared the zero-inflated negative binomial (ZINB) and the zero-inflated Poisson (ZIP) distributions and assessed their performance through the commonly used deviance information criteria (DIC) and the results show that the ZIP ($DIC = 67363.76$) outperformed the ZINB ($DIC = 69844.72$) since the DIC was lower. This could be due to the availability of large data in this application and the control for over-dispassion through an offset variable. Thus, we adopted the Poisson distribution for $P(. \mid \boldsymbol{\mu})$, where $\boldsymbol{\mu} = \{\lambda_{it}\}$. Thus, the complete zero inflated probability distribution is given as

$$\begin{aligned} P_0(Y_{it} = y_{it} \mid \lambda_{it}) &= \pi_{it}\mathbb{I}_{(y_{it}=0)} + (1-\pi_{it})\frac{\lambda_{it}^{y_{it}}}{y_{it}!}e^{-\lambda_{it}}, \quad y_{it} \in \mathbb{N},\ \lambda_{it} > 0,\ \forall i, t \\ \log(\lambda_{it}) &= \eta_{it} + \log(E_{it}). \end{aligned} \tag{2}$$

We modeled the expected fatality count parameter λ_{it} by introducing an offset variable E_{it}, which is the population at risk in a spatial and spatio-temporal model. That is, $\log(\frac{\lambda_{it}}{E_{it}}) = \eta_{it}$, where η_{it} is the linear predictor.

Besides the zero-inflated count model described above for the count response, we modeled the occurrence and non-occurrence of fatality. That is, we construct auxiliary variable z_{it} such that

$$\begin{aligned} z_{it} &= \begin{cases} 1 & \text{if } y_{it} > 0 \\ 0 & \text{otherwise} \end{cases}, \\ z_{it} &\sim Bernoulli(p_{it}), \\ p_{it} &= \frac{1}{1+\exp(-\eta_{it})}, \end{aligned} \tag{3}$$

where p_{it} is the probability of fatality occurrence irrespective of the count. The inferences derived from this model can be resourceful in understanding the underlying process of fatality occurrence, disregarding the associated count. This could be useful to identify locations highly probable to experience any amount of fatality. We adopted the logit link function on the covariates, denoted as $\log(\frac{p_{it}}{1-p_{it}}) = \eta_{it}$. Model (3) is particularly important for understanding the risk of fatality occurrence across regions and time.

We considered six different linear predictors for η_{it} for the binary and count components and evaluated their performances. The models are given as:

$$\begin{aligned} \text{Model M1: } & \eta_{it} = \mathrm{x}_{it}^T\boldsymbol{\beta} + f_t(c_{it}) + f_{d,s}(w_{it}), \\ \text{M2: } & \eta_{it} = \mathrm{x}_{it}^T\boldsymbol{\beta} + f_{d,s,t}(w_{it}), \\ \text{M3: } & \eta_{it} = \mathrm{x}_{it}^T\boldsymbol{\beta} + f_t(c_{it}) + f_{c,s}(w_{it}), \\ \text{M4: } & \eta_{it} = \mathrm{x}_{it}^T\boldsymbol{\beta} + f_{c,s,t}(w_{it}), \\ M1\_M2: & \eta_{it} = \mathrm{x}_{it}^T\boldsymbol{\beta} + f_t(c_{it}) + f_{d,s}(w_{it}) + f_{d,s,t}(w_{it}), \\ M3\_M4: & \eta_{it} = \mathrm{x}_{it}^T\boldsymbol{\beta} + f_t(c_{it}) + f_{c,s}(w_{it}) + f_{c,s,t}(w_{it}) \end{aligned} \tag{4}$$

Here w_{it} is the spatial/geographical coordinate where the event *i* in year *t* was observed, and $c_{it} = t$. $\boldsymbol{\beta}$ is the $p \times 1$ vector of linear effect corresponding to the covariate vector $\mathrm{x}_{it} = (x_{1it}, x_{2it}, ..., x_{pit})^T$, $f_t(c_{it})$ is the non-linear function for modeling the year covariate $c_{it} = t$. The covariate x_{it} is used to model the type of violence and the temperate season, as classified by the ACLED. Dummy variables were constructed to represent the different types of violent events, which include: "Violent demonstration", "Suicide bomb", "Shelling/artillery/missile attack", "Sexual violence", "Remote explosive/landmine/IED", "Non-state actor overtake territory", "Mob violence", "Grenade", "Government regains territory", "Attack", "Air/drone strike", and "Armed clash". The "Armed clash" event type was designated as the reference category. Additionally, dummy variables were created to represent the temperate seasons: "Autumn", "Summer", "Winter", and "Spring", with "Spring" serving as the reference category.

The use of the non-linear function, $f_t(c_{it})$, for the years, was motivated from Fig. 2 since the average fatality count is shown to be non-linear in time. $f_{c,s}(.)$ is the spatial effect function on a continuous spatial domain to model the continuous spatial covariate w_{it} according to the longitude and latitude where the event occurred. The spatial interaction was determined by using distances between coordinate locations, as described in Section 2 in the supplementary material. Moreover, $f_{d,s}(.)$ is a spatial effect function on a discrete (d) spatial domain, which we considered as the aggregation of events per a finite number of the administrative states of Nigeria for the spatial covariate w_{it}. That is, for any administrative state with label *k* ($k = 1, 2, ..., 37$), all w_{it} geographical locations that lie within the administrative region receive a label *k*. In the discrete spatial model, the spatial interaction was determined using the contiguity of the administrative states, as illustrated in Section 1 in the supplementary material. $f_{d,s,t}(.)$ is a spatio-temporal effect function on a discrete spatial domain, and $f_{c,s,t}(.)$ is the equivalent spatio-temporal model on a continuous spatial domain. The use of spatial functions was motivated by the evidence of spatial autocorrelation is the occurrence and prevalence of fatality in the country as shown in Fig. 2. This evidence is also supported by the estimated Moran I value 0.052 (*p* value: 0.000), which suggests significant positive spatial autocorrelation. The discrete and continuous spatial domains were chosen to investigate the impact of reporting bias. That is, in a situation where the reporting longitude and latitude coordinate is a deviation from the true coordinates due to measurement and reporting errors, using a spatial model on a continuous spatial domain may be biased. A way to mitigate this problem is to group the reporting spatial coordinates according to administrative regions, such as states, and then model the data using a spatial model on a discrete domain. In this way, the reporting or measurement bias is minimized.

