Interaction Effects of Natural Resource Dependence, Environmental Degradation, and Economic Inequality on Civil Conflict and Terrorism: A Spatial Econometric Approach

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Abstract

The linkages between natural resource extraction and civil conflict have long been objects of social scientific interest. While past studies have established that countries and regions that are highly dependent on natural resources tend to experience more civil conflict, the drivers of this relationship, and even the direction of causality, remain subjects of intense debate. The paper contributes to the large quantitative literature on natural resource conflict by applying spatial autoregressive regression analysis to a cross-country panel dataset of civil conflicts and conflict events, including terrorist attacks. The final sample includes conflict, environmental, economic, and political data on 163 countries over fifteen years. Results show a strong and statistically significant spatial effect, supporting the contention that conflict is contagious among neighboring countries. Measures of horizontal economic and environmental inequality, constructed using remote sensing methods, are found to interact with resource dependence to increase the risk and intensity of conflict events and terrorist attacks. The findings support a nuanced relationship between natural resources and civil conflict, whereby conflict is not merely the result of economic opportunism on the part of would-be insurgents, but rather of a complex confluence of geographic, environmental, economic, and political factors.

1. Introduction

This paper contributes to the recent literature investigating the conditions under which natural resource extraction can affect the onset, duration, and intensity of civil conflicts. Recent empirical analyses have suggested that, although natural resources are generally not the sole cause of armed conflict, the exploitation of resources may, under certain circumstances, facilitate the emergence or increase the intensity of conflicts by exacerbating grievances among would-be insurgents, altering incentive structures for belligerents, or serving as sources of financing for rebel groups and national governments. Among those factors thought to link natural resources and conflict is the extent to which the benefits and costs of natural resource extraction are equally distributed among groups defined by shared ethnic or cultural characteristics. The analysis presented below tests this hypothesis using a series of cross-country spatial panel regressions. Specifically, it tests for interaction effects between horizontal economic inequality among ethnic groups, environmental scarcity, and exploitation of natural resources on the number of conflict and terrorist events at the country level.

The original contributions of the study are threefold. First, rather than using binary conflict indicators, georeferenced events data are used to construct dependent variables. The two sources of conflict events data are the Global Terrorism Database, which records terrorist attacks, including attacks against civilians and political targets by non-state combatants during civil wars and the Armed Conflict Location and Event Data project, which tracks battles, attacks, riots, protests, and other events in a limited number of countries.

Secondly, the study incorporates new measures of subnational economic inequality and environmental scarcity using satellite imagery; these are (1) estimates of subnational vertical and horizontal economic inequality were generated from remotely sensed population density and nighttime lights data and (2) a measure of country level resource scarcity was generated from remotely sensed land classification data.

And, finally, the quantitative analysis employs a spatial autoregressive model to control for autocorrelation in the dependent conflict variables, a characteristic of conflict that has not been sufficiently accounted for in existing studies. The spatial effect of conflict proves in the analysis to be an important consideration, suggesting that, consistent with a number of other studies, the risk of civil conflict in a country increases when conflict is present in neighboring countries.

The results of the analysis also strongly support the contention that natural resource exploitation, in conjunction with economic inequality and resource scarcity, increases the risk of and intensity of civil conflict. In the model predicting terrorist attacks globally, statistically significant joint effects were observed between natural resource rents, environmental scarcity, and economic inequality between ethnic groups. The paper proceeds as follows: Section 2 summarizes the relevant literature; Section 3 introduces the empirical methods; Section 4 presents the results of the analyses; and Section 5 concludes.

2. Background

(a) Natural Resources and Conflict

The relationship between natural resources and conflict—particularly intrastate conflict—has been of scholarly interest for decades (see Ross 2004, Van Der Ploeg and Poelhekke 2016). The vast literature on the topic can be broadly categorized into two groups. On the one hand are those studies interested in understanding the motivations of belligerents and the role that the wealth or scarcity of natural resources plays in defining those motivations. On the other, a more recent body of work emphasizes the role of natural resources as financing mechanisms for state and non-state actors.

With regard to the motivational component of civil conflict, an abundance of natural resources may, according to some observers, create incentives for would-be rebels to gain political control of territory from which they can extract resource wealth. This ‘greed’ mechanism was popularized by a series of influential papers by Collier & Hoeffler (2004, 2005), who find, in a series of econometric analyses, evidence of a statistically significant relationship between economic dependence on the export of primary commodities—in particular petroleum—and the risk of experiencing a civil war. Those authors directly compare the significance of the relationship between natural resource exports and civil conflict to an insignificant relationship between conflict and economic inequality, a classical proxy measurement for social grievance, and conclude that economic motivations trump the grievance motivations that had previously been invoked as the primary driver of civil conflict.

In reaction to Collier & Hoeffler's findings, a number of authors have argued that exploitation of and economic dependence on natural resource may create or exacerbate grievances that, in turn, motivate individuals to support or join insurgent groups. Natural resource wealth may, it has been argued, lead to state weakness, increase vulnerability to trade shocks, or "reduce a country's level of internal trade, which in turn could diminish the conflict-alleviating properties of commercial interaction" (Ross, 2004: 344). Such arguments engage closely with the more general 'resource curse' literature.

Alternatively, the processes by which resources are extracted may more directly create grievances related to local environmental and socioeconomic impacts of extraction, which may then become incorporated into the defining 'master' cleavages underlying the broader conflict (Homer-Dixon 1999; Ikelegbe 2005, 2006; Le Billon 2008; Baral & Heinen 2005; Holden 2013, 2014). Examples of such an effect include the sporadic violence in southeastern Nigeria in 1994 and 1995, when the Ogoni people protested pollution of the Niger Delta by multinational oil companies and secessionist rebellion in Papua New Guinea from the late 1980s to mid-1990s, which was partly motivated by anger against a foreign-owned copper mine that had severely damaged the environment. Although often treated as a separate phenomenon, conflicts involving scarcity of (usually renewable) natural resources—in particular farmland, water, and forests—often entail significant overlap with natural resource extraction. Mining projects, logging operations, and similar projects contribute to scarcity by commandeering land that might otherwise be utilized by local people for subsistence, degrading soil or water quality, or otherwise affecting the provision of ecosystem services. Indeed, it is the incompatibility of traditional resource uses with extractive industry that underlies grievances theories of natural resource conflict. As Homer-Dixon (1999) writes:

> If the historical identity of a clearly defined social group is strongly linked to a particular set of natural resources or a particular pattern of resource use, degradation or depletion of

> that resource can accentuate a feeling of relative deprivation. Members of the group can come to feel that they are being denied their rightful access to resources that are key to their self-definition as a group. This relative deprivation boosts grievances that may eventually be expressed through aggressive assertion of group identity (147-148).

