



Regular Article

Space-time cube approach in analysing conflicts in Africa

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ARTICLE INFO

Keywords:

Emerging hotspots
 Political geography
 Spatial statistics
 Conflict
 Peace
 Africa

ABSTRACT

In terms of conflict types and occurrences, there is a mesh of old, new, and concurrent conflicts which coexist and are affecting each other over space and time. Existing conflict studies are unable to fully explicate the space-time elements, hence this generates static and two-dimensional hotspots/coldspots. Using Africa as a case, this study used three-dimensional space-time cube, with conflict occurrences grouped into bins where space is mapped horizontally and time is mapped vertically for analysis. Analysis of conflict based on the three dimensional space-time cube produced four main categories of hotspots namely consecutive, sporadic, oscillating, and new hotspots. Furthermore, the causes of conflicts in Africa varied significantly across each time-based hotspot, providing insight into why straightjacket solutions have been unsuccessful. Conflict managers can learn from the patterns of time-based hotspots which helps to see conflicts as three-dimensional entities needing with three levels of orientation that focus on type, space, and time instantaneously.

1. Background

Globally, conflict are on the rise with Africa facing fresh waves of extremism, rioting, and protest. Between 2018 and 2019, Africa experienced about 36% rise in conflict occurrences, with a total of 21600 conflicts (Allison, 2020). Climate change, catastrophes, religious extremism, poverty, corruption, foreign meddling, poor education, ethnic tension, unemployment, declining wages, rising commodity prices, weak institutions, and resource competition contribute to the emergence and perpetuation of conflicts in Africa (Adaawen et al., 2019; Cabot, 2017; Petrova, 2022). Consequently, conflicts have sunk the continent into its current socioeconomic distresses, which causes tens of thousands of deaths per year. Conflicts have also created hunger, malnutrition, internal and external displacement, degraded social structures, conflict traps, and economic stagnation on the continent (Burke et al., 2009; Manotas-Hidalgo et al., 2021).

Conflict events, causes, and consequences exist within space and time, providing possibilities for analysing past trends and future patterns for mitigation purposes. Existing analytical approaches have relied on spatial analysis (absolute and relative location mapping, spatial autocorrelation, Getis Ord G, and local Anselin Moran's I), for distribution mapping and clustering of conflict zones as hotspots or coldspots across the continent (Kotsadam & Østby, 2019; Raleigh et al., 2018; O'Loughlin & Raleigh, 2008). A significant finding from such geospatial research in

Africa is that civil war tends to cluster within 15% of a state's territory, with different kinds of political violence exhibiting high rates of repetition (Raleigh et al., 2018). Wars are shaped by the collateral damage suffered by belligerent parties in neighbouring areas, as well as spatial-temporal spillovers (Kibris, 2021). Mineral resource locations in low-cost extraction countries are hotspots for conflicts (Raleigh, 2014). While border regions/towns are clusters for insurgent crime-related incidents (Johnson & Braithwaite, 2017). These insights are useful for the development of military strategies, consolidation of peacekeeping operations, and solutions targeted at the regional, national, and zonal levels (Mack et al., 2021).

In spite of the useful information provided by most spatial analysis techniques on conflicts, they are less time sensitive, so a sequence of discrete outputs is employed to demonstrate the impact of time, preventing the discovery of time-based clusters. Space-time cube analysis has a superior advantage over absolute and relative location mapping, spatial autocorrelation, Getis Ord G, and local Anselin Moran's I by using three-dimensional model to describe space horizontally and time vertically (Li et al., 2010). The space time cube aggregates discrete events into bins, resulting in highly accurate representations of spatio-temporal data in time-based clusters such as new, consecutive, persistent, oscillating, and sporadic hotspots or coldspots (Purwanto et al., 2021). The importance of the spatial-time cube has been crucial in understanding the spread of Covid-19, forest decline, urban mobility

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patterns, and people's life histories (Harris et al., 2017; Kveladze et al., 2015; Purwanto et al., 2021) but its benefits are yet to be experienced in conflict studies.

Conflict studies would benefit from space-time cube analysis especially in Africa because of the unique overlay of conflicts predating colonial periods and cemented by recent geopolitical events. Thus, new conflict patterns cannot be blended with old conflict patterns since the two coexist with separate underlying causes and may require different practical solutions (Allison, 2020). Hence, this study sought to assess the space-time effect on conflicts in Africa through the following questions;

- 1 Where are the notable central points of conflicts in Africa?
- 2 How do space and time simultaneously influence the occurrence of conflicts in Africa?
- 3 What factors influence the various space-time hotspots/coldspots zones in Africa?

The study's principal argument is that conflicts in Africa are not only spatially confined but also time-bound. This is because months before and after the rainy season, herder-farmer confrontations across the continent heighten (Adaawen et al., 2019; Mack et al., 2021; Petrova, 2022). The legendary Algerian revolt sparked a wave of riots and protests across the continent (Arab Spring), particularly in Libya, Tunisia, and Egypt, and was followed by insurgencies in Nigeria, Mali, and Burkina Faso (Van den Bosch & Raubo, 2017; Aghedo & James Eke, 2013). Furthermore, recent military takeovers in Africa have sparked a chain reaction of violence and demonstrations that must be understood from a spatio-temporal perspective (Elischer, 2021). Another relevance of this work is the ability to trace conflict clusters as time-dependent output rather than static output (Beetar, 2019). Understanding the development or re-emergence of conflicts and their varied causalities is critical for providing meaningful information and resource mobilisation for conflict resolution.

2. Literature

2.1. Central points of conflicts in Africa

Early studies on space and conflict discovered no association between these two phenomena because conflicts were analysed at the country level before World War II (Lis et al., 2021). By the end of World War II, Cold War outplays resulted in the spread of conflicts both internally and internationally, necessitating new spatial analysis through the advancement of philosophy, geography, and technology (Barnes, 2011, 2022). Consequently, this promoted the study of conflict diffusion. According to the diffusion conflict hypothesis, conflicts start at a key location and then spread to other geographic areas (O'Loughlin & Raleigh, 2008). The concept further argues that the location of conflict-prone nations is not only a characteristic but also a cause of conflict (O'Loughlin & Raleigh, 2008).

Furthermore, conflict tend to follow borderlines where similar socio-economic conditions exist between neighbouring countries (Murdoch & Sandler, 2002). Thus, conflict spreads through a two-way reflexive process between the originating conflict location and spread to other places with similar population characteristics or ideology (Zupancić et al., 2018). Evident is the diffusion of the Afghan war into Pakistan while the Iraq war triggered the Syrian and the spread of ISIS into Asia and North Africa. According to Ruggeri et al. (2017), identifying the loci and conflict directions are significant in reducing the time and cost of mobilising peacekeeping forces.

2.2. Space and time influence on conflict

Several methodologies have been explored to study the relationship between conflict, space, and time. Nearest neighbour analysis, Getis Ord General G., incremental autocorrelation, and Ripley's K function are used to explore the statistical significance of conflict distributions. Getis Ord G_i^* and Anselin Moran's I, are used as density and clustering techniques for identifying conflict hotspots (Griffith, 2021). However, the minimal focus on time is one of the limitations of these spatial approaches. Space-time cube analysis developed by Hägerstrand (1970) solves for time through a simultaneous analysis of representing space horizontally and time vertically on a cube (Li et al., 2010). The weakness of the cubes is treating space and time as a container for boxing social life and interactions rather than a social construct (Simandan, 2016, 2020; Thrift, 1996, 2005). However, cubes give a better conceptual and visual representation of space and time concurrently than any two-dimensional display and InfoVis (Bach et al., 2017).

Although the space-time cube is based on Getis Ord G_i^* hotspot analysis, it generates bins with an identification (ID) showing geographic position, as well as a time-step ID (Fig. 1). It also applies the Mann-Kendall statistic to decide if a statistically significant temporal trend exists based on a time-slice of Z-scores generated by the Getis-Ord G_i (Harris et al., 2017). The characteristics of a space-time cube enable it to produce statistically significant patterns such as new, historical, consecutive, persistent, intensifying, sporadic, as well as diminishing and oscillating (Bass, 2017). New hotspot/coldspot locations mean it has never been statistically significant previously, while consecutive hotspots/coldspots have areas significant in the final time-step but not prior to the final hotspot/coldspot analysis (Li et al., 2010). An intensifying hotspot/coldspot defines areas that have about ninety percent of the time-step intervals being significant areas including the final time step. This results in persistent hotspots/coldspots having ninety percent of the time-step intervals with no noticeable movement towards increasing or decreasing over time (Shimazaki & Shinomoto, 2007). Diminishing hotspots/coldspots are areas that were once statistically significant hotspot/coldspot for ninety percent of the time-step intervals but decreased in intensity over time (ESRI, 2022). Sporadic hotspots/coldspots are on-again then off-again hotspots/coldspots with oscillating hotspots/coldspots as statistically significant hotspot for the final time-step interval that has a history of statistically changing its entity as hotspot or coldspot a prior time step. The last hotspots/coldspots category is historical hotspots/coldspots having its recent period as neither hot/cold, but at least ninety percent of the time-step intervals have been statistically significant hotspots/coldspots (ESRI, 2022).