Models M1 and M3 separate the temporal component from the spatial component and therefore model them independently. Whereas, models M2 and M4 considered the modeling of the spatial and temporal interactions. In this application, x_{it} is the variable that represents the temperate season and event type and w_{it} identifies the spatial location where the crime that led to y_{it} count fatalities was committed. The spatial models $f_{d,s}(.)$, $f_{c,s}(.)$, $f_{d,s,t}(.)$, $f_{c,s,t}(.)$, and the non-linear function on time $f_t(.)$ are unknown; however, the spatial models are approximated through a Gaussian Markov random field over a spatial domain $\mathcal{G}$, which represents Nigeria's territory in this application, and the non-linear model in time is approximated using an auto-regressive model of order 1.

To explicitly define the spatial effect functions, let $\mathrm{w}_t = (w_{1t}, ..., w_{nt})^T$, we specified $f_{d,s,t}(\mathrm{w}_t) \approx \mathrm{C}_t\boldsymbol{\gamma}_t$ and $f_{d,s}(\mathrm{w}_t) \approx \mathrm{C}_t\boldsymbol{\delta}$, where C_t is an $n \times 37$ binary matrix that links the 37×1 spatial effect parameter vector $\boldsymbol{\delta}$ and 37×1 spatio-temporal effect parameter vector $\boldsymbol{\gamma}_t$ at time *t* to the response variable. The major difference between these two functions is that $\boldsymbol{\gamma}_t$ varies with time whereas $\boldsymbol{\delta}$ does not. The variability in time helps to capture the temporal evolution of the spatial effect. We adopted the autoregressive model of order 1(AR1) for the temporal aspect of $\boldsymbol{\gamma}_t$, which is given as $\boldsymbol{\gamma}_t = \rho\boldsymbol{\gamma}_{t-1} + \boldsymbol{\epsilon}_t,$ where $\boldsymbol{\epsilon}_t$ is a vector of the error term. Similarly for the continuous spatial domain, the spatial effects $f_{c,s,t}(\mathrm{w}_t)$ and $f_{c,s}(\mathrm{w}_t)$ are approximated using a finite element method (FEM) on a mesh that captures the observed locations of violent events on the Nigerian map[18]. These effects are approximated using $f_{c,s,t}(\mathrm{w}_t) \approx \mathrm{A}_t\boldsymbol{\lambda}_t$ and $f_{c,s}(\mathrm{w}_t) \approx \mathrm{A}_t\boldsymbol{\vartheta}$, where A_t is a deterministic and known basis matrix obtained from a piecewise linear basis function linking the parameters to the response variable. The row of matrix A_t corresponds to the data points at time *t* and the column corresponds to the vertexes of the triangular mesh (see the supplementary material for more details). Additionally, $\boldsymbol{\lambda}_t = \rho\boldsymbol{\lambda}_{t-1} + \boldsymbol{\epsilon}_t$. The complete details of the theoretical formulation of the discrete and continuous spatial and spatio-temporal models are included in the supplementary material. In addition, details of the non-linear function in time, f_t, is also included in the supplementary material. We compared these models and adopted the most adequate for inference.

Estimation

We adopted the Integrated Nested Laplace Approximation (INLA)[19] to facilitate the estimation of the marginal distribution of the model parameters in R[20]. For the discrete spatial model in `R-INLA`, we adopted the Besag ("besag") model. For the continuous model, we adopted the SPDE with a mesh constructed using the `inla.mesh.2d()` function in `R-INLA` with parameters `max.edge = c(2, 2)` and a `cutoff =`

`0.1`. A PC-prior distribution was assigned to the SPDE range parameter $r = \sqrt{8\nu}/\kappa$ for fixed $v = 1$ such that $P(r < 1.38) = 0.95$ and for the marginal variance is $P(\sigma^2 > 10) = 0.95$. We chose 1.38 because it is common for violent events to be contained in a specific administrative state and only cross borders with low probability say. In Nigeria, the largest state (Niger) is about 74,363 km^2. Assuming the region is round, the radius from the center is $153.82 = \sqrt{74{,}363/\text{pi}}$. Converting to degree latitude, $1.38 = 153.82/111$. Other hyperparameters, such as those for the linear effect $\boldsymbol{\beta}$ were assigned `R-INLA` default parameters, which are flat priors, and $\rho = 2(\exp \vartheta/(1 + \exp \vartheta)) - 1$ and ϑ is assigned a univariate Gaussian distribution with mean 0 and precision 0.15. For the non-linear model of time, we assumed the autoregressive model of order 1, denoted in `R-INLA` as "$ar1''$.

Suppose for a given model (M1, M2, M3, or M4), $\mathcal{X}$ is the vector of parameters of the main effect and $\boldsymbol{\theta}$ is the vector of hyperparameters, and the combined vector $(\mathcal{X}, \boldsymbol{\theta})$ is assigned a joint prior distribution $g(\mathcal{X}, \boldsymbol{\theta})$ and marginal prior distribution $g(\pi)$. Then the posterior distribution is given as

$$f(\mathcal{X}, \boldsymbol{\theta}, \pi \mid \text{y}, .) \propto \prod_{i=1}^{n} \prod_{t=1997}^{2021} P_0(y_{it} \mid \boldsymbol{\theta}, \mathcal{X}, \pi) g(\mathcal{X}, \boldsymbol{\theta}) g(\pi), \tag{5}$$

and the marginal posterior distribution of $\mathcal{X}$ is obtained by integrating out $\boldsymbol{\theta}$ from the joint posterior distribution, while the marginal posterior distribution of $\boldsymbol{\theta}$ is obtained by integrating out $\mathcal{X}$ from the joint distribution. `R-INLA` does these integrations smartly and numerically. For details see Lindgren et al. and Egbon et al.[18,21].

Correlates of socioeconomic factors with violent event fatalities
We investigate the correlation between fatalities due to violent events and socioeconomic factors of individuals within the country. To accomplish this, we sourced data from the Nigeria Malaria Indicator Surveys (NMIS) conducted in years 2010, 2015, and 2021. The data are freely available upon request from The Demographic and Health Surveys (DHS) Program (https://dhsprogram.com/). Besides collecting information about malaria across various geographically defined clusters in the country, the surveys also collect data on demographic and socioeconomic variables of women of reproductive age, which are of interest in this work. Details about the data collection procedure are found in the NMIS technical report[22]. The enumeration cluster locations are marked by their longitude and latitude coordinates, which are spatially buffered to ensure the anonymity of the respondents. We extracted socioeconomic and geographical variables, including wealth quantile, education level, area of residence, and geopolitical region for individual respondents, leading to a total of 21,766 respondents.

