Introducing the Spatial Conflict Dynamics Indicator of Political Violence

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ABSTRACT
While the location of violent events and their propensity to cluster together in space is increasingly well known, a deeper exploration of their spatiality and spatial evolution over time remains an emerging frontier in “Big Data”-driven conflict studies. The new Spatial Conflict Dynamics indicator (SCDi) introduced in this article contributes to fill this gap, by measuring both the intensity and spatial concentration of political violence at the subnational level. Articulating between point pattern and areal spatial analyses, the SCDi allows conflict researchers and analysts to not just map which regions experience the most violence but to track how the geography of conflict evolves over time. The SCDi identifies four spatial typologies of violence and can leverage political event data from most datasets with locational information and can be used for analyses across large multi-state regions, within a single state, or in more localized contexts. In this paper, we illustrate the SCDi with an application to the case of North and West Africa, analyzing over 30,000 discrete events through a twenty-two-year time span and across a twenty-two-state geographical area. We perform a longitudinal analysis of the SCDi typologies to show how the indicator can inform a theory of the spatial lifecycle of violence in the region. The indicator, therefore, has potential as both an analytic tool and a window on conflict episodes, showing how they can change from conflict initiation through resolution.

Introduction
In recent years, our understanding of the geography of political violence has greatly benefited from the increasing application of geographic information systems (GIS) and the development of numerous datasets that track the location and timing of political violence. For example, the well-known Armed Conflict Location & Event Data (ACLED) project now boasts access to a collection of hundreds of thousands of records about discrete acts of violence spanning numerous states across multiple continents and regions. The volume, velocity, and scope of such efforts have accelerated, marking conflict studies as important component of the now established “Big Data” paradigm in the social sciences. While a number of papers have established important findings about the geography of violence, such as the potential for political violence to cluster in space and time, examinations of the dynamic geographies of political violence remain under-explored in the wake of this data expansion.

Mapping the locations of violent events remains a key approach to exploring spatial conflict data but is also just the first step in considering more substantive questions about how violence changes.
over time and space. For example, analysts may wish to move beyond a map of violent event locations represented as points on a map to know whether political violence in a specific area has increased or diminished in intensity over time or if it has contracted within or spread geographically across a set of regions. In other words, while the precise locations of violent events are increasingly well known, deeper explorations of their spatiality beyond their locational presence and of the spatial evolution of violence over time within a region remains an emerging frontier in conflict studies.

Further, when investigating the spatiality of political violence, much of the literature remains focused on detecting event clusters of point locations in space and time. While important, the locational clustering of points is only one aspect of the spatiality of political violence. Others, such as the spatial intensity of violence in a region, have the potential to offer insight as well which requires methods designed to bridge the gap between point-based and area-based analyses.

The aim of this article is to begin to address this gap by introducing a new spatial indicator designed for use with political event data that translates between point-based and area-based spatial analytic traditions. Further, the indicator is designed to allow longitudinal analyses to address questions about the evolution of violence in regions. Our goal is to move toward a more comprehensive questioning of the spatial dynamics involved with political violence and the associated understanding of the spatial properties at play. Our new Spatial Conflict Dynamics indicator (SCDi) achieves this by incorporating two fundamental spatial dimensions of political violence from point-based analyses that can vary over time within any given region: conflict intensity, which measures the amount of violence, and conflict concentration, which assesses how violent events are distributed spatially across a region. The result is an area-based tool that draws on point-based datasets to offer new insights into the space-time characteristics of violence.

The SCDi can leverage political event data from most datasets with locational information, such as ACLED, and can be used for analyses across large multi-state regions, within a single state, or in more localized contexts. The SCDi is also adaptable to any size or configuration of underlying regions or areas to be used for analysis and can utilize any temporal duration desired. In this paper, we illustrate the SCDi with an application to the case of North and West Africa, analyzing over 30,000 discrete events through a twenty-two-year time span and across a twenty-two-state geographical area. We use the SCDi to not just show which regions or places experience the most conflicts but to also demonstrate how the inherent spatiality of conflict in these regions changes over time, including a first-ever assessment of the spatial nature of a conflict’s “lifecycle,” from the initiation of conflict in a region to its end.

The article proceeds as follows. In the next section, we discuss the recent trend toward spatially disaggregated event datasets that capture the spatial dynamics of wars and conflicts and the findings of the conflict literature interested in geography. We then describe the SCDi in detail and highlight the contribution of the indicator to this burgeoning field. Next, we use the indicator to show the long-term spatial evolution of conflicts in North and West Africa. We conclude with a discussion of the key contributions and limitations of our new indicator and identify avenues for future research.

**Motivation for a new indicator**

Geographic space is a fundamental dimension of armed conflicts. Geography not only provides the physical and cultural frameworks upon which battles are fought and terrorist attacks are conducted but also shapes the strategies of political actors. Proximity and distance can act as facilitating or constraining factors of a conflict and discrete spaces can also be a source of dispute when states and/or non-state actors fight over territory, natural resources, or boundaries. To understand how conflicts emerge, cluster, spread and disappear, recent research identifies several “determinants,” “risk factors” or “features” that have an explicit spatial component.

