

Modelling Conflict Dynamics: Evidence from Africa: What Do the Data Show via Spatiotemporal Global ACLED Dataset?

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Abstract

This paper presents modeling conflict dynamics in Africa based on attributes and events of spatiotemporal ACLED dataset from January 2017 to March 2022. GIS and robust poisson regression model are considered to determine the hotspot zones and capture the relationship between various attributes and intensity of conflicts. The result finds (1) a strong spatial and temporal effects to the outbreak of multiple conflicts in Africa verifying the existence of spatial correlation. There is an evidence (2) that the spatial distribution of intensity of conflicts clustering to the Northern and Eastern regions, while in 2021 a sever intensity of conflicts recorded compared with 2017, 2018, 2019, 2020 and 2022. The study also finds that (3) the existance of a significant difference of intensity of conflicts by the event type and event subtype ($F_{value} = 178.8, P_{value} = 0.000$), while the Bonferroni test confirmed that (4) all forms of event type were significantly different in contributing to the occurrence of intensity of conflicts except riots with strategic government development, government strategic development with protests, and violence against civilians with remote violence or explosions. Somalia and South Sudan were identified as the hotspot zones of intensity of conflicts from the Eastern region, Nigeria and Mali were the two top countries from the northern region. Similarly, the result shows that battles and violence against civilians were the major event type, while armed clashes and attacks were the two predominant event subtype in Africa. The findings shows that time $(\beta = 0.1129, P_{value=0.000})$, interaction $(\beta = -0.1161, P_{value=0.000})$, latitude ($\beta = -0.0022, P_{value=0.000}$), longitude ($\beta = 0.0164, P_{value=0.000}$) and geoprecision ($F_{value} = 178.8, P_{value} = 0.000$) were significantly associated with the high number of intensity of conflicts in Africa. Africa needs to reduce the intensity of conflicts and focus on the current economic development. Attention in the hotspot areas of conflicts is highly encouraged promoting to African problems to the African solutions.

Keywords Spatial and temporal \cdot Modelling \cdot GIS \cdot Intensity of conflicts and ACLED

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Introduction

Background

The spatial analysis and modelling of events is getting attention in pandemic prediction, drought assessment (Orimoloye et al., 2019), assessing the impacts of conflict analysis on migration and economy (Da Silva & Fan, 2017), and crime detection via image reconstruction as in (Likassa et al., 2022).

A number of robust statistical methods and GIS techniques have been used for identification of hotspot areas of diseases, crime detection and conflicts across the globe. For instance, Schutte & Weidmann,(2011) addressed as the conflict events are mostly mapped along with time and space to capture the areas of hotspots. Similarly, modelling conflict dynamics, and in depth spatial and temporal clustering analysis for a rarely occurred events was well studied (Gleditsch, 2007; Salehyan, 2009; Arsenault & Bacon, 2015), however the work lacks in scrunitizing big data analysis with Robust Methods.

GIS has been considered as an essential for conflict research to clearly indicate the intensity of conflicts in the international relations (Starr, 2002). Attempting to consider the GIS for conflict dynamics analysis has brought a marked contribution in peace mitigation during armed conflicts that have been made by Braithwaite (2001) and by Buhaug and Gates (2002) regarding armed civil conflicts. The hotspot identification of conflicts using GIS techniques and its impact on the displacement were also studied by (Lischer, 2007; Gleditsch et al., 2020), however it seeks to be supported with modelling to capture the prediction. GIS based sectorial conflict analysis in a coastal district of Turkey was conducted by (Tanik et al. (2008)), where recommendation taken for policy brief and sounding decisions.

According the political and economic measures, and arms supplies were the major contributing factors for high intensity of conflicts in Angola and Mozambique of Africa (Bakewell, 2008; Castles et al., 2014), and largely responsible for high migration (Bakewell & Jónsson, 2011; Berriane & De Haas, 2012; Bilger & Kraler, 2005; Bredeloup & Pliez, 2005; De Bruijn et al., 2001; Lessault & Beauchemin, 2009; Pian, 2009; Schielke & Graw, 2012; Whitehouse, 2012) and high displacement as indicated in (Dercon, 2005). Similarly, modelling population displacement due to conflict in Syrian city of Aleppo was captured by (Sokolowski et al., 2014) and the correlational analysis between natural resource and conflicts was address by (Humphreys, 2005). However, they still require to be supported with GIS techniques and using advanced robust statistical methods to reduce the effect of conflicts in various sectorial based developments.