Although the empirical evidence for scarcity as a driver of conflict is less well developed than for resource abundance, a growing interest in the linkages between climate change and conflict emphasizes the effect of global change on resource scarcity.

A corollary to the greed mechanism, sometimes referred to as the ‘opportunity’ mechanism, also developed by Collier & Hoeffler, deemphasizes motivational drivers of conflict entirely and instead focuses on the role played by natural resources as potential sources of financing for rebel groups. The canonical example of the opportunity mechanism is the case of ‘conflict’ or ‘blood’ diamonds in Africa; others include the harvesting of timber by the Khmer Rouge in Cambodia, the extortion of mining and logging operations by the New People’s Army in the Philippines, and, to the extent that agricultural commodities can be considered natural resources, trade in narcotics by the Taliban in Afghanistan, FARC rebels in Colombia, and other groups (Collier & Hoeffler 1998, 2004, 2005; Fearon 2005; Lujala 2010; De Soysa 2001; De Soysa & Neumayer 2007; see also Ross 2004; Van der Ploeg 2011; Koubi et al. 2014).

In recent years, the conversation has moved beyond the decades-old tension between theories of ‘grievance’, ‘greed’, and ‘opportunity’ toward a more nuanced understanding of the linkage between natural resources and conflict in which memories of past conflicts, structural forms of violence associated with extractive industries, and other less immediately quantifiable drivers play important roles (Le Billon 2013; Hoelscher et al. 2012; Basedau & Pierskalla 2014). For example, Le Billon (2012), for instance, distinguishes between “resource conflicts” or “conflicts taking place over a resource for its own sake,” from “conflict resources” concept, which emphasizes the “financial opportunities that sustain armed conflicts, or the instrumentalisation of opportunities related to resources by belligerents” (13), as well as from the “resource curse” argument, whereby dependence on natural resources “results in economic underperformance and a weakening of governing institutions, rendering a society more vulnerable to armed conflict." He suggests that while diffuse and 'lootable' resources such as alluvial diamonds tend to contribute to warlordism, more concentrated resources may be more predictive of either secessionism (if resources are located in a territory remote from the center of the national government's political power center) or coup d'états (if the resources are centrally located).

This paper specifically contributes to a very recent literature that investigates the processes by which contextual factors, including preexisting resource scarcity, economic inequality, ethnic cleavages, political institutions, and historical legacies of oppression and violence, may create the preconditions for civil conflict involving natural resource exploitation (Kennedy 2015; Casertano 2012; Baird & Le Billon 2012; Wegenast & Basedau 2014; Elbadawi & Soto 2015). In a recent paper, Bodea et al. (2016) find that higher levels of specific categories of public spending can lower the risk of conflict in oil producing countries. Specifically, they find that higher military spending in highly oil dependent countries is associated with lower risk of the onset of major and minors conflicts, a finding which they attribute to a deterrent effect in those countries, while higher education, health, and social protection spending is associated with a lower risk of minor conflicts, possibly due to a reduction in grievance. The role of spending, however, appears to be affected by the level of oil dependence; countries with low levels of oil revenue saw increased risk of conflict as military spending increased, due perhaps to grievances related to militarization.

Increasingly complex empirical studies of the relationship between natural resources and conflict are evidence of a growing recognition that theories of greed, grievance, and opportunity are neither necessarily mutually exclusive nor sufficiently nuanced. In many conflicts, it appears that "greed and grievance mechanism can operate simultaneously" (Holden 2014: 78) and may indeed, when resources are considered in the contexts of the economic and social structures in which they are embedded, "coexist as two sides of the same coin" (Le Billon, 2005: 220). For this reason, Koubi et al. (2014) argue that "interactive effects, between natural resources and grievances, for example, should be studied more explicitly" (239) *(b) Inequality and Conflict*

Among the contextual factors potentially linking natural resources and civil conflict, the unequal distribution of the costs and benefits of natural resource extraction certainly ranks among the foremost.

Koubi & Böhmelt (2014) explain that "if there is high national wealth within a country, this can create or stress existing levels of grievances if a portion of the population is potentially excluded from benefiting from this wealth" (21). A similar logic underlies the relationship between natural resources, inequality, and conflict—abundance of exploitable natural resources, while not deterministically predictive of conflict, may give rise to or exacerbate grievances where the costs and benefits of natural resource extraction are not distributed equitably.

The most widely-used measure of vertical economic inequality is the Gini coefficient. Empirical studies of civil conflict have generally failed to a statistically significant relationship between national-level Gini coefficients and the outbreak, intensity, or longevity of civil conflicts (Fearon & Laitin 2003; Collier & Hoeffler 2004), a non-finding that has been interpreted by some as evidence against grievances as a cause of civil conflict (Buhaug et al. 2014). Fearon & Laitin (2003) similarly conclude that that "the conditions that favor insurgency—in particular, state weakness marked by poverty, a large population, and instability—are better predictors of which countries are at risk for civil war than are indicators of ethnic and religious diversity or measures of grievance such as economic inequality, lack of democracy or civil liberties, or state discrimination against minority religions or languages" (88).

In recent years, scholars have increasingly emphasized horizontal inequalities, or "inequalities in economic, social or political dimensions between culturally defined groups" (Stewart 2008, p. 3) as potentially important drivers of conflict. Cederman et al. (2013) postulate that "political and economic inequalities affecting entire ethnic groups, rather than merely individuals, are especially likely to fuel resentment and justify attempts to fight perceived injustice" (3). Horizontal inequality thereby increases the feasibility of rebellion by facilitating collective action. Koubi & Böhmelt (2014) write that "Mobilization depends not only on the existence of shared motivations, but also on the availability of collective identity and opportunities for collection action. Groups with shared identities, whether based on race, language or religion, have lower costs of rebellion, since they can more easily recruit from within the identity group, are less burdened by collective action problems due to suspicions/mistrust between group members, and can have/utilize cultural symbols and ideals to rally behind." Cederman et al. (2013) present convincing empirical evidence that political and economic horizontal inequalities among ethnic groups affect the outset, duration, and results of conflict. The results of Koubi & Böhmelt (2014) suggest that, "while high per capita income per se reduces the probability of conflict outbreak, a potentially unequal distribution of this wealth increases it" (28). And, Ezcurra & Palacios (2016) find that interregional inequality increases the number of terrorist attacks.

