Biological Conservation 191 (2015) 266–273

Contents lists available at ScienceDirect

Biological Conservation

journal homepage: www.elsevier.com/locate/bioc

Conservation and conflict in the Democratic Republic of Congo: The impacts of warfare, mining, and protected areas on deforestation

Van Butsic [a,*], Matthias Baumann [b], Anja Shortland [c], Sarah Walker [d], Tobias Kuemmerle [b,e]

[a] Department of Environmental Science, Policy, and Management, University of California Berkeley, 101 Sproul Hall, Berkeley, CA 94704, USA
[b] Geography Department, Humboldt-University Berlin, Unter den Linden 6, 10099 Berlin, Germany
[c] Department Political Economy, King's College London, Strand Campus, London WC2R 2LS, UK
[d] Department of Agricultural and Applied Economics, University of Wisconsin-Madison, 427 Lorch Court, Madison, WI 53706, USA
[e] Integrative Research Institute on Transformations of Human-Environment Systems (IRI THESys), Humboldt-University Berlin, Unter den Linden 6, 10099 Berlin, Germany

ARTICLE INFO

Article history:
Received 26 February 2015
Received in revised form 24 June 2015
Accepted 29 June 2015
Available online xxxx

Keywords:
Deforestation
Protected area effectiveness
Conflict
Instrumental variables

ABSTRACT

Tropical forests provide critical ecosystem services worldwide. Nonetheless, ongoing agricultural expansion, timber extraction, and mining continue to jeopardize important forest resources. In addition, many tropical forests reside in countries that have experienced violent conflict in recent decades, posing an additional, yet poorly understood threat. Conflict may decrease or increase deforestation depending on the relationship between conflict and other causes of land use change, such as mining expansion or protected area establishment. The Democratic Republic of Congo (DRC), home of the second largest tropical forest in the world, has experienced 20 years of violent conflict, resulting in the death of over 100,000 combatants and up to 5 million civilians. Expanding mining concessions also threaten the DRC's forest, even though nearly 12% of it is under some form of protection. In this study, we used spatially-explicit data on conflict, mining, and protected areas, along with a host of control variables, to estimate the impacts of these factors on forest cover loss from 1990 to 2010. Through a panel instrumental variables approach we found that: i) conflict increased forest cover loss, ii) mining concessions increased forest cover loss, but in times of conflict this impact was lessened, and iii) protected areas reduced forest cover loss, even in high conflict regions. Our results thus suggest that policy interventions designed to reduce violent conflict may have the co-benefit of reducing deforestation, especially in areas with low mining potential. Likewise, protected areas can be effective even in times of war.

1. Introduction

Tropical forests cover 6% of the Earth's surface, yet contain over two thirds of all terrestrial plant and animal species, store massive amounts of carbon, and provide livelihoods to millions of people (Bradshaw et al., 2009; Sunderlin et al., 2008). These forests are threatened by deforestation and forest degradation (Gibbs et al., 2010; Lambin and Meyfroidt, 2011), driven by a range of proximate drivers, including agricultural expansion (Phalan et al., 2013), urban sprawl (Seto et al., 2012), mining (Hirons, 2011), and timber harvest (Asner et al., 2010). As global demand for food, timber, and minerals continues to soar, the pressure on tropical forests increases. At the same time, the ecosystem services provided by tropical forests are becoming more valuable (Hansen et al., 2010; Shearman et al., 2012). Combined, these dynamics make conserving tropical forests one of the greatest conservation challenges of the 21st century (Laurance et al., 2012).

While tropical deforestation has decreased in some areas, forest loss continues unabated in much of the world (Ernst et al., 2013; Hansen et al., 2013). Payment for ecosystem services programs, such as REDD+, has become increasingly common in many tropical forests (Nepstad et al., 2011). Nonetheless, establishing protected areas is still the most widespread policy to safeguard tropical forests. Globally, approximately 27% of tropical forests have some form of protection (Nelson and Chomitz, 2011). However, the effectiveness of this protection is questionable, especially in areas with poor economic conditions and weak governance (Andam et al., 2008; Irland, 2008).

A less well understood driver of deforestation is violent conflict (Machlis and Hanson, 2008), which is unfortunately common in tropical forests worldwide (Beyers et al., 2011; Hecht and Saatchi, 2007). Empirical studies suggest a complex relationship between conflict and forest conservation (Draulans and Van Krunkelsven, 2002; Gorsevski et al., 2012; Rustad et al., 2008). Direct impacts of conflict include road building, defoliation and unsustainable use of forest resources (Machlis and Hanson, 2008). Indirect impacts may include decreased economic activity during times of conflict, which could reduce forest cover loss, and changing discount rates, which could increase the propensity to harvest forest resources (Stevens et al., 2011). These effects have been shown to remain well after conflict ends (Nackoney et al., 2014). Nonetheless, empirical studies suggest that conflict may

* Corresponding author.
E-mail address: vanbutsic@berkeley.edu (V. Butsic).

http://dx.doi.org/10.1016/j.biocon.2015.06.037
0006-3207/

have both negative and positive outcomes in terms of conservation (Rustad et al., 2008) even within small geographic areas (Gorsevski et al., 2013). Likewise, the efficacy of protected areas in times of conflict also varies over space and time (de Merode et al., 2007; Glew and Hudson, 2007).

Analyzing the effect of conflict on deforestation is particularly challenging due to the endogenous nature of forest loss in this setting. Conflict may be the result or the cause of deforestation, implying an endogenous empirical relationship. Neglecting this endogeneity bias in models of deforestation can lead to biased coefficients and standard errors, thereby inhibiting our ability to understand the causal mechanisms between conflict and deforestation in a statistical framework (Blackman, 2013). In the social sciences, an instrumental variables (IV) approach is commonly used to model such endogenous relationships, and is a standard practice in the recent conflict literature (Miguel et al., 2004) and in the deforestation literature (Chomitz and Gray, 1996; Sims, 2010). Limited use of this technique, however, has restricted our understanding of how violent conflict impacts tropical deforestation. One of the primary contributions of this study, therefore, is to understand potential causal relationships between conflicts, mining, protected areas and deforestation by implementing the IV technique.

