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The spatial effects of violent political events on mortality in countries of Africa

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ABSTRACT
Mortality due to violent conflicts or political events (whether interstate, civil wars or conflicts between antagonistic groups, etc.) in countries of Africa is an issue of great concern due to the high number of victims and constant violation of human rights, which occurs daily. The participation of different types of actors, among them rebels, ethnic groups and regular troops, in these violent processes has been widely studied in numerous theoretical works based on a process of perception and intuition. This paper uses spatial modelling methods to empirically examine how these different groups of actors explain the mortality of violent political events in African countries in the period 2014–2015. The main contributions of this work consist in identifying the actors that have the greatest impact on mortality in Africa, as well as the spatial contagion effect caused by them. The results can be of use to policymakers for the design and implementation of geopolitical strategies based on more efficient empirical data with a view to reducing the mortality these actors cause in violent political events.

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Geopolitics; armed conflict; actors; spatial econometrics; GWR; GIS

Introduction

Africa constitutes an interesting laboratory for analysing the characteristics and evolution of contemporary armed conflict (Kaldor, 2013; Le Billon, 2013; Pearlman & Cunningham, 2012; Pettersson & Wallensteen, 2015), as important examples of the complexity of the causes, actors, forms of violence and foreign intervention in internal conflicts can be found on the continent (Easterly & Levine, 1997; Le Billon, 2001). One of the aspects that has attracted the attention of scholars from a range of disciplines has been the situation of structural violence arising from many armed conflicts on the continent, especially due to their prolonged duration and intermittent phases of suspension and reactivation (Bozeman, 2015). The association between poverty indicators, levels of human development and human security (Collier & Hoeffler, 2002; Ikejiaku, 2009; Stewart, 2003; Stewart, Humphreys, & Lea, 1997) and the conflict and violence suffered by African states have also been examined in the literature (Grebmer et al., 2015). Moreover, due to the political and institutional fragility of these states, a complex

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array of actors who use violence to achieve their objectives intervene in these conflicts. These include the governments themselves, rebel groups, national or foreign militias, ethnic groups and even political and civil organizations (Deng, Kimaro, Lyons, & Rothchild, 2010; Raleigh & Choi, 2017; Salehyan, Siroky, & Wood, 2014); all of which condition the spread of violence to other areas (Schmidt, 2013). Some violent actors find economic, military and political support in neighbouring countries or come from border states that wish to transform the established political order by aiding rebel groups or political militias from other states (Nalbandov, 2013; Schmidt, 2013). On other occasions, it is ethnic groups that use violence to achieve objectives that go beyond the state logic, and obtain help within and beyond the state borders in which they operate based on shared identities, solidarity and common political objectives (Elbadawi & Sambanis, 2000; Stavenhagen, 1996; Taras & Ganguly, 2015). The consequences of the violent actions of these actors invariably result in serious violations of human rights and a significant number of civilian victims (Raleigh & Choi, 2017; Wood, Kathman, & Gent, 2012). Hence, it is of interest to examine, through spatial modelling, the relationship between the participation of these actors in violent acts and humanitarian consequences, especially with regard to the number of fatalities (Fjelde & Hultman, 2013).

Although the effect of the participation of these violent actors on the mortality in African conflicts is known, it has not been quantified in the literature. The contributions of this work consist of: a) quantifying to what extent the greater or lesser involvement of these actors leads to variations in the mortality of each country; b) determining to what extent the effects caused by these actors influence mortality in neighbouring countries through contagion; and c) demonstrating how these effects are not constant for all countries. These contributions are of interest both politically and socially because they provide political institutions tools for estimating the effect of these actors on mortality. For example, it has been observed that, globally, if the percentage of violent events caused by rebels of a country increases by 1%, the percentage of fatalities per event will increase by 6.4% in that country and by 1.7% in neighbouring countries.

A literature review and methods are displayed in the following sections. Also, the sources of information, variables used and the results obtained are presented. The study concludes with a discussion of the results and conclusions.

Literature review

There exist precedents in the literature that support the study of violent conflicts from a spatial approach and the need to model the occurrence of such events. In the field of geopolitics, some authors (Iqbal & Starr, 2015; Starr, 2013) argue that global policies must be contextualized not only in time, but also in space, and emphasize that greater focus should be placed on the spatial elements of socio-political phenomena. These authors stress the importance of the relationship between space and time in order to explain changes that occur in both dimensions. In a similar line, several studies (Collier, 2000; Van Evera, 2013) have shown the persistence of causal variables that determine the presence of conflicts, such as cultural, ideological, ethnic, political, economic, power-related and territorial variables. However, there is little research on the effect of dependence and/or spatial heterogeneity on violent conflicts. The existence of spatial dependence or autocorrelation implies that a conflict in a given area may be key to predicting an imminent conflict in a neighbouring area, because they have similar causal characteristics and are proximate in space (Buhaug & Gleditsch, 2008). For example, in two countries sharing several of the characteristics listed above and proximate in space, conflict may be contagious (Drakos & Kutan, 2003). In contrast, when spatial heterogeneity is present in conflicts, the effects of the causal variables related to them do not necessarily have to be constant in space.

Since geopolitics studies the spatial causality of political events and their near or future effects (O'Loughlin & Anselin, 1992), the use of quantitative spatial instruments in this field is fully warranted. In this regard, geographical information systems (GIS) are instruments that allow for the spatial management of information, while one of the main objectives of spatial econometric techniques is to unveil and analyse causal relations.

A fundamental aspect of spatial data analysis, and especially in spatial econometrics, is the presence of spatial dependence in the phenomenon under study. This paper focuses on determining if the mortality caused by violent conflicts is spatially distributed in a random way or, conversely, if the proximate regions in space have similar values regarding the mortality of conflicts. Furthermore, the presence of spatial clusters determines the existence of *hot* or *cold* spots, that is, areas where mortality is particularly high or low, respectively. Spatial econometrics uses particularly appropriate statistical instruments to determine the presence of spatial dependence or autocorrelation and spatial heterogeneity, hence its use in this work.

According to Longley, Goodchild, Maguire, and Rhind (2001), GIS are the result of applying information technologies to the management of geographic information. GIS also allow managing georeferenced information, as well as handling, analysing and transforming spatial data. Although GIS have not been widely applied to the study of violent conflicts in the past, they have become increasingly common (Cilliers, De Klerk, & Sandham, 2013; Raleigh, Linke, Hegre, & Karlsen, 2010a; Weidmann, 2009; Wig & Tollefsen, 2016). A review of the utility of GIS in the analysis of these conflicts can be found in Buhaug and Lujala (2005) and Branch (2016).