The ability to detect these hotspot/coldspot patterns provides researchers with a competitive advantage in tracking geographical and time-based phenomena and dissemination. It was crucial for COVID-19 spread mapping across Asia. Bass (2017) used it to track high manatee (*Trichechus manatus latirostris*) death rates in Florida, USA. Space-time cube analysis aided in the collection of baseline ecological data for understanding pilot whale subspecies habitat and migration to advise conservation management (Betty et al., 2020). Harris et al. (2017) were also able to map emergent degradation zones inside the Amazon Forest using a space-time cube. It enabled Nakaya and Yano (2010) revealed temporal inter-cluster linkages where transitory clusters appeared in a pair of hotspot zones, resulting in the discovery of a novel sort of "displacement" criminal phenomena. According to this study, the benefits of space-time cubes are significant for uncovering new sides of conflict trends in Africa that earlier studies could not. A shortcoming with space-time cubes happens to be the complexity of representing its output and difficulty in interpreting its results (Kveladze et al., 2019). Hence most researchers represent the outputs as two-dimensional rather than a three-dimensional output.

2.3. Causes of conflicts

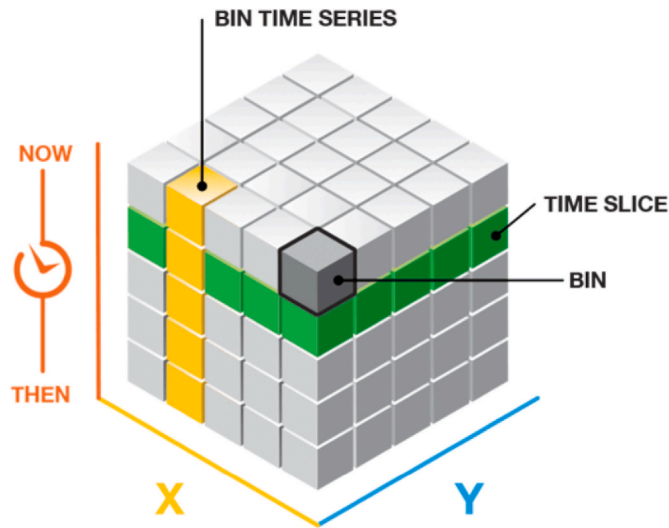


Fig. 1. Space-time cube. Source: Li et al., 2010.

According to resource-conflict theory, escalating conflicts in Africa can be attributed to the richness and reliance on natural resources (Namakula, 2022). It is responsible for thousands of conflict-related deaths every year in Africa (Bruch et al., 2019). High gold and diamond reserves encourage and feed hostilities, as witnessed in Sierra Leone, Liberia, and other countries. Natural resource reliance impairs institutional and democratic processes, making communities more vulnerable to violent conflicts, like the situation in Delta State, Nigeria (Ebiede, 2017; Omorede, 2014). According to the theory of rebellion, riots, and demonstrations by people in Africa may be traced to popular agitation against the continent’s economic woes (Engels, 2015). Rising unemployment, declining wages, and rising commodity prices give sufficient motivation to fight, protest, riot, and even join armed groups (Manotas-Hidalgo et al., 2021).

Also, the emergence of climate change, accompanied by changes in rainfall patterns and land degradation, is to be blamed for the recurrence of hostilities in many parts of Africa (Sakaguchi et al., 2017). Petrova (2022) observed increased levels of community conflict because of less rainfall in savannah regions and grasslands. In addition, high ethnic diversity and nationalism promotes and sustains conflicts because they elicit strong emotional reactions based on psychological, biological and cultural differences (Alesina & La Ferrara, 2000). Civil conflicts are stimulated and entrenched by colonial favouritism and differences in political ideology (Manotas-Hidalgo et al., 2021). Growing numbers of small arms provide tools for mercenaries, rebels, and jihadist to cause chaos across border regions.

Table 1
Centrality of conflicts in Africa per year, by subregion and conflict event.

Year	Town	Latitude	Longitude	Country
1997	Yaounde	3.867	11.517	Cameroon
1998	Odeama Creek	4.347	6.435	Nigeria
1999	Bandundu	-3.317	17.367	Democratic Republic of Congo
2000	Opala	-0.508	24.229	Democratic Republic of Congo
2001	Shabunda	-2.694	27.346	Democratic Republic of Congo
2002	Colline Rukoko	-1.65	29.267	Rwanda
2003	Kanyasi	1.391	30.441	Democratic Republic of Congo
2004	Ndrele	2.306	30.493	Democratic Republic of Congo
2005	Omee	2.189	31.367	Uganda
2006	Anaka	2.594	31.963	Uganda
2007	Iten	0.67	35.508	Kenya
2008	Kapsabet	0.204	35.105	Kenya
2009	Bavi	1.431	30.298	Democratic Republic of Congo
2010	Omoro	2.75	32.5	Uganda
2011	Jabal Kurgul	13.2	26.967	Sudan
2012	Berunda	2.336	30.299	Democratic Republic of Congo
2013	Mirmir	8.335	30.016	South Sudan
2014	Aweil	8.767	27.397	South Sudan
2015	Gumbolo	6.933	27.95	South Sudan
2016	Faraksika	5.02	29.71	South Sudan
2017	Bangusa	4.802	28.764	South Sudan
2018	Sodi	5.288	26.094	Central African Republic
2019	Sarh	9.15	18.383	Chad
2020	Goumoun	9.932	15.552	Chad
2021	Kabo	7.698	18.63	Central African Republic
Conflict by Subregion				
North Africa	As Saddadah	31.468	14.631	Libya
Southern Africa	Olievenhoutbosch	-25.917	28.105	South Africa
West Africa	Kopargo	9.841	1.542	Benin
East Africa	Khorof Harar	2.202	40.754	Kenya
Central Africa	Abongisia	0.204	25.595	Democratic Republic of Congo
Conflict type				
Battles	Tore	4.502	30.157	South Sudan
Explosions/Remote violence	Nyakma	11.417	30.533	Sudan
Protests	Fotokol	12.373	14.228	Cameroon
Riots	Kisangani	-1.167	24.4	Democratic Republic of Congo
Strategic developments	Irabanda	5.949	22.07	Central African Republic
Violence against civilians	Mabanga	2.183	27.933	Democratic Republic of Congo

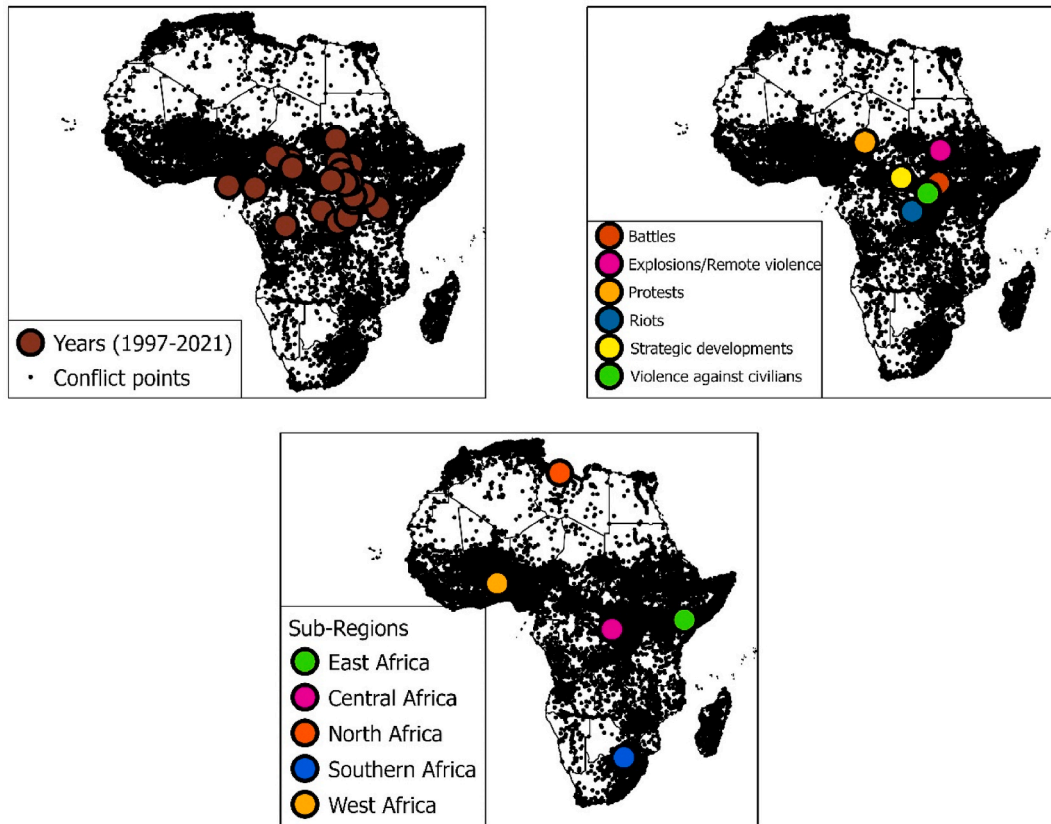


Fig. 2. Distribution of centrality of conflicts in Africa.