Geocoded event data are mapped as linear function of predominant variables in the local, demographic, political, and economic measures (Hegre et al., 2009), climatic and environmental parameters with violence against civilians(Carter & Veale, 2013; Marineau et al., 2018). The dynamics of conflict events in Burundi in 2000 relying on data from the Uppsala Conflict Data Program's Georeferenced Event Dataset (Melander & Sundberg, 2011; Sundberg et al., 2010), it however, lacks supporting with advanced robust methods and GIS techniques. The past decade has yielded a greater emphasis on developing geographically referenced political conflict event data (Schrodt & Yonamine, 2013). Moreover, geographic and temporal drivers of intensity conflicts have been extensively

described by a number of political studies assisted with modelling (Natinale, 2009; Penzar & Srbljinović, 2004; Petukhov et al., 2017), the quantitative analysis via modelling and GIS techniques of the drivers is quite not well studied. Li et al. (2022) addressed the issue of Multi-Scale Dynamic Analysis of the Russian–Ukrainian Conflict from the Perspective of Night-Time Lights, and the impact of Ukraine Russian war brings the food shortage across the globel (Nasir et al., 2022).

As conflict is a disaster and impacts the economy and the wellbeing of humanity largely, analysing the spatial and temporal pattern robustly supporting with inference via modelling based on a global ACLED dataset is important to learn the dynmaics and identify the hotspot conflicts zones in Africa to take an action for further interventions and ultimately build a stable region for the current and upcoming generation. As such, reducing the advancement and turmoil effects of conflict is highly suggested and recommended via applying GIS techniques and advanced statistical tools. In this paper, Modelling and GIS techniques to identify the spatial and temporal hotspot zonmes and conflict dynamics is suggested to bring a peace and stability to happen in Africa and lead to the economic development. The popular datasets of conflict events in the Armed Conflict Location and Event Dataset (ACLED), and Uppsala Conflict Data Program Georeferenced Event Dataset (UCDP GED) was taken into acount to achieve the proposed objectives.

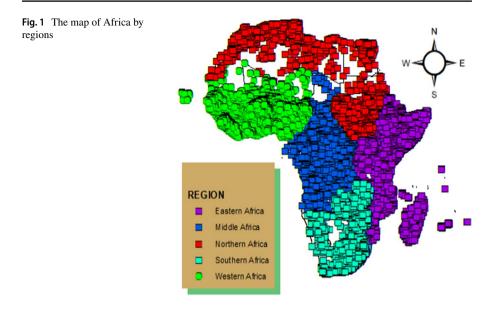
Methods

Study Area

This study is conducted in Africa, the second largest from the world, in which there are 54 countries divided into five regions, mainly Eastern, Western, Northern, Southern and Middle Africa (Fig. 1).

ACLED Dataset

To capture the dynamics and identify the hotspot areas of conflicts, the popular ACLED dataset, the collection of hundreds of thousands of records about violence across multiple continents and regions. This is a popular approach of efforts like the Violence Early-Warning System project (Hegre et al., 2019) which assume that an incident of violence is partly a function of the characteristics of the setting where it occurs. And yet, despite the proliferation of both GIS-based tools and GIS-ready data, there has been relatively little in the way of research about the dynamic geography of political violence. Since the end of Cold War in 1989, the globe has been in turmoil registering more than 137 armed conflicts (Themnér & Wallensteen, 2012), and, with continuing conflicts in Asia (Afghanistan, Iraq or Mexico) and recently more conflicts in Africa (Northern Africa and the Middle East), where great human loss, the social, economic and environmental impacts of armed conflict are enormous (Ghobarah et al., 2004). Invoked, with high conflicts across the globe, modelling the dynamics of conflicts in Africa based on



the global 'Armed Conflict Location and Event Dataset' (ACLED) dataset is recommended. The term intensity in this research article refers to death per event. Thus, to achieve the proposed objective, the data taken from 2017 to 2022 is used. Within the ACLED dataset, there are several parameters/factors like a daily based events, event type, event subtype, intensity and regions. We considered the ACLED dataset, where there are several potential predictor variables; the response variable is the intensity of conflicts. To achieve, the proposed objectives, the spatial autocorrelation, mean difference mainly the Boferroni after one way analysis, different GIS techniques and Robust Poisson Regression were considered. Finally, as the number of observations based on the ACLED dataset is count and large is 171, 453 with about eight predictor variables, Robust Poisson regression model is preferably delved.