Østby, Nordås & Rød (2009) use spatially disaggregated data for 22 countries in sub-Saharan Africa for 1986–2004. They report that civil conflict is more likely in geographic areas where the presence of natural resources coincides with relative deprivation of the local population. Likewise, Hoelsche, Miklian & Vadlamannati (2012) analyze district-level data on the Maoist conflict in India. They find that conflict is more likely in those places where mining activities coincide with stronger grievances related to socio-economic exclusion of some local group(s). And, Wayland & Kuniholm (2016) present evidence that protests against mining projects in Guatemala are more likely to occur in communities that were disproportionally targeted by the government during that country's civil war.

Morelli & Rohner (2015) develop an "Oil Gini" measure representing the extent to which oil resources in each country-year are distributed equally among ethnic groups. They also find that the spatial extent of oil extraction in each ethnic group territory is related to the onset of conflict.

> There are many cases where, when the presence of a concentrated ethnic group coincides with large natural resource abundance concentrated in its region, the concentrated minority group could be financially better off if it were independent and may under some conditions have incentives to start secessionist rebellion…In contrast, if natural resources are absent or if natural resources (and political power) are evenly dispersed in a country, there are typically fewer conflict incentives, even when there are ethnic divisions. Similarly, when there are large amounts of natural resources available, but the society is ethnically homogeneous, war incentives are weak (33).

It additions to its effect on the incentives facing belligerents, inequality in natural resource wealth also creates the conditions under which extortion, thievery, and black market trade in resources can flourish, thus creating opportunities for resources to be used a financing for rebel groups. In the Philippines, for example, owners of mining operations and the politicians to whom they pay bribes are forced under threat of violence to pay ‘revolutionary taxes,’ the major source of funding for the New People’s Army; were the rents of the mining not concentrated in the hands of a few, the insurgents would likely face a more difficulty in selecting targets for its protection racket.

There are, accordingly, several mechanisms by which the unequal distribution of the costs and benefits of natural resource extraction may lead to conflict. The purpose of this study is, therefore, to test for an impact on conflict incidence and intensity of the joint effect of natural resource extraction and two alternative definitions of inequality—inequality of economic benefits and inequality of environmental impacts—associated with natural resource extraction.

(c) Defining Civil Conflict

Studies of the drivers of civil conflict inevitably must contend with the definitional ambiguities. Most studies of conflict and natural resources rely on binary definitions of civil war typically based on the number of deaths attributable to a conflict between well-defined agents—typically a state and a nonstate group. Most often, the definition of the Armed Conflict Dataset is used, whereby a country is considered to be at war when at least 25 people have been killed by violence between the state and a subnational group. This approach has yielded important insights into the factors that drive the onset and duration of conflict, but is limited in that it cannot be used as a measure of conflict intensity, and risks excluding low level conflicts.

The recent emergence of georeferenced events datasets offers an alternative means of measuring conflict and opens the door for more precise statistical analyses utilizing continuous rather dichotomous dependent variables. This study relies on two sets of events data—terrorist events from the Global Terrorism Database (GTD) and conflict events from the Armed Conflict Location and Events Data

(ACLED) project. Although both dataset measure violence, they do so in different ways and therefore offer a useful point of comparison.

The most important distinction between the two datasets involves the difference between terrorism and conflict. Findley & Young (2012) write that "studies of civil war and terrorism have historically produced islands of cumulative knowledge but have rarely been integrated" (300) and "most scholars still view each as distinct forms of violence" (Ibid, 287-288). However, the distinction between civil war and terrorism is, as Findley & Young rightly point out, often methodological. Tilly suggests that we should "doubt the existence of a distinct, coherent class of actors (terrorists) who specialize in a unitary form of political action (terror) and thus should establish a separate variety of politics (terrorism)." For these reasons, it has been argued that a greater degree of unity between the historically disparate literatures of civil conflict and terrorism is warranted (Findley & Young 2012; Ghatak 2016).

For the purposes of this paper, terrorism is conceptualized as "a strategy or tactic implemented by groups against an established state (Findley & Young 2012)." More specifically, the definition used by the Global Terrorism Database (GTD) is used. In order to be included in the GTD, an incident must be intentional, must involve violence or the immediate threat of violence, and must be perpetrated by subnational actors. In addition, the incident must meet at least two of the three following conditions: (1) it must be aimed at attaining a political, economic, religious, or social goal; (2) there must be evidence of intent to coerce, intimidate, or convey some other message to an audience beyond the immediate victims; and (3) the action must be outside the context of legitimate warfare activities.

The definition of terrorism is broader than that used elsewhere; Fortna (2015), for instance, defines "terrorist rebel groups as those who employ a systematic campaign of indiscriminate violence against public civilian targets to influence a wider audience" (522). The GTD definition, by contrast, includes attacks by insurgents against military and political targets. Indeed, the definition is broad as to encompass most aspects of irregular warfare perpetrated by nonstate actors, including, among other events, assassinations of political leaders; attacks on mines, logging operations, and other natural resource extraction sites; bombings of government buildings; and targeted and random killings of civilians based on ethnic or religious affiliation.

Nevertheless, the GTD excludes many events that occur during civil conflicts, including riots, violence perpetrated by the state against non-state actors or civilians, and pitched battles. Such events are identified in the more comprehensive ACLED dataset, which also records protests, strategic developments in conflict, such as the establishment of bases and nonviolent changes in territorial control. Compared to GTD, however, ACLED currently has a much more limited scope, its coverage limited to Africa and eleven states in South and East Asia.

In the analysis described below, two sets of spatial autoregressive models are estimated in which the dependent variables are constructed, respectively, from the georeferenced terrorist attacks recorded in the GTD and the georeferenced conflict events from ACLED.

3. Hypotheses

As it pertains to natural resource extraction, horizontal inequality may take one of two forms or a combination therefore. First, the benefits of natural resource extraction—i.e. the economic rents, direct employment opportunities, and indirect development effects of extraction—may be unequally distributed among groups. Secondly, the costs of natural resource extraction may be unequally distributed across groups; this would occur in cases where a particular group is disproportionally affected by the resource scarcity as a result of impacts from extractive activity to land use patterns, ecosystem services, or demographic patterns.

> **Hypothesis 1:** Among countries with high levels of economic inequality among ethnic groups, economic dependence on natural resource extraction increases the incidence of terrorist and conflict events.
>
> **Hypothesis 2:** Among countries in which environmental scarcity is unequally distributed, economic dependence on natural resource extraction increases the incidence of terrorist and conflict events.