3. Materials and method

3.1. Data sources and processing

The data used for this study were obtained from a variety of repositories. The data on conflict statistics for Africa was obtained from the Armed Conflict Location and Event Data Project, which spanned from 1997 to 2021. The Greenberg Diversity Index 2021 and the Pew Research Centre provided data on ethnic and religious diversity indexes, respectively. Data on governance performance came from the Mo Ibrahim Governance Index, climate change data came from Eckstein et al. (2021) and data on guns from the Small Arms Survey database. The United Nations Sustainable Development Global database provided data on corruption, infrastructure (water, power, waste), schools, internet, health, economic growth, stunting growth, wasting, level of education, unemployment, poverty, and human rights violations. A total of thirty-six (36) independent variables were compiled from the various sources and merged into a single file. The merged data was spatially joined with a shapefile of the political boundary of African countries. Data gaps (countries without scores) were filled using the K-nearest neighbour spatial in ArcPro 2.1 software. K-nearest neighbour uses the average score of four neighbours (nations) to fill in countries without scores. Furthermore, all merged datasets were normalized $[X_{new} = (X_i - X_{min}) / (X_{max} - X_{min}) * 100]$ with X_i as the value, X_{min} = minimum value of the variable, X_{max} = maximum value of the variable] on a scale of 0–100 to ensure consistency and ease of comparison between nations.

3.2. Data analysis

The study employed several analytical techniques because of the uniqueness of each research question proposed. For *Q1 (Notable central points of conflicts in Africa)*, a spatial central tendency, measuring central

feature, (mean feature and median feature) was used to assess the centrality of the conflict locations in Africa based on the Euclidean distance function. The study further employed the standard deviation ellipsoid equation (Equation (1)).

$$C = \left(\frac{\sum_{i=1}^n \bar{x}_i^2 \sum_{i=1}^n \bar{x}_i \bar{y}_i}{\sum_{i=1}^n \bar{x}_i \bar{y}_i \sum_{i=1}^n \bar{y}_i^2} \right) \tag{Equation 1}$$

Where x and y are the coordinates of the features (i) and $\{\bar{x}$ and $\bar{y}\}$ as the mean centre for the total features. Furthermore, the standard deviation for x and y was based on the function (Equation (2)) to summarise the central tendency of conflicts, dispersions, and directional trends.

$$\sigma_{1, 2} = \left(\frac{\left(\sum_{i=1}^n x_i^{-2} + \sum_{i=1}^n y_i^{-2} \right) \pm \sqrt{\sum_{i=1}^n x_i^{-2} - \sum_{i=1}^n y_i^{-2} + 4 \left(\sum_{i=1}^n \bar{x}_i \bar{y}_i \right)^2}}{2n} \right) \tag{Equation 2}$$

The variances of the conflict points were scaled by an adjustment factor of one (1) generating an ellipse which encompassed about 68% of the conflict points. For *Q2 (Space and time simultaneously have no influence on the occurrence of conflicts in Africa)* the incremental spatial autocorrelation analysis based on Moran's I function (Equation (3)) was employed.

$$I = \frac{n}{S_o} \frac{\sum_{i=1}^n \sum_{j=1}^n w_{ij} z_i z_j}{\sum_{i=1}^n z_i^2} \tag{Equation 3}$$

Table 2
Mean conflict fatalities per year, subregion, and conflict event.

	Latitude	Longitude	Fatalities	Nearest Conflict Town	Country
1997	4.104	10.775	8	Pouma	Cameroon
1998	3.139	9.275	16	Kribi	Cameroon
1999	0.139	14.318	33	Akouaka	Gabon
2000	2.159	17.246	6	Imese	Democratic Republic of Congo
2001	1.228	19.462	7	Bokakata	Democratic Republic of Congo
2002	0.519	25.192	7	Kisangani	Democratic Republic of Congo
2003	2.425	23.866	6	Gubu	Democratic Republic of Congo
2004	2.986	25.980	6	Mboki	Democratic Republic of Congo
2005	2.645	27.421	3	Banda	Democratic Republic of Congo
2006	4.453	27.574	3	Dalundue	Democratic Republic of Congo
2007	2.847	30.276	3	Biringi	Democratic Republic of Congo
2008	0.862	31.028	2	Kyebando	Uganda
2009	1.010	27.990	4	Basiri	Democratic Republic of Congo
2010	2.967	28.899	3	Tora	Democratic Republic of Congo
2011	14.082	24.571	3	Amar Allah	Sudan
2012	3.953	26.349	2	Samongo	Democratic Republic of Congo
2013	8.924	27.470	2	Akuem	South Sudan
2014	8.948	25.557	2	Khor Shamam	South Sudan
2015	7.078	25.137	2	Abd El Lait	Sudan
2016	6.687	26.205	2	Abd El Lait	Sudan
2017	7.390	24.768	2	Khor Dulu	South Sudan
2018	7.123	22.934	1	Bani	Central African Republic
2019	10.655	19.156	1	Boum-Kabir	Chad
2020	9.920	17.635	1	Kouno	Chad
2021	8.739	18.490	1	South Danamadji	Chad
Subregion					
North Africa	28.407	17.148	2	Zillah	Libya
Southern Africa	-25.537	27.307	0	Thekwane	South Africa
West Africa	10.203	0.146	3	Nazawni	Ghana
East Africa	1.652	38.960	3	Hadado	Kenya
Central Africa	0.568	22.505	6	Djolu	Democratic Republic of Congo
Conflict type					
Battles	7.302	26.667	7	Abulu	Sudan
Explosions/Remote violence	14.066	28.336	3	Umm Badr	Sudan
Protests	11.642	15.972	0	Dourbali	Chad
Riots	0.195	20.490	1	Befale	Democratic Republic of Congo
Strategic developments	7.384	19.273	0	Kouanga	Central African Republic
Violence against civilians	3.863	24.276	3	Yangili	Democratic Republic of Congo

Z_i as the deviation of the conflict attributes i from the mean ($x_i - \bar{X}$) with $w_{i,j}$ as weight between i and j spatially, S_0 as the aggregate of the spatial weights and n as the total number of conflicts. Aggregated spatial weight was defined as $S_0 = \sum_{i=1}^n \sum_{j=1}^n w_{ij}$. The z-score (Z_i) function is given as

$$Z_i = \frac{I_i - E[I]}{\sqrt{V[I]}} \tag{Equation 4}$$

$$\text{with } E[I_i] = \frac{-1}{(n-1)} \tag{Equation 5}$$

$$\text{and } V[I] = E[I^2] - E[I]^2 \tag{Equation 6}$$

With I is the Moran's I value and n = number of conflicts.

Incremental autocorrelation was employed to measure the intensity of clustering based on the spatial distance between conflict points by assessing a series of distances and their statistically significant peak z-scores. The modelling parameters for the incremental spatial autocorrelation were the number of bands as twenty and the distance function as Euclidean and incremental distance determined by the incremental spatial autocorrelation algorithm automatically. With significant peak z-scores and distances identified, the study modelled the locations of conflicts and their corresponding time/day of occurrence by structuring them into space-time bins based on the Mann-Kendell trend test (Kendall, 1955; Mann, 1945). The study adopted the space-time cube algorithm from ArcPro 2.1 to generate emerging hotspots/coldspots by aggregating conflict points to netCDF data cube space-time bins. Major

hotspots/coldspots produced from the analysis were new, consecutive, intensifying, persistent, diminishing, sporadic, and oscillating.

Q3 (Factors influencing the various conflict space-time hotspots/coldspots in Africa) analysis was possible by interpolating the independent variables based on inverse distance weighted interpolation technique to generate a surface for the thirty-six (36) individual variables. Per the interpolated variables, a surface extraction tool was used to generate the values for each specific space-time hotspot/cold spot. A multicollinearity test was used to assess the variance of inflation (VIF) factor for the thirty-six (36) variables with VIF below 3.5 accepted for further analysis. A VIF below 3.5 is a good measure of ensuring independent variables are not related to one another (Prather & Kaspari, 2019). Fourteen variables (access to internet, access to pipe water, access to universal health, climate change, corruption index, ethnic diversity, municipal waste management, poverty, restrictions on press freedom, primary education, religious diversity, subjective well-being, unemployment and unsentenced detained) met the 3.5 VIF criteria. A multinomial logistic regression was performed to assess the likelihood of the fourteen variables determining the various types of space-time hotspot and coldspots.

4. Results

4.1. Notable central points of conflicts in Africa

Per spatial central tendency analysis, the study identified one central point for each year. In 1997, the central conflict point was in Yaoude (Cameroon) whereas in 2021, it was found in Kabo (Central Republic of