It is important to note that the violent event fatality data from the ACLED (see section "Data") and socioeconomic data from NMIS have spatial location mismatches, meaning that they do not share identical spatial locations. To address this discrepancy, we computationally integrated the fatalities from the 2010, 2015, and 2021 ACLED datasets with the 2010, 2015, and 2021 NMIS datasets by linking each violent event location to the nearest NMIS cluster. This process involved first identifying the nearest NMIS enumeration cluster to each violent event recorded in the ACLED dataset for a given year. Then, the observations of the socioeconomic and geographical variables from that cluster for the same year were assigned to the violent event location, providing contextual information about the surrounding environment. Thus, respondents in a specific NMIS cluster are linked to the fatality counts the cluster was assigned. The distance between the nearest NMIS cluster locations to violent event locations in the datasets ranges from 0.095 to 96.788 km. This integration process enabled us to associate each fatality count per violent event with the relevant socioeconomic covariates in the NMIS datasets. We then fit a zero-inflated model as defined in Eq. (2).

Result
Model adequacy
Table 2 displays the adequacy measure of the competing models using the Deviance Information Criterion (DIC) and Watanabe-Akaike Information Criterion (WAIC). The results indicate that the continuous spatio-temporal model outperformed the discrete spatio-temporal model, as evidenced by the significantly lower DIC and WAIC values of the continuous models compared to the discrete models. This suggests that the SPDE approach effectively reduces the impact of possible reporting bias in pinpointing the exact locations of events. This improvement may be attributed to the use of mesh triangulation, which divides the study area into smaller non-overlapping polygons, as opposed to the discrete approach that relies on administrative boundaries. Among the continuous spatio-temporal models, model M3∪M4 stands out with the lowest DIC and WAIC values, making it the most suitable model among the contenders. This model incorporates both spatial and temporal

		Discrete spatial domain			Continuous spatial domain		
Fatality		M1	M2	M1 ∪ M2	M3	M4	M3∪M4
Binary	DIC	15,608.13	15,615.15	15,457.06	15,416.09	15,301.08	15,251.93
	WAIC	15,608.16	15,626.93	15,460.64	15,410.43	15,298.07	15,244.09
Count	DIC	104,185.90	81,550.42	81,774.17	87,403.31	67,648.40	67,275.71
	WAIC	647,009.80	387,512.40	467,475.70	333,873.5	188,936.00	187,784.40

Table 2. Model adequacy.

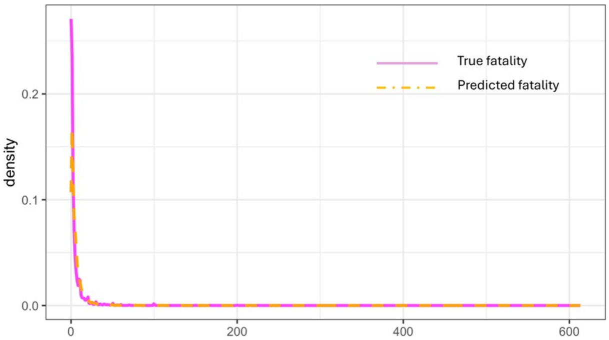

Fig. 3. Density of the posterior predicted fatality counts overlayed on the observed fatality counts.

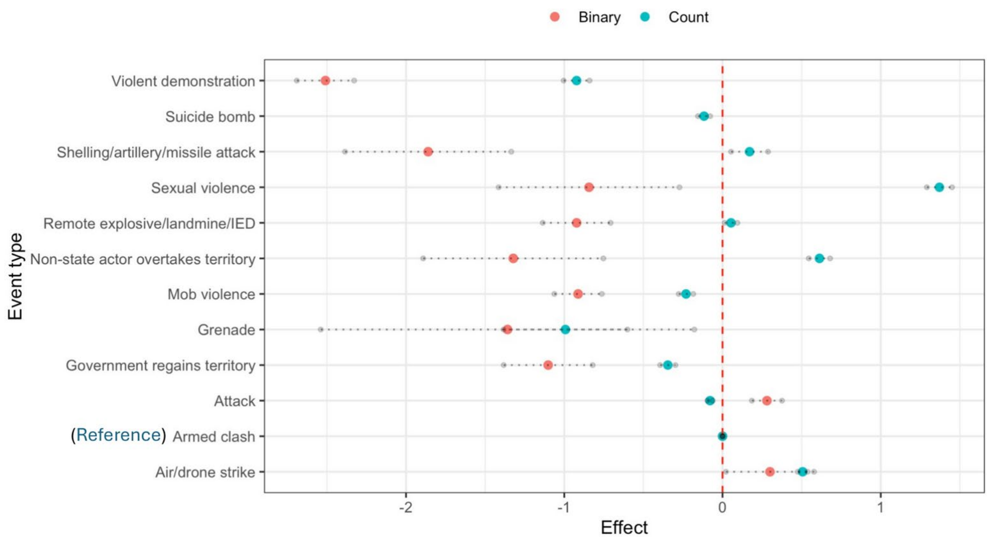

Fig. 4. Posterior mean of the effect of event types on fatality occurrence (binary) and counts. Event types with a non-inclusion of zero in their credible intervals are significant. '*Reference*' here indicates that the posterior means of the other event types show whether the fatalities caused by those events are higher (+ve values) or lower (−ve values) compared to those caused by *Armed clash*.

interactions, while also capturing time in a non-linear fashion. Furthermore, Fig. 3 shows the density of the posterior predictive counts overlayed on the observed fatality counts used in the parameter estimation. The overlap provides compelling evidence of the model's adequacy and reliability, except for the peak at zero in the observed fatality count.

Statistical inference

Henceforth, the results obtained from the best model are presented. The developed model helps quantify how each covariate contributes to the fatality counts in Nigeria. The posterior mean and credible interval for the zero-inflated parameter π is 0.184 (CI 0.176, 0.193). This result implies that $1 - \pi = 81.6\%$ of violent events in Nigeria are expected to lead to fatality.

