Using front lines to predict deaths in the Bosnian civil war

Andreas Beger
Florida State University
ab05h@my.fsu.edu

March 2012

What static, readily observable indicators might help us predict levels of killing in civil wars? Research using disaggregated event data and spatial models has reported strong relationships between various indicators of ethnic diversity and violent conflict during the Bosnian War (1992-1995). Bosnia is a rare case for empirical research on ethnic violence in civil wars: a census was conducted a few months before violence broke out in a country which recognized and recorded ethnic group membership, and extensively documented post-war fact-finding has recorded over 75,000 deaths and their location. Applying the resulting ethnic conflict models to other conflicts that lack such data will be difficult. This paper examines the relative fit of an alternative model based on distance to front lines and other factors that can be obtained through remote sensing, and which hence are more generalizable. Results from a spatial negative binomial count model estimated with Markov Chain Monte Carlo (MCMC) methods show that front lines model performs similarly to the ethnic conflict model in terms of fit, and both are improvements over a base model which accounts for spatial diffusion of violence and local population size only.

Prepared for the 2012 International Studies Association (ISA) conference in San Diego, California. An earlier version of this paper was presented at the 2012 Southern Political Science Association (SPSA) conference in New Orleans, Louisiana.

1 Introduction

What readily observable indicators can we use to predict killings in civil war? This paper compares an "ethnic conflict" model for reported killings during the Bosnian War from 1992 to 1995 that uses data likely to be unavailable for ongoing civil conflicts (e.g. Weidmann, 2011) to a "front lines" model based on readily observable or static indicators like areas of active fighting (e.g. front lines) and terrain characteristics. The goal is to evaluate whether such an alternative model can predict killings in civil war as well as an ethnic conflict model.

Research on the Bosnian War from 1992 to 1995 has developed sophisticated models of ethnic conflict that provide a detailed examination of ethnic violence (Weidmann, 2011), and similarly sophisticated models have been developed for other cases in which disaggregated data is available (e.g. Berman, Shapiro and Felter, 2008; Hegre, Østby and Raleigh, 2009).

As more detailed data on violence in civil wars, with exact geographic locations and dates giving days and even the hour of a violent event, have become available, models of civil war violence are becoming increasingly complex. Previous research for example has examined the relationship between complex measures based on ethnic group data and ethnic violence in Bosnia (Weidmann, 2011), poverty and war in Liberia (Hegre, Østby and Raleigh, 2009), and reconstruction spending and violence in Iraq (Berman, Shapiro and Felter, 2008).

With the focus provided by disaggregated data, statistical models are now working at the level of small geographic units the size of U.S. counties or smaller, and with time periods measured in weeks or months. The complementary utility of such models for real-world forecasting of violence in ongoing conflicts has accordingly increased. We now have data to, at least in theory, construct statistical models that can forecast levels of violence in specific parts of a country.

One of the obstacles to implementing such models for forecasting in practice is that much of the existing research uses high-quality data, like detailed census data on ethnicity and income figures, unemployment levels, etc. These are desirable from a theoretical standpoint for developing models designed primarily to test hypotheses about causal inferences, but are likely not available in countries experiencing large-scale insurgency or civil war in which the government is to weak or it is too dangerous to attempt to collect similar statistical or census data.

This study develops an "ethnic conflict" model of killings during the Bosnian War from 1992 to 1995 similar to Weidmann (2011). It takes into account detailed census information on ethnicity and income. To address several technical challenges, I also develop a negative binomial model appropriate for the count nature of the data, capable of dealing with overdispersion and exposure effects, and which includes a spatial lag to allow for spatial diffusion of violence.

In contrast to models focused on hypothesis testing, the requirements for a model that is useful for forecasting are different: data needs to be practical and either available in real-time or static in nature, while also producing good fit with observed violence. An intuitive source of such data are information on where fighting occurs, e.g. front lines in a relatively conventional conflict, and time-invariant (at least in the short-term) features such as terrain.

Thus I also estimate an alternative "front lines" model based on distance to the frontline, population, urbanization, and rough terrain. All of the covariates are either time-invariant in the short term, like terrain and urbanization, or could be estimated in real time using some form of remote sensing. For example, aerial imagery has been used to track fighting by military forces for a century, and there have been many efforts to estimate population sizes, etc. using remote sensing with satellites (Wu, Qiu and Wang, 2005).

Using front lines to estimate civilian deaths sounds almost tautological. That certainly is true, although the extent to which it is can be disputed. But more importantly, it is irrelevant: endogeneity is a problem for accurately determining causal effects, whereas the goal here is to assess if front lines can be used to accurately predict civilian deaths. The more endogeneity, the better!

A comparison of the "ethnic conflict" and "front lines" models in Bosnia shows that both improve fit over a baseline model, and that both fit the data roughly equally well. This suggests that models using data on front lines and other static variables are appropriate alternatives for forecasting efforts.

The next sections review current studies using disaggregated spatial data on violence and how they are used. Focusing on the case of Bosnia, an example of the relationship between Yugoslav self-identification, ethnic diversity, and violence shows how unusual these data are for researchers interested in ethnic conflict. An intuitive alternative model based on front lines is developed, and a statistical model appropriate for the spatial count data on killings is introduced.

2 Disaggregated studies of civil conflict

An increasing number of studies examine civil war and other forms of political violence at a sub-national level using disaggregated data and GIS (geographic information systems), rather than cross-nationally with samples that span continents or the entire globe. One of the advantages of this approach is that it allows for a closer examination of arguments that might otherwise be subject to ecological fallacy (Buhaug and Lujala, 2005). Rather than relying on cross-national variation of measures of interest in different civil wars to evaluate arguments, sub-national data allows researchers to evaluate hypotheses in a single country, and thus to establish with more confidence whether the data fit the proposed explanation.

Several common arguments in the civil war literature have implications for the location of violence within countries. For example, if civil wars are fought primarily because the opportunity for predation is high (e.g. weak state and structural conditions that favor control over primary commodity export), then we should expect to see violence in areas within a country where such conditions are met (Collier and Hoeffler, 2002). Rebel groups in Colombia should be based in rural jungles and mountains which allow for drug production and where government control is weak, not in urban areas, where government control is typically strong. Using disaggregated data to develop smaller units of observation thus is useful to ensure that the lower-level implications of an argument are empirically reasonable.

Because data on civil violence was unavailable below the country level, early work in this literature focused on identifying the location and extent of conflict zones within countries that experienced civil war (Buhaug and Gates, 2002; Buhaug and Lujala, 2005). This presents new problems in using geographically disaggregated data on various explanatory variables in a consistent manner, and limits the ability of statistical models to predict specific conflict locations within a country, but is also more easily adapted to existing, cross-national conflict research.

More recently, point data that associate events such as killings or press reports of violence with a specific geographic location have become available. The three major types of such data are distinguished by the source for the coding of events: public media reports, e.g. ACLED and Uppsala GED, state collected statistics, e.g. crime statistics or U.S. military significant activities (SIGACT) databases, and (post-war) fact-finding efforts. (Raleigh et al., 2010; Melander and Sundberg, 2011; Sundberg, Lindgren and Padskocimaite, 2010)

None of these sources are likely to be error or bias-free, and this is an important caveat to research that uses them (Davenport and Ball, 2002). Event-coded data for media reports are at minimum biased by the extent to which public media have access to certain areas of a country, and typically do not include measures of event intensity (a demonstration and massacre might both be coded as single events each). State collected statistics reflect state control and bureaucratic efficiency, assuming they are not outright manipulated. And even fact-finding efforts are unlikely to catch, accurately, all violence.

3 Ethnic violence and point data on deaths

Because point data, in theory, provide the exact location of an event or death, there is flexibility in how they are aggregated for empirical analysis. One of the major constraints however is the availability of other spatial data for covariates of interest, and how to translate concepts and measures to a spatial context. Bosnia has been studied in the context of ethnic conflict, but in many ways is a quite unique case for empirical research, as demonstrated with an example at the end of this section.

3.1 How the data are used

Specific point data on violence or violent events are now available and for empirical research they are typically aggregated to areas to produced count data of the number of events, number killed, per capita killed, etc. Cross-national studies tend to use grid cells as the basic unit of observation to which all other data are merged or aggregated (Buhaug and Rød, 2006; Raleigh and Urdal, 2007), while studies focusing on a single or small number of countries tend to use local administrative units (Weidmann and Ward, 2010).

The grid cells used in such research are approximately square cells created using a coordinate system. Nearly square at the equator, they become more distorted at higher latitudes. Although arbitrary, they are easier to use in cross-national studies that cover multiple countries with potentially very different sub-national administrative units. Global data on population, income, etc. estimates are also commonly available for similar arbitrary grids.

Buhaug and Rød (2006), using 100 × 100 km cells covering Africa, found several relationships between the incidence of territorial and governmental conflict within states and factors such as the distance to the border or capital city, proximity of diamonds, and open terrain. Raleigh and Hegre (2009) uses smaller 8.6 km cells, also covering Africa, to examine complex relationships between distance, population, and other factors. Using population density as a proxy for the value of an area, their results imply that although distance has an effect on conflict, the most significant factor is population density. And, in an example of a single country study using grid cells, Hegre, Østby and Raleigh (2009) examine conflict and poverty in Liberia and find that events were more frequent in wealthy areas. They interpret this finding as offering support for arguments in which opportunities for profit drive civil violence.