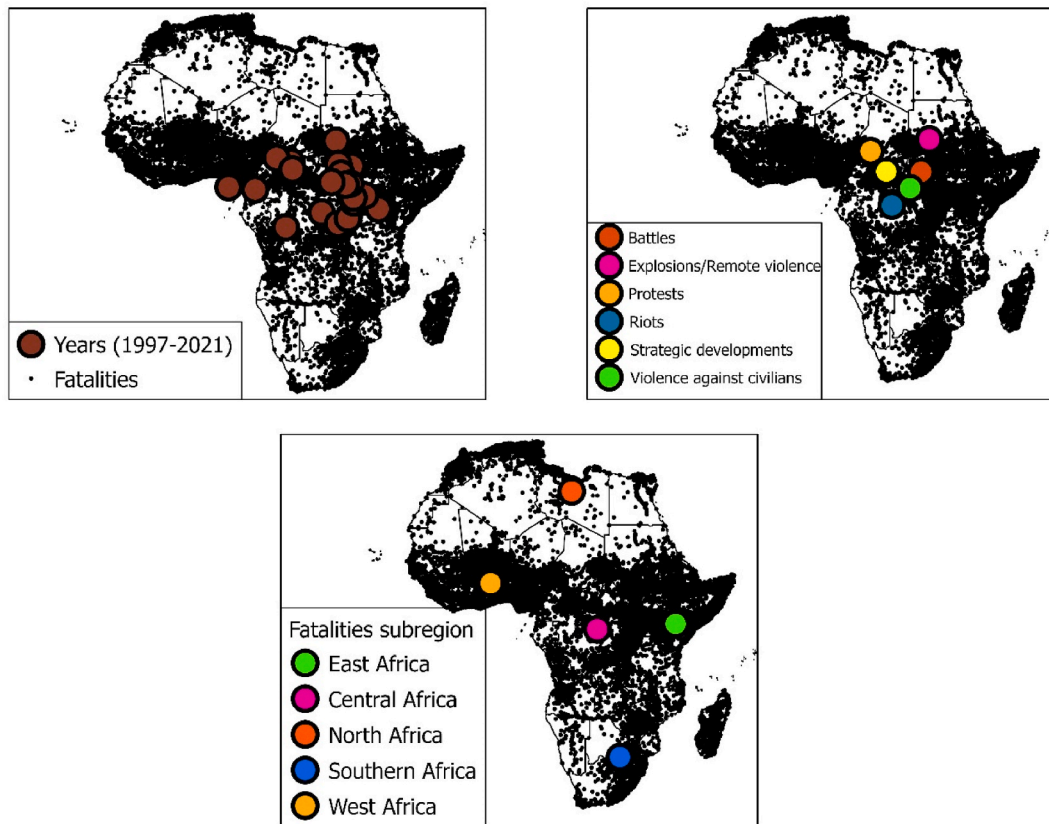


Fig. 3. Mean distribution of conflicts in Africa.

Africa). Between 1997 and 2021 countries with more central conflict points were the Democratic Republic of Congo and South Sudan with 7 and 6 points respectively (Table 1; Fig. 2).

Per subregions in Africa, North Africa had As Saddadah (Libya), West Africa had Kopargo (Benin), Khorof Harar (Kenya) for East Africa, Abongisia (Democratic Republic of Congo) for Central Africa and Olievenhoutbosch for Southern Africa as the central points. In terms of conflict types, the Democratic Republic of Congo had central points for riots and violence against civilians in Kisangani and Mabanga, respectively.

The concentration of mean distribution of conflicts from 1997 to 2021 was within Central Africa with no point in West, North and Southern Africa. Democratic Republic of Congo had the highest counts of mean conflicts from 1997 to 2021 with about eleven different periods (Table 2; Fig. 3).

Democratic Republic of Congo had eleven mean points from 2000 to 2012. Akouaka (Gabon) had the highest mean fatality with about 33 deaths in 1999. Per conflict types, Abulu (Sudan) had the highest mean fatality with 7 deaths while Dourbali (Chad) had no fatality. Mean analysis per subregion indicated that Djolu (Democratic Republic of Congo) had the highest mean of 6 fatalities (Table 2; Fig. 3).

Based on the standard deviation ellipsoid, the study identified the direction and number of conflict points within each ellipsoid. The year 2011 had the largest ellipsoid of 21,248,408.33 km² with 560,295 fatalities while 2014 had the least ellipsoid of 13893876.40 km² and 417,252 fatalities. The year with the most fatalities was 2012 with 684,037 deaths and ellipsoid of 21054891.29 km².

Protest exhibited the largest ellipsoid compared with other conflict types with an area of 26,424,782.63 km² and 582,808 fatalities. For subregions Central Africa had the largest ellipsoid, 3,304,200.23 km²,

but East Africa had the highest number of fatalities (144,251). Although, Southern Africa had an ellipsoid of 2,087,609.44 km² it recorded fewer fatalities (22,786) when compared to other subregions (Table 3; Fig. 4).

Conflicts in East Africa and Southern Africa had trends of conflicts with rotations less than 50°. Southern Africa had zero (0) fatality while East Africa had a mean of 3 fatalities. The ellipsoid for the year 1998, riots type of conflict, and West Africa had the most countries and fatalities (Table 3).

4.2. Space and time simultaneously influence conflicts in Africa

Initial spatial analysis identified significant spatial distribution of conflicts based on years, type, and region. With conflict events per specific year, the average number of peaks at which conflict points cluster was two (Table 4). It was observed that 2006 had the most incremental distance of 52.53 km with a peaking distance of 1267.18 km while 2020 had the least distance of 16.47 km. Maximum peak distance was 2279.46 km attained in 1997 (Moran's I = 0.02, Z-score = 30.78, p = 0.00) reduced significantly to 681 km in 2017 (Moran's I = 0.02, Z-score = 63.14, p = 0.00).

Conflict type with the least peak distance (472.30 km) was violence against civilians (Moran's I = 0.05, Z-score = 303.31, p = 0.00) with an incremental distance of 12.91 km. At the subregional level conflicts in East Africa (Moran's I = 0.05, Z-score = 546.02, p = 0.00) had the least peak distance at 276.32 km.

Results showed that four hotspots were persistent thus new hotspots, sporadic, oscillating, and consecutive. Oscillating conflict hotspots were the most frequent in Africa accounting for the most of riots (70.9%) and strategic developments (41.25%) hotspots (Table 5; Fig. 5). Per region,

Table 3
Standard deviation ellipsoid for conflict fatalities in Africa.

	Rotation	X Standard Deviation (Km)	Y Standard Deviation (Km)	Area of ellipsoid (Km ²)	No. of conflict points	No. of Fatalities	Mean Fatalities	No. of countries within ellipsoid
1997	110.31	3153.78	1712.68	16968143.57	123,678	516,130	4	18
1998	106.75	3219.24	1481.74	14984835.21	110,882	322,159	3	19
1999	107.94	2816.31	1646.81	14569727.44	103,291	447,493	4	16
2000	115.06	3161.21	1881.65	18686201.40	128,955	557,376	4	17
2001	127.82	3005.80	1813.80	17126816.70	124,404	535,883	4	17
2002	137.24	1732.07	2853.78	15527882.06	118,947	536,565	5	12
2003	119.51	2907.45	1788.97	16339608.52	143,012	467,107	3	17
2004	132.36	2592.68	1705.87	13893876.40	117,622	417,252	4	8
2005	129.75	2570.27	1814.93	14654349.81	135,026	504,101	4	9
2006	128.83	2711.22	1689.03	14385656.67	132,952	501,869	4	9
2007	132.06	2856.00	1872.07	16796061.19	134,417	514,991	4	10
2008	141.64	1907.34	2560.72	15343237.48	132,239	494,180	4	10
2009	143.43	1959.24	2813.44	17316287.91	142,613	645,871	5	13
2010	117.94	2681.66	2110.78	17781755.55	147,044	554,918	4	15
2011	149.33	2109.79	3205.97	21248408.33	160,220	560,295	3	12
2012	148.39	2194.51	3054.13	21054891.29	155,341	684,037	4	18
2013	158.12	2213.71	2926.41	20350931.20	153,112	560,464	4	13
2014	153.25	2068.12	2899.82	18839736.38	141,931	549,768	4	12
2015	157.57	2011.19	2988.76	18883032.32	129,036	640,409	5	13
2016	153.82	1980.57	2933.68	18252846.13	141,767	538,709	4	11
2017	140.68	1995.32	2985.48	18713504.41	145,207	550,946	4	10
2018	134.72	2947.84	1972.08	18262290.27	134,009	532,592	4	14
2019	142.92	1949.78	3383.67	20725394.41	131,952	448,972	3	14
2020	139.59	1936.49	3336.09	20294642.81	124,779	432,235	3	16
2021	137.01	1880.89	3295.75	19473548.69	123,876	430,776	3	17
Conflict Event								
Battles	113.22	2636.36	1633.10	13525228.21	136,701	527,107	4	8
Explosions/Remote violence	130.96	2927.00	1588.34	14604772.86	122,620	473,376	4	9
Protests	155.48	2124.15	3960.03	26424782.63	158,894	582,808	4	18
Riots	156.54	2147.87	3697.91	24951172.08	138,763	553,124	4	24
Strategic developments	107.10	3031.34	1777.49	16926621.68	153,870	535,884	3	18
Violence against civilians	120.81	2527.13	1642.90	13042685.58	116,608	414,870	4	10
Subregion								
North Africa	124.44	2329.43	1112.33	8139731.38	31,095	39,566	1	2
Southern Africa	24.82	563.70	1178.88	2087609.44	15,446	2,278	0	1
Central Africa	122.53	1184.78	887.77	3304200.23	37,901	111,076	3	1
East Africa	42.26	954.59	1100.75	3300913.66	56,078	144,251	3	1
West Africa	93.88	1401.18	567.25	2496875.12	28,313	68,219	2	3