The analysis described in the following section is designed to test these hypotheses by testing for statistically significant interaction effects between natural resource dependence and two measures of inequality based on remotely sensed (satellite) data. In the spatial panel regression analysis, strong evidence is found in support of Hypothesis 1, but little to no evidence is found for Hypothesis 2.

4. Research Design and Data

(a) Dependent Variables

As noted above, two dependent variables were defined based on two independent sources of conflict events data. The first comprises the number of events in each country-year recorded in the GTD. In order to exclude incidences of international terrorism, events were included only if they occurred in a country that was experiencing a civil conflict, as defined by the Armed Conflict Data Program, during the year of the event. The final panel dataset for the terrorist events models includes 163 countries from 2000 through 2014, comprising a total of 2445 country-year observations (see Figure 1).

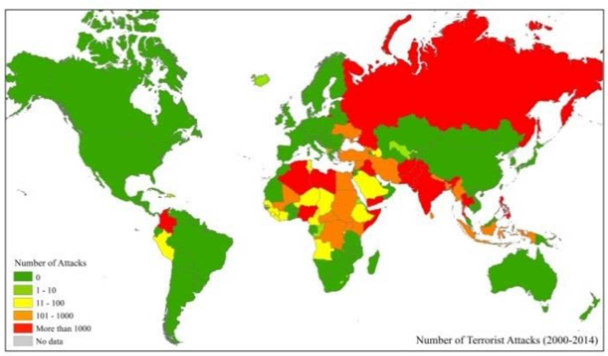

Figure 1.*Terrorist attacks by country from GTD*

The second dependent variable comprises the number of conflict events that occurred in a country-year, as recorded in ACLED. Because the ACLED dataset is limited in geographical scope, the second portion of the analysis covers the same time period, but includes only 48 countries in Africa, for a total of 720 observations. As shown in Figure 2, the ACLED dataset is substantially more comprehensive that the GTD in terms of the types of events that it includes. For the purposes of this study, four categories of conflict events were used to create the dependent variable—battles between government and nongovernmental forces; remote violence, which ACLED defines as “events in which the tool for engaging in conflict did not require the physical presence of the perpetrator," such as IED attacks, mortar attacks, and missile attacks; riots and protests; and violence against civilians.

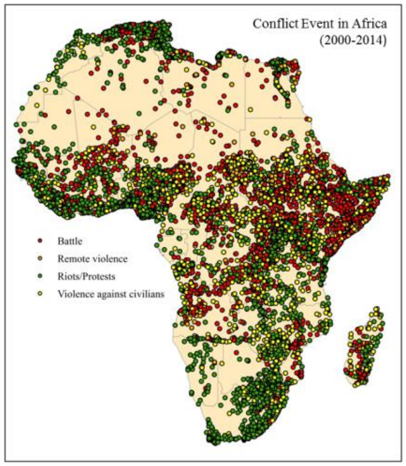

Figure 2. Conflict events from ACLED

(b) Independent Variables

The explanatory variables of interest in this study include estimates of economic dependence on natural resources—obtained from the World Bank Development Indicators (WDI) dataset—and measures of economic and environmental inequality produced using remote sensing methods. Economic dependence on natural resources is measured in terms of the value of resource rents divided by GDP. For the purposes of this study, economic rents from three categories of resources were independently considered. These are oil rents, calculated as the difference between the value of crude oil production at world prices and the total costs of productions; mineral rents, which are calculated in the WDIs as the sum of value of production at world prices for tin, gold, lead, zinc, iron, copper, nickel, silver, bauxite, and phosphate production minus the costs of production; and forest rents, or total roundwood harvest volume multiplied by average world prices and a region-specific rental rate, each as a percentage of GDP (World Bank 2016). In Figure 3 below and in the statistical model descriptions to follow, resource dependence refers to the sum of resource rents from those three resource categories.

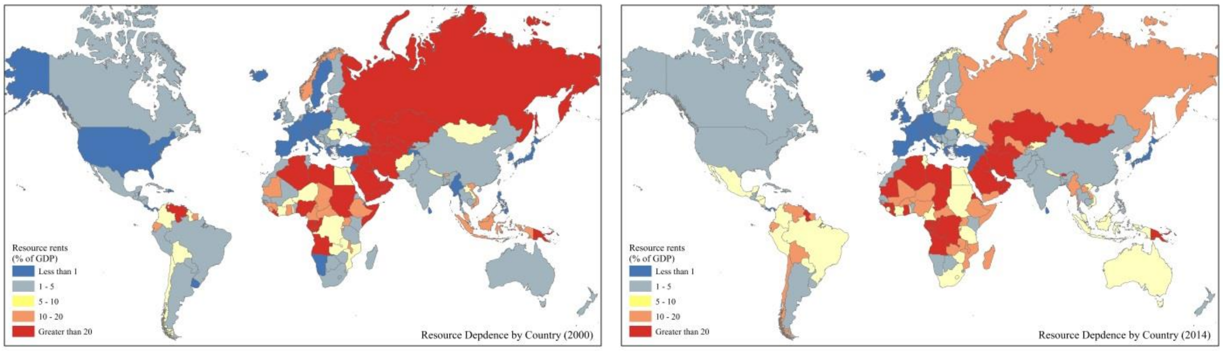

Figure 3. E*conomic dependence on natural resources by country from WDI dataset (2000 and 2014)*

The estimates of economic dependence on natural resources were interacted with a measure of horizontal economic inequality produced using remote sensing and GIS methods. Polygons representing ethnic group territories were obtained from the Geo-referencing of Ethnic Groups (GREG) dataset (see Weidmann et al. 2010). For each polygon, a measure of population density was generated using data from the LandScan project, which estimates population globally in approximately 1 square kilometer areas based on the presence of structures and buildings.

Economic productivity in each polygon was estimated using nighttime lights data collected by the visible infrared imaging radiometer suite (VIIRS). The VIIRS nighttime lights used in this study are annual composites processed to minimize cloud cover and to remove ephemeral events, such as fires. Light from gas flares, which are a stable source, but are not relevant components of economic productivity, were removed using masks obtained from the National Oceanic and Atmospheric Administration and by comparing the processed product with high resolution GoogleEarth imagery.

Nighttime lights data have been used successfully as a proxy measure of economic productivity and urbanization when alternative measures are not available (see, for example, Keola & Andersson 2015, Wu et al. 2013, Zhou et al. 2015). When aggregated to the country level, the final nighttime lights digital number is strongly correlated (r=0.927) with GDP estimates from the WDI dataset (see Figure 4).