Starting in 1996 and continuing in various forms until today, one of the deadliest conflicts since World War II has raged in the Democratic Republic of Congo (DRC), with over 100,000 combatant fatalities and up to 5 million more deaths of civilians from malnourishment and preventable diseases (Coghlan et al., 2006; Tollefsen et al., 2012). Much of this conflict occurred in the Congo Basin forests — one of the world's most biodiverse regions (Mittermeier et al., 1999), which provides habitat to the critically endangered mountain gorilla (*Gorilla beringei beringei*), okapi (*Okapia johnstoni*), bonobo (*Pan paniscus*) and forest elephant (*Loxodonta cyclotis*), among other species (IUCN, 2012). In addition, these forests store vast amounts of carbon (Saatchi et al., 2011), of which large volumes are released every year through deforestation (Tyukavina et al., 2013), and also contain some of the most valuable mineral deposits in the world (The World Bank, 2008). Mining contributes nearly 25% to DRC's GDP (The World Bank, 2008), but threatens forests in the Congo Basin — approximately 12% of which are currently protected (UNEP, 2009). Together, biodiversity, minerals, and conflict make the tropical rainforest of the DRC one of the most valuable and vulnerable in the world.

We contribute to the growing literature on conflict and conservation by compiling and analyzing a long-term (1990–2010) large-scale (the majority of the DRC) database on deforestation, conflict, mining concessions and protected areas in the DRC. Using this dataset, along with the instrumental variables approach combined with policy simulations, we address four questions about deforestation in the DRC: (1) does conflict increase deforestation, (2) do mining concessions increase deforestation, (3) do protected areas reduce deforestation, and (4) does conflict interact with mining and protected areas to jointly impact deforestation?

2. Methods

2.1. Study area

The DRC extends from the Atlantic Ocean in the west to the Great Lakes region in the east, covering an area of over 2,345,409 km^2 (Central Inteligence Agency, 2013). Our study area contained all of the DRC that is part of the Congo Basin – the second largest tropical rainforest in the world – and is based on the extent of previously published forest change maps (Hansen et al., 2008; Potapov et al., 2012) (Fig. 1), which includes 559 out of 685 secteurs (similar to a U.S. county).

The conflict in the DRC has been termed "Africa's World War" and its complexity compared to that of Europe's thirty years of war (Prunier, 2008). As the Congo Basin contains some of the world's most valuable mineral deposits, the conflict is usually viewed through the lens of the "resource curse" (Matti, 2010) and has been described as "economics by other means" (Jackson, 2002; Keen, 1998; Reno, 1998). Furthermore, the DRC is surrounded by politically unstable countries: Angola, Sudan, the Central African Republic and Rwanda. With cross-cutting ethnic solidarities and lack of resources to patrol them, national borders are porous, facilitating cross-border raids, ethnic insurgencies and occasionally "proxy wars" (Prunier, 2004, 2008). Altogether, this has led to frequent bouts of violence, particularly in the eastern portion of the DRC.

Since the official end of the war, the country has been plagued by fighting between local rival militias (Marriage, 2013). Where the state does not provide public services or security, people often turn to warlords and rebels for protection, generally mobilizing along ethnic lines, often leading to organized ethnic conflict. Power struggles over territory

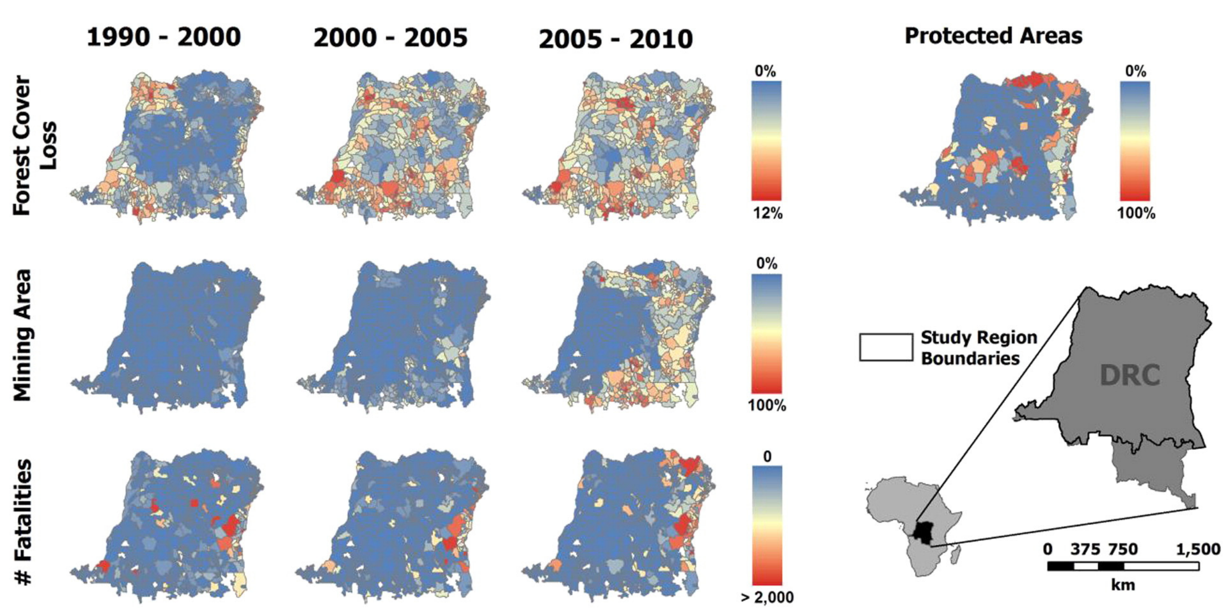

Fig. 1. Percentage of forest cover loss, number of fatalities, and mining concessions 1990–2010; percent protected area.

are most frequent in the mineral rich Eastern DRC, but occur wherever the DRCs vast natural resources present opportunities for personal enrichment (Karbo and Mutisi, 2012).

2.2. Data sources

Our identification strategy was based on spatial variation and temporal variation in forest cover loss, conflict events (reported number of fatalities in each secteur), and mining concessions (percent of secteur under mining concession), as well as spatial variation in protected areas (percent of each secteur protected) from 1990 to 2010. A detailed description of each of our predictor variables is provided in the Supporting information. Key data sources included: the Armed Conflict Location and Event Database (ACLED, Raleigh et al., 2010) for data on conflict fatalities; the DRC Department of Mining (supplied to us by the International Peace Information Service; http://ipisresearch.be), which provided detailed maps of mining concessions (as polygons) and valid dates of each concession; the World Database on Protected Areas, which was used to identify protected areas; the Peace Research Institute Oslo (PRIO) dataset (Themner and Wallensteen, 2012), which provided control variables on climate and population; and the Central African Regional Program for the Environment (CARPE), for spatial data on road density, percent of secteur in water, and administrative boundaries. We also incorporated ruggedness as a measure of accessibility (Nunn and Puga, 2012), which was calculated at the mean for each secteur. Information on extreme weather (Rainfall shocks) was obtained from PRIO-GRID (Guttman, 1999).

