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Research Article

Beyond Conflict Presence:
Cumulative Armed Insecurity and Childhood Stunting in Nigeria

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ABSTRACT

Background: Stunting remains a major public health challenge in Nigeria, affecting 40% of children according to the Nigeria Demographic and Health Survey (NDHS, 2024) amid persistent insecurity orchestrated by Boko Haram/ISWAP insurgency, farmer-herder conflicts, and banditry. However, much of the existing studies treat conflict exposure as a binary condition, overlooking important differences in event frequency and fatality intensity and their potentially distinct implications for child growth and development.

Aims: We aimed to assess whether cumulative conflict exposure, captured by event frequency and fatality intensity, better explains childhood stunting in Nigeria than measures of conflict presence alone.

Methods: This cross-sectional analysis used the 2024 NDHS dataset (children under 59 months = 9,410), ACLED events (2009-2025 = 73,147), and UCDP GED (1990-2025 = 8,255) as data sources. Conflict events were geocoded to NDHS clusters using 5 km, 10 km, and 50 km buffers. The frequency and intensity of conflict exposure were estimated separately and jointly using weighted cluster-robust logistic regression. Model performance for cumulative exposure versus binary presence/absence exposure was assessed using AIC, BIC, and McFadden's pseudo-R^2.

Results: Weighted prevalence of stunting was 39.1%, with the highest rate observed in the North-West at 52.4% and the lowest in the South-South at 17.9% ($p < .001$). Conflict experience also differed significantly across geopolitical zones based on both ACLED and UCDP GED indicators ($p < .001$). The adjusted result showed a significant negative correlation between higher frequency of ACLED events and stunting (AOR = 0.85, 95% CI: 0.76–0.97, $p = .012$). Overall, the findings indicate that the relationship between armed insecurity and stunting varies by the frequency, intensity, and cumulative nature of conflict exposure.

Conclusions: Insecurity involving conflict was correlated with childhood stunting, although this was context-specific, depending on how conflict was captured and what data were utilised. Frequency was a better indicator than fatality, and cumulative metrics were not superior to non-cumulative indicators of conflict. Based on this study's results, we recommend that nutrition interventions focus on regions experiencing the highest levels of insecurity and childhood stunting.

Keywords: *Malnutrition; Armed conflicts; Growth disorders; Cross-sectional studies; Nigeria*.

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1. Introduction

Armed conflict continues to be among the biggest obstacles in the pursuit of the global child health and nutrition targets, given that about 470 million children are in conflict-affected areas where the violence affects food systems, healthcare, and social protection systems (UNICEF, 2024; FAO et al., 2024). Stunting, defined as low height-for-age exceeding two standard deviations below the median in the WHO Child Growth Standards, is the best indicator of the cumulative effects of nutritional deprivation resulting from disruptions during the first 1,000 days of life (WHO, 2006; de Onis & Branca, 2016).

The relationships between conflict and stunting are of paramount importance in Nigeria because stunting continues to prevail and impacts 40% of children, according to the 2024 NDHS. The situation exists amid the backdrop of ongoing insecurity in the form of insurgency carried out by Boko Haram/ISWAP, conflicts between farmers and herdsmen, as well as banditry (Katsina, 2012).

Health effects associated with armed conflict can be extended beyond singular cases of conflict or violence. Rather, it could be that exposure occurs repeatedly through disruptions to livelihoods, food availability, access to healthcare, and other critical services. It is also noteworthy that conflict can occur frequently, yet not necessarily lethally, and vice versa, which can affect children's nutrition differently (Howell et al., 2018). Thus, treating conflict as a single exposure factor may be misleading.

There is an extensive body of literature linking armed conflict to child undernutrition. This association between conflict and the risk of undernutrition has been supported by a systematic review across Africa (Azanaw et al., 2023) as well as some studies in Nigeria (Howell et al., 2018; Makinde et al., 2023; Leao et al., 2024; Oyinwola et al., 2025) and a comparator in Colombia (Kreif et al., 2022) and India (Tranchant et al., 2014). Most studies, however, were based on a single conflict database and rarely tested whether multidimensional cumulative exposure measures are superior to simpler binary measures. Eck (2012) demonstrated that the two major geocoded conflict datasets, ACLED and UCDP GED, differ in their inclusion and coverage, making it difficult to rely on either dataset alone. Studies by Grace et al. (2022) and Ogbu et al. (2026) indicate that the type and intensity of conflict are not only about whether conflict was present or absent, but also about the intensity of its impacts, which affect nutritional risk. However, no study has yet used cumulative frequency and intensity of fatalities in multiple independent conflict datasets to explain childhood stunting as a specific outcome and formally compared this approach with the traditional binary exposure.