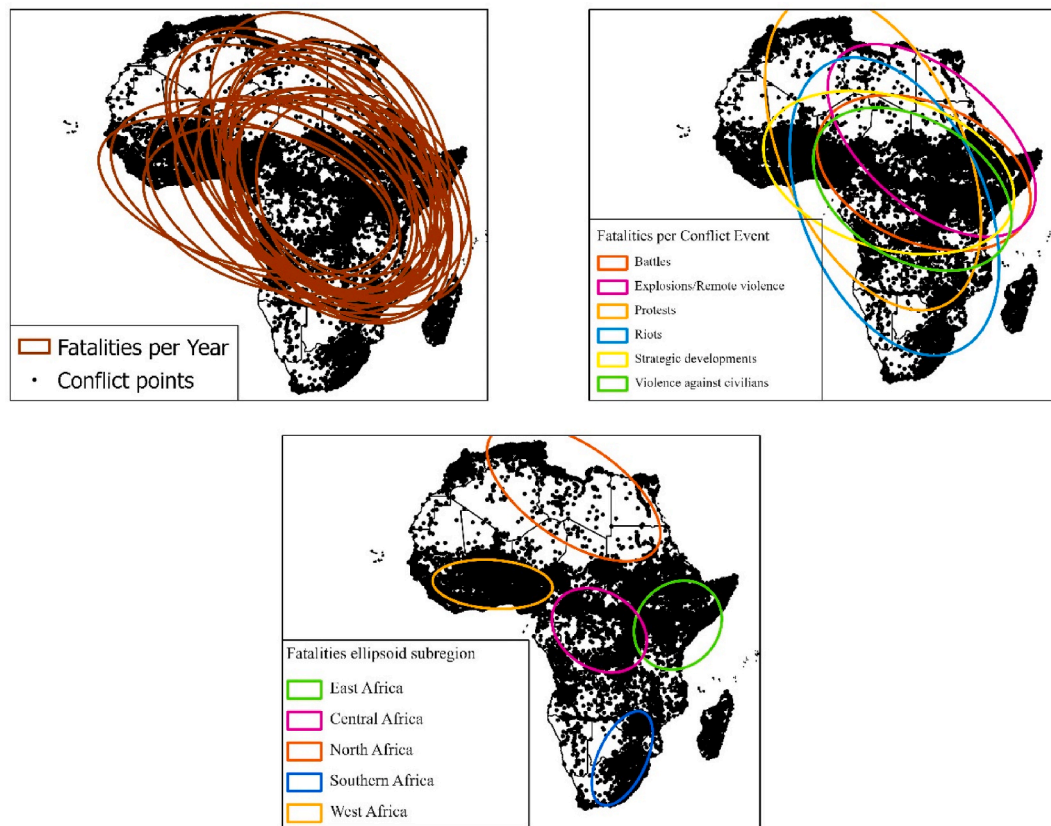


Fig. 4. Areas covered by standard deviation ellipsoid for conflict fatalities in Africa.

oscillating hotspots dominance was evident in Southern Africa (46.96%), North Africa (29.91%) and West Africa (10.46%) (Table 5; Fig. 6).

Hotspots in Africa are sporadic, accounting for less than 20% of hotspot types when analysed per conflict type and at the subregional level. Emerging new conflict hotspot types were explosions/remote violence (EE) and much confined to East (6.42%) and West Africa (6.22%) (Table 5; Figs. 5 and 6).

Space and time cumulatively revealed areas of significantly low number of conflicts (coldspots) in Africa. The coldspots spatial distribution was limited to North Africa which had sporadic (0.65%) and consecutive (0.65%) coldspots (Table 5; Fig. 6).

In general, the conflict types with the most hotspot coverage were explosions/remote violence (EE) and protests (EP) with 6652.94⁽¹⁰⁰⁰⁾ km² and of 7100.25 km² area, respectively. Battles (Cube area = 71.75 km² and total cube area = 15420.03⁽⁰⁰⁰⁾) had the lowest coverage area. East Africa had the most hotspot zones followed by North Africa and the least as Southern Africa.

4.3. Causes of conflicts vary across space-time hotspots/coldspots in Africa

Using variables which had VIF below 3.5 the study found fourteen variables to explain the difference in hotspots and coldspots across Africa (Tables 6 and 7). Ethnic diversity was less likely to influence the occurrence of new NHS for EB ($\beta = -0.25$, $p < 0.01$), EV ($\beta = -0.26$, $p < 0.01$), EP ($\beta = -0.89$, $p < 0.05$) and ES ($\beta = -1.19$, $p < 0.05$) (Table 6). New hotspots (NHS) for EB were influenced by access to universal health ($\beta = 0.70$, $p < 0.01$), solid waste management challenges ($\beta = 0.87$, $p < 0.01$) and unemployment ($\beta = 0.74$, $p < 0.01$). Subjective well-being ($\beta = 0.39$, $p < 0.05$) was the main factor likely to cause NHS for ES. For EV, NHS were determined by accessibility to internet ($\beta = 0.51$, $p < 0.01$), solid waste management challenges ($\beta = 0.46$, $p < 0.01$), unemployment ($\beta = 0.46$, $p < 0.01$) and restriction on press freedom ($\beta = 0.36$, $p < 0.01$). Consecutive hotspot areas were influenced by solid waste management challenges for EP ($\beta = 2.65$, $p < 0.01$) and EV ($\beta = 0.40$, $p < 0.01$). Religious diversity ($\beta = 0.20$, $p < 0.01$) influenced areas with CHS for EB. In North Africa ethnic diversity ($\beta = 3.43$, $p < 0.01$), access to universal health ($\beta = 2.31$, $p < 0.01$) and restrictions on press freedom ($\beta = 2.67$, $p < 0.01$) were more likely to influence CHS for EB (Table 7). Central Africa had over eight factors likely to influence CHS and three for NHS (ethnic diversity, unsentenced detained, access to pipe water). In East Africa, access to universal health, pipe water and unemployment were more likely to affect NHS with CHS and entrenched by unemployment, restrictions on press freedom and climate change.

Climate change, religious diversity and subjective well-being were more likely to influence CHS in West Africa. Emerging NHS were less likely to be a result of increasing poverty ($\beta = 0.84$, $p < 0.01$), and primary education ($\beta = 0.18$, $p < 0.01$) but not restrictions on press freedom ($\beta = 1.34$, $p < 0.01$). Also, unemployment, subjective well-being, primary education, and restrictions on press freedom were more likely to account for OHS in West Africa.

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5. Discussion

This study reaffirms Lis et al. (2021) and Simanda's (2019a, 2019b) results about the impact of space and time on conflicts. According to the study, the centrality of conflict in Africa is determined by the year of the conflict, the type of conflict, and the subregion. Communities in the Democratic Republic of Congo were found to be the central conflict points

Table 4
Maximum peak distance of clustering for conflict fatalities in Africa.

Year, event, subregion	Number of peaks	Distance Increment (Km)	Peak Distance (Km)	Moran's I	Expected Index	Z-score	p-value
1997	2	46.93	2279.46	0.02	-0.0001	30.78	0.00
1998	2	37.14	1676.80	0.05	-0.0002	75.09	0.00
1999	2	42.38	1199.94	0.09	-0.0002	108.85	0.00
2000	2	43.06	1340.02	0.02	-0.0002	27.31	0.00
2001	2	41.78	830.16	0.02	-0.0002	12.80	0.00
2002	2	45.23	1156.21	0.02	-0.0002	25.88	0.00
2003	2	47.47	1013.43	0.08	-0.0002	60.02	0.00
2004	2	50.06	1647.25	0.02	-0.0003	25.47	0.00
2005	1	51.25	1482.38	0.02	-0.0003	14.95	0.00
2006	2	52.53	1267.18	0.03	-0.0003	22.27	0.00
2007	1	48.06	870.57	0.06	-0.0002	41.25	0.00
2008	1	38.76	1500.25	0.02	-0.0002	26.40	0.00
2009	2	48.50	1313.72	0.01	-0.0003	10.77	0.00
2010	2	48.79	2023.22	0.02	-0.0002	29.84	0.00
2011	1	39.22	1796.29	0.00	-0.0001	9.02	0.00
2012	2	34.20	1332.55	0.01	-0.0001	19.53	0.00
2013	2	32.92	1314.19	0.02	-0.0001	91.78	0.00
2014	2	27.09	815.37	0.05	-0.0001	133.15	0.00
2015	2	25.23	780.33	0.05	-0.0001	142.70	0.00
2016	2	23.19	872.46	0.02	-0.0001	63.89	0.00
2017	1	23.68	681.13	0.02	-0.0001	63.14	0.00
2018	1	23.45	721.24	0.03	-0.0001	62.84	0.00
2019	2	18.85	1009.64	0.03	0.0000	171.21	0.00
2020	2	16.47	878.39	0.02	0.0000	137.29	0.00
2021	1	18.16	830.04	0.03	0.0000	111.72	0.00
Conflict Event							
Battles (EB)	2	14.46	609.01	0.04	0.0000	404.41	0.00
Explosions/Remote violence (EE)	2	23.24	886.19	0.04	0.0000	135.09	0.00
Protests (EP)	2	20.09	543.64	0.004	0.0000	21.55	0.00
Riots (ER)							
Strategic developments (ES)	2	21.45	936.19	0.005	0.0000	10.10	0.00
Violence against civilians (EV)	1	12.91	472.30	0.05	0.0000	303.31	0.00
Subregion							
North Africa (NA)	2	12.68	593.08	0.03	-0.0001	364.69	0.00
Southern Africa (SA)	2	15.27	443.34	0.01	0.0001	85.39	0.00
Central Africa (CA)	1	11.38	318.22	0.08	0.0000	535.34	0.00
East Africa (EA)	2	8.90	276.32	0.05	0.0000	546.02	0.00
West Africa (WA)	2	98.90	316.32	0.05	0.0000	552.02	0.00

Table 5
Space-time cube analysis of conflict hotspots in Africa from 1997 to 2021.