Spatial econometrics has been applied particularly in regional and urban sciences (Anselin, 2010). Although not vast, some research highlights the importance of using this methodology together with GIS in geopolitics and in the study of violent conflicts (Buhaug & Lujala, 2005; O'Loughlin & Anselin, 1992). In this regard, O'Loughlin (2008) highlighted the scarcity of political geography studies using quantitative spatial analysis. Pioneering works in this line of investigation include those of O'Loughlin (1986) and O'Loughlin and Anselin (1992), who analysed international war conflicts using spatial autoregressive models (SAR) or the work of Anselin (1995), who studied spatial clusters of violent conflicts in Africa. Another research contribution in this area is that of Gleditsch (2002), who examined the spatial dependence of war conflicts in different decades and showed the presence of spatial dependence in certain years. This author (Gleditsch, 2007) performed a spatial econometric analysis using an autologistic model of civil wars with an international scope to detect the presence of spatial contagion. Buhaug and Gleditsch (2008) used a logit econometric model to study the outbreak of civil wars at the international level in the period 1950–2001. Cunningham and Sawyer (2017) employed a multilevel spatial autologistic model to analyse self-determination claims and found evidence of spatial diffusion. Other works include those of Raleigh, Witmer, O'Loughlin, and Denemark (2010b), who performed a spatial analysis of conflicts in the Congo to detect their areas of influence and Weidmann and Ward (2010), who conducted a space-time study of conflicts in Bosnia. In a similar line, Chi and Flint (2013) studied the main interstate conflicts worldwide using geographically weighted regression (GWR), O'Loughlin and Witmer (2011) used this method to study violence in the North Caucasus of Russia, and Öcal and Yildirim (2010) analysed the regional effects of terrorism on economic growth in Turkey.

The following methods have been used in this work: GIS, global and local spatial autocorrelation tests, GWR and spatial econometric models. These instruments are suited to the main objective of this study, which is to analyse the relationship between the participation of actors involved in violent political events and the mortality recorded in such events based on available statistical information regarding the spatial location of the number of fatalities in these conflicts.

Methodology

In order to analyse whether the mortality caused by these events in African countries is spatially dependent, global and local indicators of spatial association traditionally applied in the field of spatial econometrics have been used. This type of analysis allows us to determine if the spatial distribution of mortality presents global and local autocorrelation. In order to detect global autocorrelation, Moran's I statistic is normally used, whereas local indicators of spatial association (LISA) are used to detect local autocorrelation, that is, the existence of spatial clusters at the local level (Anselin, 1995).

The analysis of global autocorrelation allows detecting if the spatial distribution of the mortality is random or, conversely, if there exists a spatial autocorrelation structure. As indicated, to detect the presence of global autocorrelation, we use Moran's I test (Moran, 1950):

$$I = \frac{n}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(y_i - \bar{y})(y_j - \bar{y})}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{1}$$

where y_i is the i-th observation of the variable of interest; $\bar{y}$ is its arithmetic mean and w_{ij} are the spatial weights corresponding to countries i and j. These weights are the elements of matrix W, which defines the 'neighbourhood' between the different countries. Moran's I statistic provides a formal indicator of the degree of linear association (positive or negative) between the values of the variable of interest (y) and the values that variable takes in its neighbours (Wy).

In order to determine the presence of spatial clusters between the countries, a LISA analysis was performed. This statistic not only determines the hot clusters formed by countries with high mortality values next to countries with high values (high-high) or countries with low mortality values next to countries with low values (low-low), but also determines the presence of outliers (i.e. high-low or low-high). The analysis is performed using a local index obtained for each i-th country, which indicates if the spatial concentrations of the variable of interest are higher or lower than expected.

In particular, the objective of this paper is to determine in which areas of the African continent the spatial association is positive (i.e. countries with high mortality surrounded by countries with high mortality or, conversely, countries with low mortality surrounded by countries with low mortality) or negative (i.e. countries with high mortality surrounded by countries with low mortality or, conversely, countries with low mortality surrounded by countries with high mortality), which would indicate the existence of outliers. The expression of the LISA statistic to detect the presence of spatial clusters is as follows:

$$I_i = \frac{y_i - \bar{y}}{S^2} \sum_{j \in J_i} w_{ij}(y_j - \bar{y}) \tag{2}$$

where J_i is the set of neighbouring countries of country i and S^2 is the variance.

There is a wide range of methods for modelling the relationship between a variable of interest (in this case mortality) and a set of independent variables, such as the actors involved in the conflicts or other auxiliary variables. The classical regression model uses the OLS estimator, which has some limitations. One of them is that the observations must be independent of each other to ensure the efficiency of the OLS estimators (Anselin, 1988; Pace & LeSage, 2009). In the case of spatial data, such as those analysed in this paper, this hypothesis is not always fulfilled due to the main law of geography stated by Tobler (1970): 'Everything is related to everything else, but near things are more related than distant things.' This association can be detected by quantifying the presence of spatial autocorrelation in the dependent variable, in the independent variables or in the perturbations. In addition, another of the basic assumptions of the regression model is that the coefficients of the model are constant for all individuals (spatial stationarity), which does not always have to be fulfilled.

There are three classic approaches for modelling the effects of geographical location on spatial dependence in an econometric model (Anselin, 1988):

(1) Spatial lag model or spatial autoregressive model (SAR)

$$\begin{aligned} y &= \rho W y + \alpha \iota + X\beta + \varepsilon \\ \varepsilon &\sim N(0, \sigma_\varepsilon^2 I) \end{aligned} \tag{3}$$

(2) Spatial error model (SEM):

$$\begin{aligned} y &= \alpha \iota + X\beta + u \\ u &= \lambda W u + \varepsilon \end{aligned} \tag{4}$$

(3) Spatial Durbin model (SDM):

$$y = \rho W y + \alpha \iota + X\beta + W X \theta + \varepsilon \tag{5}$$

where α is an n x 1 vector of the values of the dependent variable; β is an n x 1 vector of ones associated with the intercept parameter Wy; X is an n x k matrix of the k explanatory variables of the model, which is related to the vector of parameter ρ; W is an n x n spatial weights matrix, w_{ij}, which reflects the spatial structure of the neighbourhood between observations; WX is a vector which represents the spatially lagged dependent variable (endogenous interaction relationships), which is related to parameter θ; Wu denotes the spatially lagged explanatory variables and λ is its associated vector; ε represents the spatially lagged perturbations, Wy is its associated parameter and WX is a vector of independent, identically distributed (i.i.d.) normal perturbations. It is important to note that models including $\hat{\beta}(s_i) = (X'W^*(s_i)X)^{-1}X'W^*(s_i)Y$ induce a global form of spillovers and $W^*(s_i)$ represents local forms of spillover (Anselin, 2002).