The importance and the gap of this study lie in the fact that treating conflict as a unidimensional exposure factor can distort children’s actual levels of insecurity and lead to ineffective intervention strategies. Thus, the present study attempts to overcome this problem by combining multiple conflict indicators with geographically precise measurements of their impact on childhood stunting in Nigeria.

This study therefore adopts the Cumulative Risk Theory (CRT; Evans, Li & Whipple, 2013) which posits that health outcomes depend on the sum of adverse exposures rather than a single event, and the UNICEF's Conceptual Framework of the Determinants of Child Undernutrition (Heidkamp et al., 2021) which argues that armed insecurity is a structural determinant operating through immediate and underlying pathways (food security, caregiving, health services) to affect chronic growth. These frameworks support the approach of treating insecurity as a cumulative geospatial exposure rather than a binary state. The objective of this study was to explore the relationship between the cumulative exposure of armed insecurity, as operationalised by conflict events frequency and fatality intensity (from ACLED and UCDP GED, respectively), and childhood stunting in the context of children living in Nigeria (age 0-59 months) and investigate if multi-source cumulative exposure indices relate to stunting more strongly than traditional binary exposure. We hypothesised that stunting prevalence and cumulative conflict exposure would each vary significantly across Nigeria's geopolitical zones, that cumulative insecurity would be significantly associated with stunting after adjustment for child, maternal, household, and geographic factors, and that cumulative exposure measures would outperform binary presence/absence measures in explaining stunting.

Objectives of the Study

One of the major objectives of this research project is to examine the association between cumulative exposure to armed insecurity and childhood stunting in Nigeria using a cumulative geospatial exposure approach which surpasses the traditional dichotomous approach to measuring conflict exposure. Specifically, the study seeks to:

1. Estimate the prevalence and spatial distribution of stunting in children aged under five years in Nigeria's six geopolitical regions using the 2024 NDHS.
2. Determine cumulative indices of armed insecurity by combining geocoded conflict events from the ACLED and UCDP GED datasets and connecting such events to the location of NDHS clusters through several spatial buffers.
3. Examine the association between cumulative armed insecurity, measured separately as conflict event frequency and fatality intensity, and childhood stunting, controlling for child, maternal, household and geographic factors.
4. Statistically compare, using model-fit criteria (AIC, BIC and McFadden's pseudo-R^2), whether multi-source cumulative conflict exposure indices explain childhood stunting better than conventional binary presence-based conflict exposure measures.

2. Methods

Research Design and Study Setting

This study employed a nationally representative cross-sectional design by integrating individual-level data from the 2024 Nigeria Demographic and Health Survey (NDHS) with georeferenced conflict data from the Armed Conflict Location and Event Data Project (ACLED) and the Uppsala Conflict Data Program Georeferenced Event Dataset (UCDP GED). The connection between the household survey data and the conflict events provided a means to evaluate the geospatial exposure to cumulative armed insecurity and its effects on childhood stunting. While a cross-sectional approach cannot establish a cause-and-effect relationship, it is well-suited to studying population-level correlations. The study covered all 36 Nigerian states and the Federal Capital Territory, spanning the country's six geopolitical zones. Nigeria provides an appropriate setting because of its persistently high burden of childhood stunting and the coexistence of multiple forms of armed conflict, including insurgency, farmer–herder violence, banditry, kidnapping and communal unrest.

Data Sources and Study Population

Three secondary datasets that complement each other were used. Data on child, mother, household, and anthropometric variables were drawn from the Children's Recode of the 2024 NDHS (NGKR8BFL), whereas data on the locations of survey clusters were obtained from the NDHS Geographic Dataset (NGGE8AFL). Conflict exposure was determined using data from ACLED, which considers all forms of political violence, and UCDP GED, which includes organised armed conflict (Raleigh et al., 2010; Sundberg & Melander, 2013). The use of both databases was necessary to determine conflict exposure more precisely. Data on children aged 0-59 months with valid anthropometric measures were used for analysis. In accordance with WHO guidelines, biological plausibility of height-for-age z-scores (< −6 or > +6 SD) and the observations with missing data for key variables were excluded, leaving 9,410 children for further analysis.

Sample size was estimated based on the entire population of children within the scope of the 2024 NDHS two-stage cluster sampling methodology; no power calculation was performed because this is a secondary analysis of a complete national sample. Out of 27,783 children within the Children's Recode, 18,373 children were removed because of implausible or incomplete anthropometry (z-scores for height-for-age outside ±6 SD or not measured), resulting in 9,410 children with ages from 0 to 59 months who had complete biometric information and other relevant variables; there was no drop out beyond the removal of children with missing measurement information, since it is a secondary data analysis.