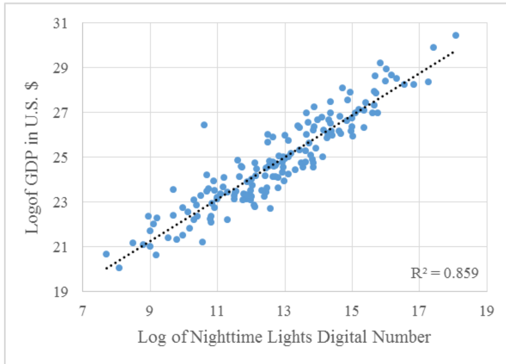

Figure 4. *VIIRS nighttime lights and GDP*

Because the VIIRS nighttime lights and Landscan population estimates are generated independently using different methods, it is possible to generate an estimate of per capita economic productivity in each ethnic group territory by dividing the former by the latter, as shown for selected years in Figure 5.

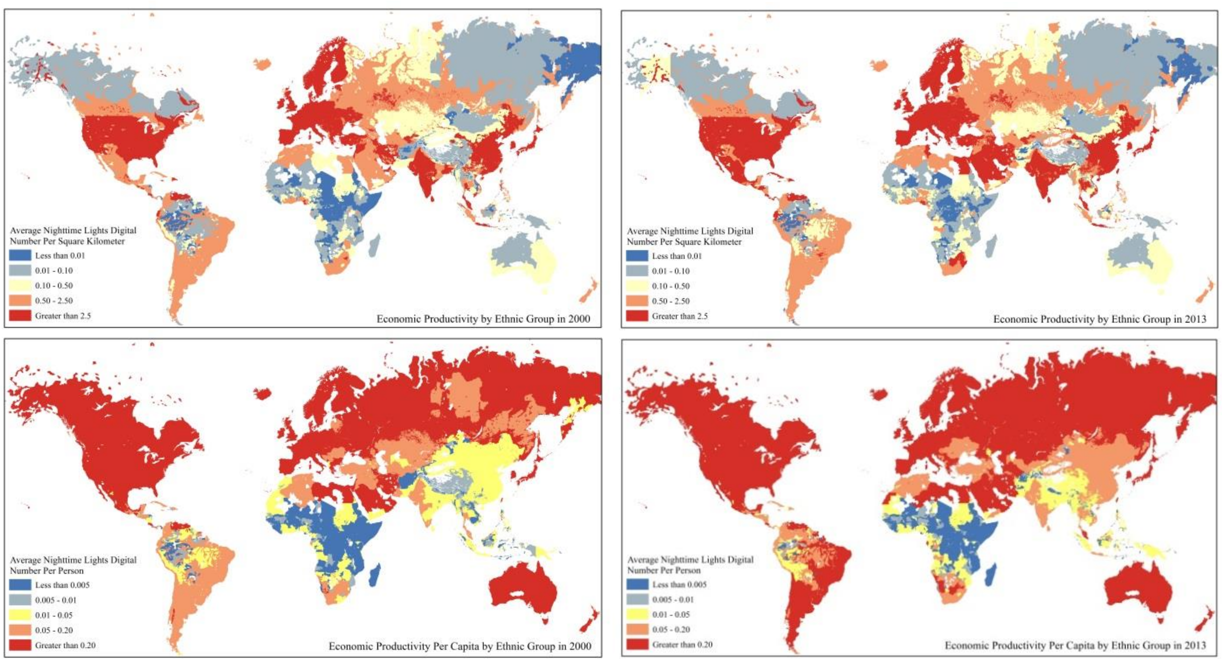

Figure 5. *GDP and GDP per capita by ethnic group in 2000 and 2014*

From the estimates of per capita productivity at the ethnic group level, a country-level measure of economic inequality was defined using Theil's (1967) mean logarithmic deviation method, such that:

$$T_i = \frac{1}{N}\sum_{j=1}^{j}\frac{x_i}{\mu}\log\left(\frac{x_i}{\mu}\right)$$

Where y_j is GDP per capita in region j of country i, p is the population share of region j, and μ is average GDP per capita across all region of country i. This index has several advantages over other measures of inequality, including, importantly, the fact that T is not sensitive to the number of regions in each country. Because it measures horizontal, rather than vertical, inequality, the Theil index calculated for each country is not highly correlated with the Gini coefficient (r=0.51). As shown in Figure 6, however, it appears to be a reasonable predictor of conflict in many cases. Across the time period of interest—the years between 1999 and 2015—the three countries with the highest index values were, in order, Sudan, the Democratic Republic of the Congo, and Afghanistan, all countries in which major civil conflicts have occurred.

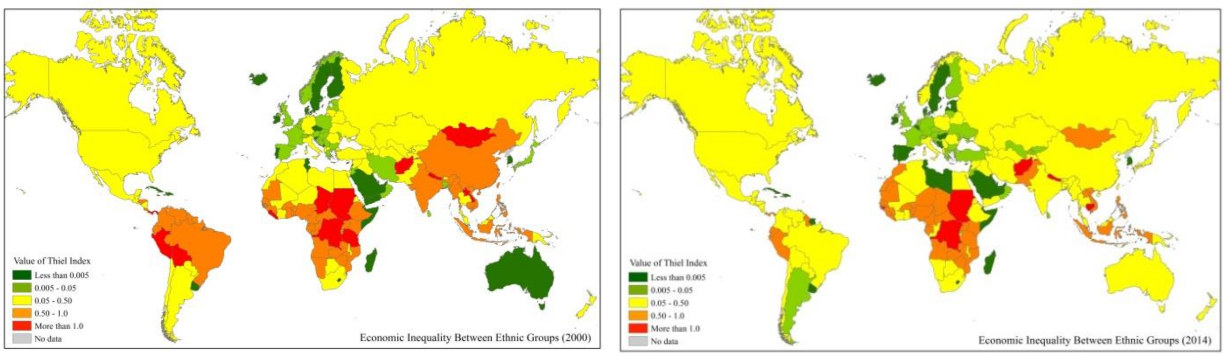

Figure 6. *Economic inequality among ethnic groups in 2000 and 2014*

In order to test Hypothesis 2, an alternative measure of inequality was calculated to measure the extent to which environmental scarcity is unequally distributed across ethnic groups within a given country. As a broad proxy measure of scarcity, the annual change in vegetated area within each ethnic group was calculated based on remotely sensed data collected by the Moderate Resolution Imaging Spectroradiometer (MOSIS) suite. MODIS collects data on the intensity of reflected light in different parts of the electromagnetic spectrum, which can be used to make conclusion about land use cover and change. Because photosynthesizing plants reflect near infrared light and absorb visible red light, a measure of plant greenness can be calculated the normalized difference vegetation index (NDVI) by dividing the difference between near infrared and visible red reflectance by their sum. As described in Broxton et al. (2014), maximum annual NDVI can be adjusted to generate a Maximum Green Vegetation

Fraction (MGVF) as a global measure of maximum green vegetation, which is available in the form of annual composite datasets from the U.S. Geological Survey.