Variables	Conflict event						Subregion				
	EB	EE	EP	ER	ES	EV	NA	SA	CA	EA	WA
No. of cubes	2149	937	937	1692	1549	2230	926	988	1297	1699	2122
Unit area of cubes (km ²)	71.75	7100.25	7100.25	7283.94	7165.62	7180.36	3798.63	998.94	2204.49	2418.57	1276.85
Total area of cubes (1000, km ²)	15420.03	6652.94	6652.94	12324.43	11099.60	16012.20	3517.53	986.95	2859.22	4109.60	2709.47
%No pattern	68.31	59.98	73.53	23.52	46.68	63.05	51.30	45.65	69.01	75.81	37.89
% Hotspots											
New	7.40	17.29	10.78	6.09	2.13	1.57	1.19	0.40	2.16	6.42	6.22
Sporadic	8.47	3.31	7.15	0.18	4.45	18.92	0.54	0.81	13.57	8.48	10.13
Oscillating	-	-	-	70.09	41.25	-	29.91	46.96	-	-	10.46
Consecutive	15.82	19.42	8.54	0.12	5.36	16.46	15.77	6.17	15.27	9.30	35.30
Persistent	-	-	-	-	-	-	-	-	-	-	-
Intensifying	-	-	-	-	-	-	-	-	-	-	-
Diminishing	-	-	-	-	-	-	-	-	-	-	-
Historical	-	-	-	-	-	-	-	-	-	-	-
% Cold spots											
New	-	-	-	-	-	-	-	-	-	-	-
Sporadic	-	-	-	-	0.13	-	0.65	-	-	-	-
Oscillating	-	-	-	-	-	-	-	-	-	-	-
Consecutive	-	-	-	-	-	-	0.65	-	-	-	-
Persistent	-	-	-	-	-	-	-	-	-	-	-
Intensifying	-	-	-	-	-	-	-	-	-	-	-
Diminishing	-	-	-	-	-	-	-	-	-	-	-
Historical	-	-	-	-	-	-	-	-	-	-	-
Mean Trend z-score											
No pattern	1.53	1.37	1.3	4.24	3.09	1.9	2.93	1.9	1.48	1.87	2.54
Hotspots											
New	2.62	4.67	4.79	4.25	4.35	3.88	4.06	4.49	4.2	3.69	3.77
Sporadic	3.19	4.63	4.88	5.27	4.62	4.38	4.62	4.97	4.83	2.55	3.23
Oscillating	-	-	-	4.8	4.12	-	4.36	5.01	-	-	4.35
Consecutive	4.86	5.08	5.15	5.41	4.6	4.42	3.80	5.05	4.4	4.6	4.26
Persistent	-	-	-	-	-	-	-	-	-	-	-
Intensifying	-	-	-	-	-	-	-	-	-	-	-
Diminishing	-	-	-	-	-	-	-	-	-	-	-
Historical	-	-	-	-	-	-	-	-	-	-	-
Cold spots											
New	-	-	-	-	-	-	-	-	-	-	-
Sporadic	-	-	-	-	-0.04	-	-3.42	-	-	-	-
Oscillating	-	-	-	-	-	-	-	-	-	-	-
Consecutive	-	-	-	-	-	-	-3.59	-	-	-	-
Persistent	-	-	-	-	-	-	-	-	-	-	-
Intensifying	-	-	-	-	-	-	-	-	-	-	-
Diminishing	-	-	-	-	-	-	-	-	-	-	-
Historical	-	-	-	-	-	-	-	-	-	-	-
Mean Trend p-value											
No pattern	0.13	0.21	0.21	0.2	0.11	0.15	0.03	0.31	0.26	0.38	0.12
Hotspot											
New	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.02
Sporadic	0.04	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.04	0.00
Oscillating	-	-	-	0.00	0.05	-	0.00	-	-	-	0.00
Consecutive	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Persistent	-	-	-	-	-	-	-	-	-	-	-
Intensifying	-	-	-	-	-	-	-	-	-	-	-
Diminishing	-	-	-	-	-	-	-	-	-	-	-
Historical	-	-	-	-	-	-	-	-	-	-	-
Cold spot											
New	-	-	-	-	-	-	-	-	-	-	-
Sporadic	-	-	-	-	0.9	-	0.00	-	-	-	-
Oscillating	-	-	-	-	-	-	-	-	-	-	-
Consecutive	-	-	-	-	-	-	-	-	-	-	-
Persistent	-	-	-	-	-	-	-	-	-	-	-
Intensifying	-	-	-	-	-	-	-	-	-	-	-
Diminishing	-	-	-	-	-	-	-	-	-	-	-
Historical	-	-	-	-	-	-	-	-	-	-	-

Battles (EB), Explosions/Remote violence (EE), Protests (EP), Riots (ER), Strategic developments (ES), Violence against civilians (EV), North Africa (NA), West Africa (WA), East Africa (EA), Central Africa (CA) and Southern Africa (SA).

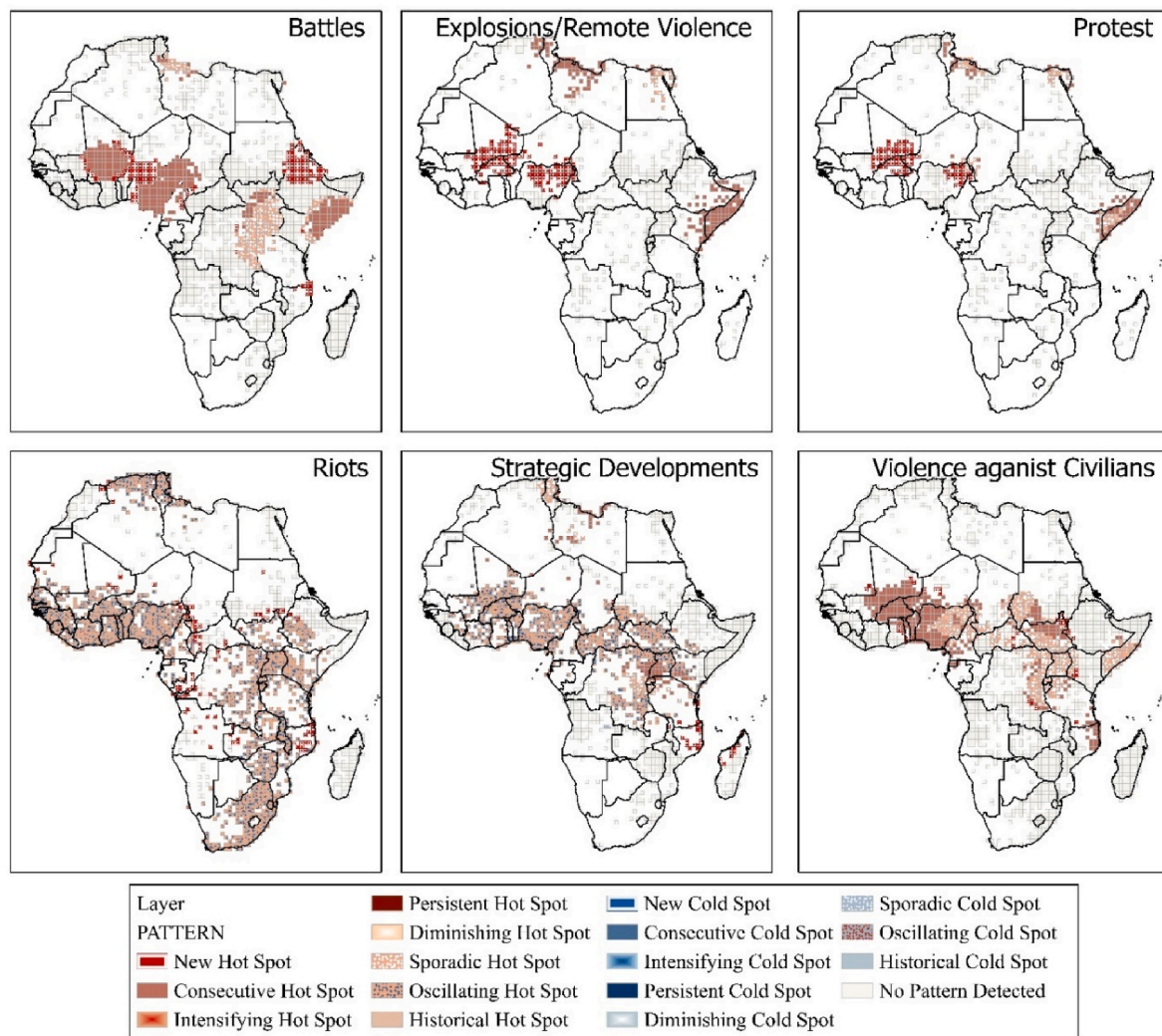


Fig. 5. Space-time analysis of conflict per events from 1997 to 2021.

on a year-to-year basis and for riots and violence against civilians. The Democratic Republic of Congo's high count of centrality can be linked to the country's high natural resource base, rurality, forested areas, and the large number of armed groups that go through villages rapping, recruiting, stealing, and murdering innocent people (Perera, 2017; Stearns, 2017). South Sudan took over from the Democratic Republic of Congo as the focal point of conflict in 2013, but things have changed dramatically since then, as Chad and the Central African Republic have taken centre stage recently. The emergence of South Sudan can be ascribed to the surge in conflict between ethnic groups fighting for control of the new country, as well as Sudanese succession issues (Kulang & Ogbonna, 2021; Mohammed & Baba, 2021). Although more interventions are needed in South Sudan, international bodies and peacekeeping agencies need to be commended for their support and interventions.