Study Vairables

In this research, the intensity of conflicts is taken as a response variable while time, location, latitude, longitude, interaction, geo precision, event type, event subtype are all considered as a predictor variables.

Results and Discussions

In this section, the key findings and discussions are presented. The findings are robust to the inclusion of additional more time and spatial covariates, regions, countries, and the use of the alternative Global ACLED dataset. Investigating the relationship between temporal and spatial with conflict events via modelling and GIS techniques has been challenging so far. Several researches conducted in the areas of spatial Conflict Dynamics indicator of violence; while identified the existence of robust positive relationship between temporal and spatial with intensity of conflicts conflict.

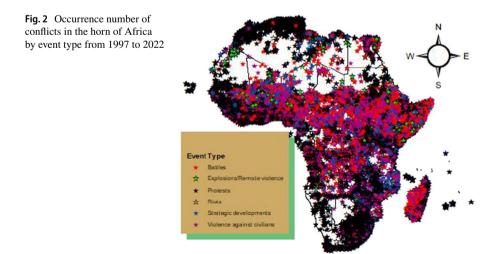
Spatial and Temporal Variation of Intensity of Conflicts in Africa

The results corresponding to the occurrence of high number of conflicts in Africa from 1997 to 2022 is given in Fig. 2, from which the top intensity of conflicts in Africa is observed from 2017 to 2022. This indicates that the temporal distribution of intensity of conflicts in Africa is varying temporally showing the pattern is increasing.

Figure 3 presents the temporal intensity of conflicts analysis, where high intensity of conflicts is observed from 2017 to 2021 while small intensity of conflicts was observed from 1997 to 2021. Thereby, high intensity of conflicts is more clustered in 2017 to 2021 just as compared with the other consequentive years.

Based on the intensity level of conflicts in Africa, in this research we focused spatial and temporal analysing supported with modelling conflict dynamics is emphasized from 2017 to 2021. Figure 4 presents the spatial and temporal distribution of intensity of conflicts in Africa, from which we note that the spatial and temporal distribution of intensity of conflicts in the horn of Africa is varying both in space and time.

Figure 4 presents how the dynamics and global spatial density of intensity of conflicts can vary according to the number of violent events within a hypothetical study region that is divided into five sub regions similar to the techniques employed by (Diggle et al., 2003). High number of intensity was clustered in Eastern and Western regions in Africa, where Battles and violence against civilians were the two predominant event type in registering high deaths in eastern and western regions of Africa (Fig. 4). Our finding is relatively better to (Adelaja et al., 2021) as it additionally incorporats the spatial and temporal effects, the event type. The results corresponding to Fig. 4 confirms that high death is



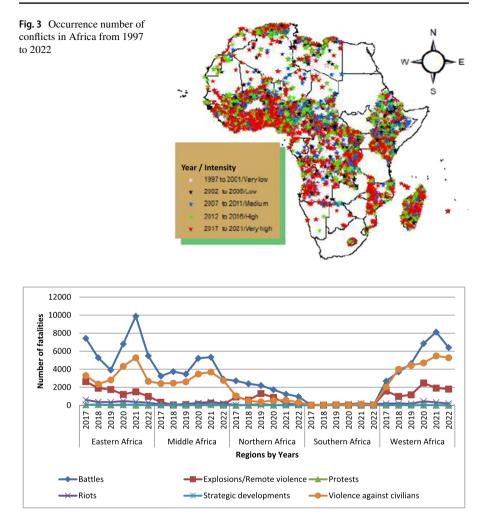


Fig. 4 Intensity of conflicts in Africa

observed in Eastern and Western Africa with high clustering of the intensity of conflicts registered in 2021.