From the MGVF composites, the percent decrease in MGVF was calculated for each ethnic group in each year. A Theil index was then calculated for each country-year to represent the extent to which the loss of vegetation was unequally distributed among ethnic groups in each country (see Figure 7). Where the economic inequality variable described above can be conceptualized as a measure of the unequal distribution of the benefits from natural resource extraction, therefore, the environmental inequality variable measures equality in the distribution of the costs of extraction.

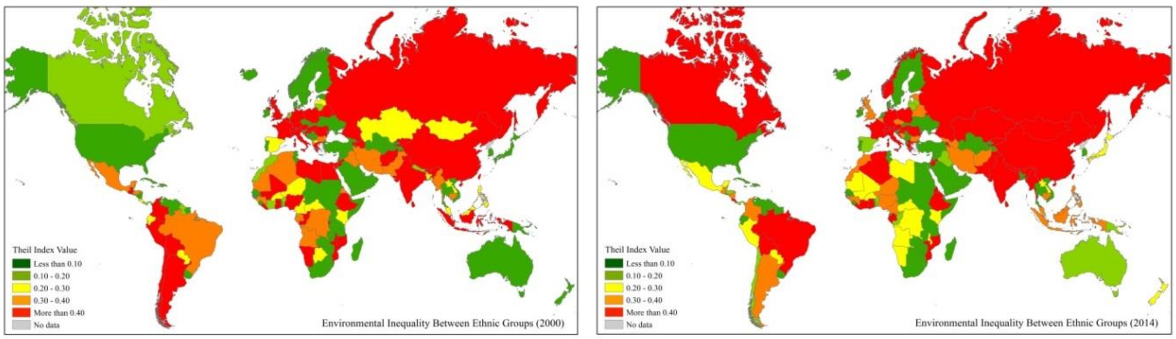

Figure 7. *Environmental inequality among ethnic groups in 2000 and 2014*

(c) Control Variables

Several control variables were included in the statistical models, based on the findings of the existing literature. Because total population and wealth have both consistently been shown to be important predictor of conflict onset and intensity in the existing literature, total population and GDP per capita in constant (2009) dollars, both obtained from the WDI dataset, are included in all of the models described below. Population density, in persons per square kilometer, also from the WDIs, and the total number of ethnic groups, from the GREG dataset, are included as well. Finally, a time variable is included in order to control for any general trend in the number of conflict events across time. Missing data for the control variables were estimated by linear interpolation.

(d) Model Specification

It has been noted by a number of observers than “civil war appears to be contagious” (Danneman & Ritter 2014: 254). Existing empirical studies of civil conflict have dealt with this tendency by including regional dummy variables, by generating spatially lagged variables, or, in some cases, by ignoring it altogether. To explicitly control for spatial autocorrelation in the dependent variable, this study employs a spatial autoregressive regression model of the form:

$$y_{i,t} = \beta_0 + \rho W y_{j,t} + \beta_1 x_{i,t} + \lambda_i + \mu_{i,t}$$

Where $y_{i,t}$ represents the number of conflict events or the onset of conflict in the linear and probit model, respectively, in country *i* at time *t* and λ and μ represent the country-specific random effect and the country-year specific error, respectively. Included in the vector of explanatory variables $x_{i,t}$ is a interaction term representing the joint effect of economic dependence on natural resource rents and the presence of high vertical or horizontal inequality in country-year *i*, the coefficient of which is of primary theoretical interest for this study.

The term *W* represents the spatial weights matrix, a block diagonal matrix that defines the spatial structure of the model. In this study, a standard spatial weights matrix was used, such that, if each row in the matrix represents an observation *i* and each column represents an observation *j* , then each entry is defined as 1 divided by the number of observations neighboring observation *i*, if observation j is among the neighbors of observation *i*, and zero otherwise. By design, the entries for each row sum to one; for example, if a municipality or city has 5 neighbors, the entry for each neighbor is 0.2 and the entries for all non-neighboring observations is 0. Following Millo & Piras (2012), equation is estimated by maximum likelihood estimation.

5. Analysis

(a) Results

The tables below report the key results from models predicting terrorist attacks reported in the GTD and conflict events from ACLED, respectively. The results from both analyses strongly support the hypothesis that horizontal economic inequality between ethnic groups affects the relationship between natural resources and civil conflict. The coefficient of the interaction term between resource dependence and inequality among ethnic groups is positive and statistically significant predictor of terrorist attacks in the global sample (see Table 1) and of conflict events in the restricted sample of African countries (see Table 3). The effect is consistent for all three categories of resources—oil, minerals, and timber—that were tested. When interacted with economic inequality, dependence on each of the resource categories is positive and statistically significant at the five percent level or above.

Independent of this clear interaction effect, the relationship between natural resource dependence and conflict is mixed. Consistent with Basedau & Lay (2009), dependence on oil resources has a consistently negative relationship with the incidence of conflict events; controlling for the interaction effect of resource dependence and horizontal economic inequality, dependence on minerals and (in the global sample, though not in the restricted sample) forest resources also tended to reduce conflict. Horizontal economic inequality is, however, statistically significant and positive independent of an interaction with resource dependence. This is an important finding in its own right, as it supports recent work by Cederman et al. (2011), Cederman et al. (2013), Buhaug et al. (2014), and Deiwiks et al. (2012), among others.