Study Variables

Childhood stunting was defined as the dependent variable, including a height-for-age z-score below -2 standard deviations (SD) of the WHO Child Growth Standards (WHO, 2006). The explanatory variable considered was the cumulative exposure to armed insecurity. It is defined by the counts of conflict events and deaths in the ACLED and UCDP GED databases. Haversine distances were estimated for each NDHS survey cluster relative to each documented conflict event. The count of events and deaths was taken within 5-km, 10-km, and 50-km buffers. The 10 km buffer was selected as the main buffer because it could include both spatial error and DHS GPS displacement without sacrificing spatial accuracy (Burgert et al., 2013; Altay et al., 2025). Additionally, a buffer distance sensitivity analysis was performed. The UNICEF Conceptual Framework was used to fit models based on the child's sex, age, the mother's level of education, household wealth (in quintiles), and the geopolitical zone of residence.

Construction and Specification of Cumulative Conflict Exposure

Cumulative conflict exposure was calculated separately for ACLED and UCDP GED. For each NDHS cluster, the number of geocoded events within 5-, 10-, and 50-km radii of the cluster's displaced GPS location was summed. The exposure to cumulative conflict was obtained individually for ACLED and UCDP GED by summing the number of geocoded events within 5-, 10-, and 50-km radii around the GPS location of each NDHS cluster. The frequency of events was defined as the number of conflict events recorded in each buffer during the entire time frame covered by each dataset (ACLED, from 2009 to 2025; UCDP GED, from 1990 to 2025). The fatal intensity was defined as the sum of the best-estimate number of conflict-related deaths occurring within the same buffers. Both variables, frequency of events and fatal intensity, were included in the primary regression specification. Both variables were scaled to z-scores before regression analysis. Hence, the regression coefficient represents the change in the odds of stunting resulting from a one-standard-deviation increase in the cumulative exposure to either event frequency or fatal intensity. The fatalities were counted in each buffer without further weighting by their exact distances to the cluster centre.

A 10-km buffer was used for exposure assessment. This is a greater distance than any maximum geographical displacement ever used in cluster formation for rural DHS sites, thereby minimising the risk of exposure misclassification due to geographical masking (Burgert et al., 2013; Altay et al., 2025). However, to ensure robustness, sensitivity analyses were carried out using 5- and 50-km buffers. Since ACLED and UCDP GED utilise different event definitions and inclusion criteria, events were not deduplicated between the two sources, and both were treated as independent measures of armed insecurity and included together in the model's primary specification.

Geospatial Exposure Assessment

The main methodological innovation of this study is the ability to combine data from nationally representative household surveys with two independent georeferenced conflict databases. This study quantified cumulative exposure to conflict, in contrast to traditional methods that determine exposure based on administrative units or binary presence-absence measures, using the frequency of conflicts and the intensity of conflict deaths within a spatial buffer surrounding children's residential communities. The use of both ACLED and UCDP GED also allowed for comparison of data from different conflict data sources.

Statistical Analysis

The data was analysed in Python using the packages pandas, NumPy and SciPy. Descriptive statistics gave an account of the sample used in the analysis and the prevalence of stunting. The Pearson's Chi-square test was used to compare the prevalence of stunting in the different geopolitical zones of Nigeria, while multivariate binary logistic regression models were used to analyse the association between cumulative armed insecurity and childhood stunting, with iterative reweighted least squares estimation. Given that the NDHS survey is based on a stratified/clustered sample, the regressions were run using DHS individual sampling weights (V005 adjusted for analysis) and cluster-robust standard errors (sandwich estimators) at the PSU level (V001). The survey design full adjustment that incorporates the sampling stratum variable (V023) was not performed. This methodological limitation is acknowledged.

For the 10 km buffer at the primary level, four specifications were used: (1) a frequency only model with standardised ACLED and UCDP GED event counts; (2) an intensity only model with fatality counts; (3) a frequency and intensity combination model, which included both exposure types from the two databases, and was the main specification used; and (4) the binary presence model, where an event from either database occurred within the 10 km buffer. The combination model was further run for 5 km and 50 km buffers as sensitivity analysis. To investigate whether cumulative exposure had more explanatory power than presence measures, model fitting was performed using the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and McFadden's pseudo-R^2. The results are reported as adjusted odds ratios (AORs) with 95% confidence intervals (CIs). A p-value $< .05$ was considered statistically significant. All estimates should be interpreted as associations, as the data were cross-sectional.

Ethical Considerations

The data used in this research work has been anonymised; no personal information is included. The 2024 NDHS is authorised by the National Health Research Ethics Committee of Nigeria and the Institutional Review Board of ICF International. The ethical approval was obtained from the Research Ethics Committee of the University of South Africa prior to data collection (approval number 14245). Confidentiality is ensured by redacting household identification codes and repositioning survey clusters in accordance with the DHS confidentiality protocol (Burgert et al., 2013). The datasets from ACLED and UCDP GED are open-source and contain no personal information.