Spatial Dynamics of Conflicts in Africa

The result shows that the spatial distribution of intensity of conflicts by region in Africa is given in Fig. 5 confirming spatial distribution of intensity of conflicts in Africa is varying from region to region with high intensity of conflicts clustering is observed in Eastern and Western Africa while the lowest intensity is Southern Africa. The percentage of intensity versus hotspot regions in Africa is given Fig. 6,

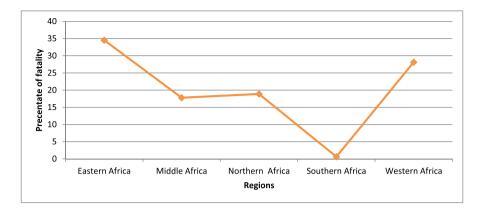


Fig. 5 Spatial distribution of intensity of conflicts in Africa by regions. Source: ACLED dataset

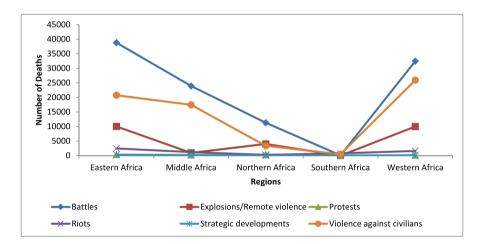


Fig. 6 Spatial distribution of intensity of conflicts in Africa by the event type

from which we note that eastern and western regions were the two top African country where there is high clustering of intensity of conflicts.

The spatial distribution of intensity of conflicts associated with event type in Africa are highly observed in Eastern and Western Africa where there is a high intensity of conflicts captured (Fig. 6).

Figure 7 presents the spatial and temporal pattern of intensity of conflicts in Africa based on the ACLED dataset. Eventhough a considerable number of intensity of conflicts is observed from 2017 to 2019, in 2020 high intensity of conflicts was clustered in Africa. Battles and violence against civilians were responsible for high intensity of conflicts in Africa (Fig. 7).

The result corresponding spatial distribution of intensity of conflicts by regions and event type in Africa is given in Fig. 8. High percentages of intensity of conflicts

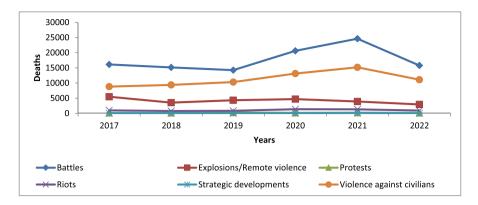


Fig. 7 Spatial and Temporal distribution of intensity of conflicts in Africa

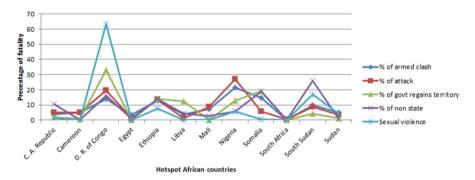


Fig.8 Spatial distribution of intensity of conflicts by regions and event type in Africa. Source: ACLED Dataset

are registered by the armed clashing and attacks in countries such as democratic republic of Congo, Nigeria and south Sudan.

In Africa, the spatial distribution of intensity of conflicts due to event types such as the battles, violence against civilians, Riots, Explosions and remote violence, protests, strategic developments based on the ACLED dataset is illustrated Figure 9, from which we note that high intensity of conflicts is observed in Eastern Africa, where battles, violence against civilians and expositions/remote violence are the predominat event type contributing. Similarly, western Africa is the second top in registering high intensity of conflicts, due to battles, violence against civilians, and explosions/remote violence were the predominant event type related to the conflicts (Figure 9). This work is better as compared with (Abay et al., 2022) which addresses the intensity of conflicts in Ethiopia lacking the depth analysis. Moreover, (Checchi et al., 2013) considered the impact of Ethiopia and Kenya conflicts on the displacement of households via satellite data, however clearly identification the hotspot area is not yet captured.

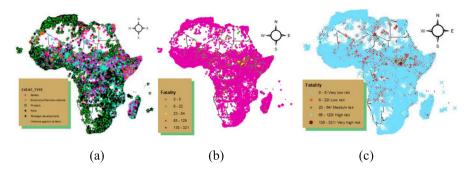


Fig. 9 Spatial distribution: (a) event type; (b) intensity; and (c) level of risks in Africa

Spatial Distribution of Intensity of Conflicts in the Hotspot Countries in Africa

In this subsection, the descussion of spatial distribution of event type by regions for selected twelve African countries made. Battles and violence against civilians are the two popular event types in the Eastern, Northern and Western African countries, where in the southern Africa, the protest is the predominant event type for high intensity of conflicts in Africa. The result of the study revealed that South Sudan and Somalia were the two hotspot areas of conflicts from the eastern African countries, Nigeria and Mali where the top countries with high intensity from the Western Africa, South Africa is the top from Southern Africa, Sudan, Libya and Egypt were the top country from the Northern Africa while Democratic Republic of Congo, Central Africa Republic and Cameroon were the top hotspot countries with high intensity from the Middle Africa African countries. Based on this, the event type that is more responsible for the high intensity is mapped and given in (Figure 10a and b).