The source of conflict data is in all three of these studies is ACLED, which codes media reports of violence. An important issue to keep in mind therefore is also how various factors that are hypothesized to impact violence relate to the probability that an event is reported in Western media.

The alternative, sub-national administrative areas, are more intuitive, but spatial data for them is often more difficult to obtain. Research using districts and provinces in Iraq, Afghanistan, and the Philippines has found that unemployment does not increase insurgent attacks against either the military or civilians (Berman et al., 2009), but that improvements in the provision of government services are related to reduced violence, at least in Iraq (Berman, Shapiro and Felter, 2008).

In one of the most comprehensive examinations of the role of ethnic conflict in civil war violence, Weidmann (2011) looks at two complementary processes of ethnic violence: top-level pressures to consolidate ethnic territories, and violence due to local interethnic resentment. The two alternative processes are evaluated using data for Bosnia, including killings documented after the war through fact-finding efforts. Top-level territorial contestation is measured using the relative value of a municipality to each ethnic group's territory, given the municipalities and it's neighbors' ethnic populations. For example, a municipality with significant populations of 2 ethnic groups bordered on one side by areas in which one of the groups dominates and on the other side by areas dominated by the other group would have a high score for contestation, whereas a municipality with a clear majority borders by areas in which coethnics also have a majority would have a low score. Local ethnic resentment is measured using municipality-averaged village level ethnic polarization (Montalvo and Reynal-Querol, 2005).

Weidmann finds that both measures are associated with significant increases in per capita violence in Bosnia. The potential for ethnic violence is usually measured using an ethnolinguistic fractionalization (ELF) index constructed as $1-\sum e_i^2$, where e_i is ethnic group i's share of the population. The index can be interpreted as an overall measure of ethnic diversity. Although the two measures of territorial contestation and local polarization constructed by Weidmann are based on specific theoretical processes while the ELF is not, the latter has been used much more widely and both are useful starting points for an ethnic conflict model of violence.

3.2 The special case of Bosnia

The Bosnian civil war is becoming a canonical case in the study of civil war and ethnic conflict, and for several reasons it is well suited for sub-national research. Several sources of event data are available for the conflict, a census was conducted several months before war broke out by an efficient bureaucracy, and there is significant variation in the distribution of several ethnic groups within the country.

Bosnia and Herzegovina was the ethnically most diverse republic in the former Yugoslavia, with significant minorities of Bosnian Muslims, Serbs, and Croats. After secession and war in Croatia, Bosnia was by early 1992 left in a Serb-dominated rump Yugoslavia. A successful vote for secession and months of preparation by nationalist leaders lead to open war in April 1992.

During the Cold War, Yugoslavia's defense strategy was based on guerrilla warfare in the mountainous center, and there were extensive, republic-controlled territorial defense units and local militias (Nation, 2003, 150-151). As in the other republics, these territorial defense units and local police formed the core of the new sectarian militaries. Bosnian Serbs benefited from material, personnel, and command support from the remnants of the JNA (Yugoslavia's federal army) in Bosnia as well. The resulting Serb army was dominant in the beginning of the war and able to secure half of Bosnia's territory.

Despite the initial gains in the conflict by the Bosnian Serb army, in the end all three ethnic armies were fairly makeshift and not strong enough to decisively defeat any other side. By the end of 1992, the war had militarily become a stalemate with static front lines. Behind the lines, in areas controlled by each factional army, ethnic cleansing perpetrated by semi-professional armies and paramilitary forces became a strategy to consolidate control (Nation, 2003, 151-168).

For empirical studies of civil war, Bosnia is particularly well suited. A census was conducted in the republic in 1991, right in the prologue to the civil war which was already starting to engulf other republics in Yugoslavia. The communist federal state had long recognized the fact that Yugoslavia was a multi-ethnic state and distinct categories for Serbs, Croats, Muslims, and other minorities had been well-established for decades (Glenny, 2000). Considering the set of countries which have seen civil war, Yugoslavia was well-developed and thus likely had an efficient bureaucracy. It's 1991 GDP per capita puts it in the top 20 percent of countries experiencing civil war onset, while it's much higher 1990 GDP per capita puts it in the top 5 percent (replication data for Fearon and Laitin, 2003). Comparison to the 1981 census shows that there are no gross inaccuracies and that it is probably accurate (Stevanovic and Breznik, 1991). The results show that three ethnic groups, Bosniaks (or Bosnian Muslims), Serbs, and Croats together constituted the vast majority of Bosnia's population, with 43, 31, and 17 percent of the population each, and there is significant variation in the ethnic diversity of municipalities.

The other side of the equation, deaths, has also been fairly well documented. A post war fact finding organization, the Research and Documentation Center (RDC; www.idc.org.ba/) in Sarajevo, has collected extensive data on dead and missing, and made that data publicly available. The records include names and the location of documented deaths are are available for use with Google Earth. In total there are 95,000 casualties, with over 77,000 confirmed deaths and 17,000 missing.

Media-based event data for Bosnia are also available from ACLED (Raleigh et al., 2010). The maps in figure 1 show ACLED events and RDC documented killings. In terms of their spatial distribution one can see noticeable discrepancies between the two sets of data. They also have quite different frequency distributions–many municipalities have no ACLED events (shaded light grey on the map)–while at least some deaths are recorded in every single municipality by the RDC.

3.3 Yugoslav identification

In addition to the historical ethnic groups one could identify with in Bosnia, e.g. Muslim, Serbs, Croats, etc., there was an additional category for those who saw themselves as Yugoslav (Malcolm, 1996; Glenny, 2000; Judah, 2000; Bringa, 2010). The word "Yugoslav", which literally means

"South Slav", started to enter use in the late 19th and early 20th centuries and eventually was adopted as the term of choice for a pan-south slavic movement among slavs in the Austro-Hungarian and Ottoman Empires and their successor states, as opposed to the traditional ethnic movements in Croatia, Serbia, and Bulgaria. Maybe the best way to describe it is as nascent, supra-national identity, similar to the way Americans at some point started to identify as "Americans", not as residents of their particular state, or similar to German nationalism that developed in the 18th century from distinct regional (Bavarian, Prussian, Austrian, etc.) identities.

The south slavic Kingdom of Serbs, Croats and Slovenes became Yugoslavia after a coup which led to royal dictatorship in 1929. The communist Yugoslavia after World War 2 continued to use the term as a means to foster federalist sentiments and in opposition to ethnic nationalism (Glenny, 2000).

Although few people ever identified as Yugoslavs, no more than 2 percent nationally in Yugoslavia and around 5 percent in Bosnia, it was explicitly a pro-federal and anti-nationalist concept/ethnicity. Common reasons for identifying as a Yugoslav were probably intermarriage or lack of clear membership in one of the defined nationalities, communism, and idealism or some other belief in federalism (Bringa, 2010).[1] Regardless, it was distinctly opposed to nationalism, and thus can be used as a measure of anti-nationalist sentiment.

The distribution of people who self-identified as Yugoslav in the 1991 census in Bosnia is shown in map 2. It was highest in several urban areas, reaching past 15 percent in Tuzla and parts of Sarajevo. Compare this to the distribution of ethnic diversity in figure 3. The fractionalization index of ethnic diversity (ELF) is calculated as $1 - \sum e_i^2$, where e_i is ethnic group i's share of the population. Higher numbers indicate diversity, and it can be interpreted as the chance that two randomly picked individuals will be from different ethnic groups. Bosnia in general was a very heterogenous place and the diversity scores for most municipalities reflect this. The national-level diversity score is 0.68.

The plot in figure 4 shows the relationship between self-identification as Yugoslav and ethnic diversity, measured using the fractionalization index. The x-axis shows the proportion of Yugoslavs, and the y-axis shows ethnic diversity. Each circle represents one of the 109 pre-war municipalities. As one would expect, few people identified as Yugoslav in ethnically homogenous areas. In ethnically diverse areas, near the top of the plot, there is more variance in the proportion of self-identified Yugoslavs.

The size of the circles shows the per capita rate of killed. Looking at the top right quarter of the plot, one can see that in municipalities that were ethnically diverse but also anti-nationalist (high Yugoslav identification) there were relatively few per capita deaths during the civil war. Municipalities that were ethnically diverse but also nationalized, in the top left quarter of the plot, had some of the highest per capita deaths during the civil war. In terms of ethnic diversity by itself, violence was worst in municipalities that are moderately high in diversity, and actually lower in those with very high diversity. The extent of nationalism, as measured by Yugoslav self-identification, is what seems to distinguish those highly diverse municipalities that see a lot of deaths from those with few.