Methodological Limitations

There are several cautions to be noted in this study. First, cumulative conflict exposure was calculated over the entire period recorded by the ACLED and UCDP GED databases, rather than the prenatal and early-life exposure period for each child, which should be done in future longitudinal studies to improve temporal inference. Second, changes in the cluster's spatial coordinates may cause misclassification of the exposure, but using multiple buffer distances minimises this misclassification (Burgert et al., 2013; Altay et al., 2025). Thirdly, due to the cross-sectional design of the study, causal inferences cannot be drawn, and conclusions must be made as associations. Lastly, there might still be residual spatial collinearity between conflict exposure and geopolitical areas even after controlling statistically. However, a combination of two separate conflicts, linked by fine-scale geospatial data, offers a more robust measure of cumulative armed insecurity than traditional administrative or binary conflict indicators.

Further limitations of the study are that cumulative exposure was assessed using the total exposure within each conflict dataset, rather than exposure during pregnancy and early childhood, when the risk of stunting is most sensitive to nutritional deprivation. The lack of control over exposure timing and the cross-sectional design preclude causal interpretation. The buffer-sensitivity analysis also showed that event intensity was significant only at a 50 km radius, implying that the extent of the nutritional impact of high-fatality events exceeds their event frequency.

3. Results

The findings from this study are presented in this section based on the joint analysis of the 2024 Nigeria Demographic and Health Survey (NDHS) and the Armed Conflict Location and Event Data Project (ACLED), as well as the Uppsala Conflict Data Program Georeferenced Event Dataset (UCDP GED). The findings will be presented in line with the objectives of this study, beginning with descriptive analyses of childhood stunting and cumulative armed insecurity, followed by multivariable analyses examining the association between cumulative conflict experience and childhood stunting. Graphs and figures are used to present the findings clearly. In line with scientific publication guidelines, all figures in this study are accompanied by their respective numerical data presented in tables.

Characteristics and Prevalence of Childhood Stunting

Table 1 summarises the demographic, maternal, household and geographic characteristics of the 9,410 children included in the analysis, together with the unadjusted prevalence of childhood stunting. On average, 36.6% of the children were stunted, signifying that more than one-third of the Nigerian children below the age of five years had grown stunted. The prevalence of stunting differed significantly across children of different ages, maternal educational status, wealth, residential location and geopolitical zones. This description sets the scene for the multivariate analysis to examine whether the accumulated insecure environment affects childhood stunting independent of the confounding factors. Table 1 reveals that stunting prevalence (weighted) is 39.1%, and there is significant variation in the prevalence rate across the six geopolitical zones of Nigeria, from 17.9% in South South to 52.4% in North West ($\chi^2(5, N=9{,}410) = 86$.

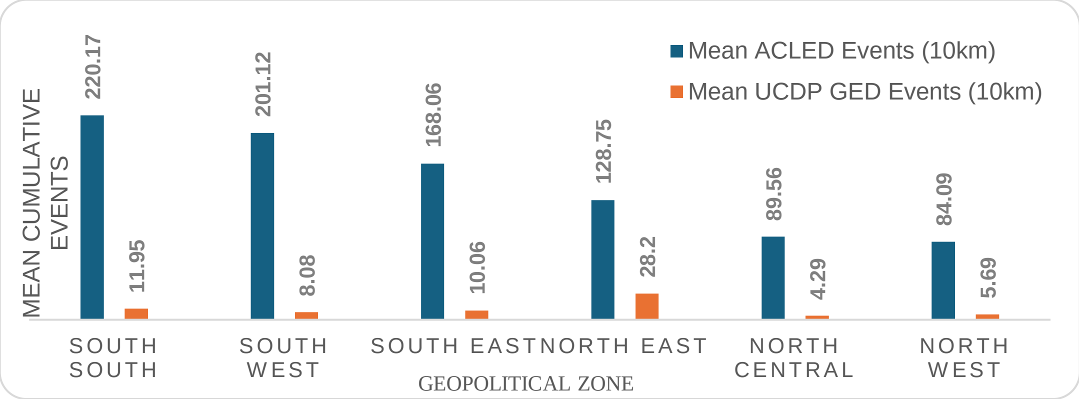
Figure 1 shows that exposure levels measured by ACLED were high in the South-South and Southwest regions, whereas those by UCDP GED were high in the Northeast regions. There was a statistically significant difference in cumulative conflict exposure in various zones according to both ACLED (Kruskal-Wallis H=1433.15, $p<.001$) and UCDP GED (H=1337.90, $p<.001$). This proves the validity of Hypothesis 2. As shown in Figure 2, stunting rates decreased with increasing ACLED exposure.