Figure 11 presents the spatial distribution of intensity of conflicts due to violence against civilians and battles, where large scale intensity of conflicts is observed in Eastern African countries mainly in South Sudan, Somalia, while small scale deaths are observed in every other African countries.

Figure 12 shows the spatial distribution of intensity of conflicts in Africa is clustered with the global Moran's I = 0.059 (Fig. 12). This indicates that a country where there is high intensity of conflicts is surrounded by a country with similar high intensity of conflicts in Africa due to the issue of spatial dependency.

The result indicates that there is a positive spatial autocorrelation of intensity of conflicts in Africa, which is to mean that a country with high intensity of conflicts is surrounded by another country with high intensity of conflicts $(I = 0.0592, E(I) = 0.000, Mean = 0.000, sd = 0.0011, Z_{value} = 52.18, P_{value} = 0.0100)$ The spatial distribution of intensity of conflicts by event type in African countries, from which we note that the distribution is varying from country to country (Fig. 13).

As noted in Fig. 14, the spatial distribution of intensity of conflicts in hotspot areas of Africa is varying where Nigeria is sharing the largest portion and Democratic Republic of Congo is the second hotspot areas in Africa. 2021 year is the

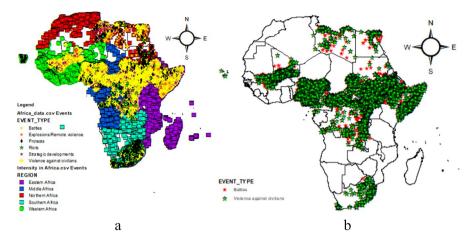
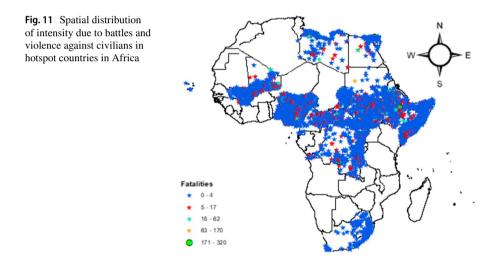


Fig. 10 Spatial distribution of intensity of conflicts in Africa (a) all forms of event type (b) battles and violence against civilians



most sever year over the last years in registering high intensity of conflicts in Africa. After four years of 2017, the figure rises to its climax of registering deaths in 2021 in Africa (Fig. 14). Our finding is more resembled with the findings of (Williams, 2016) high number of intensity of conflicts were observed in Sudan (17,991), Nigeria (15,329), DRC (12,173), Somalia (10,847), which accounted for 76.3% of the continental total.

The result shown in Fig. 15 shows the spatial distribution of intensity of conflicts by event type in Africa.