Our dependent variable – the natural log of secteur level percent of forest cover loss in each time period – was calculated by combining two maps of forest cover change using Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper Plus (ETM+) imagery from 1990 to 2000 (Hansen et al., 2008) and 2000–2005–2010 (Potapov et al., 2012). The datasets were originally created using different analysis schemes and therefore feature small differences in the resulting maps for the year 2000 and therefore are not directly comparable. To account for these discrepancies, we used the 2000–2005–2010 map, which is considered more reliable (P. Potapov, pers. comm.), as our base map. We used the 1990–2000 dataset only to identify prior deforestation in places that were labeled as non-forest in the 2000–2005–2010 dataset. This mitigated some of the problems common to post-classification change detection approaches (Coppin et al., 2004).

While accuracy information exists for one of our input datasets (i.e., the 2000–2010 map, Tyukavina et al., 2013), no such assessment was available for the second dataset. Thus, we performed an independent accuracy assessment for our new forest cover change map to ascertain its quality. In order to do so, we adopted a cluster sampling strategy (Stehman and Wickham, 2011) in which we randomly selected 10 Landsat footprints across our study area and randomly sampled 200 points per class (i.e., stable forest 1990–2010, stable non-forest 1990–2010, deforestation 1990–2000, deforestation 2000–2005, and deforestation 2005–2010) inside the 10 footprints. Using a combination of Landsat time series and Google Earth high-resolution imagery, we then performed our own independent classification of the 200 sampled points (Cohen et al., 2010; Griffiths et al., 2014). We removed points from the analysis that fell inside clouds or cloud shadows. We then compared the dataset to the classification map, generated an error matrix, and calculated standard accuracy metrics including overall classification accuracy as well as class-wise classification accuracies (Foody, 2002; Olofsson et al., 2014). Our accuracy assessment revealed an overall accuracy of 88%, indicating that the data were of sufficient quality for our analysis. A more detailed description of how this dataset was generated and validated, including the error matrix and class-wise accuracies is provided in the Supporting information (Table S2.1).

2.3. Instrumental variables model

In order to identify the impacts of conflict, mining and protected areas on forest cover loss at the secteur level, we specified the basic empirical model:

$$y_{it} = \theta C_{it} + \gamma P_i + +\rho M_{it} + BX_{it} + u_{it} \quad (1)$$

where y is the *log of percent of forest loss* in secteur i and year t, C is the log of the number of conflict fatalities in secteur i and year t, P is the log percent of protected area in secteur i (and does not vary over time), M is the log percent of secteur covered by mining concessions in secteur i and year t, X is a vector of control variables that influence y in a given secteur and year, such as km of roads or average ruggedness, and u is the random error component. This equation matches the results from model 2 presented later.

If *conflict* was endogenous to forest cover loss, $E[C_i u_i] \neq 0$, resulting in biased coefficient estimates. This bias is eliminated through the use of an instrumental variable (or multiple instruments in our empirical models), Z, which is correlated with *conflict*, but uncorrelated with the dependent variable (i.e., *forest cover loss*) and the random error component u, such that Z only affects forest cover loss through *conflict*. Using this method, we therefore exogenously predicted conflict as:

$$C_{it} = \delta Z_{it} + \gamma P_i + \rho M_{it} + BX_{it} + n_{it} \quad (2)$$

where n_{it} represents a random error component. C_{it} in Eq. (1) was then replaced by the predicted value of C_{it} from Eq. (2).

Two necessary conditions must be met in order to provide a consistent estimate of y_{it}: i) $\delta \neq 0$, and ii) $E[Z_i u_i] = 0$. The first condition requires that the instrument, Z, is statistically significantly correlated with conflict after conditioning on P, M, and X. The second requires that Z not be correlated with forest cover loss except through *conflict*. Given a valid instrument we could estimate the unbiased impact of *conflict* and its interactions on forest cover loss. This procedure is most often accomplished using a generalized method of moments estimator (Cameron and Trivedi, 2005).

We used three variables as an instrument for *conflict*. First, we used the *number of ethnicities* historically present in each secteur (Esteban et al., 2012). Ethnic violence was a leading cause of conflict in the DRC, and while some ethnic groups may be more likely to clear forests than others, there is little reason to believe that the number of ethnicities in a given secteur would influence forest cover loss, except through increased conflict. Second, we used a dummy variable that indicated whether a secteur shared a border with another country, as armed militias, migrants and refugees from neighboring countries were more likely to settle in these secteurs. Finally, we used the variance of rainfall in each of the three time periods to proxy for extreme weather seasons. Extreme weather events have been correlated with conflicts in other African nations (Burke et al., 2009; O'Loughlin et al., 2012). While rainfall shocks may also influence forest harvest directly if it leads people to utilize forests resources, we did not observe this in our data.

In each specification, the dependent variable was the natural log of the percent of forest cover lost (*forest loss*). Overall, we parameterized five regression models: model one was a baseline random effects model where we did not instrument for *conflict*. Models two, three and four were random effects specifications where *conflict* was instrumented as: i) *conflict* alone (i.e., no interactions between *conflict* and other drivers of *forest cover loss*), ii) *conflict* interacted with *mining*, and iii) *conflict* interacted individually with *mining* and *protected* areas. Model five was a fixed effects model where *conflict* and its interactions were also instrumented. While the fixed effects model was arguably stronger in its ability to account for unobserved time invariant variation in the data, it was not necessarily the preferred model in our study due to the fact that only one of our instruments was time varying (*rainfall shocks*). Thus, there was a trade-off between the random effects and fixed effects model in terms of instrument quality and controlling for unobserved time invariant variation in the data.

Due to the spatial nature of our data we were concerned about potential spatial autocorrelation. While options to account for spatial autocorrelation in panel instrumental variable models are limited, we identified two models as robustness checks, which are available in the supplemental material: 1) an IV estimator where we clustered the standard errors at the Territoire level (i.e., one administrative unit higher than the secteur level) and 2) a panel instrumental variable spatial error model (spgm package in R), which allowed for spatial correlation between secteurs that share a border. Accounting for spatial autocorrelation led to slight changes in the significance of individual coefficients, but did not change the results qualitatively (Table S3.9). Lastly, as an additional robustness check, we also ran regressions on the 2000–2010 data alone, because of concerns that the 1990–2000 data was not as robust as the 2000–2010 data.. These results, once again, were quite similar to results using the full dataset and are included in the SI (Table S3.10).