Stunting prevalence rose from 22.1% among infants aged 0-11 months to a peak of 44.3% among children aged 36-47 months (Figure 3), consistent with the well-documented first-1,000-days accumulation pattern (de Onis & Branca, 2016); this age pattern is summarised in Table 1 and is not duplicated as a separate figure.

Table 1. Characteristics and Unadjusted Stunting Prevalence, Nigeria DHS 2024 (N=9,410)

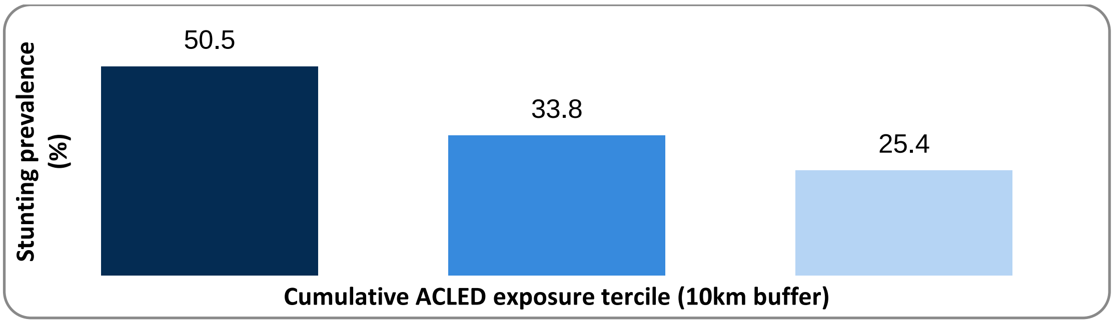
Characteristic	N	%	Stunting Prevalence (%)	p-value
Sex				
Female	4,654	49.5	36.1	
Male	4,756	50.5	42.1	<0.001
Residence				
Rural	5,403	57.4	47.4	
Urban	4,007	42.6	27.8	<0.001
Maternal education				
Higher	1,200	12.8	14.0	<0.001
No education	3,458	36.7	55.1	
Primary	1,145	12.2	40.5	
Secondary	3,607	38.3	28.8	
Wealth quintile				
Middle	1,847	19.6	40.5	
Poorer	1,709	18.2	51.7	
Poorest	2,033	21.6	55.6	
Richer	2,078	22.1	30.2	
Richest	1,743	18.5	14.8	<0.001
Geopolitical zone				
North Central	1,681	17.9	36.6	
Northeast	1,653	17.6	51.8	
Northwest	2,392	25.4	52.4	
Southeast	1,692	18.0	19.6	
South South	1,111	11.8	17.9	
South West	881	9.4	21.1	<0.001
Age group (months)				
0-11	2,032	21.6	23.3	
12-23	1,943	20.6	40.4	
24-35	1,768	18.8	46.2	
36-47	1,800	19.1	48.1	
48-59	1,867	19.8	40.1	<0.001
Total analytic sample	**9,410**	**100.0**	**39.1**	

Source: Calculations by authors based on Nigeria Demographic and Health Survey (NDHS) 2024, Children's Recode (NPC & ICF, 2025).



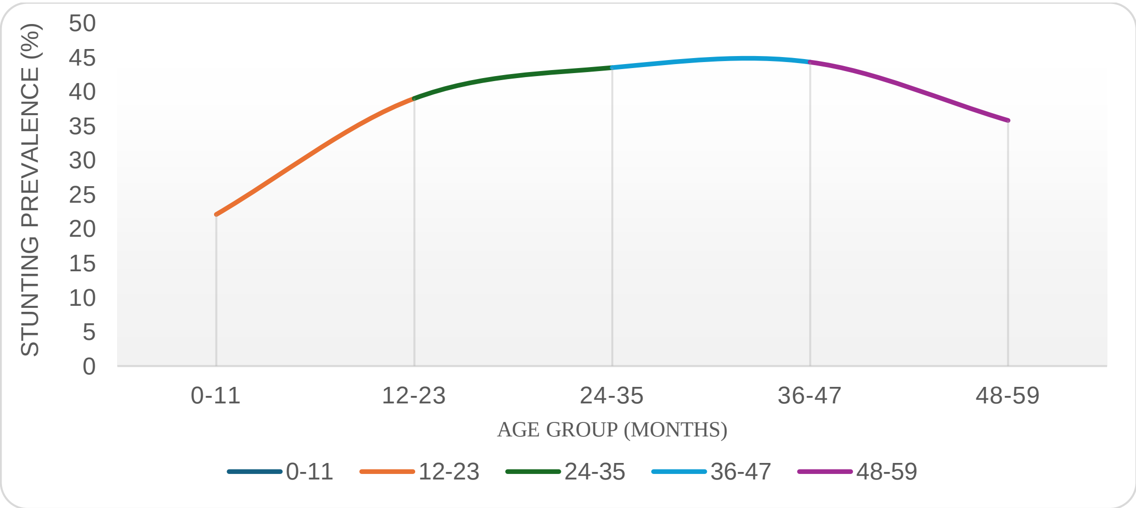
***Source:** Authors' calculation by based on ACLED (Raleigh et al., 2010; Nigeria events 2009-2025, n = 73,147) and UCDP GED v26.1 (Sundberg & Melander, 2013); Nigeria events 1990–2025, n=8,255), buffered to NDHS 2024 cluster coordinates (NPC & ICF, 2025).*