The Seleka rebels, foreign operations, and resource control have all contributed to an increase in mass killings and sexual violence in Central Africa Republic (Ahmat, 2018), while the conflict in Chad can be linked to the rise of violent extremist religious groups partly due to the fall of Muammar Gadhafi regime in Libya and the subsequent rise of ISIS in the Arab region (Mahdi, 2020). South Africa was undeniably the focal point of violence in southern Africa, which is not surprising given the country's high crime rate, violent protests, and xenophobic attacks (Lancaster, 2018). Due to increasing conflicts since the Arab Spring, towns in Libya have become the focal point of conflicts in North Africa (Daw, 2020). Protests in Africa have been centralized in Cameroon because of

increased Anglophone prejudice, herder-farmer conflicts, and land grabbing (Feldt et al., 2020; Mbih, 2020; Ngong, 2021).

According to O'Loughlin and Raleigh (2008), central conflict spots become areas from which it spreads to other areas was evident in this study as most grew outward from conflict zones. The largest conflict zone was in 2012 which encompassed most nations in East and Central Africa. The countries engulfed share similar socio-economic characteristics, which Zupančić et al. (2018) and Murdoch and Sandler (2002) claim facilitates conflict spread across neighbouring borders. One feature of the conflict zones was that they were all oriented in a north-west direction, implying the merging of conflicts from the West, Central, East and North Africa, this is a major concern for sub-Saharan Africa.

Using the three-dimensional space-time cube analysis, notable conflict hotspots in Africa derived were consecutive, oscillating, sporadic, new hotspots while coldspot type was sporadic coldspot. Battles in Nigeria, Burkina Faso, and Somalia were more common, as were explosions/remote violence conflicts in Somalia, and violence against civilians in Burkina Faso, Ghana, Nigeria, Somalia, South Sudan, and the Democratic Republic of Congo. Poverty, ethnic diversity, access to health, pipe water, education and waste management were the driving forces behind these consecutive hotspots. But at the subregional level, West Africa had factors such as subjective well-being, climate change, and restrictions on press freedom which need to be considered in predicting the occurrence of consecutive hotspots. New conflict hotspots on the continent were mainly because of poverty, religious diversity,

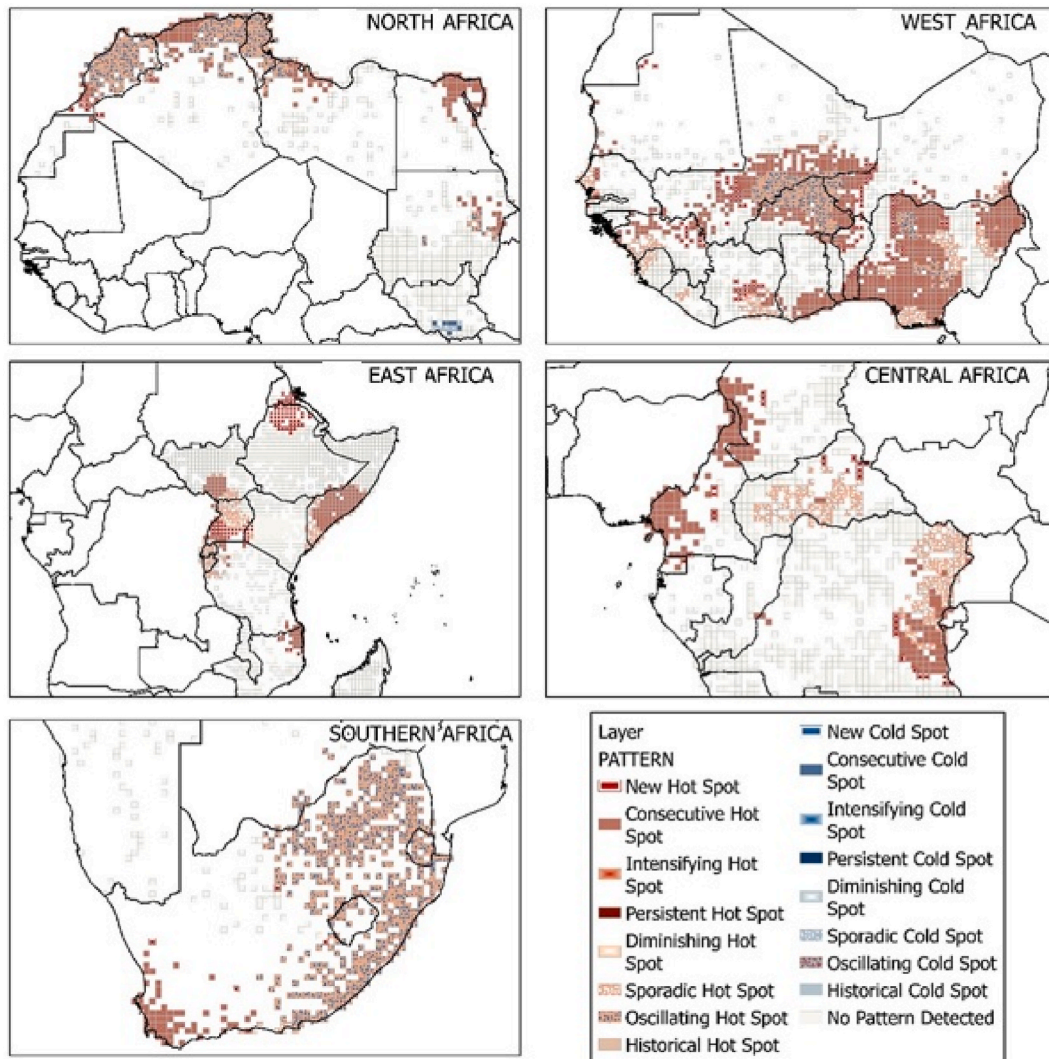


Fig. 6. Space-time analysis of conflict for subregions from 1997 to 2021.

Table 6
Determinates of space-time hotspots and coldspots per conflict types in Africa.

Variables	EB			EE			EP			ER			ES			EV		
	CHS	NHS	β	CHS	NHS	β	CHS	NHS	β	CHS	NHS	β	CHS	NHS	β	CHS	NHS	β
Intercept	3.81	-74.96 ^b	134.97	-247.63	-29.88	-66.11	-31.38	5.47	5.59	37.63 ^b	-58.98	58.16 ^b	208.32	-36.41 ^b	-64.21 ^b			
Ethnic Diversity	-0.09	-0.25 ^b	-2.75	2.12	-0.87 ^a	116.28	0.27	0.09	0.07	-0.08	-1.19 ^a	-0.14	-0.54	-0.26 ^b	-0.20 ^b			
Corruption Perception Index	0.00	-0.06	2.15	0.41	0.83	14.27	0.23	-0.23	0.06	-0.23	-2.94 ^a	-0.74 ^b	4.27	-0.23 ^a	-0.22			
Access to Universal Health	0.00	0.70 ^b	4.42	-3.97	0.25	226.01	0.04	0.09	0.09	0.02	2.49	-0.29	-10.56	-0.45 ^b	-0.38 ^a			
Access to Pipe Water	-0.01	0.09	0.21	-0.51	-1.79 ^b	7.15	-0.05	-0.03	-0.14	-0.52 ^b	0.37	-0.75 ^b	-1.53	0.00	-0.04			
Net Primary School enrolment	-0.08	-0.13	-2.30	1.45	-0.13	74.75	0.28	-0.03	0.04	-0.14	-0.32	0.18	0.47	0.14 ^b	-0.03			
Municipal Solid Waste Management Challenges	0.19 ^a	0.87 ^b	-0.83	-0.35	2.65 ^b	914.69	0.16	0.16	0.06	0.06	0.72	0.18	0.47	0.40 ^b	0.46 ^b			
Access to Internet	-0.31 ^a	0.15	-1.54	3.20	-1.28	117.83	0.29	-0.02	0.26	1.06 ^b	1.95	0.89 ^b	1.63	0.43 ^b	0.51 ^b			
Poverty	0.26 ^a	-0.32 ^a	-0.48	0.73	0.59	-266.06	-0.36	-0.14	-0.30	-0.50	-2.43 ^a	-0.49	1.20	-0.05	0.17			
Unemployment	0.20	0.74 ^b	4.15	2.24	0.74	31.35	-0.37	-0.35	-0.31	-0.08	0.77	-0.44 ^b	-2.29	0.04	0.46 ^b			
Unsentenced Detained	-0.22	-0.24	0.03	-1.31	0.46	14.63	0.22	0.13	0.13	0.14	-0.27	0.24 ^b	0.14	0.07 ^a	0.19 ^a			
Restrictions on Press Freedom	-0.18	-0.37 ^a	-0.18	1.74	-0.12	-5.13	-0.24	0.09	0.07	-0.06	0.75	0.51 ^b	0.70	0.43 ^b	0.36 ^b			
Religious Diversity	0.20 ^a	0.20 ^a	-0.81	-3.46	-0.15	-172.54	-0.18	-0.08	-0.08	-0.23	0.26	-0.22	-1.77	-0.16 ^b	-0.20 ^b			
Climate change	-0.06	0.08	-1.15	-1.41	0.09	62.22	0.13	0.13	0.13	0.04	0.39 ^a	0.04	-0.64	0.16 ^b	0.11 ^a			
Subjective Well-being	-0.02	-0.34	-3.13	0.14	-2.02 ^b	-379.16	0.30	0.15	0.22	0.37 ^b	-0.30	0.15	-3.89	-0.43 ^b	-0.68 ^b			
Model Fit			29.6		150.3		473.3			352.8				761.5				
-2 Log Likelihood (Final)	547.9		0.96		0.72		0.40			0.73				0.45				
McFadden	0.61																	

p < 0.01 = a, p < 0.05 = b, Reference category: Sporadic hotspot, CHS=Consecutive Hotspots, NHS=New Hotspots, OS=Oscillating Hotspot, SCS=Sporadic Coldspots, Battles (EB), Explosions/Remote violence (EE), Protests (EP), Riots (ER), Strategic developments (ES), Violence against civilians (EV).

restrictions on press freedom and rising unsentenced detainees. For East Africa, the influence of climate change enhanced the formation of new conflict hotspots.