The effect of event types on fatality

Figure 4 presents the parameter estimates of the event types in both model components, showing the posterior means and 95% credible intervals. The descriptive table of the event and fatality counts are shown in Table 1 in the supplementary material. We used the *Armed clash* event type as the reference category, meaning that the posterior means of the other event types indicate whether the fatalities caused are higher or lower compared to those caused by *Armed clash* events. Specifically, a higher (lower) posterior mean corresponds to a greater (fewer) number of fatalities compared with *Armed clash* event. The non-inclusion of zero in the credible interval is used to judge the significance of the estimates. A positive effect means the occurrence of such violent event type increases the likelihood of fatality and a negative effect indicates a decrease in the likelihood. Surprisingly from the figure, *sexual violence* significantly has the highest effect on fatality counts compared with the reference category (armed clash). This could be attributed to sexual exploitation that often characterizes the most violent events in the country, where women and children are often abducted and in some cases, forcefully married off to the actors. For instance, the Human Rights Watch reported that approximately 200–300 women and children were abducted from Yelwa town in Plateau State during a religious-based violence incident in 2004 where most of these individuals were subjected to repeated acts of sexual violence by their captors (*ACLED report*). Similar cases have been reported in various parts of the countries at different times, especially in the northeast region plagued by Boko Haram extremists[23,24]. Moreover, the findings indicate that *shelling/artillery/missile attack, remote explosive landmine/IED, non-state actor overtake territory, and airborne strike* have significantly higher effects on fatality count when compared with the reference, but the other event types have lesser effects on fatality count. For the binary case, only estimates for *attack* and *air/drone strikes* are significantly higher than the reference. This means that fatalities due to these two events occur more frequently when compared with armed clashes, but fatalities resulting from the other events occur less frequently.

The effect of temperate season on fatality
Table 3 presents the estimates for the four temperate seasons on the fatality count and occurrence in Nigeria. The Table shows the posterior means and 95% credible intervals. The spring season (*March, April, and May*) was set as the reference category. Thus, all estimated effects are compared with the reference. The results show that the Summer period (*June, July, and August*) has significantly fewer fatality counts when compared with the base category. However, Autumn (*September, October, and November*) and Winter (*December, January, and February*) have significantly higher fatality counts when compared with Spring. For the binary component, fatality occurrence is lower in the Autumn and Winter periods when compared with Spring, whereas it is not significantly different in Summer compared with Spring.

The spatio-temporal patterns of fatality
Figures 5 and 6 present the maps of Nigeria showing the posterior means for the spatio-temporal effect during the twenty-five-year period, respectively for the fatality occurrence (binary component) and fatality count (count component) after adjusting for event type and temperate seasonality. The corresponding posterior standard deviations are shown in Fig. 1 in the supplementary material. The posterior mean and credible interval for the temporal correlation parameter ρ is $0.657\,(0.593, 0.711)$, indicating that fatality due to violent activities in a given year strongly and positively depends on events during the immediate past year.

In Fig. 5, the estimate represents the projected posterior mean of the estimated spatial effect on new spatial location w' from the binary model, which is linked to the probability of fatality occurrence across the country over time through the logit function. A higher effect indicates a greater likelihood of fatality in that region, regardless of the season or type of violent event. The projected posterior mean of the spatial effects $\hat{f}_{c,s,t}(\mathrm{w}'_t)$ on new spatial locations shown in Fig. 5 were obtained using the definition $\hat{f}_{c,s,t}(\mathrm{w}'_t) = \mathrm{A}'_t\,\hat{\boldsymbol{\lambda}}_t$, where w'_t is the new spatial locations formed from a fine grid over the Nigerian map, and A'_t is the corresponding projection matrix whose column corresponds to the mesh nodes and rows corresponds to the new locations. $\hat{\boldsymbol{\lambda}}_t$ is the estimated vector of the latent parameters of the mesh nodes in the binary component of the model. Between 1997 and 2001, fatality occurrences due to violent events were most common in states bordering the North-West and North-East geopolitical zones, including Bauchi, Kaduna, Kano, Jigawa, and Plateau in the northern region. Similarly, in the southern states, Edo, Delta, Anambra, Ondo South, and Kogi South experienced high fatality occurrences. This trend began to decline from 2002 to 2006. From 2007 to 2011, there was a shift in fatality occurrence dynamics, with a concentration in the northern and middle belt regions, particularly in 2011. This pattern intensified from 2012 to 2021, spreading towards the south, with notably higher fatality occurrence in Cross Rivers and neighboring states in 2017. However, in the last three years of the study period (2019-2021), there was a slight decrease in prevalence, although fatality occurrence remained high in the North-Eastern and North-Western states such as Kebbi, Sokoto, Zamfara, and Niger. Overall, the fatality occurrence had a deep dive from 2003 to 2009 during which the country experienced the least frequency of fatality occurrence due to violent events, and nearly all the states benefited from this pattern over these years. However, it became quickly complicated, and fatality occurrence soared in 2011 beginning from the northeast region and spreading far west and south until the end of the study period.

Figure 6 shows the projected posterior mean of the estimated spatial effects, which is directly linked to the likelihood of fatality counts through the log link function. Similar to the binary component, the projected spatial effect $\hat{f}_{c,s,t}(\mathrm{w}'_t)$ on the new spatial locations w'_t formed from a fine grid across the Nigeria map is obtained from the relation $\hat{f}_{c,s,t}(\mathrm{w}'_t) = \mathrm{A}'_t\,\hat{\boldsymbol{\lambda}}_t$, where $\hat{\boldsymbol{\lambda}}_t$ is a vector of the estimated mesh node parameter obtained from the count model component. Regions with elevated values indicate a higher number of fatalities per violent event in those areas. The results reveal a steady and gradual increase in fatality count per event from 1997 to 2001, primarily concentrating in Kaduna, parts of Plateau, Nassarawa, Bauchi, and Taraba in the northern part of the country. During the years 1999 and 2000, higher fatality counts per event were observed in the

	Count			Binary		
Season	Mean	2.5% CI	97.5% CI	Mean	2.5% CI	97.5% CI
Spring	Reference					
Autumn	0.062	0.041	0.083	−0.204	−0.319	−0.089
Summer	−0.085	−0.105	−0.064	−0.102	−0.212	0.007
Winter	0.072	0.052	0.091	−0.132	−0.240	−0.024

Table 3. Effect of temperate season on fatality.