In order to determine if an SAR or an SEM model is more adequate, the Lagrange multiplier (LM) tests were used: the test for error dependence (LM-err) and the test for endogenous spatially lagged dependent variables (LM-lag). When these last two statistics were significant, following Anselin, Bera, Florax, and Yoon (1996), the robust LM-err and robust LM-lag were used. If both are significant again, the model corresponding to the statistic whose p-value is lower is selected. To determine if an SDM model is more suitable than a SAR model, a likelihood ratio (LR) test is used (Elhorst, 2014).

The above methods are considered to be global since they assume that the model parameters are spatially stationary. However, as indicated above, there are reasons to assume that these parameters are not spatially stationary, thus warranting the use of local models that consider spatial heterogeneity. A recent method that has been shown to be suitable for modelling spatial heterogeneity is the previously mentioned GWR method (Brunsdon, Fotheringham, & Charlton, 1996; Fotheringham, Brunsdon, & Charlton, 2003; Paez & Scott, 2004). The GWR estimator takes the following form:

$$\hat{\beta}(s_i) = (X'W^*(s_i)X)^{-1}X'W^*(s_i)Y \tag{6}$$

where β_k is a n x n diagonal matrix containing the weights ($(I - \rho W)^{-1}\beta_k$) of the observations. The influence of the observations surrounding observation i is given by a kernel function, which will usually assign more weight to near locations in the space than to those that are further away. Basically, there are two methods for determining kernel size in GWR: fixed and adaptive. Both methods have pro and cons. Adaptive kernel is preferred to ensure a valid amount of observation in each kernel and better reflect the geographic realities caused by the variation in state size and the number of neighbours across the space (Chi & Flint, 2013).

In this paper we have used R packages software: spdep (Bivand & Piras, 2015), GWmodel (Gollini, Lu, Charlton, Brunsdon, & Harris, 2013), ggmap (Kahle & Wickham, 2013) and sp (Pebesma & Bivand, 2005).

Study area, data and variables

In this paper, we study the mortality of politically violent events in countries of Africa for the period 2014–2015. A period of two years has been considered in order to reduce the number of countries in which these events caused no fatalities and have sufficient information available to carry out the analysis. The main objective of spatial modelling is to determine the impact of actors' intervention on the mortality of violent political events in countries of Africa. In this work, mortality has been associated with the number of violent political events and also with the population size of each country. Thus, we consider both the ratio between the number of fatalities in violent political events and the number of these events and the ratio between the number of fatalities in these events and the population of the country.

Data sources and variables

In order to study the linkage between mortality and the intervention of the actors that cause these violent political events in the African continent, diverse sources of information have been used. The main database used to test the hypothesis on this linkage has been the Armed Conflict Location & Event Data Project (ACLED) of 2016. In addition, other sources of auxiliary information have been used to obtain contextual variables which, according to the literature on the topic, could be related to the mortality produced in these events. Some of these sources have developed indices, such as the human development index, the democracy index and the global peace index, that are used in research on various types of conflicts.

The ACLED database was developed by researchers at the University of Sussex (Raleigh et al., 2010a). The database codes the dates and locations of violent political events that occur within civil wars, periods of instability, public protests and the breakdown of regimes. The events are georeferenced by means of geographic coordinates of the location where the event has occurred. In addition to dating, locating and classifying the type of event, information on the type of actor involved in each event (rebels, government troops, armed groups, demonstrators and civilians) and interactions between the different actors involved (government troops against rebels, government troops against civilians, etc.) is also provided. The ACLED database has been used in several studies (de Villiers, 2015; Dowd & Raleigh, 2013); Schutte & Weidmann, 2011), as it is considered to contain the most comprehensive subnational political violence data (Raleigh, 2012). In addition, ACLED has an advantage over other conflict databases in that it considers violent events that produce or do not produce fatalities (Eck, 2012). ACLED is used here precisely because we are interested in analysing the impact of the actions of different types of actors on the mortality rate of violent events, whether these cause fatalities or not.

The Human Development Index (HDI) was created by the United Nations Development Program (UNDP). The HDI is an aggregated social indicator that measures the quality of life of human beings by country. The index comprises three dimensions: knowledge (literacy rate and schooling), a long and healthy life (life expectancy) and basic income for a decent standard of living (GNI per capita) (Srinivasan, 1994). The HDI has been widely used in various fields for the analysis of sustainable development (Neumayer, 2001), the relation between corruption level and human development (Akçay, 2006) or the importance of geographical factors to sustain terrorist activities (Abadie, 2006), among others.

Moreover, The Economist Intelligence Unit's Democracy Index provides a snapshot of the state of democracy worldwide for 165 independent states. The 2014 index, which is the one used in this paper, reflects a decrease in the level of democracy in three regions: Latin America, the Middle East and North Africa and Sub-Saharan Africa (Economist Intelligence Unit, 2015); two of which belong to the geographical area under study.

The Institute for Economics and Peace (IEP) is an independent, non-profit research centre that has developed the Global Peace Index (GPI). The GPI information is aggregated by country and has succeeded in generating a credible assessment (Barash & Webel, 2013; Mac Ginty, 2013). This index takes into account a set of 23 variables, including the perception of criminality, military expenditure, violent demonstrations, political instability, political persecution, terrorism, relations with neighbouring countries, external and internal conflicts and displaced persons, among others.

Finally, additional sources of information used in this study include the Pew Research Center's Religion & Public Life (PRCRP), which reports on the percentage of the population of each country belonging to the main religious groups, and the African Development Bank Group, which provides information on the urban population of each country in its database.

As indicated, mortality in each country is measured from two points of view in this study. Firstly, mortality associated with the number of events is considered, for which the ratio between the number of fatalities in violent political events and the number of such events (ME) has been obtained. Secondly, mortality associated with population size has been considered through the ratio between the number of fatalities in violent political events and the country's population in thousands of inhabitants in 2010 (MP).