Higher ELF values seem to be associated with more variance in death rates–they are uniformly low with low diversity, but vary quite a bit in the top half of the plot. This is consistent with

[1] Also, Makul and McRobie, 2011, "Yugoslavs in the twenty-first century: 'erased' people".

previous, cross-national research on civil war incidence (Blimes, 2006). Theoretically this makes sense. Deaths will not be high in ethnically homogenous areas unless people are killing members of their own group, which probably makes little sense in the logic of ethnic violence. In very diverse areas the potential for unrestrained killing is high since there are many people who are not members of the same ethnic group, and thus many potential victims. But clearly, the potential for violence does not seem to uniformly lead to actual violence, depending on nationalist sentiment and other factors.

3.4 Frontlines

As much as it is interesting, this example shows how unique the case of Bosnia is in terms of data availability. Although media-coded event data is widely available now, detailed ethnic data at a subnational level is not available for many conflict regions. For a model to be useful in prediction violence in other conflicts, it has to rely on other information that is easier to collect.

An intuitive alternative is to look at where the fighting is–frontlines–and assume that is where people tend to die. Collecting data on civil war front lines using remote surveillance and some combination of local reports is possible for governments and non-governmental groups. The Satellite Sentinel Project (www.satsentinel.org/about) for example uses satellite images to monitor violence in southern Sudan.

Is the relationship between front lines and civilian deaths tautological? Front lines are areas in which opposing military forces actively fight, and there certainly will be civilian fatalities as a consequence. Furthermore, in an ethnically-driven conflict like Bosnia, the front lines also reflected underlying ethnic settlement patterns. But there are at least two reasons for why one might expect significant civilian deaths somewhere other than near the front lines. The first is simply a matter of logistics. If the armed groups are busy fighting each other, they will have less time to engage in systematic violence against civilians. And second, an armed group might even have an incentive to be more lenient in contested areas than areas further back in which it has a more secure presence (Kalyvas et al., 2006).

In any case, the aim of this paper is not causal inference, but to assess whether front lines can be used to predict civilian deaths as accurately as a state of the art ethnic conflict model. This turns the argument about endogeneity on its head: more endogeneity is desirable, because it will increase predictive accuracy.

The long military fronts in the war and relatively static nature, with sieges and limited offensives, encouraged the use of land mines, and Bosnia remains heavily mined (Nation, 2003, 158-159).[2] Data collected by post-war demining efforts shows clear dividing lines and matches other depictions of the wartime front lines. The static nature of the front lines simplifies the empirical analysis of their relationship with deaths since changes over time are less important, but it is also possible to work with front lines that change over time, provided data on violence also includes the time of the event.

In addition, measures of rough terrain and urbanization are easily collected or available, and can reasonably be expected to relate to violence. Rough terrain has been extensively examined in the context of civil war, with various expectations and results. Fearon and Laitin (2003) find that

[2] See BiH Mine Action Center and State Department BiH information .

rough terrain and poverty, as a consequence of weak states, increase the probability of civil war. Areas with rough terrain and weak state control allow rural militant groups to challenge conventional government forces that usually would be dominant in a conventional conflict. Therefore violence should be more intense in inaccessible areas. Similarly, one should expect more violence in less developed rural areas with low urbanization rates.

Thus a reasonable alternative to the ethnic conflict model is one that uses front lines, urbanization, general (non-ethnic) population data, and measures of rough terrain. How well does such a model perform compared to a ethnic conflict model taking advantage of the detailed census data?

4 Data and model

Prior to the war, Bosnia had 109 municipalities. These constitute the basic unit of observation. Data on deaths comes from the Research and Documentation Center (RDC), a non-governmental, non-profit institution based in Sarajevo. It has documented and published extensive and detailed records of killed and missing persons. The records for confirmed killed total 78,000. Their distribution across Bosnia is depicted in figure 5, adjusted for area and population, and shows that fighting was most intense in central Bosnia around Sarajevo and in eastern Bosnia, along the border with Serbia.

4.1 Model setup

There are several issues in modeling the death counts, including spatial correlation and choosing an appropriate statistical model for the data. Death counts are by definition positive integers, which suggests a standard linear normal model is inappropriate. One possibility is to transform the counts by taking the natural log or dividing by total population (thus creating a rate) so as to create something closer to a normal distribution. As the histograms in figure 6 show, neither of those transformations produces a normal distribution. In both transformations, the data are skewed. Using a linear model in practice can produce several problems, among them worse predictions (Cameron and Trivedi, 1998).

More appropriate is a Poisson or negative binomial distribution. The observed deaths data by municipality have a mean of around 700, but the variance far exceeds this and overdispersion is potentially a problem. A standard Poisson model is inappropriate if there is overdispersion in the conditional mean, and as an alternative I use a negative binomial distribution to model deaths, with mean λ and a dispersion parameter, r. Another parameter, θ, includes the exponentiated covariates, $x_i\beta$, with two exceptions.

The first is to account for varying exposure. Deaths are theoretically dependent on a municipality's total population, which varies significantly. To correct for this, standard MLE negative binomial regression models would include an offset of logged population, with coefficient constrained to 1, among the exponentiated covariates. Equivalently, θ is multiplied by municipality population in the model here (i.e. $e^{x_i\beta+\ln p} = e^{x_i\beta} \times p$).

Since the deaths counts in each municipality likely are related to other, near municipalities, spatial dependency or correlation is also a potential issue. The second exception therefore is a spatial lag to model this. Spatial correlation in general occurs when the value of a variable is related to values in some set of neighbors, and can be positive or negative (Ward and Gleditsch, 2008). Negative correlation occurs when high values in one area are associated with low values in the neighborhood, and would show on a map colored according to that variable as a checkerboard pattern. Positive spatial correlation shows on a map as clustering and occurs when neighboring units have similar values. Previous research on Bosnia has identified it as an issue with different data, and it is a problem here as well (Moran's I, z= 3.38, p<0.0004) (Schutte and Weidmann, 2011).

One way to deal with spatial correlation is to include a spatial lag that captures a measure of dependent variable values in the neighborhood. A straightforward version of this is a neighborhood average that provides, for any municipality, the average number of deaths in bordering municipalities. It can be constructed by multiplying a row-standardized matrix indicating contiguity for each pair of municipalities (W) with the list of death counts (y). Although other ways of accounting for spatial diffusion, e.g. spatially-lagged error terms, using distance or some other weighting scheme instead of contiguity, and so on, are possible, a spatially-lagged dependent variable (or neighborhood average) is more intuitive and appropriate in this context given that we would expect deaths to be positively related (Ward and Gleditsch, 2008).

The spatial lag, $y_s = Wy$, enters the model as a multiplicative term in λ, with an exponentiated coefficient ρ that measures its impact (Lambert, Brown and Florax, 2010). Exponentiating the coefficient allows for both positive and negative spatial diffusion, while constraining the overall spatial term $(y_s)^\rho$ to be a positive number. Holding the remainder of λ constant, a positive ρ will lead to a spatial term greater than 1, thus increasing mean deaths, while a negative ρ will lead to a spatial term between 0 and 1, thus reducing mean deaths.

The final model is:

$$
\begin{aligned}
y_i &\sim NegBin(\text{mean} = \lambda_i, \text{dispersion} = r) \quad (1)\\
\lambda_i &= (y_{s,i})^\rho \times \theta_i p_i \quad (2)\\
\ln \theta_i &= x_i \beta \quad (3)
\end{aligned}
$$

where y_s is the neighborhood average or spatial lag, and p_i is the municipality's population. The parameter ρ can be interpreted as the strength of spatial diffusion of violence, with values greater than 0 indicating positive diffusion. The other term, $\theta_i \times p_i$, can be seen as the municipality-specific factor by which observed deaths differ from what one might expect due to spatial diffusion alone.

4.2 Model specifications and variables

I examine four versions of this model: a constant-only, base, ethnic conflict, and frontline model. They differ in the covariates included in theta, but otherwise match the form above. The constant model only includes a constant term in theta, while the base model also adds the spatial lag and local population offset. The ethnic conflict model furthermore includes ELF index scores, territorial contestation and local polarization, as well as income per capita. The front line model includes distance to the front line, urbanization rate, and a measure of rough terrain. The variables are described in more detail below.

Population. Population for each municipality is taken from the 1991 census.

ELF index. Scores for each municipality were computed as $1-\sum e_i^2$, where e_i is ethnic group i's share of the population, using municipal data from the 1991 census (Petrovic, 1992; Weidmann, 2011).

Strategic importance. An indicator that measures the extent to which a particular municipality is contested by two ethnic groups vying for territorial consolidation. It comes from the replication data for Weidmann (2011). The indicator is fairly complex and the original source has a detailed explanation for which there is no room here. But in essence, it depends on the population shares the the two largest ethnic groups in a municipality and it's neighboring municipalities.

Local polarization. Ethnic polarization scores are calculated on the village level and averaged to the municipality using 1991 census data, also from Weidmann (2011). The score measures how far a the distribution of ethnic group population shares deviates from an ideal in which two groups share half the population each, and is calculated as $4\times\sum p_i^2(1-p_i)$ (Montalvo and Reynal-Querol, 2005).

Per capita income. Measures local wealth using 1991 per capita income. The original source is also the 1991 census via the replication data for Weidmann (2011). It is included as a control variable in the ethnic conflict model, but not the frontline model.