In Israel, for example, Berrebi and Lakdawalla suggested that terrorists are more likely to attack areas that are close to their operational bases and near international borders. In Iraq, Siebeneck et al. identified variations in patterns of attack frequency and intensity during the period 2004–2006 and found a strong local concentration of incidents in some cities. Modelling the use of Improvised Explosive Devices in Iraq in 2005, Braithwaite and Johnson also confirmed that remote attacks and
Counterinsurgency (COIN) operations tend to cluster in space and found that targeted COIN raids against specific buildings are associated with a decrease in insurgency while more spatially diffuse operations are not. In Belfast, Marchment et al. used risk terrain modelling to identify areas of the city where terrorism is more likely to occur. Their study suggests that violent dissident Irish Republican clusters near other known activity of the group, government buildings and areas dense with pubs and bars.

The previous examples are cases at national or urban scales but similar findings have been documented at the global level by Braithwaite and Li, who used local spatial statistics to identify hot-spot neighborhoods where the number of incidents is much larger than one would expect if terrorist events would be randomly distributed. Their analysis of 112 countries from 1975 to 1997 suggests that terrorism tends to disproportionately affect those countries located within terrorist neighborhoods. Medina and Hepner reached similar conclusions using a subnational approach: global Islamist attacks tend be strongly concentrated in a few geographical areas such as the Pakistani borderlands and Iraq.

The growing body of research documenting the impact of space on conflict has greatly benefited from the development of highly geographically detailed conflict data in the past decade. While past analyses on armed conflict were characterized by state-centric approaches and a general lack of reliable data at the substate level, the development of such “spatially disaggregated” datasets have made it possible to locate thousands of events based on their geographic coordinates, rather than just assigning them as occurring within a specific country or administrative region, for example.

Numerous datasets now track subnational expressions of political violence, including the Global Terrorism Database, the aforementioned ACLED, and the Uppsala Conflict Data Program. Other more specialized geocoded datasets include the Militarized Interstate Dispute Location or MIDLOC dataset, the Ethnic Power Relations data, the Geo-PKO dataset on peacekeeping operations, and the Leadership Changes in Rebel Groups dataset. What these examples all have in common is a reliance on identifying the location of an event as precisely as possible; events in these databases are “geocoded” or assigned geographic coordinates which allows them to be mapped using a GIS.

Accordingly, a growing number of studies have used such data to investigate the onset, duration, and impacts of armed conflicts by explicitly focusing on the location of events and their determinants. For example, the literature often models geocoded event data as a function of different local demographic, political, and economic measures, including factors as diverse as the nature of government, population composition, ethnic divisions, poverty, income, inequality, or number and morale of troops. Environmental factors such as rainfall and temperature variability, visibility and windy conditions, frequency of droughts, and endowment of natural resources are also commonly used to model episodes of organized violence around the world.

Another advantage of such geocoded data is that they are delinked from any underlying administrative areas which can enable several spatial techniques to be used to capture the enduring importance of space in the study of armed conflicts. Two of the most widely documented techniques are point pattern analysis (PPA) and areal analysis. Both approaches are interested in clustering of events in geographic space and can be used to identify “hot spots,” or areas where more violence is occurring relative to some standard or baseline.

Point pattern analysis investigates whether violent attacks are randomly scattered across space or whether they show systematic spatial distributional patterns, such as clustering near one another or repelling one another, within a single study region or area. For example, Lohman used point pattern analysis to determine that attacks by the Viet Cong were highly clustered across South Vietnam during the Vietnam War. Somewhat differently, areal analysis examines the geography of violence by assessing the spatial correlations between events in a focal region with a mean value of events with neighboring or nearby regions. In Nepal, for example, Khatriwada found that violence was similarly high among a group of neighboring western districts and similar low among eastern districts.

While geolocated event data are now standard for the reasons described above, point pattern analyses are still not as common as areal analyses in the literature. This means that the aspects of the inherent spatiality of political event data that are present in a point pattern analysis remain largely
underexplored even though the data could be used to consider how political violence emerges and spreads geographically over time. While the literature has established connections between rough terrain, the proximity to porous borders, the structure of the road network, and distance from centers of political power and the potential for violence, the overall process of the diffusion of violence remains understudied. For example, in an analysis of four different national cases of conflict, Schutte and Weidman clarified that violence can spread through multiple and different processes, including through both the escalation and relocation of a conflict between belligerents. However, treating states as individual cases can make little sense for regions where cross-border mobility of armed groups is common and the motives of the various belligerents transcend the politics of the state.

In sum, direct investigations of the dynamic spatiality of disaggregated conflict event data have lagged behind other applications, such as using event locations as a link to other areally-organized datasets for modeling purposes. Further, while many of the subnational factors that purport to explain why violence occurs have been investigated, the processes involved in the spatial diffusion of political violence remain underexplored. These are some of the animating issues behind our efforts and the Spatial Conflict Dynamics indicator (SCDi) is intended to be a first step to help fill this gap.