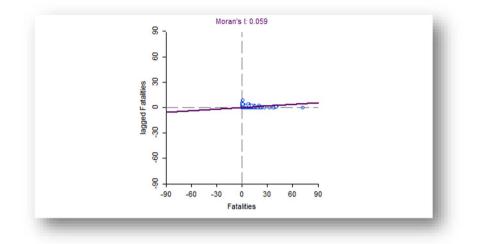


Fig. 12 Moran scatter plot

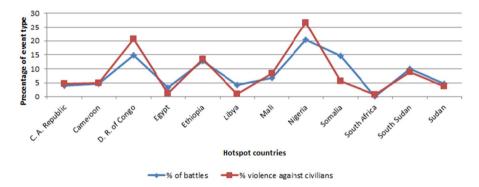


Fig. 13 Intensity of conflicts in hotspot areas in Africa by event type

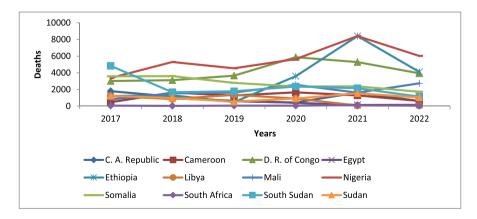


Fig. 14 Spatial and temporal distribution of intensity of conflicts in Africa

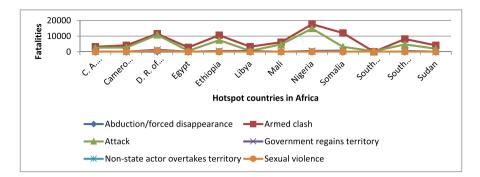
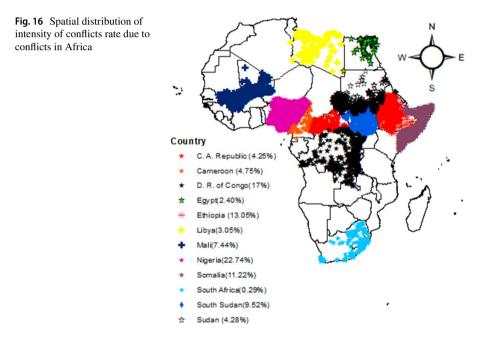


Fig. 15 Spatial distribution of intensity of conflicts in Africa by the event type



The armed clash and attack were the two predominant event subtypes related to the hotspot areas registered in African while the severity level is becoming agony in Democratic republic of Congo, Nigeria and south Sudan (Fig. 15).

The result shown in Fig. 16 shows that the spatial distribution of intensity of conflicts rate by the top 12 countries in Africa, from which we observe that Nigeria, democratic republic of Congo and Somalia are the first three top countries where there is high intensity of conflicts.

Figure 17 presents the result corresponding to the temporal and spatial pattern of intensity of conflicts from 2017 to 2022 based on the top twelve African hotspot countries, which also shows variation of intensity of conflicts both in spatially and

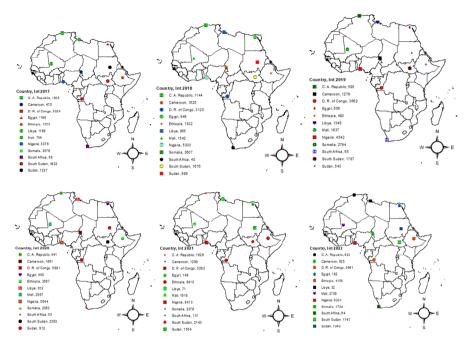


Fig. 17 Temporal and spatial distribution of intensity of conflicts in Africa

-		-			
Source of variation	SS	DF	MS	F	P value
Between Event type	2089781.49	5	417956.298	511.38	0.000
Errors	236542010	289415	817.310816		
Total	238631791	289420	824.517281		

Table 1 Comparisons of overall intensity of conflicts by event types in Africa

temporally, Nigeria and democratic republic of Congo the two vulnerable countries compared with the other countries in Africa (Fig. 17).

Results of One Way of ANOVA

Table 1 shows as there is a significant difference of intensity of conflicts in Africa by the event type at 5% level of significance.

After intensive intensity conflict analysis, the result corresponding to multiple pairwise via the Bonferroni test at 5% level of significance is given in Table 2, from which we also confirmed that there is a significant difference of intensity of conflicts by the event type.

Table 2 Bonferroni test of multip	le pairwise intensity of i	Table 2 Bonferroni test of multiple pairwise intensity of intensity of conflicts based on event type	ype		
Mean and mean difference	Battles	Explosions/remote violence	Protests	Riots	Strategy developments
Explosions/remote violence	-224.539(0.000)				
Protests	-271.933 (0.000)	-47.3938(0.003)			
Riots	-313.933(0.000)	-89.3597(0.000)	-41.9659(0.021)		
Strategy developments	-361.145(0.000)	-136.606(0.000)	-89.2123(0.091)	-47.2463(1.000)	
Violence against civilians	-218.204(0.000)	6.33519(1.000)	53.729(0.000)	95.6949(0.000)	142.941(0.000)

Spatial distribution of intensity of conflicts based on the battles and violence against civilians in Africa, from which we note that Nigeria, Somalia and democratic republic of Congo the three top countries registering high intensity of conflicts (Fig. 18).