To explain and model mortality, the previous sources of information have been used as they provide information on the types of actors or aggressors involved in violent acts, the contextual variables that quantify the quality of life for each country, the level of democracy, the degree of violence in the country, the rural-urban distribution of the population, religious diversity and the number of neighbouring countries. The explanatory variables are shown in Table 1.

An increase in the intervention of actors, such as PREBEL, PETHNIC and PPOLIT, is expected to be associated with an increase in mortality. Table 2 shows the descriptive statistics of the two variables used to measure mortality (ME and MP), the variables capturing the types of actors involved in the events and the contextual variables. As can be observed, the highest mean percentage corresponds to events in which protests constitute the main actor (37.608%). This is followed by the mean percentage of countries in which a political group (13.067%), rebel groups (5.967%), ethnic groups (4.498%) and external actors (1.476%) intervene.

Moreover, the mean HDI for the African continent is 0.513, whereas this same figure is, for example, 0.915 for the USA and 0.916 for Germany. The lowest HDI value in the world corresponds to Niger (0.348) and the highest value to Norway (0.944). As for the democracy index, the mean of the African countries is 4.068, while the country with the highest democracy rate is Norway (9.93) and the country with the lowest is North Korea (1.08). As for the mean GPI of the African continent in 2014 (2.269), it is close to the mean in the USA (2.243), while in Germany, for example, it is 1.506. The lowest value in the world corresponds to Iceland (1.196) and the highest value to Syria (3.684).

Results

During the period studied (2014–2015), 31,141 violent political events occurred in the 49 countries of Africa, which resulted in a total of 70,774 fatalities (source: ACLED). It should be noted that more than 80% of the fatalities caused by these violent conflicts in Africa are

Table 1. Explanatory variables.

Name	Description	Source	Comments
Actor variables			
PREBEL	Percentage of total events in a country whose main actors are rebel forces	ACLED	This variable defines rebels as organized political groups whose aim is to counter a national governing regime by violent acts. For example, Al Qaeda in the Islamic Maghreb, Boko Haram, the Democratic Liberation Forces of Rwanda, etc.
PETHNIC	Percentage of total events whose main actors are ethnic groups	ACLED	Ethnic militias are associated with a direct ethnic community. For example, the Fulani ethnic militia (Central African Republic and Nigeria), the Misrata communal militia (Libya) or the Abala ethnic militia (Sudan), among others.
PPOLIT	Percentage of total events whose main actors are political militias	ACLED	In the ACLED database, political militias are defined as a diverse set of violent actors that are often created for a specific purpose or during a specific time period. These organizations do not seek the removal of a national power, although they are allied with a political elite, and can be the military arm of an opposition political party. They include, for example, Ansar al-Sharia (Libya), Anti-Balaka (Central African Republic) or the Dahalo militia (Madagascar).
PEXT	Percentage of total events whose main actor is an external actor, such as the UN interim forces	ACLED	An increase in the percentage of events in which an external actor intervenes is also expected to be associated with higher mortality, since these actors usually intervene when there is a resurgence of conflict.
PPROTEST:	Percentage of total events whose main actors are protesters involved in spontaneous, atomic acts produced by individuals who engage in demonstrations	ACLED	A high percentage of these events is expected to be associated with lower mortality.
Contextual variables			
HDI	Human development index for 2014	UNDP	This indicator ranges from 0 to 1 such that the closer it is to one, the higher the level of development in the country.
DEMI	Democracy index	The Economist Intelligence Unit's Democracy Index	The Democracy Index is based on five categories: electoral process and pluralism; civil liberties; the functioning of government; political participation; and political culture. The index ranges from 0 to 10. The level of democracy in countries has been considered as a factor to explain the existence of violent conflicts (Elbadawi & Sambanis, 2000), the escalation of violent conflicts (Reed, 2000) and the relationship of such conflicts with political protest (Dubrow, Slomczynski, & Tomescu-Dubrow, 2008). The lack of strong democratic institutions increases the risk of violent political conflicts (Elbadawi & Sambanis, 2000). Therefore, a higher level of democracy should be associated with a lower level of mortality.

(*Continued*)

Table 1. (Continued).

Name	Description	Source	Comments
UPOP	Percentage of urban population	African Development Bank Group	This variable has been used in studies on the level of violence in civil war (O'Loughlin & Witmer, 2011; de Villiers, 2015).
GPI	Global peace index for the year 2014	IEP	This index reflects the degree of violence in the countries, and is constructed in such a way that it takes higher values in countries of greater conflict. These indicators are normalized from 1 to 5.
NEIGH	Number of neighbouring countries	Own elaboration	Some authors have linked the number of borders with conflict and wars (O'Loughlin, 1986; Raleigh et al., 2010b). In addition, a greater number of neighbouring countries would imply greater ease for the entry of armed groups.
RELIGION	Number of religions with at least 5% of adherents in each country	PRCRP	Rebellions tend to be less frequent in societies divided into many small groups by religion (Elbadawi & Sambanis, 2000).

Table 2. Descriptive statistics on mortality, types of actors and contextual variables.

		Min	Mean	Max	Q1	Median	Q3	SD
Mortality	**ME**	0.000	1.527	9.775	0.133	0.348	2.024	2.372
	MP	0.000	0.096	1.152	0.002	0.004	0.042	0.256
Actors	**PREBEL**	0.000	5.967	51.292	0.000	0.000	7.812	11.706
	PETHNIC	0.000	4.408	18.509	0.325	2.542	8.571	4.824
	PPOLIT	0.000	13.067	54.083	2.857	8.701	20.433	14.060
	PEXT	0.000	1.476	22.222	0.000	0.000	0.529	4.120
	PPROTEST	5.324	37.608	80.000	16.981	37.608	55.555	21.426
Contextual variables	**HDI**	0.348	0.513	0.736	0.441	0.497	0.579	0.101
	DEMI	1.490	4.068	7.820	3.030	3.760	5.175	1.534
	GPI	1.770	2.269	3.327	1.981	2.189	2.409	0.426
	UPOP	10.999	41.938	88.112	27.254	27.625	56.743	18.401
	NEIGH	0.000	4.298	9.000	3.000	4.000	6.000	2.010
	RELIGION	1.000	1.957	4.000	1.000	2.000	2.000	0.884

concentrated in six countries (Nigeria, South Sudan, Somalia, Sudan, Libya and the Central African Republic), which is in line with other works (de Villiers, 2015). The two events with the greatest number of victims occurred in 2014 (around 600 fatalities) and 2015 (500 victims) in Maiduguri, Nigeria, with the main actor of both events being the Boko Haram jihadist group. This group is playing an important geopolitics role, because it frequents crossing the international boundaries (Elden, 2014).