Figure 1. Shows Mean Cumulative Conflict Event Exposure (10km buffer) by Geopolitical Zone using ACLED versus UCDP GED



***Source:** Authors' computation from NDHS 2024 (NPC & ICF, 2025) linked to ACLED (Raleigh et al., 2010).*

Figure 2. Unadjusted Stunting Prevalence by Cumulative ACLED Conflict Exposure Tercile



***Source:** Authors' calculation based on the Nigeria DHS 2024, Children's Recode (NPC & ICF, 2025), n=9,410.*

Figure 3. Stunting Prevalence by Child Age Group, Nigeria DHS 2024

Multivariable Regression Analysis of Childhood Stunting

Standardised ACLED and UCDP GED event frequency and fatality intensity were added to a single model along with child-, maternal-, household-, and geographic-level covariates in the primary multivariable logistic regression model, which was estimated at the 10-km buffer (combined frequency-intensity model). All analyses were performed using survey weights and cluster-robust standard errors, which were applied throughout. To differentiate the associations of frequency and intensity, both variables were also estimated in separate models (frequency-only and intensity-only) before being combined. The combined model found that the frequency of ACLED events was negatively associated with stunting (AOR=0.85, 95% CI: 0.76-0.97, p=.012) as did the frequency-only model (AOR=0.85, p=.010). Stunting (intensity-only model: AOR=1.05, p=.577; combined model: AOR=1.01, p=.931) was not significantly associated with fatality intensity. Fatality intensity was shown to have a non-significant positive association with UCDP GED (AOR=1.14, p=.405) and a non-significant association with UCDP GED event frequency (AOR=0.93, p=.500). The reduction in the UCDP GED frequency estimate following the survey and cluster adjustment highlights the need to consider the clustered nature of the NDHS data.

As seen from Table 2, after adjusting for cluster sampling and considering the survey weights in the analysis, only the frequency of ACLED events was found to be statistically significantly associated with stunting (AOR=0.85, 95% CI: 0.76-0.97, p=.012), with the relationship being inverse a finding that should be interpreted with caution and is not to be read as evidence that conflict is protective against stunting, more details in the discussion section. None of the other variables tested (ACLED fatality intensity, UCDP GED event frequency and UCDP GED fatality intensity) was statistically significant at the 10 km buffer once proper adjustments for cluster sampling were considered. Maternal education and household wealth were positively correlated with the absence of stunting, while male gender and increasing age were positively correlated with the presence of the condition. Children residing in the North West and North East still had a significantly higher risk of stunting than those from the South East.

Table 2. Adjusted Odds Ratios (AOR) for Childhood Stunting, Multivariable Logistic Regression (n=9,410). *** p<0.001, ** p<0.01, * p<0.05, ns = not significant.

Predictor	AOR	95% CI	p-value	Sig.
Cumulative ACLED conflict event frequency (10km buffer, z-score)	0.85	0.76-0.97	0.012	*
Cumulative ACLED conflict fatality intensity (10km buffer, z-score)	1.01	0.78-1.32	0.931	Ns
Cumulative UCDP GED conflict event frequency (10km buffer, z-score)	1.14	0.83-1.57	0.405	Ns
Cumulative UCDP GED conflict fatality intensity (10km buffer, z-score)	0.93	0.76-1.15	0.500	Ns
Rural residence (ref: urban)	1.22	1.01-1.49	0.043	*
Maternal education (ordinal: none→higher)	0.81	0.75-0.88	<0.001	***
Household wealth index (ordinal: poorest→richest)	0.85	0.80-0.91	<0.001	***
Male child (ref: female)	1.34	1.21-1.49	<0.001	***
Child age in months	1.02	1.02-1.02	<0.001	***
Zone: North Central (ref: South East)	1.79	1.44-2.24	<0.001	***
Zone: North East (ref: South East)	2.79	2.19-3.57	<0.001	***
Zone: North West (ref: South East)	2.95	2.33-3.74	<0.001	***
Zone: South South (ref: South East)	1.13	0.88-1.45	0.327	Ns
Zone: South West (ref: South East)	1.40	1.07-1.82	0.015	*