The spatial distribution of intensity of conflicts due to the event subtype by armed clash and attacks is given in Fig. 19. The result indicates that Somalia, Nigeria and democratic republic of Congo were three hotspot areas of registering high intensity of conflicts, while democratic republic of Congo and Nigeria were the two top African countries with high intensity of conflicts due to attacks (Fig. 19).

In addition to assessing the effect of time, space, event type and event subtype on the intensity of conflicts in the horn of Africa, additionally we also run the Poission regression model based on the several predictor variables(time, interaction, latitude, longitude, geo precision) on the response variable(called as the number of intensity of conflicts) from which we note that the year ($\beta = 0.1129, P_{value=0.000}$), interaction ($\beta = -0.1161, P_{value=0.000}$), latitude ($\beta = -0.0022, P_{value=0.000}$), longitude ($\beta = 0.0164, P_{value=0.000}$) and geo precision ($\beta = 0.2159, P_{value=0.000}$) were significantly associated with the high number of intensity of conflicts in Africa.

Conclusions

In this article, how the intensity of conflicts is varying both spatially and temporally in Africa based on the global ACLED dataset is investigated. The spatiotemporal pattern of intensity of conflicts is well scrutinized with the help of GIS and robust methods. There is an evidence that the spatial and temporal pattern of intensity of conflict is clustering $(I = 0.0592, E(I) = 0.000, Mean = 0.000, sd = 0.0011, Z_{value} = 52.18, P_{value=0.0100})$ in Africa. The result shows that high intensity of conflicts were observed in Eastern and Western regions in Africa; while in 2021 high intensity of conflicts registered. There is a significant difference intensity of conflicts observed due to the event type $(F_{cal} = 178.78, P_{value=0.000})$. The predominant event types for high clustering of intensity of conflicts were due to battles and violence against civilians while armed clash and attacks remotely from the event subtype. The result of the study revealed that South Sudan and Somalia were the most vulnerable countries from the Easter, Nigeria and Mali were from the Western, South Africa was from the Southern regions, and Sudan, Libya and Egypt were from the Northern Africa while Democratic Republic of Congo, Central Africa Republic and Cameroon were the

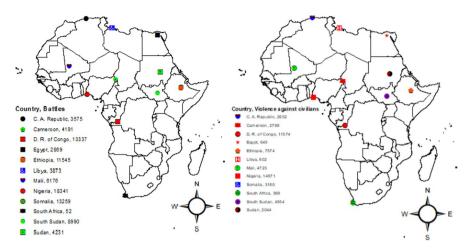


Fig. 18 Spatial distribution of intensity of conflicts by battles and violence against civilians

hotspot countries from the Middle Africa. The result of Robust Poisson regression showed that time ($\beta = 0.1129, P_{value=0.000}$), interaction ($\beta = -0.1161, P_{value=0.000}$), latitude ($\beta = -0.0022, P_{value=0.000}$), longitude ($\beta = 0.0164, P_{value=0.000}$) and geoprecision ($F_{value} = 178.8, P_{value} = 0.000$) were significantly associated with intensity of conflicts in Africa. Africa needs to reduce the intensity of conflicts promoting the culture of African problems to African solution. As such, the economic and trade integration for economic and social development is highly encouraged.

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Data Availability The data used in this article are freely available for the user. The input data used for both GIS based analysis and modelling conflict dynamics can be downloaded via various web portals of global ACLED database. All the derived data are included in the manuscript and the statistical tools including models were trained and tested using statistical packages. This is an independent academic research which doesn't have any value judgment relationship to any country in the horn of Africa. This research is conducted only to contribute for advancement of science and indicate some concluding remarks.

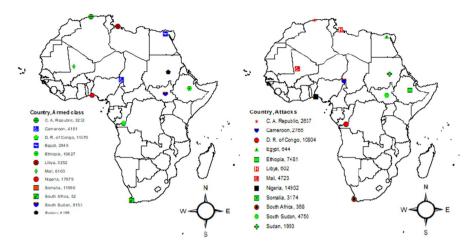


Fig. 19 Spatial distribution of intensity of conflicts by armed clash and attacks

Declarations

Competing Interests

O The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

O The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Conflicts of Interest The author declares that there is no conflicts of interest.

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