**The spatial conflict dynamics indicator of political violence**

The SCDi reflects two central themes about the spatial properties of a point pattern, the spatial intensity of a series of points, and the degree to which that same pattern exhibits clustering. It is therefore comprised of two complementary metrics that focus on these different but interrelated spatial properties of violence: the relative intensity of conflict within a region or zone and the distribution of conflict locations relative to each other.

In the language of PPA, spatial intensity is a “first-order” property of a point pattern that provides a *local* insight into the distribution of events across a single study region and shows subregions where the patterns may differ. Spatial concentration is then a “second-order” property that provides a *global* insight into how events are expressed and shows whether the pattern is generally clustered, regular, or dispersed across the entire region. The specific methods used for both metrics are described below followed by a discussion of how they are combined by the SCDi.

**Measuring conflict intensity**

A first-order property of a point pattern refers to the intensity of the underlying process that produces events across a study area that can be represented as points at discrete locations. Measurements of this property are concerned with the variation in the expression of points across a defined or bounded study region. The intensity of conflict events can be estimated from a point pattern’s observed spatial density, which is simply derived from dividing the sum of the number of events in a region by a measurement of the study region’s area for a defined time period. This can be applied to the entire study region, yielding a single estimate of the “global” spatial density.

Spatial density can also be “localized” by first subdividing the study region into smaller and ideally identically-sized subregions, and then calculating the density for each subregion. Figure 1 illustrates how the local spatial density of violence can vary according to the number of violent events within a hypothetical study region that is divided into nine subregions of ten square kilometers each. This approach is the basis for many area-based methods to investigate point patterns, such as quadrat analysis, a technique that examines whether events are distributed randomly or according to a pre-arranged pattern.

When applied to such smaller subregions, spatial density measures can help identify localized differences in the intensity of conflict across a larger region or identify localized changes to the intensity of violence over time. From this perspective, spatial density is useful in clarifying trends in violence both over space and time and may be helpful in recognizing the potential implications of an
intensification of violence over time in certain subregions. For example, if an increase in the number of violent events takes place adjacent to an international boundary, this may indicate a conflict process is at risk of becoming regionalized.

It is important to note that while spatial density is calculated using point data, it is not a measurement of the absolute location of points relative to each other. Instead, it is a measurement of a relative variability of events based on subregional divisions. The size and configuration of these divisions is always the prerogative of the researcher and the imposition of a uniform grid is common. Nonetheless, other choices are possible, including the use of unevenly sized- and shaped-areas, like political administrative units as the number of events is standardized by the amount of area within the subregion.

This spatial density measurement, which we refer to from here forward as conflict intensity or CI, has a lower bound of 0 when there are no events within a subregion during a given time interval. Because there is no conceptual limit to the number of conflict events that can occur, the CI measure also has no upper bound. Accordingly, as the CI measure increases from 0, it reflects a higher intensity of events within a subregion during a given time interval.

In our study, we use CI scores as one half of the SCDi but they can also be used separately. For example, it is possible to classify a subregion as exhibiting a local CI score that is either higher or lower than expected when compared to some expected CI measurement. To do this, a cutoff value must be established to create a threshold for classification purposes. While this can be done in a number of ways, we illustrate it in our study by first dividing the study region using a uniform grid, then calculating the CI score for every grid cell for every year in the study. We use this set of CI measures to calculate the mean CI score (excluding zeros) over that time span. This resulted in what we called the CI “generational mean” or the average conflict intensity for a subregion. Like other spatial analytic methods that use mean values for classification purposes, we classify a subregion as high density if it is greater than the generational mean and as low density otherwise.37

**Measuring the concentration of violence**

A second-order property of a point pattern refers to the relative concentration of points to each other across a study area and is concerned with whether points are clustered together or dispersed from each other. A variety of measures have been proposed to estimate this property, including those that capture a point pattern’s observed average distance between each point and its nearest point. Unlike a localized measure of spatial density then, spatial concentration is a “global” measure of the propensity for patterning of points relative to each other across an entire study region. In this way, distance-based concentration measures can help identify tendencies in how points are expressed or realized across a larger region.
Most measures of point concentration take departures from a randomly generated pattern (either toward clustering or dispersion) as an open question and the development of statistical methods to evaluate the concentration of point patterns has been a major focus in spatial analysis. However, for most human-caused phenomena that are represented as points, randomness is the exception rather than the rule. Therefore, we have not emphasized the statistical potential for point randomness in the development of the indicator. Rather, we are concerned with characterizing the amount of either clustering or dispersion in the patterning of conflict events for a given time period.