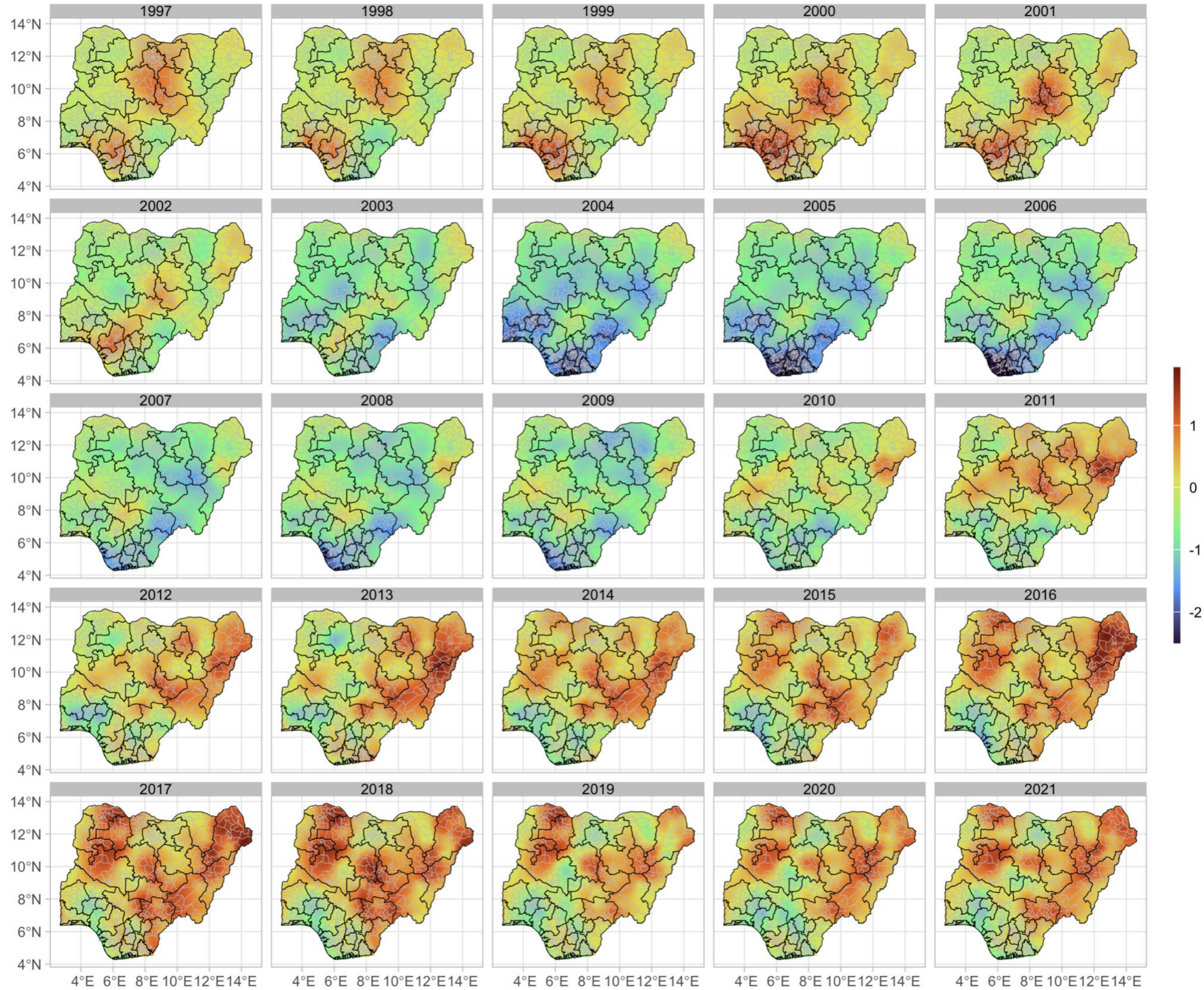

Fig. 5. The projected posterior mean of the spatio-temporal effect $f_{c,s,t}(\mathrm{w}'_t)$ across the entire spatial region for the binary component, computed using $f_{c,s,t}(\mathrm{w}'_t) = \mathrm{A}'_t\hat{\boldsymbol{\lambda}}_t$, where $\hat{\boldsymbol{\lambda}}_t$ represents the estimated spatio-temporal parameter derived from the binary component of the model. State and local government administrative boundaries were overlaid on the projected map to provide geographical context. Regions with higher values indicate a relatively greater likelihood of experiencing fatalities due to violent events. This figure was generated by the authors using the ggplot2 package (version 3.5.1) in R version 4.4.1.

southwest, parts of the south-south, and southeast regions of the country. The major states affected in the South include Edo, Lagos, Ondo South, Delta, Anambra, Akwa Ibom, and Cross Rivers. In particular, between 2000 and 2002, there were some concentrations of high fatality count per event around Kaduna, spreading to parts of the neighboring states. Beyond this period, the count per event declined rapidly through 2007. In 2008, the fatality count per event increased in the border areas shared by Kaduna, Plateau, and Bauchi. By 2009, the count per event rose in the border regions shared by Edo, Delta, Anambra, and Kogi, but decreased in other areas except Borno. From 2010 to 2015, the results show that the fatality count per event surged in most states in the Northeast and North Central regions, including Borno, Adamawa, Taraba, Benue, Nassarawa, and the shared border between Zamfarawa, Kaduna, and Katsina, while remaining low in the southern states, but beyond this period the intensity of the fatality count per event appear to decline across the country.

Figure 7 shows the posterior probability of fatality whenever a violent event occurs, and is marginalized across time within each state. Regions with high probabilities indicate areas with frequent and high numbers of fatalities per violent event. In overview, the northern states are more susceptible to fatality compared with the southern states. The states with a probability of a fatality above 0.6 include Borno, Adamawa, Taraba, Plateau, Nassarawa, Kaduna, Zamfara, and Sokoto states, and states below 0.5 probability of fatality per violent event include Ondo, Bayelsa, Federal Capital Territory, Oyo, Osun, Ekiti, and Rivers.