2.4. Policy simulations

Interpreting the coefficients on interaction terms between key variables is difficult. Therefore, we used spatial policy simulations to describe the total effect of *conflict*, *mining*, and *protected areas* on deforestation, accounting for their interactions. Our policy simulations calculated the change in deforestation for a given change in the policy variable of interest, holding every other variable constant. We chose to use 2005 as our baseline data, as it represented the end of the second war. We spatially simulated three alternative scenarios in each secteur, using the coefficients from model 4 as the input: A) a 10 percentage point increase in mining, B) a 10 percentage point increase in protected areas concessions, and C) a 10% decrease in conflict.

We chose these values because we believe they represent realistic potential changes in policy variables. The simulations should not be interpreted as policy suggestions (i.e., the government should increase mining by 10 percentage points), but rather as values that might be realistic marginal changes in the present climate. Moreover, the simulations are intended to demonstrate the dynamics of our models, which include a number of interaction terms that are not easily understood by simply evaluating coefficients. We caution about the interpretation of the mining simulation, as it is only valid if future mining concessions are made in places where mineral resources are similar to the mineral resources in which current concessions exist. Given that mineral resources are likely not evenly distributed across space, the results of this simulation are reasonably most accurate for areas that already have some mining activity.

2.5. Other potential endogenous variables

Casual interpretation of the impacts of mining and protected areas on deforestation requires that these variables are not endogenous to the model of land use change. While we would ideally instrument for these variables as well, we could not find suitable instruments. Since mining concessions vary over time, we were able to exploit this variation in our estimates to produce arguably causal impacts of mining concessions. Protected areas, however, were more problematic due to the lack of temporal variation (i.e., the amount of protected area did not changed during our study). Endogeneity would be a problem if protected area effectiveness was correlated with unobservable factors that also influence deforestation or if the underlying covariates that affect deforestation were correlated with protected and non-protected areas differentially (Andam et al., 2008; Joppa and Pfaff, 2010). We were able to control for many of the covariates which may be correlated with protected areas and deforestation (population density, road density and ruggedness). All of these variables were statistically significant in our models. In addition we ran a number of tests in the SI, which support our interpretation of protected areas as arguably causal (see SI Section 3).

3. Results

3.1. Summary statistics

Forest cover loss increased in each panel, with an annual disturbance rate of 0.08% from 1990 to 2000, 0.31% from 2000 to 2005, and 0.34% from 2005 to 2010 (Fig. 1). Violent conflict increased in each time period from an average of 27 fatalities per secteur in the first panel, to 29 fatalities in the second panel, and 35 fatalities in the third panel. These data were highly skewed due to the large number of conflict events in Eastern DRC in the second and third time period (Fig. 1). Mining concessions increased as well, with an average of 0.52% of each secteur under mining concession between 1990 and 2000, 2.71% between 2000 and 2005, and 17.56% between 2005 and 2010 (Fig. 1).

3.2. Statistical model results

Conflict had a positive and statistically significant impact on deforestation in the instrumental variables random effects models, but was insignificant in the fixed effects and panel regression model. In the instrumental variables regressions random effects, the direct impact of *conflict* increased as more interactions were added (Table 1). The effect of protected areas, however, was more ambiguous. In the models without interaction terms, the direct impacts of *protected* were negative and significantly different from zero. When *protected* was interacted with *conflict* the point estimate was negative but statistically insignificant, while the interaction term was negative and statistically significant. The direct impact of *mining* was positive and statistically different from zero in the instrumental variable models. The interaction term between *mining* and *conflict* was negative and statistically significant in the instrumental variable random effects models, indicating that as conflict increased in regions with relatively more mining concessions, forest cover loss decreased.

Our results suggest that the magnitude of the total impact of mining and protected areas on forest cover loss was dependent on the number of fatalities in the area. Therefore, we calculated the percent forest change that would result from increasing mining and protected areas 1% over a gradient of conflict values using the coefficients of Model 4 (Fig. 2). At low levels of conflict, the total effect of increased mining concessions on forest cover loss was positive, while at high levels of conflict, forest cover loss decelerated in areas with high mining density. The total effect of protected area establishment on deforestation was always negative, indicating that they did reduce deforestation.

In order to understand the sensitivity of our results, we implemented a number of robustness checks. First, we included a host of control variables that are known to impact deforestation and found that intuitive relationships hold (Table S1.1). We also tested for over-identification (using the Sargan–Hansen (SH) statistic) and weak identification (by investigating the joint significance of the instruments in the first stage regressions) in our instrumental variables regressions. We found that the models were never overidentified (SH p-value = .15 (model 2), .15 (model 3) and .15 (model 4)). Likewise the joint significance of our excluded instruments was large and statistically significant. Finally, changing our *conflict* variable from fatalities to the number of conflict events, and including or excluding the capital Kinshasa, did not affect our results (Tables S6 and S7).

3.3. Policy simulation results

Interaction effects between conflict, mining, and protected areas can be seen in our policy simulations (Fig. 3). Increasing mining concessions by 10 percentage points increased forest cover loss by 468 km^2. Most of this forest loss was in the central and eastern part of the country where

Table 1
Regression results. Model 1 shows results for a non-instrumented baseline random effects model. Models 2, 3 and 4 are random effects instrumental variable models with different interactions. Model 5 is a fixed effects instrumental variables model. For instrumented models, second stage regression results with adjusted standard errors are shown. Conflict is measured by the log of the number of fatalities. The natural logarithm of all independent variables, except distance to capital, is taken to improve model fit. Standard errors are in parenthesis.