Among distance-based point-pattern measures, a widely used technique is the average distance to the nearest neighbor. With this method, the average distance to a neighboring point is compared against the expected distance under an assumption of a spatially random pattern. The Average Nearest Neighbor (ANN) ratio is given as: \( ANN = \frac{D_O}{D_E} \) where \( D_O \) is the observed mean distance between each violent event and its nearest neighbor (2) and \( D_E \) is the expected mean distance for violent events given in a random pattern (3):

\[
D_O = \frac{\sum_{i=1}^{n} d_i}{n}
\]

\[
D_E = \frac{0.5}{\sqrt{\lambda A}}
\]

In the above equations, \( d_i \) equals the distance between event \( i \) and its nearest neighboring event, \( n \) corresponds to the total number of events, and \( A \) is the area of minimum enclosing rectangle around all events.

If the ratio of the observed average nearest-neighbor distance and the expected distance is less than 1 the pattern is clustered, and if it is greater than 1 the pattern is dispersed. The ratio has a lower bound of 0 with no conceptual upper bound which would represent an extreme geographic clustering of events together in a region (all events at the exact same location). A ratio score of 1 would represent a random pattern of event locations as some would be near each other with others far away but there would be no overall detectible locational pattern. A ratio score of more than 1 would represent the relative dispersion of events across the region as they will be further apart from each other than expected.

This is illustrated in the example below in Figure 2. Ten randomly placed events in an area would result in an average nearest neighbor distance of twelve kilometers. Observed-to-expected ratios smaller than one would indicate clustered events while ratios greater than one indicate dispersed events. The distribution of events on the left-hand side of Figure 2, for example, is clustered compared with a random distribution of the same number of events, as shown by its ratio of 0.5. The distribution on the right-hand side is more dispersed, with a ratio of 1.5.

The SCD indicator uses this average nearest neighbor ratio to determine if violent events are clustered or dispersed. While this can be done across an entire study region, it can also be applied using the same division of a study region into subregions as discussed in the previous section. To do this, we first measure the distance between each violent incident in a subregion to its nearest neighbor’s location, then average all these nearest neighbor distances. The average nearest neighbor ratio is then used to determine whether the patterns of violent events exhibit clustering or dispersion.

This measurement of conflict concentration (or CC hereafter) comprises the other half of the SCDi. Similar to conflict intensity, CC can also be used as a stand-alone metric to classify a subregion as exhibiting clustering or dispersion. However, unlike CI, the threshold value to use for classification purposes is already provided by the method. CC scores lower than 1 can be classified as clustered and scores higher than 1 classified as dispersed.
**Four conflict geographies**

By applying the two metrics of conflict intensity and conflict concentration to the same subregion, the SCDI allows the classification of such areas along both a high/low intensity continuum and a clustered/dispersed continuum. Moving beyond just detecting clusters of points in space, our approach then allows the identification of four different spatial typologies of conflict within an area or subregion (Table 1). Each typology is based on whether violence is more or less intense in a subregion (above or below the mean intensity) and dispersed or clustered within a subregion (using the ANN ratio threshold).

The first type applies to subregions where there is an above-average intensity and a clustered distribution of violent events, suggesting that violence is more frequently realized yet localized within the subregion. The second type is when a conflict is characterized by a higher-than-average intensity and a dispersed distribution. In this circumstance, violence occurs frequently but without the clustering that characterizes the first type. This indicates that the violence is impacting more different locations across the subregion than with the previous type. The third type applies to subregions where there are below-average violent activities and that most of them occur near each other. The fourth type is then when a lower-than-average intensity and a dispersed distribution of events are combined.

These spatial typologies are interesting on their own and point out that conflict is a political process that occurs in both space and time. For example, when the first type (which combines high intensity and clustering) persists over time, it may indicate that the belligerents are relatively balanced in terms of capabilities with no group able to claim outright control in the subregion. The last type combining low intensity and dispersion may be expected to occur when a conflict is occurring between parties with clear capability imbalances (e.g., hit-and-run style attacks).

**Figure 2.** Spatial concentration distinguishes between clustered, random, and dispersed events as measured by the ANN ratio. Source: authors.

**Table 1.** Spatial typologies of conflict according to intensity and concentration of events

|                | High intensity                                      | Low intensity                      |
|----------------|-----------------------------------------------------|-----------------------------------|
| Clustered      | Type 1. More events than mean and closer together than expected | Type 2. Fewer events than mean and closer together than expected |
| Dispersed      | Type 3. More events than mean and further apart than expected          | Type 4. Fewer events than mean and further apart than expected |

Source: authors.
The typologies also move past a concern about detecting spatial clustering by allowing for the possibility of dispersion as an outcome of interest. For example, the spread of violence from one region to another necessarily involves the introduction of violence into new locations. When that process is occurring, the spatial patterning may not be clustered at all but rather appear as dispersed. The indicator therefore provides a window into the process of diffusion by identifying subregions that may be undergoing differing aspects of that process at any given moment.