Source: *The Authors' computation of multivariable logistic regression integrating NDHS 2024 (NPC & ICF, 2025), ACLED (Raleigh et al., 2010), and UCDP GED (Sundberg & Melander, 2013).*

Table 3 presents the buffer sensitivity analysis, comparing the narrower 5 km and wider 50 km buffers against the primary 10 km specification to assess whether the associations reported above are robust to the choice of buffer distance. The negative association between ACLED frequency and stunting was highly stable across 5-, 10-, and 50-km buffers. Meanwhile, the ACLED fatality intensity had a positive association with stunting only in the 50 km buffer (AOR = 1.24, 95% CI: 1.05–1.45; p = .011), but remained insignificant at 5 and 10 km buffer distances. The frequency and fatality intensity of UCDP GED events were insignificant in all buffer distance cases.

Table 3. Shows sensitivity of Cumulative Conflict Exposure Associations with Childhood Stunting across Spatial Buffers (5km, 10km, 50km)

Buffer	Predictor (z-score)	AOR	95% CI	p-value
5 km	ACLED event frequency	0.86	0.75-0.99	0.032
5 km	ACLED fatality intensity	1.12	0.98-1.28	0.101
5 km	GED event frequency	0.96	0.80-1.16	0.701
5 km	GED fatality intensity	1.03	0.87-1.20	0.758
10 km	ACLED event frequency	0.85	0.76-0.97	0.012
10 km	ACLED fatality intensity	1.01	0.78-1.32	0.931
10 km	GED event frequency	1.14	0.83-1.57	0.405
10 km	GED fatality intensity	0.93	0.76-1.15	0.500
50 km	ACLED event frequency	0.82	0.73-0.93	0.001
50 km	ACLED fatality intensity	1.24	1.05-1.45	0.011
50 km	GED event frequency	0.96	0.80-1.15	0.653
50 km	GED fatality intensity	0.85	0.70-1.02	0.076

Source*: Authors' computation. Model specification matches the combined frequency-intensity model (combined frequency and intensity), reestimated at each buffer radius; covariates as in Table 2.*

Table 4 compares the cumulative continuous exposure model with the conventional binary presence/absence approach. It should be noted that both models performed almost identically, as the difference in AIC values is equal to +0.6, and the binary approach is more preferred in accordance with BIC (the difference between the two approaches equals +14.9); McFadden's pseudo-R^2 is also almost identical for the two approaches (0.1209 vs. 0.1206). Therefore, H_4 is not supported, as the given sample shows that multi-source exposure provides no additional explanatory power compared with the binary nearby-conflict measure. From a substantive point of view, this means that merely knowing whether there was any conflict event near the community the child comes from is almost as informative about the likelihood of stunting as the detailed conflict variables are.

Overall, maternal education (AOR=0.81 per level increase, p<.001) and household wealth (AOR=0.85 per level increase, p<.001) were independently associated with reduced odds of stunting, whereas male sex (AOR=1.34, p<.001) and older child age (AOR=1.02 per month, p<.001) were associated with increased odds. The North West (AOR=2.95, p<.001) and the North East (AOR=2.79, p<.001) had the highest adjusted odds of stunting when compared to the South East region.

The frequency of ACLED events was significantly and negatively associated with stunting across all three buffer sizes (5, 10, and 50 km). ACLED fatality intensity was not significant at 5 or 10 km but was significant and positive at 50 km.

Table 4. Model Fit Comparison: Cumulative (Continuous) Exposure versus Binary Presence/Absence Exposure (10km buffer, n=9,410)

Model	Specification	AIC	BIC	McFadden's pseudo-R2
The combined frequency-intensity model	Cumulative frequency + intensity (continuous, standardised)	11023.1	11130.4	0.1209
The binary presence/ absence model	Binary presence/absence (any ACLED/GED event within 10km)	11022.5	11115.4	0.1206

Source: *Authors' computation. A lower AIC/BIC score reflects a better fit; the difference between AIC (the combined frequency-intensity model and the binary presence/absence model) is +0.6, and BIC is +14.9, which is more supportive of the simpler presence/absence model using the BIC test.*

In contrast with Hypothesis 4, there was no evidence that the multi-source exposure model (the combined frequency-intensity model) was better fitted to the data compared with the simpler presence/absence model (the binary presence/absence model): the two models were not statistically distinguishable with the AIC test, and the latter model was supported in the more stringent BIC test. Thus, Hypothesis 4 was not supported by the results.