Table 1. Natural Resources, Economic Inequality, and Terrorism

Variables	Model1	Model 2	Model 3	Model 4
Spatial lag	0.115*** (0.024)	0.123*** (0.024)	0.116*** (0.024)	0.121*** (0.024)
Intercept	-3.832*** (0.939)	-3.919*** (0.973)	-3.832*** (0.950)	-3.864*** (0.976)
Time variable	0.038*** (0.004)	0.037*** (0.004)	0.036*** (0.004)	0.037*** (0.004)
No. of ethnic groups	0.025*** (0.007)	0.022*** (0.007)	0.023*** (0.007)	0.022*** (0.007)
Ln(GDP)	-0.013*** (0.002)	-0.013*** (0.002)	-0.013*** (0.002)	-0.013*** (0.002)
Ln(Population)	0.203*** (0.064)	0.227*** (0.067)	0.204*** (0.065)	0.225*** (0.067)
Ln(Population density)	0.158** (0.071)	0.129* (0.074)	0.155** (0.072)	0.128* (0.074)
Economic inequality (Theil index)	0.507*** (0.016)	0.059 (0.178)	0.511*** (0.014)	0.069 (0.186)
Resource rents (% of GDP)	-0.013*** (0.003)	-0.030*** (0.004)		
Resource rents*Economic inequality		0.030*** (0.006)		
Oil rents (% of GDP)			-0.016*** (0.004)	-0.029*** (0.005)
Mineral rents (% of GDP)			-0.009* (0.005)	-0.033*** (0.010)
Forest rents (% of GDP)			-0.008 (0.009)	-0.044*** (0.014)
Oil rents*Economic inequality				0.026*** (0.007)
Mineral rents*Economic inequality				0.040*** (0.014)
Forest rents*Economic inequality				0.037*** (0.011)

Notes: *$p < 0.1$ **$p < 0.05$ ***$p < 0.01$

Table 2. Natural Resources, Environmental Inequality, and Terrorism

Variables	Model 1	Model 2	Model 3	Model 4
Spatial lag	0.118*** (0.024	0.119*** (0.024)	0.121*** (0.024)	0.119*** (0.024)
Intercept	-3.984*** (0.951)	-3.992*** (0.951)	-4.011*** (0.960)	-4.146*** (0.980)
Time variable	0.035*** (0.004)	0.035*** (0.004)	0.034*** (0.004)	0.034*** (0.004)
No. of ethnic groups	0.023*** (0.007)	0.022*** (0.007)	0.023*** (0.007)	0.023*** (0.007)
Ln(GDP)	-0.013*** (0.002)	-0.013*** (0.002)	-0.012*** (0.002)	-0.013*** (0.002)
Ln(Population)	0.237*** (0.065)	0.239*** (0.065)	0.238*** (0.065)	0.256*** (0.067)
Ln(Population density)	0.108 (0.071)	0.108 (0.071)	0.106 (0.072)	0.095 (0.073)
Environmental inequality (Theil index)	-0.096 (0.177)	-0.016 (0.205)	-0.114 (0.118)	-0.364* (0.214)
Resource rents (% of GDP)	-0.013*** (0.003)	-0.015*** (0.004)		
Resource rents*Environmental inequality		0.007 (0.011)		
Oil rents (% of GDP)			-0.017*** (0.004)	-0.015*** (0.005)
Mineral rents (% of GDP)			-0.010* (0.005)	-0.003 (0.011)
Forest rents (% of GDP)			-0.001 (0.009)	-0.050*** (0.015)
Oil rents*Environmental inequality				-0.013 (0.013)
Mineral rents*Environmental inequality				-0.016 (0.026)
Forest rents*Environmental inequality				0.109*** (0.028)

Notes: *$p < 0.1$ **$p < 0.05$ ***$p < 0.01$

Table 3. Natural Resources, Economic Inequality, and Conflict in Africa

Variables	Model 1	Model 2	Mode 3	Model 4
Spatial lag	0.346*** (0.049)	0.354*** (0.048)	0.346*** (0.049)	0.359*** (0.049)
Intercept	-6.027*** (2.317)	-6.102*** (2.298)	-6.867*** (2.347)	-5.966*** (2.415)
Time variable	0.080*** (0.014)	0.080*** (0.014)	0.073*** (0.015)	0.076*** (0.015)
No. of ethnic groups	0.026* (0.014)	0.030** (0.015)	0.025* (0.015)	0.031** (0.015)
Ln(GDP)	-0.358*** (0.118)	-0.331*** (0.117)	-0.269** (0.134)	-0.315** (0.139)
Ln(Population)	0.618*** (0.142)	0.647*** (0.141)	0.637*** (0.140)	0.628*** (0.144)
Ln(Population density)	-0.260* (0.142)	-0.309** (0.141)	-0.270* (0.138)	-0.302** (0.144)
Economic inequality (Theil index)	0.692** (0.273)	-0.099 (0.343)	0.643*** (0.272)	-0.027 (0.366)
Resource rents (% of GDP)	3.9×10^{-4} (0.005)	-0.027*** (0.009)		
Resource rents*Economic inequality		0.039*** (0.010)		
Oil rents (% of GDP)			-0.003 (0.006)	-0.024** (0.011)
Mineral rents (% of GDP)			0.001 (0.008)	-0.039** (0.017)
Forest rents (% of GDP)			0.016 (0.014)	-0.027 (0.023)
Oil rents*Economic inequality				0.031** (0.013)
Mineral rents*Economic inequality				0.068*** (0.025)
Forest rents*Economic inequality				0.041** (0.017)

Notes: *p<0.1 **p<0.05 ***p<0.01

Table 4. Natural Resources, Environmental Inequality, and Conflict in Africa

Variables	Model 1	Model 2	Model 3	Model 4
Spatial lag	0.342*** (0.049)	0.343*** (0.049)	0.343*** (0.049)	0.363*** (0.048)
Intercept	-5.659*** (2.298)	-5.663*** (2.303)	-6.868*** (2.305)	-4.353* (2.524)
Time variable	0.081*** (0.014)	0.081*** (0.014)	0.072*** (0.015)	0.080*** (0.015)
No. of ethnic groups	0.027* (0.015)	0.027* (0.015)	0.026* (0.014)	0.035** (0.016)
Ln(GDP)	-0.440*** (0.114)	-0.445*** (0.115)	-0.316** (0.131)	-0.495*** (0.137)
Ln(Population)	0.671*** (0.139)	0.672*** (0.139)	0.696*** (0.134)	0.625*** (0.149)
Ln(Population density)	-0.324** (0.138)	-0.325** (0.138)	-0.329** (0.133)	-0.342** (0.147)
Environmental inequality (Theil index)	-0.367 (0.456)	-0.280 (0.550)	-0.421 (0.449)	-1.388** (0.625)
Resource rents (% of GDP)	0.003 (0.005)	0.005 (0.009)		
Resource rents*Environmental inequality		-0.006 (0.022)		
Oil rents (% of GDP)			-0.001 (0.006)	0.004 (0.010)
Mineral rents (% of GDP)			0.002 (0.009)	0.067*** (0.021)
Forest rents (% of GDP)			0.024 (0.014)	-0.056*** (0.026)
Oil rents*Environmental inequality				-0.016 (0.028)
Mineral rents*Environmental inequality				-0.152*** (0.046)
Forest rents*Environmental inequality				0.160*** (0.046)