Distance to front lines. Since the front lines in the Bosnian War were fairly static (Nation, 2003), I digitized on set of front lines using period maps of front lines and data on minefield location from the BiH Mine Action Center (posted at www.mine.ba). The latter has includes a map of minefield locations and rough front lines, which I traced to recreate front lines. The result is shown in the map in figure 7. They reflect the approximate location of the 1993 front lines, and in any case the major changes in front lines were in sparsely populated areas. Only with the joint Croat-Muslim offensive in 1995 following the collapse of the Serb state in Croatia did the front lines change drastically–and the war ended as a result of this offensive. The distance to the front lines was calculated as the straight line distance from centroids for each municipality to the closest frontline, not counting borders of Bosnia with other republics. The natural log of this measure is used as a covariate.

Urbanization. Urbanization is measured as population concentration in each municipality (or the chance that two randomly selected individuals will be from the same sub-municipality village) using 1991 census data (Weidmann, 2011).

Rough terrain. Rough terrain is measured as the proportion of a municipality's terrain that has a slope greater than 15 degrees. Sloped is calculated using SRTM (Shuttle Radar Topography Mission) 90 meter raster elevation data from the U.S. Geological Survey. I reduced the resulting slope data were in resolution by a factor of 10 to make the data more manageable and then aggregated to the proportion of cells in each municipality with a slope greater than 15 percent. In other words, this indicator measures the extent to which a municipality has mountainous terrain.

5 Results

The four models were estimated using Markov-chain Monte Carlo simulation with 5 separate chains in which every 5th observation after the first 4,000 of 20,000 draws was recorded. The end result is a distribution of estimates, i.e. posterior densities, for each parameter in the model that provides a picture of the estimated effect associated with that parameter. One way to look at these is as densities similar to the ones from which we derive coefficient and standard error estimates using maximum likelihood estimation, with the mean matching the coefficient estimate, and variance of the posterior density akin to a standard error.

The posterior densities for the models are shown in figures9, 10, 11, and 12 for reference.

The densities for ρ show the direction and strength of spatial diffusion. Values below 0 indicate negative spatial diffusion in which high counts of deaths in one area reduce counts of deaths in neighboring areas, while values above 0 indicate positive diffusion in which high deaths are associated with high deaths in the neighborhood. All three models show positive diffusion averaging between 0.4 and 0.5. The dispersion parameter r for the negative binomial distribution shows the extent to which variance diverges from that in a Poisson distribution–as r reaches infinity a negative binomial distribution approaches a regular Poisson distribution in which mean and variance equal.

The other coefficients can be interpreted similar to the way one would interpret maximum likelihood regression coefficients, with distributions centered on 0 indicative of no relationship, either positive or negative. A density excluding zero for most simulation draws could be interpreted as significant evidence for a positive or negative relationship. For example, there seems to be a certain positive association between local polarization (b[4]) and deaths in the ethnic conflict model in figure 11.

To evaluate relative model fit of the ethnic conflict and alternative frontline models, figure 8 shows plots of predicted over observed values for all 3 models as well as DIC (deviance information criterion) values. The plots give a rough visual impression of model fit. The black line indicates points on which observed equal predicted values, and give a rough visual indication of model fit. The DIC provides a rough summary measure of relative model fit, and is shown in each plot as well (Gelman and Hill, 2007, 524–526). Compared to the constant-only model, the base model with spatial lag and population offset improves fit dramatically. In turn, both the ethnic conflict and front lines models improve over the base model with spatial lag and population offset only. Compared to each other they have similar fit to the data with DIC values of 1530 and 1529 respectively.

6 Conclusion

Statistical models of conflict that include detailed, high-quality information as covariates can, unsurprisingly, improve fit to observed data and therefore predictive ability. At the same time, such models are less useful for prediction in general because they can only be applied where similar high-quality information is available as well. The cross-sectional analysis of killings in the Bosnian war in this paper shows that a model based on front lines and other data that can be estimated using remote sensing and surveillance fits the data as well as an alternative model based on detailed ethnic information.

The front lines during the Bosnian War were fairly static, allowing a simpler, cross-national analysis to be used. But to be practically useful for forecasting future violence in a conflict, a feasible-data model will also have to include a time component. Disaggregating data and modeling not just in space but also over time is a logical extension of this project that is feasible given currently available event data, such as for Iraq and Afghanistan.

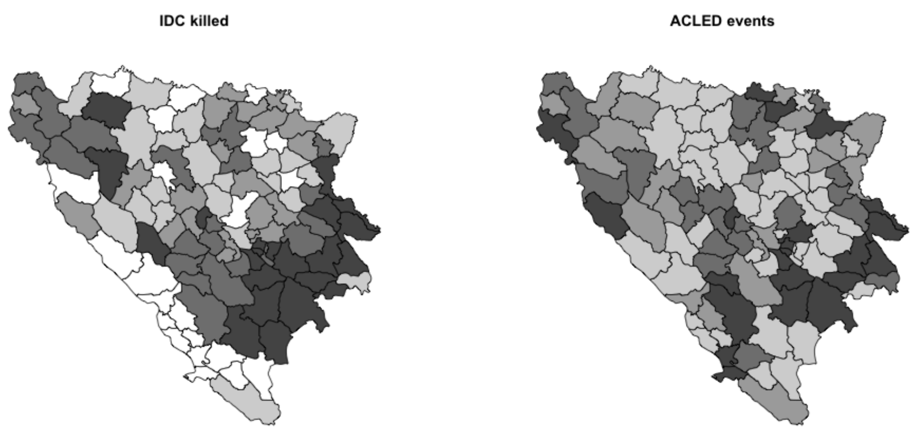

Figure 1: Comparison of ACLED and RDC events.

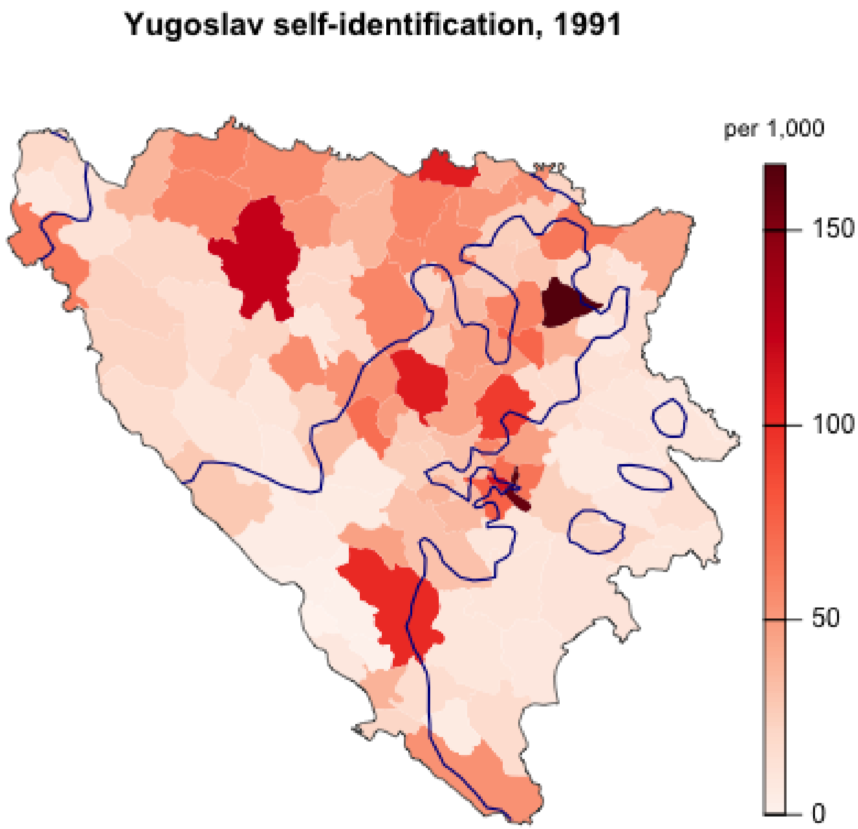

Figure 2: Proportion of people who self-identified as being Yugoslav, rather than Serb, Muslim, Croat, etc. during the 1991 census. The rates are higher in cities, especially Tuzla and Sarajevo, where 15 to 20 percent of all respondents labelled themselves as Yugoslav, and lower in eastern Bosnia, Herzegovina in the south, and parts of western Bosnia adjacent to Dalmatia.