Model	(1)	(2)	(3)	(4)	(5)
Error structure	Random effects	Random effects	Random effects	Random effects	Fixed effects
Instruments	None	# of ethnicities, rainfall shocks, on border	# of ethnicities, rainfall shocks, on border	# of ethnicities, rainfall shocks, on border	Rainfall shocks
Conflict	−0.0127 (0.0111)	0.117*** (0.0384)	0.215*** (0.0642)	0.340*** (0.0913)	0.340 (0.213)
Conflict ∗ mines	−0.00622 (0.00489)		−0.0768*** (0.0206)	−0.0935*** (0.0225)	−0.0475 (0.0455)
Conflict ∗ protected area	0.0117** (0.00487)			−0.0458** (0.0210)	−0.183** (0.0878)
% protected area	−0.0409*** (0.0129)	−0.0577*** (0.0152)	−0.0548*** (0.0171)	−0.0188 (0.0204)	
% mine	0.0381*** (0.0109)	0.0262** (0.0114)	0.0801*** (0.0172)	0.0871*** (0.0192)	0.0891*** (0.0336)
Mineral index	0.312*** (0.0218)	0.317*** (0.0237)	0.326*** (0.0248)	0.327*** (0.0294)	0.755*** (0.279)
Agriculture index	0.104** (0.0417)	0.0864* (0.0452)	0.118** (0.0474)	0.132** (0.0555)	0.737* (0.391)
Road density	1.471*** (0.251)	1.425*** (0.263)	1.451*** (0.0299)	1.427*** (0.282)	
Population	0.0685*** (0.0114)	0.0690*** (0.0119)	0.0643*** (0.0137)	0.0751*** (0.0132)	−1.831 (1.159)
% water	0.173*** (0.0409)	0.187*** (0.0433)	0.200*** (0.0498)	0.178*** (0.0468)	
Distance to capital	−7.69e−05** (3.42e−05)	−0.0001*** (4.19e−05)	0.000129*** (4.60e−05)	−0.0001*** (4.75e−05)	
Ruggedness	−0.00193 (0.0116)	−0.0113 (0.0126)	−0.0185 (0.0147)	−0.0193 (0.0138)	
% forested	0.0885*** (0.0143)	−0.0113 (0.0126)	0.0950*** (0.0171)	−0.0193 (0.0138)	0.0181 (0.0477)
Constant	−3.283*** (0.450)	−3.148*** (0.484)	−3.472*** (0.517)	−3.687*** (0.586)	−1.210 (7.788)
Observations	1677	1677	1677	1677	1677
R^2	0.25	0.18	0.165	0.120	−.1483

* p-Value ≤ .1.
** p-Value ≤ .05.
*** p-Value ≤ .01.

there are currently fewer conflicts and fewer mining concessions. Increasing protected areas by 10 percentage points resulted in an estimated decrease in forest cover loss of 2308 km^2 over our entire study area. Spatially, the impacts of this intervention where spread more evenly throughout the country, although some areas which already had high levels of protection saw smaller impacts. Decreasing fatalities by 10% reduced forest cover loss by 95 km^2. The largest increase in forest loss under this intervention was in the far-east of the DRC, where there are many mining concessions. Decreasing conflict in these areas may lead to increased mining activity, and therefore forest clearing.

4. Discussion

Armed conflict plagues many tropical countries (Tollefsen et al., 2012). Nonetheless, our understanding of how conflict affects tropical deforestation or impairs the effectiveness of conservation measures remains unclear. This lack of understanding is partially due to the competing effects of conflict, which can either increase or decrease in deforestation. Moreover, the interactions between conflict, other proximate drivers of deforestation such as mining, and protected areas are complex and challenging to disentangle, in spite of their occurrence

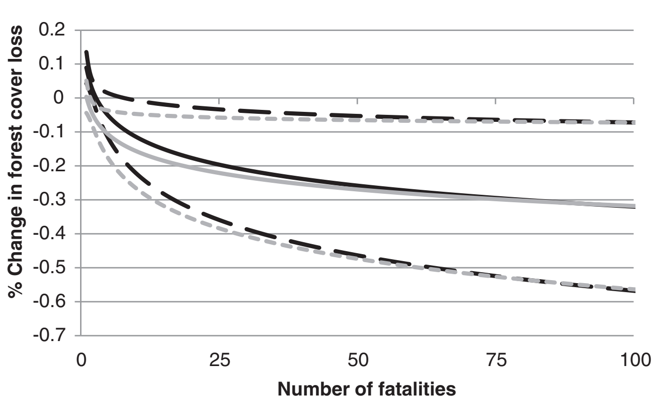

Fig. 2. Marginal effects on forest cover loss from a 1% increase in mining concessions (black line) and protected areas (gray line) at various levels of fatalities, with 95% confidence intervals (dashed lines).

throughout the world (Akiwumi and Butler, 2008; Shearman et al., 2009). Conflict is endogenous to deforestation in its true empirical relationship, and therefore requires sophisticated techniques when identifying causal relationships. In this analysis, we used an instrumental variables approach to understand the combined effects of conflict, mining and protected areas on forest cover loss in the world's second largest tropical forest.

Our results indicate that conflict led to increased levels of deforestation in the DRC. While the scale of our model (i.e., the secteur level) precludes us from identifying causal mechanisms at the scale of the individual actor, which some argue is ultimately important in linking conflict to deforestation (Lambin et al., 2003; Ostrom and Nagendra, 2006), local research suggests that high levels of violence are related to militia rule, where charcoal production for export or use in refugee camps, as well as illegal logging and mining – all activities that accelerate deforestation – are commonplace (Nellemann et al., 2010). Hence the key proximate cause of deforestation may be the short-term extractive activities of rival militias rather than the fighting itself (Stevens et al., 2011).

Our analysis also suggests that the interaction between conflict and other causes of deforestation (i.e., mining) is significant and may even counteract the effects of conflict alone. That is, our results indicate that while conflict increased deforestation, these effects may have been offset by lower forest disturbance in areas where conflict has reduced mining activity. This dual effect led to relatively small overall changes in forest cover when conflict was reduced. The end of conflicts may therefore represent a critical “hot moment” for conservation — a time of political and economic transformation where conservation activities may be particularly effective (Radeloff et al., 2013). Conservation organizations and governments should be ready to act when violent conflicts are settled (Gorsevski et al., 2013).

Independent from conflict, mining concessions were positively correlated with increased forest loss. Our current datasets can identify mining concession areas, but are not able to locate the exact sites of actual mines. Therefore, it is unclear whether deforestation was from increased destruction of forests by mining or from increased road building and economic activity around mining areas, which itself leads to forest cover loss via conversion of land to non-forest uses. Our simulations suggest that increasing mining concessions led to higher forest cover loss in most secteurs at 2005 conflict levels, although we do not know

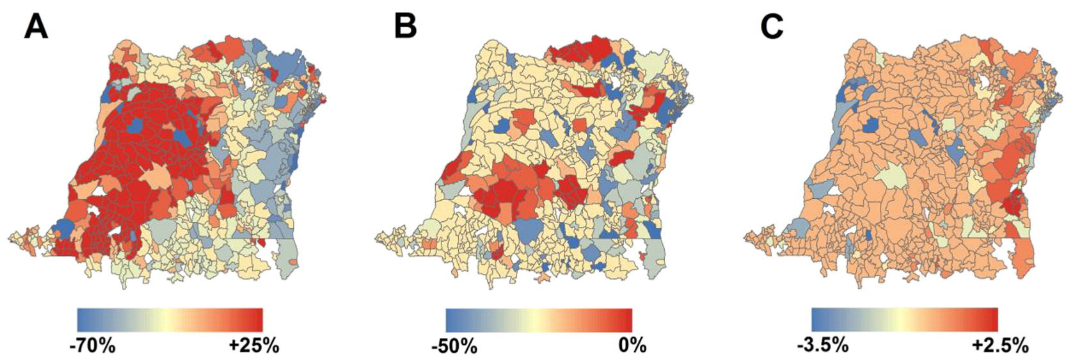

Fig. 3. Spatial distribution in percent changes in forest cover loss caused by A) a 10 percentage point increase in mining concessions (mean decrease in deforestation −0.838 km^2, minimum decrease in deforestation −51.76 km^2, maximum decrease in deforestation 346.84 km^2); B) a 10 percentage point increase in protected areas (mean decrease in deforestation 4.93 km^2, minimum decrease in deforestation .001 km^2, maximum decrease in deforestation 253.56 km^2) and C) a 10% decrease in fatalities (mean decrease in deforestation .17 km^2, minimum decrease in deforestation −2.093 km^2, maximum decrease in deforestation 21.3 km^2). Note that the scales differ between maps.