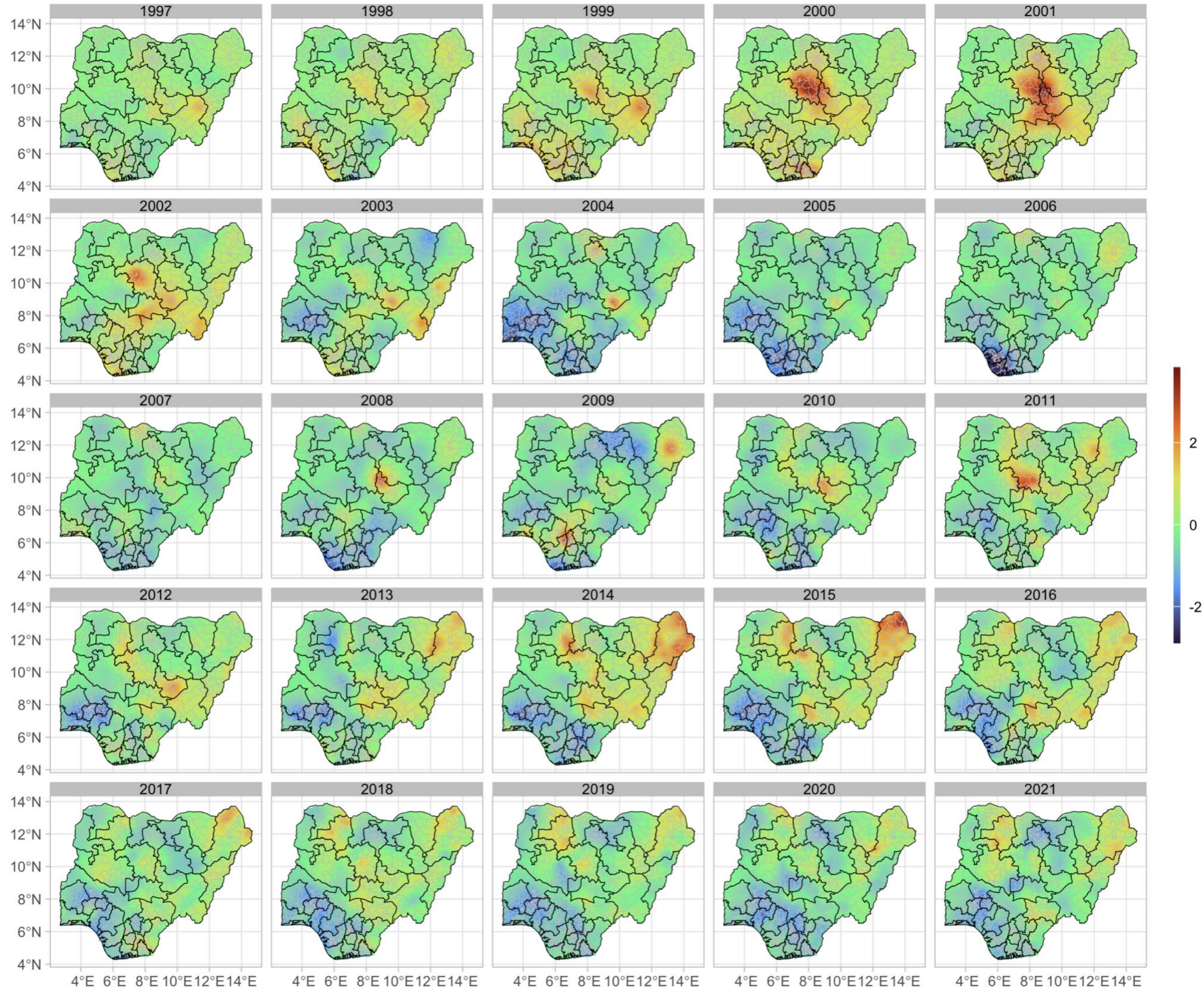

Fig. 6. The projected posterior mean of the spatio-temporal effect $f_{c,s,t}(\mathrm{w}'_t)$ across the entire spatial region for the count component, computed using $f_{c,s,t}(\mathrm{w}'_t) = \mathrm{A}'_t\hat{\boldsymbol{\lambda}}_t$, where $\hat{\boldsymbol{\lambda}}_t$ is the estimated spatio-temporal parameter for the count component. State and local government administrative boundaries were overlaid on the projected map to provide geographical context. Regions with higher values indicate a relatively greater likelihood of experiencing more fatality counts per violent event. The figure was generated by the authors using the ggplot2 (version 3.5.1) package in R version 4.4.1.

The correlates of socioeconomic factors on fatality

Figure 8a shows the spatial location mismatch between the NMIS enumeration cluster locations and the violent event locations. The figure shows the spatial coordinate mismatch between the violent event locations and the NMIS enumeration cluster locations. Figure 8b reports the estimates of the regression coefficients and credible intervals for the socioeconomic and geographical covariates on fatality counts per event. Asterisks (*) indicate significance at the 5% level compared to the reference category. The results show that households in the richest wealth quantiles are significantly less likely to experience fatalities compared to the poorest households, which serve as the reference category. This suggests that poverty is a significant risk factor for violent event fatalities. Additionally, individuals residing in the North West, North East, and North Central regions have significantly higher odds of fatality compared with the South East, which serves as the reference region. In contrast, the South West region exhibits lower odds of experiencing fatalities when compared with the South East. This indicates regional disparities in vulnerability to violence or fatal events. Regarding education, individuals with higher levels of education are significantly less likely to experience fatalities compared with those with no formal education. This suggests that education may also play a protective role in reducing vulnerability to fatal events. The result showed that the place of residence is not significant between urban and rural settlements.

Discussion

This work presents a fully Bayesian spatiotemporal statistical modeling and analysis of fatalities due to violent events in Nigeria. The aim was to quantify and understand the pattern of fatalities across Nigeria by

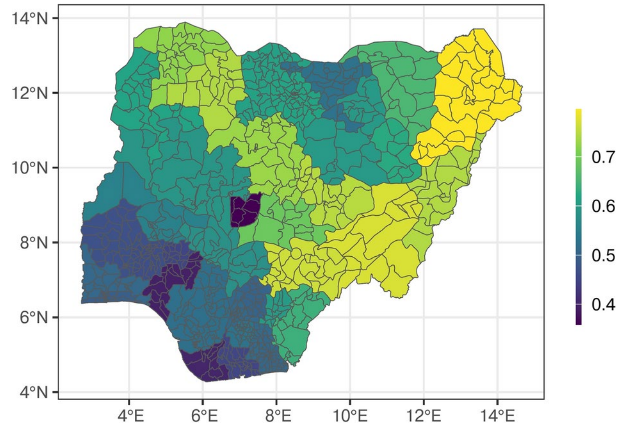

Fig. 7. Posterior predictive probability $\hat{p}_{it}$ of fatality occurrence, averaged across all years. The probabilities were obtained through the evaluation of the linear predictor $\hat{\eta}_{it}$ based on the estimated parameters and the covariates and taking the inverse logit. The local government administrative boundary was overlaid on the projected map to provide geographical context. Places with higher values indicate a relatively greater probability of experiencing fatalities from violent events. The figure was generated by the authors using the ggplot2 (version 3.5.1) package in R version 4.4.1.