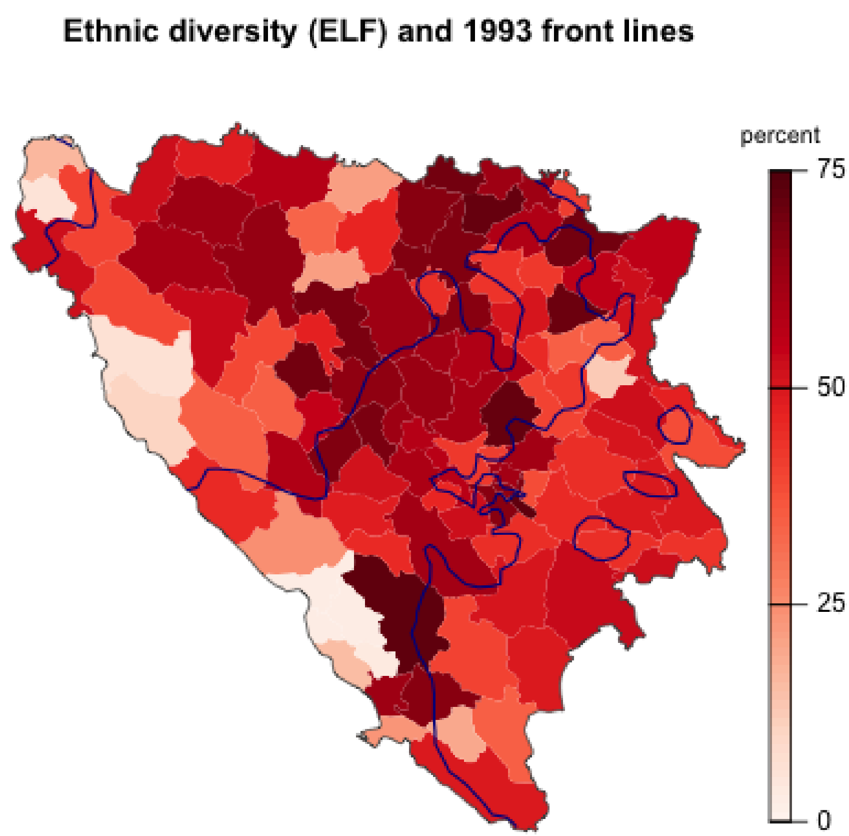

Figure 3: Ethnic diversity by municipality. Based on 1991 census.

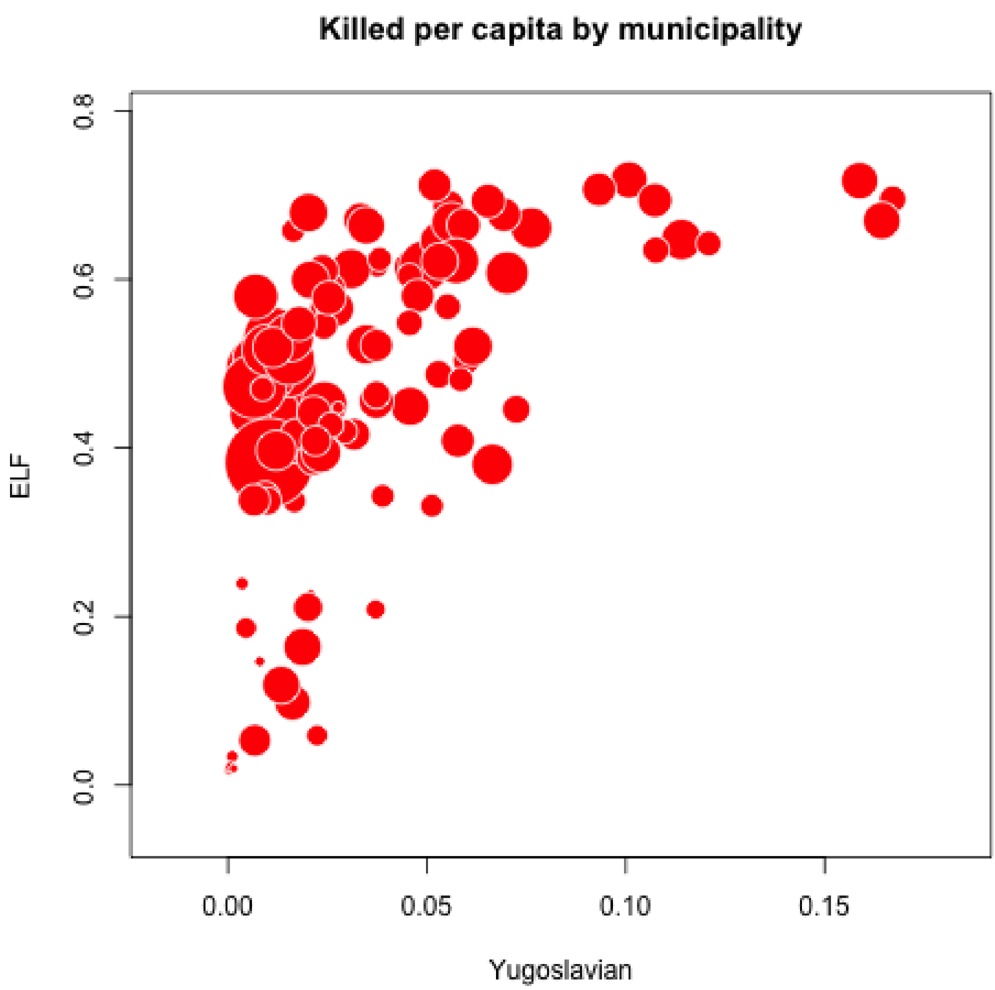

Figure 4: Bubbleplot of Yugoslav self-identification, ethnic diversity, and civil war death rates by municipality. Each circle represents a municipality, with its proportion of self-identified Yugoslavs on the x-axis and ethnolinguistic fractionalization index (ELF) value on the y-axis. The area of the circle is proportional to deaths per capita during the civil war. There are fewer Yugoslavs in ethnically less diverse municipalities, as one would expect, and those also tend to see relatively little violence. In municipalities with a high level of diversity, the proportion of Yugoslavs is related to deaths per capita, with diverse but nationalist municipalities experiencing more violence than diverse but federalist municipalities.

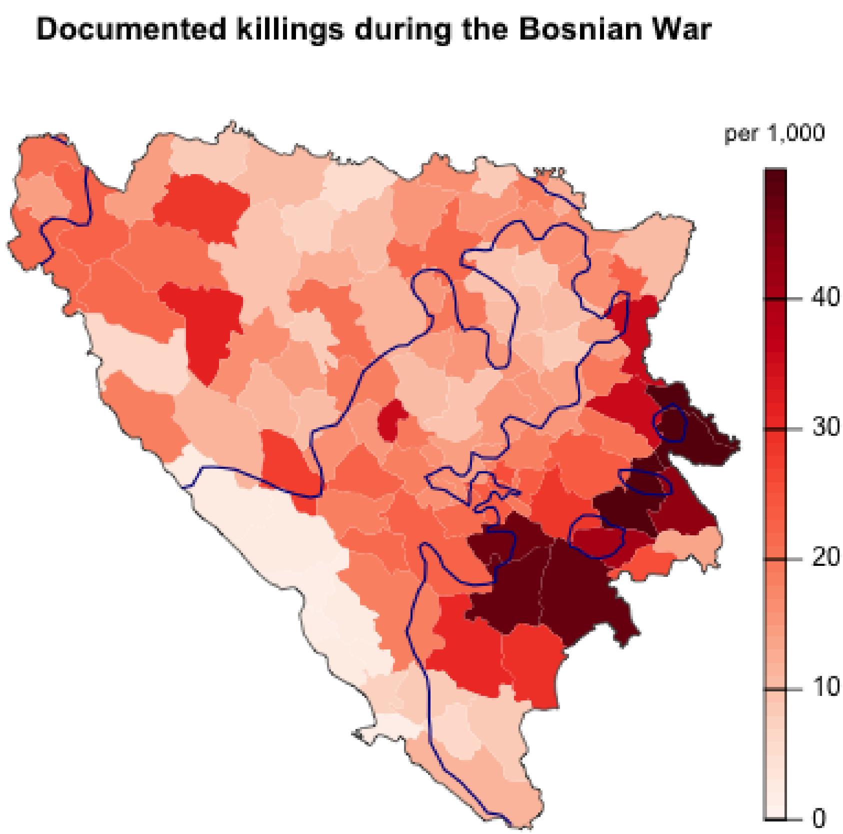

Figure 5: Deaths per 1,000 by municipality during the Bosnian War, 1992-1995. The rate of deaths is highest in eastern Bosnia in the municipalities that contained Bosniak enclaves during the war, and in areas of western Bosnia that were ethnically cleansed early in the war. From the IDC Bosnian Atlas of War Crimes.