if the mineral resources in areas which currently have low levels of concessions are similar to those that do not. Therefore, we caution that while our model captures the dynamics between conflict, mining and forest disturbance, the assumptions that support this particular simulation may not hold for areas of the DRC which do not have mineral resources. Because we cannot identify the exact mechanism that relates mining concessions to deforestation, it remains unclear if the best conservation policy would be to actually reduce mining concessions, regulate the size of mines, or attempts to lessen the impacts of economic growth – such as road building – that may cause deforestation.

Previous research suggests that in regard to the effects of protected areas, the strength of local institutions and governance is key in determining protected area effectiveness (Ostrom and Nagendra, 2006). Local institutional strength may deteriorate in times of conflict, which could lead to decreased protected area effectiveness, as well (Adano et al., 2012). Surprisingly, our results indicated that protected areas remained effective at reducing forest cover loss even in times of conflict. The mechanism for this finding is likely a combination of international interventions and local involvement. The DRC canceled and the World Bank contributed to over 25 million ha of illegal logging concessions throughout the DRC in 2002 (World Bank, 2013) and contributed over $7 million to rehabilitate parks in 2009 (World Bank, 2009). Likewise, international efforts to guard endangered “flagship species” such as gorillas, okapi or forest elephants in the DRC were heightened immediately after the conclusion of the war. In addition, the dedication of park rangers is well documented — over 200 have died protecting the parks (Nellemann et al., 2010) and many patrols continued during the war (de Merode et al., 2007). Thus, our research suggests that funding and staffing protected areas in times of conflict is important and may be an effective conservation strategy, although potentially at high costs to those enforcing protection.

Protected area effectiveness in our study was measured in terms of forest cover loss, which is consistent with previous studies on the topic (DeFries et al., 2010). It is important to note that effective protection against forest cover loss does not necessarily mean that protected areas are able to safeguard biodiversity inside them. Bushmeat hunting and poaching are also strong drivers of species loss in the Congo basin (Beyers et al., 2011; Blake et al., 2007), but were not included in our analysis of deforestation due to a lack of systematic data. Therefore, effective maintenance of forest cover, while a positive sign for DRC protected areas, must be viewed only as a partial indicator of their success. At the same time, maintenance of habitat is a key component in species recovery, and policies that limit deforestation may at the very least help provide habitats for species recoveries. Likewise, any expansion of protected areas should include mechanisms to assure benefits to local people in addition to conservation goals.

From a modeling perspective our results illustrated the importance of correctly specifying endogeneity in policy relevant variables and suggested that the IV approach, combined with panel data, may be a powerful tool for studying causal mechanisms of land-use change. This highlights the value of the IV approach for conservation research, which can be a useful tool for conservation scientists studying a host of applications in which covariates of interest may be endogenous. In addition, our results demonstrated that the use of interaction terms between conflict and other drivers of forest cover loss, such as protected areas and mining, is important in identifying the nuanced mechanisms through which conflict affects deforestation.

A few uncertainties in our analysis remain, especially with regard to our dependent variable: forest-cover loss at the secteur level. We argue, however, that these uncertainties are small for three reasons. First, by merging the two input datasets, rather than applying a simple map comparison, we account for the fact that the two input maps were produced using different processing techniques. The results of our independent accuracy assessment confirmed this. Second, by aggregating the forest-cover loss maps at the administrative level (i.e., the secteur-level) we increased the robustness of the dependent variable, since errors in remote sensing maps are usually randomly distributed and aggregation reduces the influence of the error. Third, we ran our models for the entire time period (i.e., 1990–2000–2005–2010) as well as for the second time period (i.e., 2000–2005–2010) only. While some coefficients changed in magnitude and significance, the overall empirical relationships remained the same, which suggested that our models are not biased by an erroneous dependent variable. Finally, we did not consider the environmental impact of displaced people away from the conflict, which can be substantial (Baumann et al., 2014) due to a lack of spatial data on refugee movements.

5. Conclusions

Overall, our results indicate that conflict and mining are important drivers of deforestation in the world's second-largest intact tropical forest, and that interactions between conflict, mining, and protected areas affect conservation in important ways. As conflict remains unfortunately widespread in many countries, interactions between conflict and other drivers of land-use change are important to consider when assessing the causal mechanisms of land system dynamics. It is not readily clear if the interactions found in the DRC will be present in other locations, although we suggest that ignoring these interactions may limit our understanding of how conflict impacts deforestation. Conservation organizations typically do not focus on reducing conflict as a core mission, but our results show that peace-building can potentially be a win for nature as well, and that conservation organizations and governments should be ready to seize conservation opportunities that may arise once peace is reestablished. This suggests that conservation organizations may be wise to partner with peace building organizations in order to protect wildlands. Likewise, our analysis showed the importance of continued enforcement of protected areas during times of conflict. Indeed our research hints that continuing to fund protected areas even in places with low institutional strength may still be a wise investment for nature.

Acknowledgments

We are deeply grateful to P. Potapov and M. Hansen for making the remote sensing results of their Congo Basin Mapping Project publicly available, and for valuable comments and suggestions on the use of these data. We also thank W. Reed for assistance with the geodata processing, and J. Alix-Garcia and D. Mueller for helpful comments on an earlier version of the manuscript. This research was supported by the Alexander von Humboldt Foundation, the Einstein Foundation Berlin, Germany, and the Land-Cover and Land-Use Change (LCLUC) Program of the National Aeronautic and Space Administration (NASA) through grant NNX08AK77G.

Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.biocon.2015.06.037.