**An application to North and West Africa**

To illustrate the SCDi, we applied it to a large multi-state region across North and West Africa where, since the early 2000s, a mix of ethnic rebel groups, transnational extremist organizations, and self-defense militias have challenged the legitimacy of several states. While not all of these countries have experienced significant episodes of armed conflict, many of the region’s governments are increasingly confronted with non-state actors that tend to relocate to other countries when confronted by counter-insurgency efforts. In northern Nigeria, for example, the joint counter-offensive led by Nigeria and its regional allies has led the Jihadist organization Boko Haram to develop its activities in neighboring Niger, Chad and Cameroon since the mid-2010s. Al Qaeda in the Islamic Maghreb (AQIM) has followed a similar evolution: expelled from northern Algeria by government forces, the Jihadist organization has first relocated to Mali in the mid-2000s, before moving to neighboring Burkina Faso and Niger in recent years.

The geographic spread and opportunistic relocation of such conflicts is amplified by the lack of controls on many African borders that facilitate the circulation of fighters, hostages and weapons. In this section, we describe how the SCDi can contribute to understand changes in the evolution of conflict in the region over the last twenty years.

**Data source**

The SCDi can leverage spatial data from most disaggregated datasets. In this paper, we used event data from the ACLED project, which provides detailed and georeferenced information on actors in armed conflict without imposing a threshold on the number of fatalities recorded for each event. It was applied to five North African countries (Algeria, Morocco, Libya, Tunisia and the Western Sahara) and seventeen West African countries (Benin, Burkina Faso, Cameroon, Chad, Côte d’Ivoire, Gambia, Ghana, Guinea, Guinea-Bissau, Liberia, Mali, Mauritania, Niger, Nigeria, Senegal, Sierra Leone, Togo) from January 1997 to June 2019. We used also calendar years as the temporal interval in our example, which resulted in SCDi scores for each full year between 1997 and 2018 (twenty-two years).

For our example, we focused on the three main categories of events classified as violent by ACLED: battles, explosions and remote violence, and violence against civilians (Table 2). During the period of observation, these 30,360 events have involved 2551 unique organizations and caused 138,207 fatalities. Demonstrations and non-violent events such as agreements, arrests, disrupted weapons use, headquarters established, looting and non-violent transfer of territory were excluded from the analysis. Apart from excluding the types of events described above, we used ACLED’s classifications without modification. Readers are referred to the ACLED codebook for more detailed information.

**Choosing the right grid for the region**

The SCDi can be applied to event data across any group of regions or areas. We adopted the conventional approach in the literature by dividing the larger study region into a uniform grid that provided a much more homogeneous representation of violence than existing administrative units, whose size differs enormously across countries and bioclimatic zones. Administrative regions tend to be much bigger in the sparsely populated Sahara than anywhere else, for example, which would greatly affect the density and diffusion of violent events.
For our example, we partitioned the larger study region into 6,540 subregions (or cells from here forward) of 50x50 kilometers. Each cell therefore encompassed the same amount of land area (2,500 square kilometers). At this resolution, each cell in the grid was large enough to aggregate a sufficient number of violent events for meaningful analysis while small enough to provide a localized assessment of political violence across the region. This allows comparing the evolution of conflicts from Dakar to N’Djamena, and from Lomé to Algiers.

By comparison, using a much smaller grid of 10x10 kilometers across such a vast region would have potentially provided a more granular understanding of violence. However, because political violence is already highly clustered at this scale, more than 90 percent of the cells this size would have been empty. Of the small proportion of cells that would have had events within them, fewer than half would have had more than one event. The indicator would not have been particularly meaningful with such small numbers of points in each cell. Larger cells, such as a 100x100 kilometers grid, are another option but would have aggregated distant events that would not be necessarily linked to one another (Figure 3).

The grid was first overlaid onto the study region and the event locations using a GIS. The cells were then used to determine the two separate calculations needed for the indicator: conflict intensity and conflict concentration per cell. We calculated the CI generational mean to use for classification purposes, which was 0.0017 events per square kilometer between 1997 and 2016. Given that the study uses a region of 2,500 square km, a low-intensity region is then one with four or fewer events in

| Event type               | Sub-event type                        | Events | Fatalities |
|-------------------------|---------------------------------------|--------|------------|
| Battles                 | Armed clash                           | 12,206 | 59,733     |
|                         | Government regains territory          | 898    | 4748       |
|                         | Non-state actor overtakes territory   | 827    | 4277       |
| Explosions/Remote violence | Chemical weapon                        | 0      | 0          |
|                         | Air/drone strike                      | 1487   | 5564       |
|                         | Suicide bomb                          | 483    | 4882       |
|                         | Shelling/artillery/missile attack     | 725    | 1176       |
|                         | Remote explosive/landmine/IED         | 2137   | 7605       |
|                         | Grenade                               | 53     | 48         |
| Violence against civilians | Sexual violence                       | 119    | 887        |
|                         | Attack                                | 9948   | 49,287     |
|                         | Abduction/forced disappearance        | 1477   | 1487       |
| Total                   |                                       | 30,360 | 138,207    |

Source: authors based on ACLED data.

**Figure 3.** Examples of alternative grids and the associated number of events by cells. Source: authors based on ACLED data.
a calendar year. Therefore, when the CI of a subregion was at or less than 0.0017, it was classified as low-intensity, when it was above that value it was classified as high-intensity.