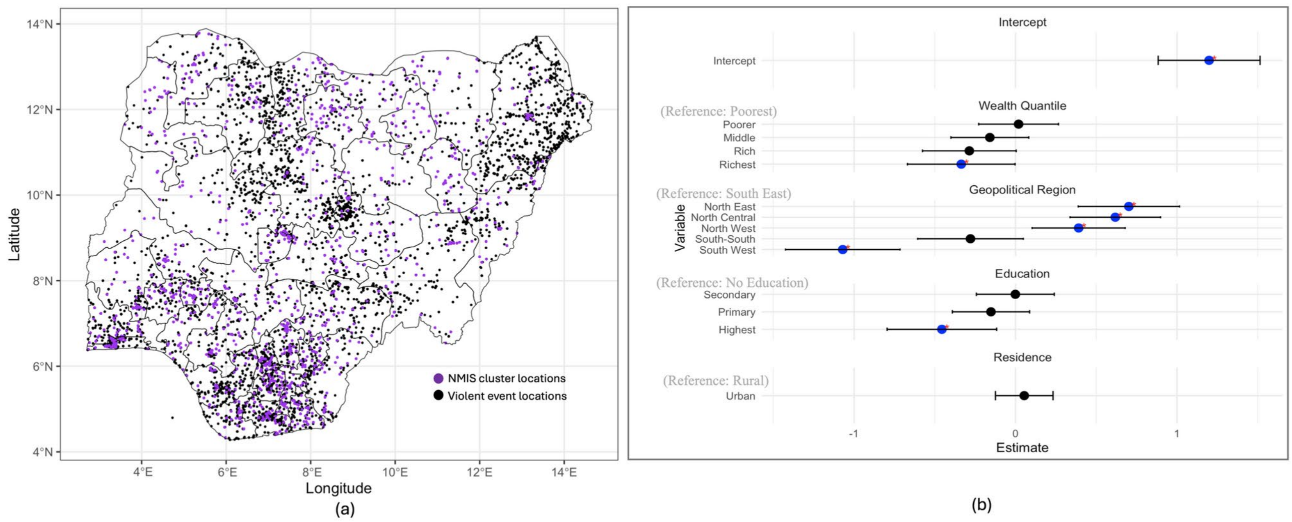

Fig. 8. (**a**) Locations the NMIS enumeration cluster locations and violent event locations, revealing the mismatch in the two independently observed data sets. (**b**) The estimated effects of socioeconomic/geographical factors on fatality counts.

simultaneously tracking the dynamics in space and time from 1997 to 2021 to determine the locations exposed to a high level of danger in the country and determine the risk factors, which could be useful for policy responses. Spatial and spatio-temporal statistical models with continuous and discrete spatial domains were investigated, assuming a zero-inflated Poisson distribution for the fatality counts and using the population of people in each administrative state as the exposure. In addition, a Bernoulli response model was also leveraged in the additive model to account for the probability of occurrence and non-occurrence of fatality per violent event. Furthermore, we investigated the connection between fatality counts and socioeconomic and geographical covariates, such as wealth index, level of formal education, place of residence, and geopolitical region, which was accomplished by integrating ACLED violent event data and socioeconomic and geographical covariates in NMIS survey datasets. Findings suggest that using the SPDE model for the continuous spatial domain outperformed the discrete spatial model in the discrete domain. This could be attributed to the use of mesh triangulation, which divides the spatial domain into smaller non-overlapping polygons, as opposed to the discrete approach that relies on administrative boundaries.

The featured violent events that demonstrate high influence on fatalities in Nigeria are sexual violence, non-state actors overtaking territory, air or drone strikes, remote explosions or landmines, shelling, and artillery or missile attacks. Findings from the results showed that sexual violence had an alarming contribution to fatalities, which was estimated to be the highest and more than twice the contribution of air or drone strikes. Sexual violence could occur concurrently with other types of violent events such as being a by-product of conflicts between armed actors across regions or inter-ethnic groups within the country[25]. Despite the "state of emergency" declaration against gender-based violence in the country[26], the incidence rate is still high, causing a severe public health burden. Swift and specific actions by stakeholders are required to protect the vulnerable groups across the country thereby mitigating sexual violence, particularly during violent events. The role of enlightenment in the fight against sexual violence cannot be overemphasis because the victims often fail to report violence due to shame, guilt, embarrassment, concern about confidentiality, and the fear of tarnishing the family's name[27].

The findings from the results also show that "non-state actors overtaking territory" event type significantly increases fatality. This outcome is anticipated, as such violent events are typically executed by heavily armed non-state groups like Boko Haram or armed bandit groups, who in some cases, subdue government forces during conflict, yielding to them a temporal monopoly of force within the subdued territory[28]. Household members in the captured territory could lose their means of livelihood, be at a socioeconomic disadvantage, starvation, and possibly death[29]. Thus, preventive measures should be set up as it is costlier to regain territory from terrorist groups. A more realistic measure to prevent capturing is to devise a strategy that targets the capabilities of the terrorist groups and cripples their source of funding[30].

Furthermore, we found from the results that airstrikes, remote explosions, and missile attacks significantly increase fatality in the country. These violent events often occur during clashes between governmental forces and terrorist groups, and civilian causalities are inevitable in traditional conflict zones. Conflicts involving such events could lead to loss of farmland, means of livelihood, and properties thereby causing a long-term detrimental effect on the communities and psychology of surviving household members. A regulatory mechanism on the use of drone warfare to combat terrorist groups may need to be enforced to ensure safe and secure operations during conflicts, and protection for the affected communities[31]. As for the lower fatality occurrence obtained for disruptions of the use of weapons by terrorists or bandits and the government regaining territory could be expected as the mentioned events do occur to avert fatality due to violent events.

This study identified significant temperate seasonal discrepancies in the pattern of fatalities from violent events after adjusting for event types and spatio-temporal effects in the modeling. From the results, fatalities due to violent events were found to be higher during the Autumn and Winter seasons but lower during Summer when compared with the Spring season. These findings could be attributed to weather conditions, which play an essential role in people's daily life activities[32–34]. During dry seasons or drought, herders often have little to feed their livestock and sometimes resort to feeding their animals with crops planted by farmers and this causes conflict between the farmers and herdsmen leading to human rights abuses and avoidable loss of lives and properties[35]. Previously, herdsmen migrated to the country's Benue valley during the dry season to fend for their animals and return to the north during the rainy season, but many of them are now settling and competing for the scarce resources with the locals, resulting in violent conflict with potentials of spilling into ethnic and religious clashes[36]. The often conflict caused by bandits in the northwestern part of the country has also been attributed to climate change, environmental-induced migration, and contested land grazing rights among others[37].