References

Adano, W.R., Dietz, T., Witsenburg, K., Zaal, F., 2012. Climate change, violent conflict and local institutions in Kenya's drylands. J. Peace Res. 49, 65–80.
Akiwumi, F.A., Butler, D.R., 2008. Mining and environmental change in Sierra Leone, West Africa: a remote sensing and hydrogeomorphological study. Environ. Monit. Assess. 142, 309–318.
Andam, K., Ferraro, P., Pfaff, A., Sanchez-Azofeifa, G., Robalino, J., 2008. Measuring the effectiveness of protected area networks in reducing deforestation. Proc. Natl. Acad. Sci. U. S. A. 105, 16089–16094.
Asner, G.P., Loarie, S.R., Heyder, U., 2010. Combined effects of climate and land-use change on the future of humid tropical forests. Conserv. Lett. 3, 395–403.
Baumann, M., Radeloff, V.C., Avedian, V., Kuemmerle, T., 2014. Land-use change in the Caucasus during and after the Nagorno-Karabakh conflict. Reg. Environ. Chang.
Beyers, R.L., Hart, J.A., Sinclair, A.R.E., Grossmann, F., Klinkenberg, B., Dino, S., 2011. Resource wars and conflict ivory: the impact of civil conflict on elephants in the Democratic Republic of Congo—the case of the Okapi Reserve. PLoS One 6, e27129.
Blackman, A., 2013. Evaluating forest conservation policies in developing countries using remote sensing data: an introduction and practical guide. For. Policy Econ. 34, 1–16.
Blake, S., Strindberg, S., Boudjan, P., Makombo, C., Bila-Isia, I., Ilambu, O., Grossmann, F., Bene-Bene, L., de Semboli, B., Mbenzo, V., S'hwa, D., Bayogo, R., Williamson, L., Fay, M., Hart, J., Maisels, F., 2007. Forest elephant crisis in the Congo Basin. PLoS Biol. 5, e111.
Bradshaw, C.J., Sodhi, N.S., Brook, B.W., 2009. Tropical turmoil: a biodiversity tragedy in progress. Front. Ecol. Environ. 7, 79–87.
Burke, M.B., Miguel, E., Satyanath, S., Dykema, J.A., Lobell, D.B., 2009. Warming increases the risk of civil war in Africa. Proc. Natl. Acad. Sci. U. S. A. 106, 20670–20674.
Cameron, A.C., Trivedi, P.K., 2005. Microeconometrics: Methods and Applications. Cambridge University Press, Cambridge.
Central Inteligence Agency, 2013. CIA — The World Factbook [WWW Document]. URL, https://www.cia.gov/library/publications/the-world-factbook/geos/cg.html (accessed 12.21.12).
Chomitz, K.M., Gray, D.A., 1996. Roads, land use, and deforestation: a spatial model applied to Belize. World Bank Econ. Rev. 10, 487–512.
Coghlan, B., Brennan, R.J., Ngoy, P., Dofara, D., Otto, B., Clements, M., Stewart, T., 2006. Mortality in the Democratic Republic of Congo: a nationwide survey. Lancet 367, 44–51.
Cohen, W.B., Yang, Z.G., Kennedy, R., 2010. Detecting trends in forest disturbance and recovery using yearly Landsat time series: 2. TimeSync — tools for calibration and validation. Remote Sens. Environ. 114, 2911–2924.
Coppin, P., Jonckheere, I., Nackaerts, K., Muys, B., Lambin, E., 2004. Digital change detection methods in ecosystem monitoring: a review. Int. J. Remote Sens. 25, 1565–1596.
De Merode, E., Smith, K.H., Homewood, K., Pettifor, R., Rowcliffe, M., Cowlishaw, G., 2007. The impact of armed conflict on protected-area efficacy in Central Africa. Biol. Lett. 3, 299–301.
DeFries, R., Karanth, K., Pareeth, S., 2010. Interactions between protected areas and their surroundings in human-dominated tropical landscapes. Biol. Conserv. 143, 2870–2880.
Draulans, D., Van Krunkelsven, E., 2002. The impact of war on forest areas in the Democratic Republic of Congo. Oryx 36.
Ernst, C., Mayaux, P., Verhegghen, A., Bodart, C., Christophe, M., Defourny, P., 2013. National forest cover change in Congo basin: deforestation, reforestation, degradation and regeneration for the years 1990, 2000 and 2005. Glob. Chang. Biol. 19, 1173–1187.
Esteban, J., Mayoral, L., Ray, D., 2012. Ethnicity and conflict: theory and facts. Science 336, 858–865 (80-.).
Foody, G.M., 2002. Status of land cover classification accuracy assessment. Remote Sens. Environ. 80, 185–201.
Gibbs, H.K., Ruesch, A.S., Achard, F., Clayton, M.K., Holmgren, P., Ramankutty, N., Foley, J.A., 2010. Tropical forests were the primary sources of new agricultural land in the 1980s and 1990s. Proc. Natl. Acad. Sci. U. S. A. 107, 16732–16737.
Glew, L., Hudson, M.D., 2007. Gorillas in the midst: the impact of armed conflict on the conservation of protected areas in sub-Saharan Africa. Oryx 41, 140–150.
Gorsevski, V., Kasischke, E., Dempewolf, J., Loboda, T., Grossmann, F., 2012. Analysis of the impacts of armed conflict on the Eastern Afromontane forest region on the South Sudan — Uganda border using multitemporal Landsat imagery. Remote Sens. Environ. 118, 10–20.
Gorsevski, V., Geores, M., Kasischke, E., 2013. Human dimensions of land use and land cover change related to civil unrest in the Imatong Mountains of South Sudan. Appl. Geogr. 38, 64–75.
Griffiths, P., Kuemmerle, T., Baumann, M., Radeloff, V.C., Abrudan, I.V., Lieskovsky, J., Munteanu, C., Ostapowicz, K., Hostert, P., 2014. Forest disturbances, forest recovery, and changes in forest types across the Carpathian ecoregion from 1985 to 2010 based on Landsat image composites. Remote Sens. Environ. 151, 72–88.
Guttman, N.B., 1999. Accepting the standardized precipitation index: a calculation algorithm. J. Am. Water Resour. Assoc. 35, 311–322.