The mean number of events per country is 635.531 and the mean number of fatalities per country is 1444.367, thus indicating the high level of mortality due to these events. The mean mortality on the continent is 1.527 fatalities per event (obtained as the mean of the values in column ME of Table 3), while the average mortality measured as the number of fatalities per thousand inhabitants is 0.096 (See Table 2). Table 3 shows the number of events, fatalities and mortality in relation to the events (ME) and the population size of the countries. As can be observed, Somalia is the country with the highest number of events; however, it is not the country with the highest number of fatalities, which is Nigeria. It should be noted that although Niger and Cameroon do not have a high number of events, both countries have a high number of fatalities, which explains why the events in these countries show the highest level of fatalities per event (ME). The four countries that suffer the most deadly violent events are Cameroon, Niger, Nigeria and Chad, which are geographically contiguous and occupy the western part of central Africa, as shown in Figure 1(a). Moreover, in terms of fatalities per thousand inhabitants (MP), the four countries with the highest mortality are South Sudan, Somalia, the Central African Republic and Libya (see Figure 1(b)).

As shown in Figure 1(a), mortality related to number of events in these African countries is not randomly distributed across the continent, but rather there is a group of countries with high mortality in the central strip and countries with low mortality in the south and north-west, thus suggesting the presence of spatial dependence. However, this spatial relationship is not clearly seen in the spatial distribution of mortality related to population size (see Figure 1(b)).

In order to detect the presence of global spatial autocorrelation, Moran's I statistic was used with three different conceptualizations of spatial relationships between states (W): (1) inverse distance between the centroids of states; (2) inverse distance squared between the centroids of states; and (3) physical contiguity between states. In the last case, the spatial weight is 1 for two countries sharing some common border and 0

Table 3. Number of events, fatalities, mortality associated with events (ME) and population size (MP) in countries of Africa.

Country	Events	Fatalities	ME	MP
Algeria	674	381	0.565	0.0107
Angola	24	23	0.958	0.0012
Benin	35	4	0.114	0.0004
Botswana	9	0	0.000	0.0000
Burkina Faso	280	59	0.211	0.0036
Burundi	549	701	1.277	0.0823
Cameroon	271	2649	9.775	0.1327
Central African Republic	1396	3855	2.761	0.8555
Chad	72	489	6.792	0.0425
Congo	51	15	0.294	0.0040
Congo DRC	1947	2971	1.526	0.0438
Côte d'Ivoire	209	58	0.278	0.0027
Djibouti	37	39	1.054	0.0444
Egypt	2155	735	0.341	0.0438
Equatorial Guinea	3	0	0.000	0.0000
Eritrea	9	20	2.222	0.0038
Ethiopia	236	900	3.814	0.0106
Gabon	52	3	0.058	0.0020
Gambia	32	3	0.094	0.0017
Ghana	130	45	0.346	0.0018
Guinea	94	46	0.489	0.0045
Guinea-Bissau	6	22	3.667	0.0134
Kenya	778	1078	1.386	0.0264
Lesotho	18	5	0.278	0.0024
Liberia	189	31	0.164	0.0076
Libya	2605	5273	2.024	0.8056
Madagascar	262	656	2.504	0.0326
Malawi	91	22	0.242	0.0020
Mali	357	791	2.216	0.0594
Mauritania	31	1	0.032	0.0003
Morocco	308	22	0.071	0.0007
Mozambique	195	121	0.621	0.0052
Namibia	159	9	0.057	0.0041
Niger	106	977	9.217	0.0615
Nigeria	3098	22,619	7.301	0.0326
Rwanda	45	9	0.200	0.0009
Senegal	291	12	0.041	0.0009
Sierra Leone	49	4	0.082	0.0007
Somalia	5274	8410	1.595	0.8986
South Africa	2594	345	0.133	0.0068
South Sudan	1803	9516	5.278	1.1520
Sudan	2605	7247	2.782	0.1678
Swaziland	20	3	0.150	0.0025
Tanzania	124	60	0.484	0.0013
Togo	35	8	0.229	0.0012
Tunisia	770	268	0.348	0.0258
Uganda	353	221	0.626	0.0065
Zambia	236	23	0.097	0.0017
Zimbabwe	474	25	0.053	0.0007
Total	31,141	70,774	–	–

otherwise. In all three cases, we have standardized the W matrix and the z-score is based on the randomization null hypothesis computation, with 999 permutations. The cut-off distance used for the inverse and inverse squared distance weights is the Euclidean distance, which ensures every feature has at least one neighbour (1,234 km). Table 4 shows the results of Moran's I statistic for mortality associated with number of events and population size. The results for the three conceptualizations