Findings from the result showed significant heterogeneity in fatality due to violent events across years and locations in the country. Overall, violence has evolved through time, and the fatalities resulting from these events vary significantly across the country. These results can be due to several complex and interrelated factors[38,39]. The result obtained identified states in the North-Central and North-East as the most exposed regions to fatality in Nigeria. This finding corroborates with the report of the National Bureau of Statistics, Nigeria[40].

Over the years, Nigeria has been plagued by different conflicts and unrest perpetrated by non-state actors, with segments of the countries experiencing their share for various reasons. The seemingly common denominator across the country is clashes due to differences in values and beliefs, claims to scarce resources including land, power, and status[41]. The concentration of fatality around Kaduna and its neighboring states up to around 2022 could be attributed to an ethno-religious crisis that started with land dispute and agitations toward the introduction of Sharia laws before it degenerated into full-blown crises along religious lines because a segment of the state are predominantly Christians while the others are mostly of Islamic group[41,42].

Across the oil-rich Niger Delta, local resistance to repressive state institutions arising from the neglect, environmental degradation due to oil exploration and persistent corruption, and deprivation of the people's rights occasioned by the unfriendly ecologically practices of the multinational oil companies could explain the conflict and violence that persisted in the region[43]. The youth leading the resistance became extremely aggressive. It resorted to vandalizing pipelines, illegal oil bunkering, armed violence, hostage taking, kidnapping, and other violent and illegal activities as means of expressing their grievances to the state and oil companies[43–45]. Collectively, these actions lead to a severe loss of lives and properties over a prolonged period. Still, recent government intervention through the offer of amnesty and post-conflict peace-building efforts has brought violent events to minimal levels in the regions vobi2014oil.

The north-east of the country had its share of violent events perpetrated by the Boko Haram insurgence that began around 2009, generating many security concerns. The insurgence started as religious-inspired violence with the group displaying fierce opposition to anything "Western education". Still, it flared up due to a deficient political system that has bred corruption, poverty, and underdevelopment across the country but particularly in the northern regions[47,48]. The insurgency group expanded their activities through the frequency and intensity of attacks, strategies deployed, target selection, and geographical scope[47]. What started in Borno state soon spread to other states in the northeast and to the neighboring countries because of the strong link the actors had with some international terror groups. Across the north-west where armed bandits are more prevalent, the proliferation of arms and poor local governance, coupled with inadequate military or police presence in the rural areas expose the local population to severe attacks from the bandits[49,50]. Furthermore, the central part of the country has witnessed farmer-herder clashes with significant spatial clustering around the Middle Belt, particularly in Benue state[51]. Collectively these different armed groups and conflicts put most of Nigeria at risk of wanton onslaught and destruction of properties.

The findings from the results also indicate that households in the wealthiest quantiles and those with members possessing the highest levels of education are significantly less likely to experience fatalities compared to the poorest households and those with members lacking formal education. This suggests that poverty and lack of education serve as risk factors for fatal events. Wealthier households may have greater access to resources, healthcare, and protective measures, thereby reducing their vulnerability to violence and other fatal incidents. Policymakers should consider focusing on poverty alleviation programs and enhancing resource access in the most disadvantaged communities, while also prioritizing education as a long-term strategy to mitigate fatalities and strengthen societal resilience[52].

While the adopted model in this work is robust, it has some limitations. Specifically, one of the limitations is that we employed an auto-regressive model of order 1 (AR(1)) to model temporal dependencies within the proposed spatiotemporal framework. While this approach effectively captures short-term autocorrelation, it does not account for more complex dependencies that could be better represented using ARMA or ARIMA models with data-driven order selection. Future work could explore these alternative specifications to enhance model flexibility and interpretability in capturing varying temporal patterns. Another limitation is the data reporting bias. Despite the adoption of mesh triangulation in the analysis, the bias associated with reporting violent event locations may not be fully mitigated. Thus, future work can develop a more robust method to adjust for the data reporting bias. Lastly, the method employed to integrate the NMIS and ACLED data for quantifying the relationship between socioeconomic factors and fatality counts may have limitations. In particular, for each violent event location in ACLED data, we find the nearest NMIS enumeration cluster location and then assign the socioeconomic and geographical covariates of that cluster to the fatality counts of that violent event location. While this approach allowed for integration and analysis, it does not fully address the spatial discrepancy concerns between the two datasets. Future research could develop modeling frameworks that explicitly account for spatial mismatch to improve accuracy and reliability.

Conclusion
This study adopted a full Bayesian spatio-temporal model to estimate the pattern of fatality due to violent events in Nigeria, which could assist in the understanding of fatality dynamics and evolution. This study found statistical significance in the fatality pattern across the country. Particularly, the finding showed a North-South divide in fatality count per violent event due to violent events identifying Northern Nigeria as a more exposed region. We found existing temperate seasonality in fatality patterns, and sexual violence was the leading cause of fatality in the country. This study unveiled the seemingly unknown violent events and spatial and temporal patterns that lead to high casualties in Nigeria. An intervention program or response policy must take account of the identified factors and patterns to speed up the pace of the fight against crimes and violent events in the country. The spatiotemporal maps produced can be placed side-by-side with other public health and social problems, such as those of malnutrition, unemployment, human development index, and corruption, among others, to devise realistic and sustainable methods to improve the lives and safety of citizens.

Data availability
The datasets analyzed in this study are available in the Armed Conflict Location and Event Data Project (ACLED) repository, which can be found at https://epo.acleddata.com/data/. Also, they are available from the correspond ing author upon request.

Code availability
The `R` code used to generate the results in this work is publicly available in the GitHub repository, accessible at https://github.com/eosafu/FatalityModelNigeria. The code is also available in the online supplementary material.

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Author contributions

O.A.E. and A.M.B. conceived the study idea. O.A.E. designed the model and the computational framework.

O.A.E. and M.A.B. analyzed the data. A.M.B. and M.A.B. wrote the first draft of the paper with input from E.G., F.L., and O.A.E. All authors revised and accepted the final version.

Declarations

Competing interests
The authors declare that they have no competing interests.

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