Calculations were completed using a Python script developed by the research team. This primarily consisted of two nested loops that first calculated the conflict intensity and then the conflict concentration for each cell, year, and type of event. Because the clustering calculation requires a minimum input of two points, the script selected only the cells that contained more than one violent event within them. The resulting output for any given year was a grid of subregions with the spatial density and clustering measures for each cell containing two or more events. Pre-processing of the ACLED data was also done in R. In the following discussion, we first consider conflict intensity and conflict concentration separately before discussing the combined SCDi results.

**Conflict intensity: More subregions are experiencing violence**

Applying the CI metric to every grid by year shows how the geography of conflict has changed over time in the region and we highlight a few takeaways from examining the CI by itself at the beginning and end of the time range of our study. First, in 1997, most of the cells classified as more intensely violent were within Sierra Leone, with additional small pockets found along the Algerian and Nigerian coasts. However, in 2018, the geography of violence was quite different. Over time, violence had shifted away from most of the aforementioned locations and was found in new places within Mali, Burkina Faso, Niger, Chad, Cameroon, and Libya (Figure 4). This shows the overall geographical dynamism inherent in political violence and why it is important for indicators or measures such as ours to include a temporal as well as a spatial view.

Second, not only has the location of violence shifted over time since 1997, but it has also expanded in scope within the region. In 1997, eighty-five subregions had two or more events but in 2018 that number had increased to 433. In the context of this example, that represents slightly more than a 500 percent increase in the total number of subregions with violence. Interestingly, this increase is consistent when considering subregions of both high- and low-intensity. The proportion of high- and low-intensity violence subregions is nearly the same between the years (59 percent high-intensity in 1997, 55 percent in 2018).

Third, while the proportion of low- and high-intensity subregions is relatively unchanged, it is clear that there is a propensity for CI-clustering to occur. Many of the high-intensity subregions form contiguous blocks adjacent to other high-intensity blocks. These groupings tend to be surrounded by similar groupings of low-intensity subregions. In short, the CI shows an inherent spatial tendency in political violence for an intensity gradient to emerge during conflict.

**Conflict concentration: Violence patterns have become more dispersed**

Considering conflict concentration by itself also highlights interesting patterns. First, conflict is largely localized within subregions and events are highly likely to occur near one another: the average percentage of subregions classified as clustered (CC < 1) is nearly 91 percent over the years considered. As a side effect of this geography, the sundry negative impacts of violence are more likely to be felt in the same subregions and populated places repeatedly. In recent years, however, the percentage of subregions that exhibited clustering of violence has dropped from 95 percent in 2011 to 82 percent in 2018. This may indicate that violence is become more slightly dispersed. This is a likely consequence of shifting tactics, including the marked increase in the numbers of attacks against civilians as these types of events may be less likely to occur in similar locations over time.

Second, subregions with dispersed violence locations are a particular cause for concern because they may be evidence of the spread of conflict to a new area from a neighboring region. Conversely, a dispersed pattern may be evidence that a conflict is weakening or that one party is dominant in a region, as fewer violent events occur in nearby locations. In other words, a dispersed pattern can
identify regions where a transition is underway in either direction. Alarmingly, the percentage of subregions in 2018 with dispersed events (CC > 1) is nearly 17 percent, the highest percentage of all the years in the study. This is 7 percent higher than the historical baseline between 1997 and 2016 and may be a sign of the incorporation of new places into the already intensely localized geography of conflicts. If correct, this would result in a negative feedback cycle by exposing more locations with the region to the effects of violence.

Third, the relative locations of clustered and dispersed pattern regions have also shifted over time. For example, all of the major conflict areas (Figure 5) across the study region include clustered regions in 2018.
Over time, dispersed patterns have mostly been associated with conflict zones in Nigeria. The most populous country in Africa, Nigeria is also the country that has, by far, the largest number of violent events (9,017) and fatalities (67,512). Nigeria is home to three major sources of continuous violence that explain the unusual intensity and geographical extent of conflicts in the country: the Boko Haram insurgency in the northeast, communal violence in the Middle Belt, and the Niger Delta insurgency in the south. Taken together, these conflicts account for 30 percent of the violent events and half of the victims recorded in North and West Africa since 1997.
The dynamic geography of political violence

Since the SCDi combines both measures to identify the four spatial typologies discussed previously, these combined classifications can be used to consider how the geography of conflict has evolved in the region over time. In particular, the SDCi results show that the last ten years have been marked by an increase in all types of conflicts in North and West Africa.

The number of subregions experiencing a high-intensity and clustering (type 1) has increased significantly faster over time than the other spatial types. Historically, this type of conflict has been widespread in the region but its proportion to the other types has continuously increased since the mid-2000s, from 38 percent in 2008 to more than half ten years later (Figure 6). Nowadays, these subregions often form the core of large epicenters of violence, as in central Mali, northern Burkina Faso, around Lake Chad, in the Middle Belt and the Niger Delta in Nigeria, and in Libya (Figure 7).