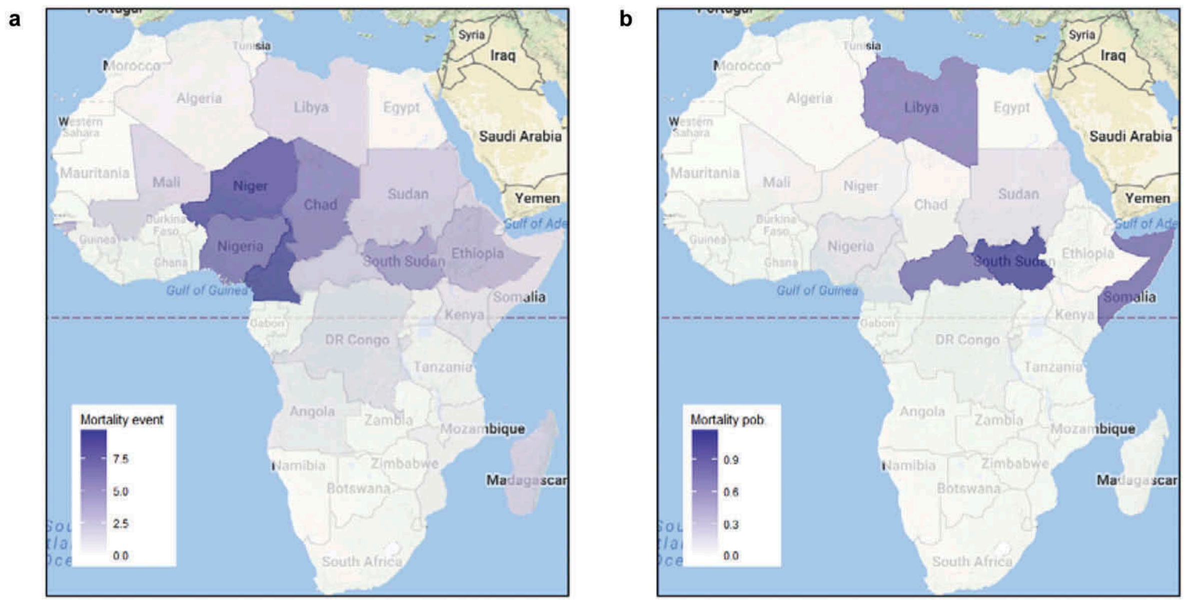

Figure 1. Mortality associated with number of events (ME, Fig. a) and population size (MP, Fig. b).

of spatial relationships show the existence of global spatial autocorrelation at a 99% confidence level for mortality related to number of events (ME), since the p-value is less than 0.01. However, this does not occur for population-related mortality (MP). This may be due to the existence of extreme values, such as those corresponding to South Sudan or Libya, which are surrounded by low values.

Therefore, it can be stated that the number of fatalities per event in a country might be explained by the mortality values in neighbouring countries. This may be due to a contagion effect between proximate countries such that that mortality in African countries is affected by variables of the surrounding areas, which causes countries within a given region to be affected in a similar form by these factors. In turn, this means that countries near in space will present similar mortality values. The notion of spatial contagion in geopolitics and the spatial diffusion of wars is not new (Most & Starr, 1980), and has been reported in other works (Starr & Most, 1983) which consider international conflicts to be contagious from one country to another in a pattern similar to the spread of epidemics (Rapoport, 1960). In fact, the Great Lakes region constitutes a laboratory for the contagion of armed conflict and structural violence. Indeed, armed groups in the region have acted in different states driven by ethnic and tribal affinities, economic interests and common political objectives (Rafti, 2006). In this sense, the policy diffusion literature emphasizes that actors in one national context may be influenced by actors in other states (Böhmelt, 2016).

Although it is difficult in practice to choose the best W matrix (Anselin, Sridharan, & Gholston, 2007), following Orford (2004), the results of Moran's statistic (see Table 4) reveal that the most significant statistics were produced by the first-order contiguity (highest z-score). Hence, we have used this measure for both LISA and the spatial econometric model.

In addition to detecting and characterizing the typology of global spatial autocorrelation using Moran's I test, the presence of local autocorrelation has also been analysed. For this purpose, spatial clusters of mortality in the African countries were analysed

Table 4. Spatial autocorrelation of mortality associated with events (ME) and population (MP) in Africa for different conceptualizations of spatial relationships.

	Moran's I		z-Score		p-Value	
	ME	MP	ME	MP	ME	MP
Inverse distance	0.3247	0.0623	3.8823	0.9863	0.0000	0.1620
Inverse distance squared	0.2839	0.0479	3.1150	0.7409	0.0009	0.2294
First-order contiguity	0.350	0.0638	3.9629	0.9597	0.0000	0.1686

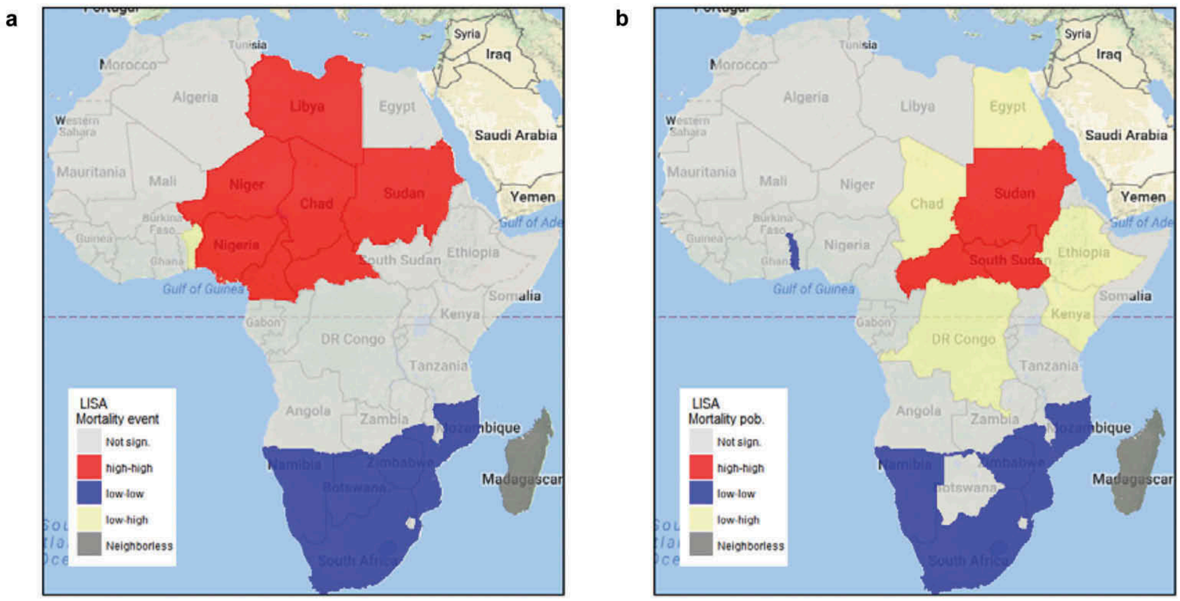

Figure 2. Spatial clusters obtained by the LISA statistic. Mortality per event (a) and mortality per 1000 inhabitants (b). Clusters with p-value = 0.05 are shown.

using the LISA statistic for a significance level equal to or lower than 5% (see Figure 2). As can be seen in the figure, there is one large high-high cluster composed of Libya, Niger, Chad, Sudan, Cameroon, Nigeria and the Central African Republic for mortality associated to events (ME). This implies that each of these countries is also surrounded by other countries with high mortality rates. A low-low cluster formed by Namibia, Botswana, Zimbabwe, Mozambique and South Africa was also obtained, as well as a low-high outlier country (Togo). As regards population-associated mortality (MP), there is a high-high cluster formed by Sudan, South Sudan and the Central African Republic. There is also a large low-low cluster comprised of Mozambique, Zimbabwe, South Africa and Namibia and another one comprising Benin. In addition, there are low-high outliers located around the high-high cluster. Some coincidences can be observed between the high-high and low-low clusters of the ME and MP variables.