Manotas-Hidalgo et al. (2021) explained that economic challenges faced by most countries such as unemployment, falling wages and increasing poverty provided enough incentives for people to fight, protest and even join armed groups. Also, the growing entrenched political divide in Africa is highly built along ethnic lines, colonial legacies and inequalities which produces high conflict-risk countries (Alesina & La Ferrara, 2000; Manotas-Hidalgo et al., 2021). The compounding effect of low rainfall serves as a multiplier effect on all other causes of conflicts because of the high dependency of socioeconomic livelihoods on climate and rain-fed agriculture. Climate change is increasing competition among herdsmen and farming communities, generating low production, and increasing famine, ethnic clashes and migration (Sakaguchi et al., 2017). It is clear from the results of the space-time cube analysis that different hotspot patterns have different causes with different levels of influence; hence all conflicts cannot be lumped into hotspots and coldspots without the time dimensions.

6. Conclusions and recommendations

The study found that central points of conflict tend to be fluid as they changed with time. The centrality of conflict points grow outwardly encompassing several communities and countries with an orientation favoured in the north-west, north, and east directions. Growing conflict zones were inversely related to the number of fatalities. Space-time cube revealed that conflict hotspots/coldspots have a time dimension with the dominant being consecutive, oscillating, sporadic, and new hotspots. Different hotspots had different explanatory variables. Consecutive hotspots are influenced by access to health, waste management, pipe water, education, ethnic diversity, and subjective well-being. For new hotspots, factors such as climate change, restrictions on press freedom, unsentenced detained, poverty and religious diversity were the major determinants. According to the study, the fluidity of conflict major points, needs continuous analysis and predictive analysis to aid peacekeepers in monitoring and providing fast response to save lives. Discovering hotspot patterns and causalities is critical for developing targeted actions to help combat Africa's growing conflict threat. Peacekeepers should also be aware that different types of conflicts coexist and require different approaches at different times of response.

7. Areas for further studies

To aid in peacekeeping missions, new studies could focus on forecasting important locations of disputes. Machine learning techniques can be incredibly beneficial in predicting future conflict locations by analysing past conflict trends to predict future scenarios. This will aid security services in preparing and supplying the necessary staff to deal with conflicts. Furthermore, investigations with spatial structural equations on the interaction between conflicts and sustainable development goals can help understand the domino effects of conflict.

CRedit authorship contribution statement

Adams Osman: Conceptualization, Methodology, Software, Methodology, Software, Data curation, Visualization, Investigation, Formal analysis, Writing – original draft, Writing – review & editing. **Alex Barimah Owusu:** Conceptualization, Methodology, Software, Investigation, Formal analysis, Writing – original draft. **Kofi Adu-Boahen:** Methodology, Software, Data curation, Visualization, Writing – review & editing. **Emmanuel Atamey:** Methodology, Software, Data curation, Visualization, Investigation, Formal analysis, Writing – original draft.

Table 7
Determinates of space-time hotspots and coldspots per subregions in Africa.

Variables	North		Southern	Central		East		West		
	CHS	NHS		CHS	NHS	CHS	NHS	CHS	NHS	OHS
	β	β	β	β	β	B	β	β	β	β
Intercept	-224.86 ^b	1000.78	-	-84.62	-878.78 ^a	-198.23 ^b	-250.23 ^a	170.66 ^b	77.92 ^a	271.66 ^b
Ethnic Diversity	3.43 ^b	35.54	-	0.87 ^a	8.09 ^a	0.33	1.52 ^a	-0.58 ^b	-0.13	-0.25
Corruption Perception Index	0.37	-19.53	-	1.20	-9.31 ^a	-2.92 ^b	-2.52 ^a	-1.16 ^b	0.37	-1.08 ^a
Access to Universal Health	2.31 ^b	-98.17	-	1.77	-8.32	-0.60	3.59 ^a	-2.35 ^b	-3.11 ^b	-4.17 ^b
Access to Pipe Water	1.13	-31.82	-	-0.30	10.29 ^a	1.52	2.39 ^a	0.10	0.11	-0.24 ^b
Net Primary School enrolment	0.20	-118.12	-	-1.21 ^b	-4.21 ^a	-2.80 ^b	-2.23 ^b	0.26 ^b	0.18 ^b	0.49 ^b
Solid Waste Management Challenges	1.11	113.59	-	1.31 ^b	6.68	0.31	0.91	-2.20 ^b	-1.28 ^b	-3.35 ^b
Access to Internet	-1.83 ^b	-107.24	-	-1.27	9.62	0.37	-1.72	-0.20	0.05	-0.90 ^b
Poverty	-0.66	248.82	-	-0.36	-4.07	-4.28 ^b	-5.58 ^b	0.17	0.84 ^b	0.64 ^b
Unemployment	-3.56 ^b	-7.21	-	0.68	2.52	2.57 ^b	2.74 ^a	-0.84 ^b	-0.67 ^b	-1.88 ^b
Unsentenced Detained	0.17	-53.12	-	1.54 ^b	10.86 ^b	0.93	-0.06	0.35	-0.59 ^b	0.10
Restrictions on Press Freedom	2.67 ^b	-104.62	-	-1.38	-11.11 ^a	2.30 ^b	-0.78	1.07 ^b	1.34 ^b	2.31 ^b
Religious Diversity	0.45	12.16	-	-1.09 ^b	-1.30	-3.88 ^b	-2.31 ^a	0.38	0.10	0.22
Climate change	-0.08	26.67	-	-0.50 ^a	-2.47 ^b	2.06 ^b	2.17 ^b	0.30 ^b	-0.16	0.12
Subjective Well-being	-0.75	24.13	-	1.87 ^b	-6.19	-0.54	-1.26	0.97 ^b	0.24	1.33 ^b
Model Fit			-							
2 Log Likelihood (Final)	134.028		-	189.15		236.27		1985.37		
McFadden	0.79		-	0.74		0.74		0.34		

p < 0.01 = a, p < 0.05 = b, Reference category = Sporadic hotspot CHS=Consecutive Hotspots, NHS=New Hotspots, OHS=Oscillating Hotspots, North Africa (NA), West Africa (WA), East Africa (EA), Central Africa (CA) and Southern Africa (SA).

Declaration of competing interest

interests or personal relationships that could have appeared to influence the work reported in this paper.

The authors declare that they have no known competing financial

Appendix 1. Variables and their level of multicollinearity

Variables	Normalized Average	VIF
Climate Change Index	51.6	2.98
Civilians with Firearms	11.6	17
No. of Military Firearms	8.2	3.96
No. of Firearms for Law Enforcers	4.6	7.27
Diversity Ethnicity index	62.7	1.42
Good Governance Score	48.8	52.81
Rule of Law	49.5	33.32
Participation and Inclusion	46.2	46.25
Economic Opportunities	47.8	72.74
Poverty headcount ratio at \$1.90/day	54.8	12.34
Poverty headcount ratio at \$3.20/day	20.7	7.14
Prevalence of undernourishment	52.2	7.94
Prevalence of stunting in children under 5 years of age	39.1	7.65
Prevalence of wasting in children under 5 years of age	54.0	8.71
Human Trophic Level	62.3	13.67
Life expectancy at birth (years)	31.3	32.8
Universal health coverage (UHC) index of service coverage	17.0	1.11
Subjective well-being	26.5	2.42
Net primary school enrollment	65.4	3.1
Secondary school completion rate	39.1	5.39
Literacy rate (of population aged 15 to 24)	59.8	6.95
Seats held by women in national parliament	43.2	8.9
Population using at least basic drinking water services	47.3	11.2
Population using at least basic sanitation services	33.9	4.76
Scarce water consumption embodied in imports	96.8	9.3
Population with access to electricity	46.5	10.86
Population with access to clean fuels and technology for cooking	25.7	7.23
Adjusted GDP growth	51.1	3.61
Victims of modern slavery	66.6	6.34
Unemployment rate	69.6	1.79
Population using the internet	25.6	2.67
Mobile broadband subscriptions	36.2	1.91
Access to Piped water	69.8	2.21
Satisfaction with public transport	43.2	10.34
Solid waste management challenges	72.3	1.25
CO ₂ emissions embodied in fossil fuel exports	99.8	6.87
Unsentenced detainees	52.8	2.55

(continued on next page)

(continued)

Variables	Normalized Average	VIF
Corruption Perception Index	26.4	2.63
Children involved in child labor	37.2	9.11
Exports of major conventional weapons	99.9	13.4
Restriction on press Freedom	61.7	1.22
Persons held in prison (per 100,000 population)	6.9	8.3
Religious diversity	54.2	2.28

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