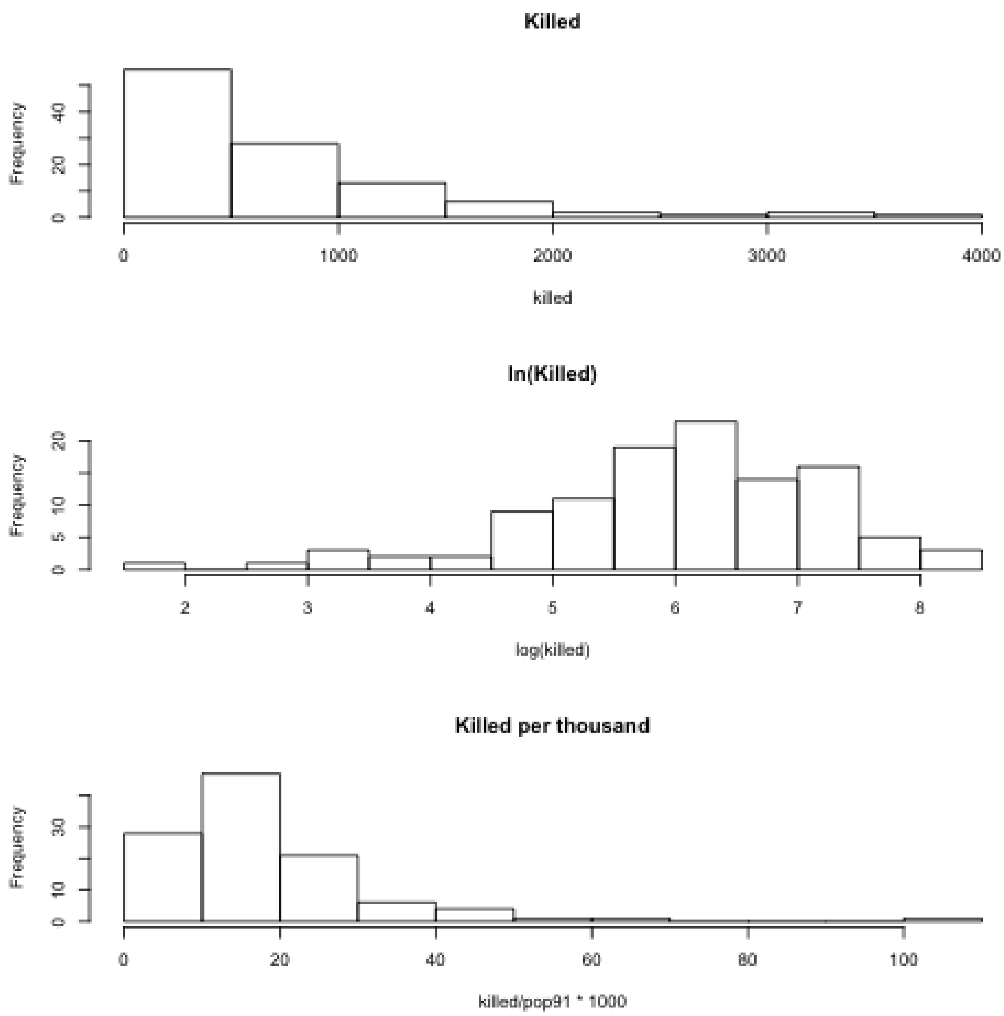

Figure 6: Histograms of deaths by municipality during the Bosnian War, 1992-1995. The untransformed count of deaths fits a negative binomial distribution with [x]. Both the log of deaths and population-adjusted deaths are skewed.

Figure 7: Approximate 1993 front lines. Digitized using information on land mines from BiH Mine Action Center (posted at www.mine.ba).

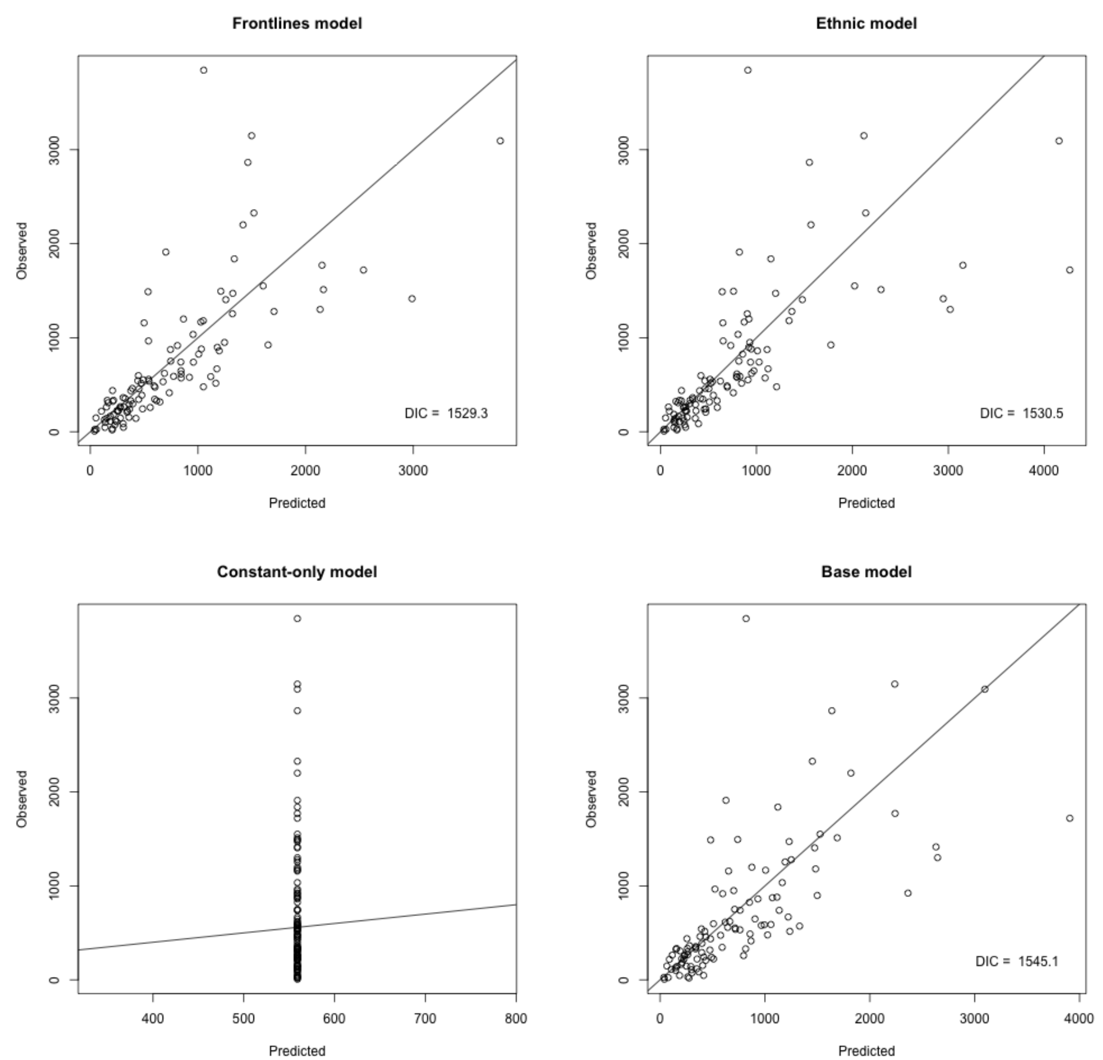

Figure 8: Predicted versus observed killings during the Bosnian War. Each panel shows a plot of predicted counts compared to observed counts for the base, ethnic, and frontline models respectively. The black line shows observed = predicted. Each plot also gives the deviance information criterion for each model (constant-only has 1676). The base model includes a spatial lag (neighborhood average deaths) and population offset, but no other covariates. The ethnic model, which also includes measures of ethnic diversity and dispersion, as well as per capita income, has by far the best fit, but also draws on census data unlikely to be available for other countries. The frontline model, which uses distance to the 1993 front lines and other structural variables without census data, significantly improves fit over the base model as well, although not as much as the ethnic model.