In order to analyse the effect of the intervention of the actors on mortality, different regression models were specified, to explain both mortality associated with violent political events (ME) and mortality associated with population size (MP). The type of model specified in all cases is a semi-log model, in which the explained variable is obtained by performing the log-transformation of mortality (ln(ME) = LME and ln(MP) = LMP) in order to normalize the variable. Table 5 shows the estimates of the regression models corresponding to the explained variables LME and LMP. In both

Table 5. Estimated regression models for mortality in African countries.

	LME							LMP			
					GWR				GWR		
Dep. Variable	OLS	SAR	SDM		Median	Min, Max	p-Value MC	OLS	Median	Min, Max	p-Value MC
Const	−0.439	0.087	−0.119	Lag. coef.	0.218	−1.248, 0.846	0.52	−9.083***	−8.189	−9.932, −6.095	0.64
Actor variables											
PREBEL	0.070***	0.063***	0.060***	0.018	0.065	0.060, 0.076	0.82	0.063***	0.055**	0.047, 0.081	0.34
PETHNIC	0.096**	0.077***	0.047	0.089	0.096	0.070, 0.118	0.68	0.081*	0.068	0.016, 0.101	0.74
PPOLIT	0.022*	0.024**	0.012	−0.019	0.016	0.006, 0.023	0.85	0.024	0.031	0.019, 0.054	0.50
PEXT	0.038*	0.037**	0.043**	0.052	0.030	0.015, 0.057	0.57	−0.034	−0.055	−0.141, −0.021	0.36
PPROTEST	−0.019**	−0.019***	−0.026***	0.012	−0.016	−0.027, −0.009	0.33	−0.035**	−0.034	−0.048, −0.017	0.37
Contextual variables											
DEMI	−0.283**	−0.228**	−0.193*	−0.176	−0.176	−0.280, −0.103	0.72	−0.039	0.028	−0.129, 0.156	0.49
UPOP	−0.0002	−0.0003	−0.004	−0.004	0.003***	−0.017, 0.009	0.01	0.020*	0.020	0.012, 0.029	0.84
HDI	1.669	1.170	3.278*	−1.658	−1.718***	−2.982, 4.025	0.00	1.154	−0.945	−2.706, 1.830	0.56
GPI	−0.245	−0.340	−0.185	−0.802	0.048	−0.065, 0.345	0.98	2.004***	2.076***	0.851, 2.912	0.07
NEIGH	−0.052	−0.057	0.004	0.318	−0.086	−0.134, −0.035	0.91	−0.172	−0.301	−0.355, 0.051	0.05
RELIGION	0.149	0.132	0.185	−0.029	0.021*	−0.124, 0.218	0.21	−0.208	−0.353*	−0.407, −0.057	0.25
Spillover effect											
W-LME	–	0.226**	0.035		–			–	–		
Model fit											
Adjusted R-squared	0.763	0.774	0.744		0.710			0.749	0.727		
AICc	133.289	132.334	189.232		170.140			163.943	195.824		
LM-error	0.077	–	–		–			0.682	–		
LM-lag	3.284*	–	–		–			0.535	–		
Robust LM-error	0.597	–	–		–			1.911	–		
Robust LM-lag	3.902**	–	–		–			1.764	–		

Notes: MC = Monte Carlo test of spatial variation. AICc = corrected Akaike information criteria. Signif. codes *** 0.01 ** 0.05 * 0.1.

cases, the procedure is the same. First, both semi-log regression models are estimated by OLS with the explanatory variables corresponding to the actors intervening in the events and the contextual variables. These OLS models do not consider either dependence or spatial heterogeneity. Secondly, the results of the robust LM and LM tests for these models are analysed to verify if a SAR or SEM model is adequate. In addition, if the SAR model is selected, an LR-test must also be performed to determine if an SDM is more adequate (Elhorst, 2014). Finally, the last method was GWR, which allows us to examine the spatial variations of the effects of the explanatory variables across the African continent and permits us to consider spatial heterogeneity or spatial nonstationarity.

No serious problems of multicollinearity were detected for either the LME model or the LMP model, since for OLS the largest variance inflation factors (VIF) value among all the independent variables was 3.095 for the LME model and for the LMP model (smaller than 10).

Moreover, in the case of the LME model, the results of the LM test and the robust LM test indicate that the SAR model is more adequate than the SEM model (see Table 5, LME), since the p-value of the robust LM lag is less than 0.05 and less than the robust LM error. On the other hand, the likelihood ratio test (LR = 13.882, df = 11, p-value = 0.2396) indicates that the SAR model is more adequate than the SDM (Elhorst, 2014).

However, in the case of the LMP model, the LM and robust LM test results indicate that neither a SAR model nor an SEM model is preferred, since the p-values of these statistics are greater than 0.05. In addition, the ANOVA performed to test whether there was a significant difference between the OLS model and the SAR model (LR = 0.621, p-value = 0.430) and between the OLS model and the SEM model (LR = 1.201, p-value = 0.273) indicate that the SAR and SEM models are not more adequate than the OLS model.

Table 5 also shows the GWR estimates for both the LME and LMP models. To determine the number of nearest neighbours, we used an adaptive bisquare kernel which was chosen by minimizing the Akaike Information Criterion (AIC) using an iterative approach (Fotheringham et al., 2003; Öcal & Yildirim, 2010). In this case, the result was 44 nearest neighbours. To test global spatial nonstationarity, we used the F1 test (Leung, Mei, & Zhang, 2000), which indicated that there is no significant difference between the OLS and GWR models, nor for the LME model (F1 = 1.174, df numerator [dfn] = 27.403, df denominator [dfd] = 35, p-value = 0.676), the LMP model (F1 = 1.034, dfn = 27.403, dfd = 35, p-value = 0.542). The Monte Carlo test of spatial variation was also performed (Brunsdon et al., 1996). In the case of the LME model, the p-values of UPOP and HDI are less than 0.05, thus indicating that only these two variables are nonstationary at 95%, while in the case of the LMP model only the p-value of NEIGH is less than 0.05, although GPI would be non-stationary at 90% (see Table 5).