Notes: *p<0.1 **p<0.05 ***p<0.01

The evidence that inequality of environmental impacts affects the incidence of conflict is weaker. The Theil index measuring inequality in land cover change was generally insignificant in all of the models in which it was included. The joint effect of horizontal environmental inequality and resource dependence was also generally insignificant, with the exception of dependence on forest resource. This exception is noteworthy, however, because forest resources, among the three resource categories tested, is generally associated with the highest levels of local land use change. The positive and statistically significant relationship between the interaction of dependence on forest resources and horizontal environmental inequality, which is evident in both the global sample and the restricted sample may be evidence of an environmental scarcity effect on conflict. In the restricted sample, but not in the global sample, the interaction term between dependence on mineral rents and horizontal environmental inequality was also statistically significant, but its sign is negative. Interpretation of this result is difficult; it may be the case that in Africa, resource rents from mineral resources can serve to ameliorate conflicts between ethnic groups involving environmental scarcity.

Among the covariates, total population is significant and positive, consistent with the results from numerous empirical studies of conflict (see Ross 2004). Per capita GDP is, as expected, consistently negative and statistically significant. The effect of population density is mixed; it is generally positive, though not consistently significant, in the global sample, but negative in the restricted sample, suggesting the presence of a regional effect with regard to demographic effects on conflict. The number of ethnic groups in each country is consistently significant and positive, though, due to the stability of this variable over time, interpretation of this finding should be approached with caution as it may be affected by other time invariant variables that are not included in the model. There is a clear positive relationship between the time variable and conflict incidence; the number of terrorist attacks globally and the number of conflict events in Africa increased universally across the time period examined (incidentally, horizontal economic inequality has generally decreased over time, suggesting further that the effect of the horizontal economic inequality variable on conflict is not an aberration owing to a general time trend). Finally, the spatial lag is consistently positive and statistically significant, confirming the utility of the spatial autoregressive approach.

(b) Sensitivity Analysis

In order to test the robustness of the results reported above, the statistical models were repeated under a wide variety of alternative specifications. These included the following:

- *Estimating a non-spatial random effects model*: The Theil index of horizontal economic inequality remained a statistically significant predictor of conflict using a standard random effects model, as did the interaction effects of that variable with resource dependence.
- *Estimating a spatial fixed effects model:* The fixed effects model estimates the effect of explanatory variables on changes in the dependent variables within each country. The fixed effects model effectively drops from the sample countries that do not vary over time in the dependent variable and cannot be used to compute accurate coefficients for independent variables that do not change over time or that change very little (for example, the number of ethnic groups in a country). Under the fixed effects specification, the Theil index of horizontal economic inequality remained a statistically significant predictor of conflict using a standard random effects model, as did the interaction effects of that variable with resource dependence.
- *Including a lagged dependent variable:* When the lagged dependent variable is included as an explanatory variable in the spatial random effects model, only the lagged dependent variable and the time effect variable are significant, suggesting that the best predictive model of conflict is past experience.
- *Including additional control variables*: The models were repeated with additional control variables, including the widely-used Polity2 score, which measures the degree of democracy and autocracy in a country; international trade (imports and exports) as a percentage of GDP; and total percentage change in NDVI as a measure of land cover and land use change. None of these variables were statistically significant.

6. Discussion

The results presented above are consistent with a number of recent studies that have found evidence of a relationship between horizontal inequalities and the onset and intensity of civil conflict (e.g. Cederman et al. 2013, Koubi & Böhmelt 2014, Buhaug et al. 2014, Ezcurra & Palacios 2016). They also support the more specific conclusion of Morelli & Rohner (2015), Bodea et al. (2016), and others who report a relationship between natural resource extraction, inequality, and civil conflict.

Does the apparent joint impact of inequality and natural resource dependence constitute evidence of a grievance mechanism linking natural resources and civil conflict? Although the existing literature generally equates inequality with grievance, there are other possible explanations for the finding that do not necessarily require a grievance motivation. Motivation may, for instance, be primarily a result of economic considerations. In countries where rents accrued through natural resource extraction are monopolized by the state or by a small subset of individuals, the incentives for controlling those resources are increased relative to the situation in which resource rents are widely shared. Concentration of resource wealth in the hands of a few may also increase opportunities for insurgents to obtain financing through extortion.

In practical terms, it is probably not necessary to disentangle the 'greed' from 'grievance' motivations in circumstances where the underlying issue is unequal distribution of the benefits of natural resource extraction. It is increasingly recognized that the structures of motivation and opportunity vary not only between insurgent groups but also among individual members, and that the objectives espoused by group leadership may differ substantially from those of the rank-and-file. In civil war, Le Billon (2005) reminds us that "notions of greed and grievances often coexist as two sides of the same coin…the border between an aggrieved rebel movement and a greedy one is often blurred" (220). By bridging the divide between theories of 'greed' and 'grievance,' factors such as horizontal inequalities in the distribution of costs and benefits of natural resource extraction offer new ways of conceptualizing the roots of conflict and, potentially, of developing the means for preventing of mitigating them.

With respect to methodology, the results support the use of the spatial regression model to account for spatial autocorrelation in the dependent variable. As anticipated, the spatial lag is consistently statistically significant in the models. This finding raises a potentially important caveat for interpreting the results of regression analyses that treat countries as independent containers of conflict events. The use of terrorist events from the GTD as a proxy measure for the intensity of conflicts also appears to be confirmed on the basis of the analytical results. With respect to the variables of interest—horizontal inequality and dependence on natural resource rents—the results of the model predicting conflict events globally and the model predicting conflict events in Africa were broadly similar.

7. Conclusions

The original analysis methods described in this paper for investigating the relationship between horizontal economic inequality, environmental scarcity, and natural resource extraction lend insight into the complex causal pathways linking natural resource extraction and civil conflict. Results from a series of spatial regressions suggest that horizontal economic inequality between ethnic groups within countries increases the risk of and intensity of conflict and can contribute to the development of resource-based conflict. Unequal distribution of the costs of natural resource extraction, measured in terms of land cover and land use change, appears to have a more limited interactive effect with resource dependence on conflict. The findings point toward a more nuanced and complex relationship between natural resources, environmental scarcity, and inequality that has heretofore been supposed and call for a reevaluation of the utility of the historical dichotomy between ‘greed,’ ‘grievance,’ and ‘opportunity’ theories of civil war.

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