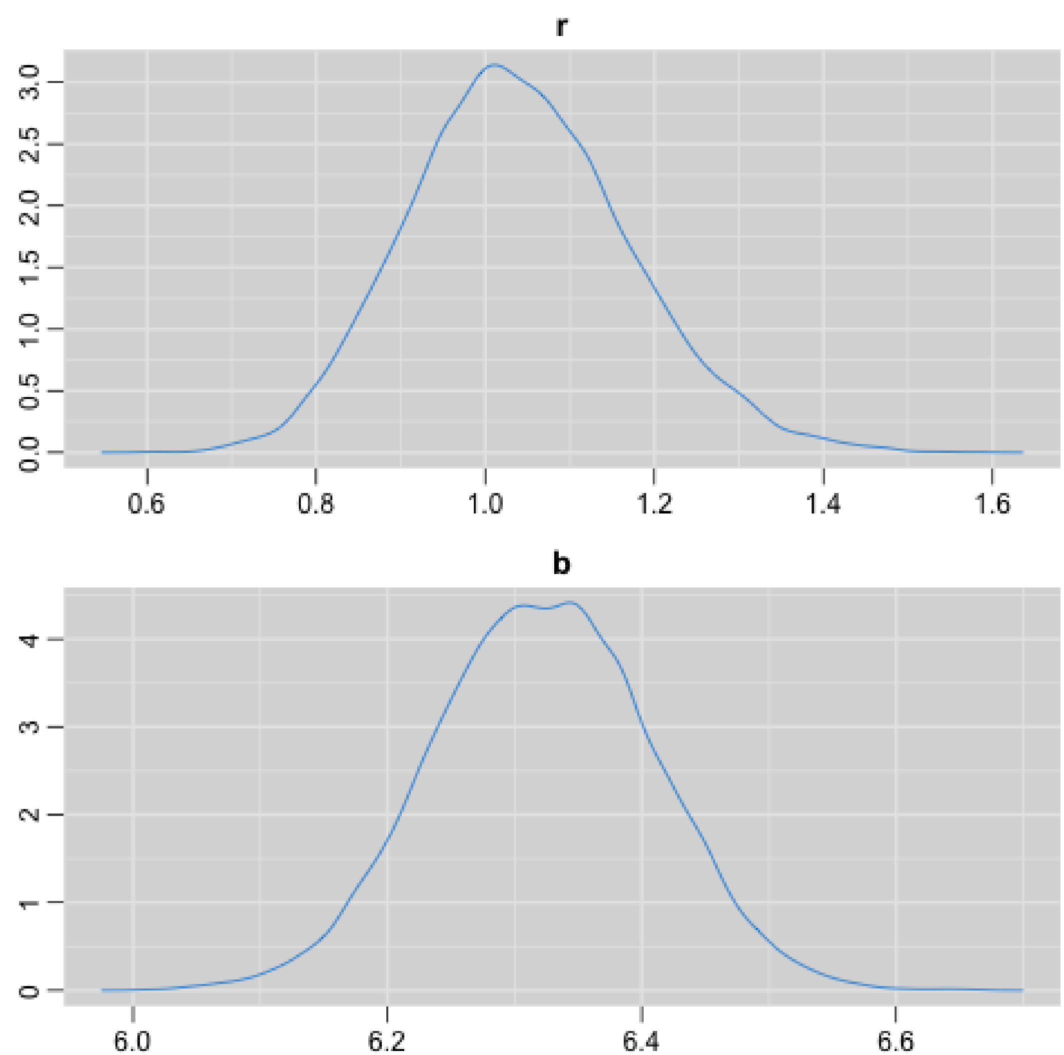

Figure 9: Posterior densities for the constant-only model: r = negative binomial shape, b = theta constant.

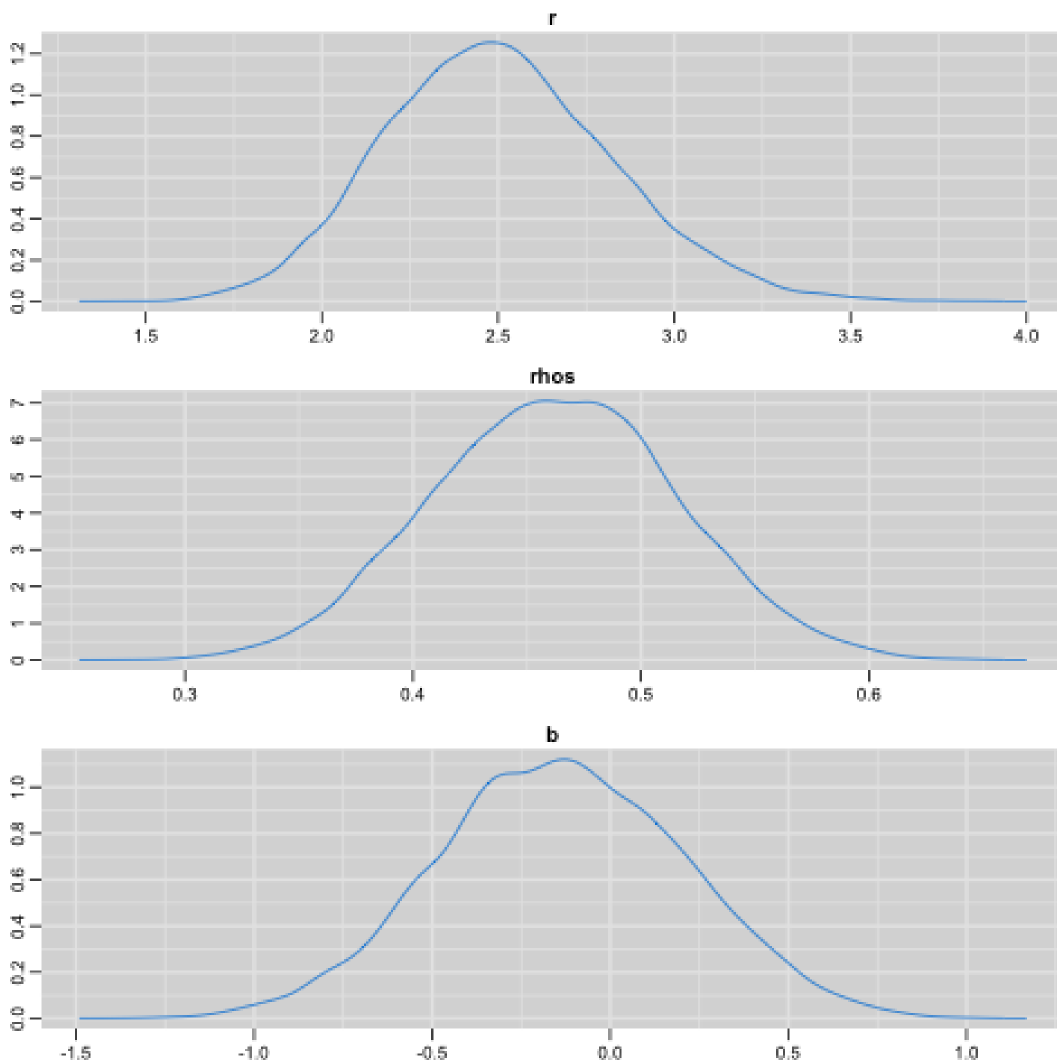

Figure 10: Posterior densities for the base model: r = negative binomial shape, rhos = spatial lag, b = theta constant.

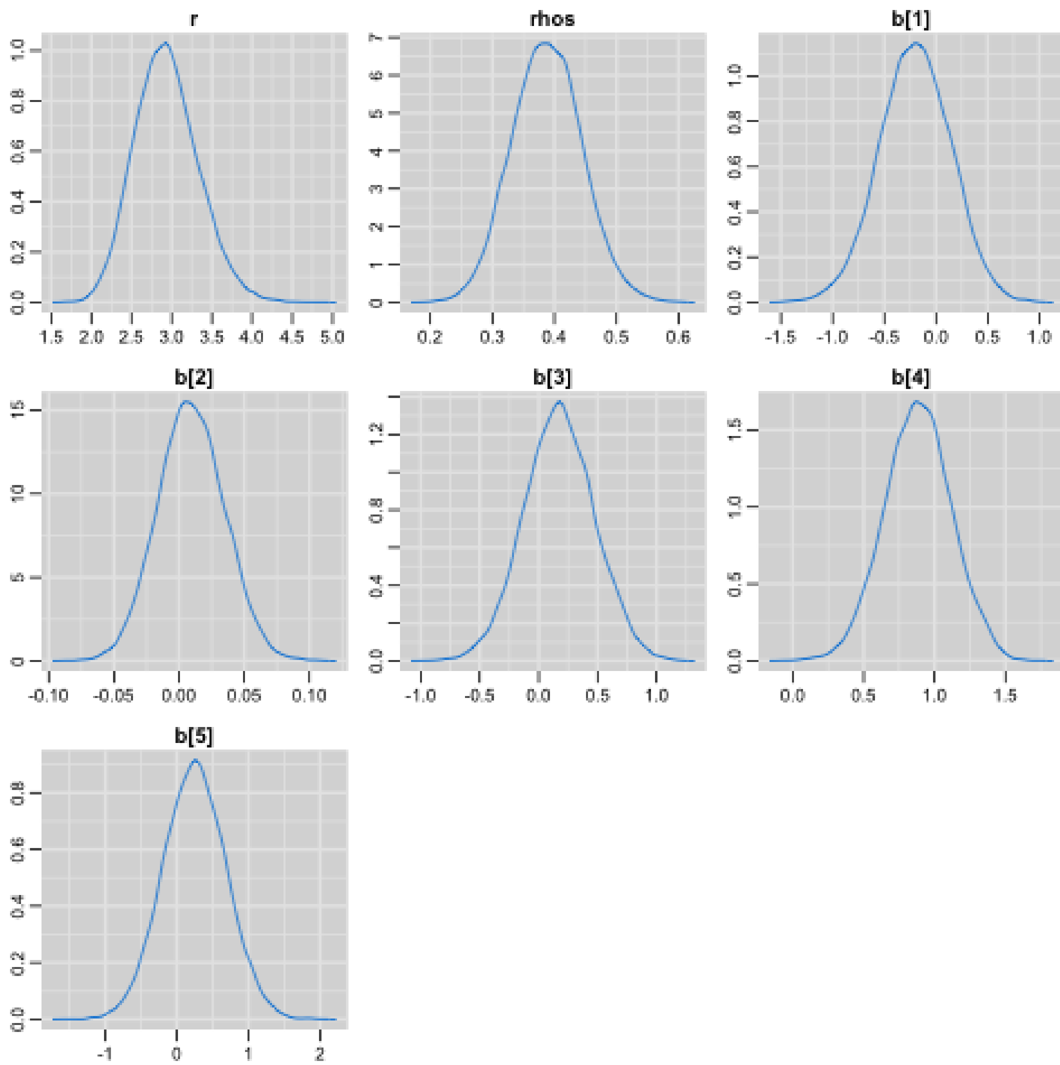

Figure 11: Posterior densities for the ethnic conflict model: r = negative binomial shape, rhos = spatial lag, b[1] = theta constant, b[2] = income per capita, b[3] = ELF index, b[4] = local polarization, b[5] = strategic significance.