Therefore, the LME-SAR model adequately captures global effects to explain mortality associated with violent political events, while the LMP-OLS model adequately captures global effects to explain mortality associated with population size in African countries. In the OLS semi-log model, the direct effects are equal to the coefficientsβ_k, which represent semi-elasticities, that is, the percentage variation that occurs in mortality due to a unit increase in the corresponding explanatory variable (Gujarati, 2009). However, in a model with spatial dependence, such as the

Table 6. Direct, indirect and total effects.

	Direct	Indirect	Total
Actors			
PREBEL	0.064***	0.017**	0.082***
PETHNIC	0.078***	0.021**	0.099***
PPOLIT	0.024**	0.007	0.031**
PEXT	0.038**	0.010	0.048**
PPROTEST	−0.019**	−0.005*	−0.024**
Contextual			
DEMI	−0.231***	−0.062*	−0.294***
UPOP	−0.0003	−0.000	−0.0004
HDI	1.184	0.320	1.504
GPI	−0.344	−0.092	−0.437
NEIGH	−0.057	−0.015	−0.073
RELIGION	0.133	0.036	0.169

Notes: Signif. codes: *** 0.01 ** 0.05 * 0.1.

SAR model, the coefficients do not represent the direct effects, and their interpretation is therefore not valid (LeSage, 2008; Pace & LeSage, 2009). Hence, in a SAR model, the direct effects are the diagonal elements of $(I - \rho W)^{-1}\beta_k$, and the off-diagonal elements of this matrix are the indirect effects (Elhorst, 2014). The indirect effects show the response of mortality in country j to a change in the explanatory variables in any of the other neighbourhood countries (Debarsy, Ertur, & LeSage, 2012). The sum of the direct and indirect effects are the total effects. The direct, indirect and total effects are shown in Table 6. For example, if the events caused by rebels (PREBEL) increase by 1% in a given country i, the percentage of fatalities per event is expected to increase in that country by 6.4% (direct effects), and will also cause a 1.7% increase in mortality in the neighbouring countries. Therefore, if the variable PREBEL increases in country i, not only will the mortality in that country increase (direct effect), but also in neighbouring countries (indirect effect). On the other hand, the percentage of indirect effects to direct effects is around 27%, while total effects account for 21%. This implies that the indirect effects caused by spatial contagion are relevant in explaining the mortality of neighbouring countries and the domino effect of violent political events among neighbouring countries.

Discussion

The Moran tests show that mortality associated with events is spatially autocorrelated, while mortality associated with population size is not. This confirms the hypothesis regarding the spatial contagion of mortality caused by these events between neighbouring countries. Moreover, the LISA analysis shows that there is a large hot spot of mortality in Africa formed by Cameroon, Niger, Nigeria, Chad and the Central African Republic associated with the number of violent political events occurring in these countries, an issue which should be addressed in geopolitics. These results coincide with the reality of these countries in recent years. Chad and the Central African Republic have suffered very violent armed conflicts, while Nigeria and Niger continue to be the scenario of clashes between state authorities and insurgent organizations, some of which are considered international terrorist groups. In the case of Cameroon, its proximity to countries in conflict has led to an increase in violence, and a flow of refugees and militia that the country's authorities are finding very difficult to manage.

The results of the LME-SAR model (see Table 5) show that the effects of the diverse actors on mortality related to the number of events have the expected signs and are significant at the 95% level. In contrast, the only significant contextual variable at the 95% level is the level of democracy. In the LMP-OLS model, only the actions of rebels, protests and the global peace index are significant at 95%. Therefore, both models show that the actions of the rebels and protests directly influence mortality.

These data could be of use to international organizations in Africa and UN agencies with a view to developing preventive policies and intervention strategies. Moreover, in order to reduce mortality linked to the number of events, it would be advisable to increase the level of democracy, since this would lead to a significant reduction in mortality (Elbadawi & Sambanis, 2000). While it is desirable to reduce mortality linked to population size, it would be more appropriate to control other variables, such as crime, military spending, violent demonstrations, political instability, political persecution or terrorism, among others, which are linked to the GPI.

From a global spatial point of view, the LME-SAR model has detected the presence of significant indirect spatial effects caused by the acts of rebels, ethnic groups and external actors, as well as the number of protests and level of democracy of neighbouring countries. This supports the hypothesis regarding the existence of spatial contagion between neighbouring countries, which implies that actions occurring in one country have repercussions on the mortality of its neighbouring countries.

Although the F1 tests of the GWR models did not detect global spatial nonstationarity, the Monte Carlo tests did detect spatial heterogeneity in some variables (UPOP and HDI in the LME-GWR model and GPI in the LMP-GWR model).

Conclusions

At present, the number of fatalities and massive violations of human rights as a consequence of armed conflicts and contexts of structural violence is one of the main concerns of international society. To address these issues, many of the resources invested by states and international organizations are monopolized for the prevention, pacification, reconstruction and treatment of victims. This study has used a spatial approach to examine mortality in countries of Africa taking into account the participation of certain violent actors. Likewise, the existence of positive spatial autocorrelation has been detected in mortality related to the number of events at both global and local levels. This autocorrelation can be interpreted in the sense that the mortality per event presents spatial contagion. In addition, mortality associated with events displays a high-high spatial cluster in the centre-north area, thus indicating a high concentration of mortality in this area. In contrast, low-low countries with low mortality are concentrated in the south. As regards mortality associated with population size, although no autocorrelation was detected, a high-high cluster was observed in the central-eastern area. This cluster is surrounded by low-high countries and a low-low cluster in the south. Moreover, rebel groups and ethnic groups were found to be the main actors that increase mortality levels in African countries, while the presence of protests is associated with lower mortality. The latter finding may be due to the fact that these protests serve as an escape valve for social and political tension. It has also been shown that the actions of these rebel and ethnic groups in one country have an effect on the increase in mortality in neighbouring countries. This supports the idea that pacification efforts should be directed mainly towards these actors, since such efforts would not only be beneficial for the countries directly involved but also have a spillover effect on their neighbours. In addition, the results show that acting on the variables that influence the level of democracy of these countries could decrease the level of conflict and mortality.

Models such as the one presented in this research are useful in predicting the geographical contexts in which a greater number of events with fatal results could occur, taking into account the dependent and control variables that can be previously identified in each case. These data could be of utility in guiding the decisions and strategies that many states and international organizations adopt when designing policies for cooperation and development and to promote democracy and fundamental rights and freedoms.

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