Subregions in which conflicts are characterized by a high-intensity of dispersed events (type 2), are fortunately quite rare in the region. They concern only 3 percent of the cells, a proportion that has not changed much over the last twenty years. Several time periods with no cells of dispersed-high density are recorded, indicating that this combination is a rather unusual occurrence in the region. However, the locations where this type has been observed are also where conflict has been the most entrenched in the last decade, including the Inner Niger Delta in Mali, southern Nigeria, the Liptako-Gourma between Niger, Mali and Burkina Faso, and the border region between Nigeria and Cameroon.

The number of subregions in which political violence is both clustered and of low-intensity (type 3) has experienced strong growth since 2010. This type concerns a third (31 percent) of the cells of the wider region. However, these conflict subregions are still less well-represented than during mid-2000s, when they accounted for half of the four categories. They are often found on the periphery of more intense conflict zones, such as on the outskirts of major cities in Libya.

Subregions that experience dispersed and low-intensity events (type 4) are rare. This type is found in only 13 percent of the cells overall but the percentage of those subregions has doubled over the last ten years. These subregions are located at the periphery of the major war zones or in some countries with fewer violent events, such as Ghana, Guinea or Algeria.

![Figure 6. Time series of conflict subregions by SCDi categories, 1997–2018. Source: authors based on ACLED data.](image-url)
**Toward a spatial conflict “lifecycle” theory**

The changing composition of the four SCDi spatial typologies over time is suggestive of other aspects of conflict geography that remain understudied in the literature. For example, how often does a subregion experience a sudden outbreak of intense and clustered violence? Do conflicts tend to begin with one type and transition to others? And what is the propensity for types to change to something else over time? The SCDi allows the exploration of questions related to these dynamics and evidence of such changes is observable when we visualize the year-to-year interplay between the indicator’s typologies. For example, a subregion might have a SCDi classification as clustered/high-intensity in 2016, of clustered/low intensity in 2017, and of no conflict in 2018; placing such shifts in chronological order has potential to reveal much about the changing spatial forms violence can take across a single subregion during an outbreak of violence.

In Figure 8 below, we tallied all these annual shifts across the entire twenty-two years of the study into an alluvial chart to show how often changes from one typology to another occur. Subregions with no events or just one conflict event in a given year are excluded in the figure; the remaining subregions are then used to highlight how the region’s conflict geography has evolved over time. There are several takeaways from this type of presentation which we discuss below from the perspective of how violence emerges and ends in a subregion and what tends to happen in between.

First, when violence initially emerges in a subregion (moving from no conflict on the left of Figure 8 to one of the other categories on the right), the primary outcome is to shift to clustered/low-intensity, which accounts for 54 percent for all cases of the initiation of violence. Clustered/high-intensity is

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**Figure 7.** Spatial conflict dynamics indicator categories in North and West Africa, 2018. Source: ACLED. Calculations and cartography by the authors.
the second-most common pathway for the initiation of violence at 33 percent. These two clustered categories are also the most common types overall as subregions experiencing dispersed violence are far less common. This suggests when violence first emerges, it is likely to be concentrated within a subregion rather than dispersed throughout.

Second, once violence has emerged, it is most persistent year-to-year as the same type in the same subregion in its clustered/high-intensity form. Over 70 percent of the cases of cluster/high-intensity subregions remain in the same category the following year. This is markedly different from the other typologies which tend to be far less consistent over time in the same subregion, as they show more evidence of either changing to another typology or to no conflict year-to-year. This suggests that clustered/high-intensity conflict subregions are those where violence is most likely to endure over time and therefore, are likely to be the most difficult to resolve.

Third, while violence both initiates and ends from all of the SCDi typologies, the dispersed categories (dispersed/low-intensity and dispersity/high-intensity) are most common either at the beginning or ending of a sequence of violence in a subregion. In addition to being relatively rare overall compared to their clustered counterparts, these forms are quite unlikely to persist over time in the same subregion. Further they tend to change quickly to no conflict once they have emerged (54 percent of dispersed/high-intensity and 59 percent of dispersed/low-intensity cases). This suggests that subregions exhibiting these typologies are either toward the early stages of a conflict episode or near the end.

Finally, conflict in a subregion most commonly ends by transitioning from the clustered/low-intensity category; 58 percent of the subregions that change from some form of conflict in one year to no conflict the next start as clustered/low-intensity. Clustered/high-intensity is the next most common at 29 percent. This suggests that the most common spatial form of violence in a subregion before its cessation is a concentration of violence just before ending.

Taken together, these insights about the dynamics of the spatial typologies form the first-ever look at what we call the spatial conflict lifecycle theory of violence in a subregion. While this is not to suggest that all subregions, places, or localities will always exhibit the same transitions between SCDi
categories, there is a predominate pathway reflected in our data which we summarize below in Figure 9. When conflict emerges, it tends to result in clustering of either type. However, if it does emerge as dispersed, these categories tend to quickly change to another category and only tend to reemerge near the end of a conflict. When conflict does result in clustered/high-density violence, this form is far more persistent than the others, resulting in a longer duration of violence in that subregion. At the other end of the cycle, while conflicts can end from any of the four typologies, it most commonly ends from the clustered/low-intensity forms.