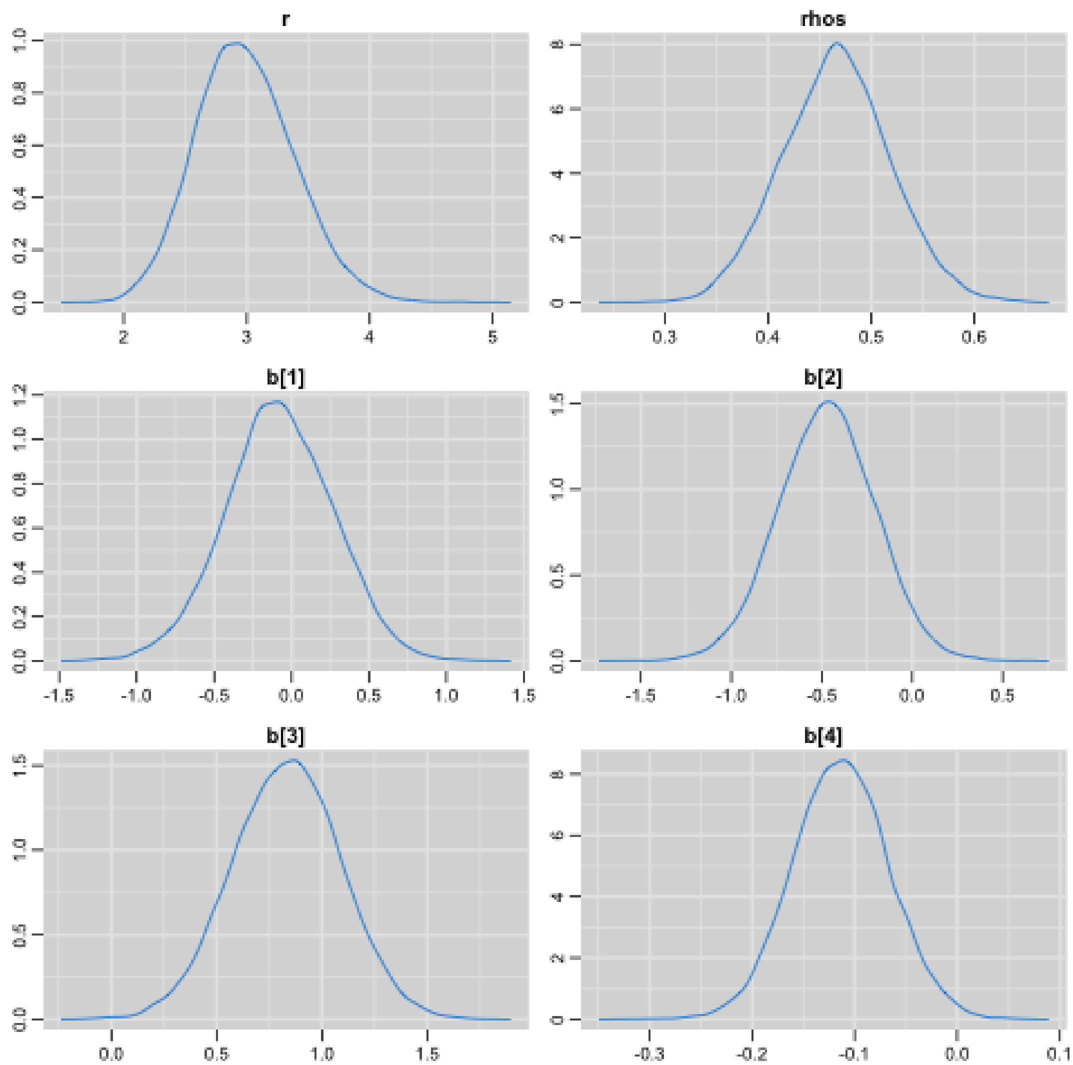

Figure 12: Posterior densities for the frontline model: r = negative binomial shape, rhos = spatial lag, b[1] = theta constant, b[2] = centered urbanization rate, b[3] = percentage rough terrain, b[4] natural log of centroid distance to frontline.

References

Berman, E., J.N. Shapiro and J.H. Felter. 2008. Can hearts and minds be bought? The economics of counterinsurgency in Iraq. Technical report National Bureau of Economic Research.

Berman, E., M. Callen, J.H. Felter and J.N. Shapiro. 2009. Do working men rebel? Insurgency and unemployment in Iraq and the Philippines. Technical report National Bureau of Economic Research.

Blimes, R.J. 2006. "The indirect effect of ethnic heterogeneity on the likelihood of civil war onset." *Journal of Conflict Resolution* 50(4):536–547.

Bringa, T.R. 2010. "Nationality categories, national identification and identity formation in" multinational" Bosnia." *Anthropology of East Europe Review* 11(1 & 2):80–89.

Buhaug, H. and J.K. Rød. 2006. "Local determinants of African civil wars, 1970-2001." *Political Geography* 25(3):315–335.

Buhaug, H. and P. Lujala. 2005. "Accounting for scale: Measuring geography in quantitative studies of civil war." *Political Geography* 24(4):399–418.

Buhaug, H. and S. Gates. 2002. "The geography of civil war." *Journal of Peace Research* 39(4):417–433.

Cameron, A.C. and P.K. Trivedi. 1998. *Regression analysis of count data.* Vol. 30 Cambridge Univ Pr.

Collier, P. and A. Hoeffler. 2002. "Greed and grievance in civil war." *The Centre for the Study of African Economies Working Paper Series* p. 160.

Davenport, C. and P. Ball. 2002. "Views to a Kill." *Journal of Conflict Resolution* 46(3):427–450.

Fearon, J.D. and D.D. Laitin. 2003. "Ethnicity, Insurgency, and Civil War." *American Political Science Review* 97(1):75–90.

Gelman, A. and J. Hill. 2007. *Data analysis using regression and multilevel/hierarchical models.* Vol. 648 Cambridge University Press New York.

Glenny, M. 2000. *The Balkans: nationalism, war, and the Great Powers, 1804-1999.* Viking New York.

Hegre, H., G. Østby and C. Raleigh. 2009. "Poverty and Civil War Events." *Journal of Conflict Resolution* 53(4):598–623.

Judah, T. 2000. *The Serbs: history, myth, and the destruction of Yugoslavia.* Yale Nota Bene.

Kalyvas, S.N. et al. 2006. *The logic of violence in civil war.* Cambridge Univ Press.

Lambert, D.M., J.P. Brown and R.J.G.M. Florax. 2010. "A two-step estimator for a spatial lag model of counts: Theory, small sample performance and an application." *Regional Science and Urban Economics* 40(4):241–252.

Malcolm, N. 1996. *Bosnia: A short history.* NYU Press.

Melander, E. and R. Sundberg. 2011. "Climate Change, Environmental Stress, and Violent Conflict: Tests introducing the UCDP Georeferenced Event Dataset." *Typescript, Uppsala Conflict Data Program* .

Montalvo, J.G. and M. Reynal-Querol. 2005. "Ethnic polarization, potential conflict, and civil wars." *The American Economic Review* 95(3):796–816.

Nation, R.C. 2003. *War in the Balkans, 1991-2002*. Strategic Studies Institute.

Petrovic, R. 1992. "The national composition of Yugoslavia's population, 1991." *Yugoslav survey* 33(1):3.

Raleigh, C., A. Linke, H. Hegre and J. Karlsen. 2010. "Introducing ACLED: An armed conflict location and event dataset." *Journal of Peace Research* 47(5):651.

Raleigh, C. and H. Hegre. 2009. "Population size, concentration, and civil war. A geographically disaggregated analysis." *Political Geography* 28(4):224–238.

Raleigh, C. and H. Urdal. 2007. "Climate change, environmental degradation and armed conflict." *Political Geography* 26(6):674–694.

Schutte, S. and N.B. Weidmann. 2011. "Diffusion patterns of violence in civil wars." *Political Geography* .

Stevanovic, R. and D. Breznik. 1991. "The population of Yugoslavia, 1948-1991." *Yugoslav survey* 32(3):3.

Sundberg, R., M. Lindgren and A. Padskocimaite. 2010. "UCDP Geo-referenced Event Dataset (GED) Codebook.".

Ward, M.D. and K.S. Gleditsch. 2008. *Spatial regression models*. Vol. 155 Sage Publications, Inc.

Weidmann, N.B. 2011. "Violence "from above" or "from below"? The Role of Ethnicity in Bosnia's Civil War." *The Journal of Politics* 1(1):1–13.

Weidmann, N.B. and M.D. Ward. 2010. "Predicting conflict in space and time." *Journal of Conflict Resolution* 54(6):883.

Wu, S., X. Qiu and L. Wang. 2005. "Population estimation methods in GIS and remote sensing: a review." *GIScience & Remote Sensing* 42(1):80–96.