4. Discussion

Geographic Disparities in Childhood Stunting

These findings show marked variation in the geographic distribution of stunting, with the South East at 19.6% and the North West at 52.4%. This is in line with the results of the NDHS (National Population Commission [NPC] & ICF, 2024) and other studies on regional and socioeconomic inequalities in child nutrition (Elmighrabi et al., 2024; Oyinwola et al., 2025). This significant geographic patterning ($\chi^2(5, N=9,410)=860.25$, $p<.001$) corroborates the overall effect of community and regional factors on childhood stunting, but does not prove causation.

Spatial Variation in Cumulative Armed Insecurity

In support of hypothesis 2, there were clear variations in cumulative armed insecurity across Nigeria's geopolitical regions and these variations differed markedly, depending on the type of dataset used. ACLED-based exposure was higher in the South-South and Southwest regions owing to the wider scope of the dataset, including low levels of political and communal conflicts, while UCDP GED-based exposure was largely limited to the Northeast due to the higher thresholds for organisational armed conflict within the UCDP dataset, particularly that of the Boko Haram and ISWAP insurgency. This difference is not an artefact of the data but rather a substantive one, indicating that the type and intensity of conflict determine where ‘conflict exposure’ occurs.

Cumulative Armed Insecurity and Childhood Stunting

Hypothesis 3 was partially confirmed from its sources following the separation of event frequency and fatality intensity measures and a cluster-robust analysis. The only measure that was significantly correlated with stunting was the ACLED event frequency. The positive correlation between UCDP GED was moderated and became non-significant after controlling for exposure dimensions and the cluster survey design. This finding does not contradict the current evidence on the link between organised conflicts and chronic undernutrition but reinforces the source-specific nature of that link (Azanaw et al., 2023; Bendavid et al., 2021; Howell et al., 2018; Makinde et al., 2023).

The negative correlation between ACLED event frequency and stunting deserves special attention and must not be regarded as a protective factor associated with conflict. Compared with the UCDP GED, ACLED measures a wider range of violence, including protests, riots, communal disorders and less intense conflict events. This difference implies that the types and intensities of conflict are more important for nutrition than the frequency of events. The positive but insignificant correlation found for UCDP GED is consistent with the idea that severe violence results in chronic nutritional deprivation. On the other hand, negative ACLED correlation might result from residual geographic confounding due to geographically uneven exposure to a wider variety of violent events.

5. Conclusion and Recommendations

This study sought to investigate whether a cumulative measure of armed insecurity (number of events and fatality intensity) is associated with childhood stunting in Nigeria, and to assess whether this cumulative measure predicts childhood stunting better than a binary measure of armed insecurity's presence. The findings showed that stunting and exposure to conflict differed significantly between geopolitical zones; that exposure to UCDP GED events was not significantly associated with stunting after adjustment, whereas exposure to UCDP GEI was; and that the cumulative exposure model performed worse than a binary presence/absence model. These results directly address the study's objectives: the type of measurement used to quantify exposure to conflict, or the data source it comes from, significantly impacts the level of conflict-stunting observed.

Future studies should focus on re-estimating exposure using child-specific time windows (for example, the prenatal and early childhood periods, when weighed against the actual period of the data set) and evaluating composite or weighted multi-source indices, in addition to the single-source indices examined here. Nutrition programmes should be targeted to the North West and North East, given that these regions experience a higher stunting prevalence and have a concurrent, independent protective association with conflict exposure; structural investments in maternal education and household economic status should be targeted concurrently but would be considered a parallel priority due to their constant, independent protective association with stunting.

Conflict of Interest

The authors declare there are no competing financial or personal interests that could have influenced this work.

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Data Availability Statement

The datasets used in this analysis have been sourced from three different places, with data accessible at varying levels of difficulty. (1) Nigeria DHS 2024 Children's Recode and Geographic dataset can be obtained from the DHS Program (https://dhsprogram.com/data), subject to registration and project-specific permission; due to the data use terms imposed on DHS Program data, the micro-level individual data cannot be publicly redistributed by the authors. (2) ACLED event data for Nigeria is available at the Armed Conflict Location & Event Data PROJECT (https://acleddata.com), subject to account registration and Research-tier access for disaggregated event-level data. (3) UCDP GED data can be obtained freely and without registration from the Uppsala Conflict Data Program (https://ucdp.uu.se/downloads/). The analytic dataset, derived by integrating DHS cluster locations with ACLED and UCDP GED exposure data at the cluster level, is included as a supplementary file to this manuscript (Nigeria_Stunting_Conflict_Integrated_Dataset.xlsx).

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