Of course, Figure 9 represents a simplified view of the complexities present within our cases and many questions remain to be explored, such as detailed examinations of the shifts relative to each individual category, the average duration of each type within a subregion, which subregions have the most expressions of violence of each type (or of any type) year-to-year, and so on. Yet, these and other investigations of the spatial form that violence takes in a region over time are not possible without a composite indicator like the SCDi, which translates the point-based spatial properties of conflict event data into area-based measurements that can tracked over time. Further, the patterns uncovered here suggest that certain spatial forms occur in specific phases of a conflict episode, which shows how the SCDi may be useful as a conflict monitoring tool. Perhaps most importantly, the SCDi can provide empirical evidence that can contribute to broader theorizations of the spatial conflict lifecycle of violence as suggested above.

Figure 9. Spatial conflict lifecycle. Source: authors.
Conclusion

The Spatial Conflict Dynamics indicator (SCDi) introduced in this article is designed to work with the emerging “Big Data” paradigm in conflict studies, which involves the production of an ever-increasing volume of location-based event data covering the great diversity of current conflicts in the world. By combining two important measures of the geography of conflict (intensity and concentration), the indicator shows promise to clarify not just where conflict occurs as point-based events but to consider the different spatial forms it can take within discrete areas and regions when it happens. In North and West Africa, where the indicator was applied for the first time, it also revealed several important elements about long-term political violence in the region that can inform analysts, policy officials and other stakeholders interested in the advancement of peace.

First, using the SCDi to track the long-term evolution of the geography of violence highlights that the location of violence is highly dynamic over time. Most of the major conflict areas of the 1990s are peaceful today and much of the current violence is observed in states that were considered stable fifteen years ago. This shifting and relocating of political instability, including across international boundaries, should encourage more research on how this diffusion process works even as disaggregated data collection efforts continue to track the locations of violence at fine-grained scales. It also highlights how a regional approach can be helpful; a focus on an individual country or even on a smaller set of states would have missed this essential character of political violence and perhaps failed to detect the direction and implications of such shifts when they occur. For those reasons, the SCDi can be used as a tool to monitor the larger patterns of violence regionally, keeping a watchful eye on the conditions that may be involved with the transitions from peace to violence and vice-versa.

Second, the SCDi illustrates how violence operates geographically over time. The recognition that violence can be differently concentrated while also varying by intensity provides a more nuanced understanding that can shape both governance strategies to deal with the circumstance and affect the relative efficacy of those efforts. For example, a highly clustered expression of violence will result in a different form of impacts on people and places than will a highly diffuse expression. Accordingly, relief and violence suppression efforts will necessarily need to take on a different character to address each. Similarly, understanding the relative intensity of violence over time in the same place or area is an important metric of human security that stakeholders can use to assess the effectiveness of their response to violence. That the SCDi addresses both aspects of the geography of violence speaks to the potential utility of it as a response tool when there is an outbreak of violence.

Third, the SCDi showed how the spatial dynamics of conflict have played out in aggregate over time. By tracking the four SCDi categories in the same subregions over time, we are able to assemble a first glimpse at the spatial conflict lifecycle. Of course, we recognize that an application of this approach to a different region and/or across a different time period may have yielded different results about the relationships between categories and more work is needed to establish how contingent or contextual these findings may be. Helpfully, the SCDi is flexible and adaptable to other geographical and historical contexts, including the configuration of the subregions used for the analysis. So long as the trends toward the development of disaggregated conflict data continue, the SCDi offers an opportunity to build data-driven profiles about the evolution of conflict within different regions and different historical eras.

The SCDi is not intended as a substitute for grounded qualitative knowledge about conflict in specific places and we recognize that no measure or indicator will be able to perfectly capture all the complexities of armed conflict and its geographies. However, we see opportunities to significantly improve upon the initial version of the SCDi. For example, the threshold value we used for the low/high intensity categories was based on data from all subregions across twenty years. This could be refined by utilizing a “moving window” method, both in space and time, to establish subregion- and year-specific thresholds. This in turn could provide a more nuanced and contextual interpretation of what counts as high- and low-intensity conflict based on the details or both where and when conflict is occurring. The intensity calculation could also be refined through weighting methods to capture...
variability in the spatial distribution of population or any other factor that may be associated with the production of political violence.

Future efforts to improve and refine the indicator will work to address these concerns. Other planned initiatives will focus on developing an open-source version to allow researchers to easily apply the indicator to other cases and to encourage other innovations not identified here. Ten years after the ACLED database was introduced to the scientific and policy communities, we view the SCDi as an important tool that can capitalize on the increasing availability of geolocated data to provide a more spatially nuanced understanding of conflict around the world.

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