Hansen, M.C., Roy, D.P., Lindquist, E., Adusei, B., Justice, C.O., Altstatt, A., 2008. A method for integrating MODIS and Landsat data for systematic monitoring of forest cover and change in the Congo Basin. Remote Sens. Environ. 112, 2495–2513.
Hansen, M.C., Stehman, S.V., Potapov, P.V., 2010. Quantification of global gross forest cover loss. Proc. Natl. Acad. Sci. U. S. A. 107, 8650–8655.
Hansen, M.C., Potapov, P.V., Moore, R., Hancher, M., Turubanova, S.A., Tyukavina, A., Thau, D., Stehman, S.V., Goetz, S.J., Loveland, T.R., Kommareddy, A., Egorov, A., Chini, L., Justice, C.O., Townshend, J.R.G., 2013. High-resolution global maps of 21st-century forest cover change. Science 342, 850–853.
Hecht, S.B., Saatchi, S.S., 2007. Globalization and forest resurgence: changes in forest cover in El Salvador. Bioscience 57, 663.
Hirons, M., 2011. Locking in carbon locking out livelihoods? Artisanal mining and REDD in sub-Sahara Africa. J. Int. Dev. 23, 1140–1150.
Irland, L.C., 2008. State failure, corruption, and warfare: challenges for forest policy. J. Sustain. For. 27, 189–223.
IUCN, 2012. The IUCN red list of threatened species [WWW Document]. URL, http://www.iucnredlist.org/ (accessed 12.21.12).
Jackson, D., 2002. Making a killing: criminality and coping in the Kivu War economy. Rev. Afr. Polit. Econ. 29, 93–94.
Joppa, L., Pfaff, A., 2010. Reassessing the forest impacts of protection: the challenge of nonrandom location and a corrective method. Ann. N. Y. Acad. Sci. 1185, 135–149.
Karbo, T., Mutisi, M., 2012. Ethnic conflict in the Democratic Republic of Congo. In: Landis, D., Albert, R. (Eds.), Handbook of Ethnic Conflict: International Perspectives. Springer.
Keen, D., 1998. Introduction. Adelphi Papers 38, 9–13.
Lambin, E.F.E., Meyfroidt, P., 2011. Global land use change, economic globalization, and the looming land scarcity. Proc. Natl. Acad. Sci. U. S. A. 108, 3465–3472.
Lambin, E.F., Geist, H.J., Lepers, E., 2003. Dynamics of land-use and land-cover change in tropical regions. Annu. Rev. Environ. Resour. 28, 205–241.
Laurance, W.F., Useche, D.C., Rendeiro, J., Kalka, M., Bradshaw, C.J.A., Sloan, S.P., Laurance, S.G., Campbell, M., Abernethy, K., Alvarez, P., Arroyo-Rodriguez, V., Ashton, P., Benítez-Malvido, J., Blom, A., Bobo, K.S., Cannon, C.H., Cao, M., Carroll, R., Chapman, C., Coates, R., Cords, M., Danielsen, F., De Dijn, B., Dinerstein, E., Donnelly, M.A., Edwards, D., Edwards, F., Farwig, N., Fashing, P., Forget, P.-M., Foster, M., Gale, G., Harris, D., Harrison, R., Hart, J., Karpanty, S., Kress, W.J., Krishnaswamy, J., Logsdon, W., Lovett, J., Magnusson, W., Maisels, F., Marshall, A.R., McClearn, D., Mudappa, D., Nielsen, M.R., Pearson, R., Pitman, N., van der Ploeg, J., Plumptre, A., Poulsen, J., Quesada, M., Rainey, H., Robinson, D., Roetgers, C., Rovero, F., Scatena, F., Schulze, C., Sheil, D., Struhsaker, T., Terborgh, J., Thomas, D., Timm, R., Urbina-Cardona, J.N., Vasudevan, K., Wright, S.J., Arias-G, J.C., Arroyo, L., Ashton, M., Auzel, P., Babaasa, D., Babweteera, F., Baker, P., Banki, O., Bass, M., Bila-Isia, I., Blake, S., Brockelman, W., Brokaw, N., Brühl, C.A., Bunyavejchewin, S., Chao, J.-T., Chave, J., Chellam, R., Clark, C.J., Clavijo, J., Congdon, R., Corlett, R., Dattaraja, H.S., Dave, C., Davies, G., Beisiegel, B. de M., da Silva, R. de N.P., Di Fiore, A., Diesmos, A., Dirzo, R., Doran-Sheehy, D., Eaton, M., Emmons, L., Estrada, A., Ewango, C., Fedigan, L., Feer, F., Fruth, B., Willis, J.G., Goodale, U., Goodman, S., Guix, J.C., Guthiga, P., Haber, W., Hamer, K., Herbinger, I., Hill, J., Huang, Z., Sun, I.F., Ickes, K., Itoh, A., Ivanauskas, N., Jackes, B., Janovec, J., Janzen, D., Jiangming, M., Jin, C., Jones, T., Justiniano, H., Kalko, E., Kasangaki, A., Killeen, T., King, H., Klop, E., Knott, C., Koné, I., Kudavidanage, E., Ribeiro, J.L. da S., Lattke, J., Laval, R., Lawton, R., Leal, M., Leighton, M., Lentino, M., Leonel, C., Lindsell, J., Ling-Ling, L., Linsenmair, K.E., Losos, E., Lugo, A., Lwanga, J., Mack, A.L., Martins, M., McGraw, W.S., McNab, R., Montag, L., Thompson, J.M., Nabe-Nielsen, J., Nakagawa, M., Nepal, S., Norconk, M., Novotny, V., O'Donnell, S., Opiang, M., Ouboter, P., Parker, K., Parthasarathy, N., Pisciotta, K., Prawiradilaga, D., Pringle, C., Rajathurai, S., Reichard, U., Reinartz, G., Renton, K., Reynolds, G., Reynolds, V., Riley, E., Rödel, M.-O., Rothman, J., Round, P., Sakai, S., Sanaiotti, T., Savini, T., Schaab, G., Seidensticker, J., Siaka, A., Silman, M.R., Smith, T.B., de Almeida, S.S., Sodhi, N., Stanford, C., Stewart, K., Stokes, E., Stoner, K.E., Sukumar, R., Surbeck, M., Tobler, M., Tscharntke, T., Turkalo, A., Umapathy, G., van Weerd, M., Rivera, J.V., Venkataraman, M., Venn, L., Verea, C., de Castilho, C.V., Waltert, M., Wang, B., Watts, D., Weber, W., West, P., Whitacre, D., Whitney, K., Wilkie, D., Williams, S., Wright, D.D., Wright, P., Xiankai, L., Yonzon, P., Zamzani, F., 2012. Averting biodiversity collapse in tropical forest protected areas. Nature 489, 290–294.
Machlis, G.E., Hanson, T., 2008. Warfare ecology. Bioscience 58, 729.
Marriage, Z., 2013. Formal Peace and Informal War: Security and Development in Congo. Routledge, London.

Matti, S., 2010. Resources and rent seeking in the Democratic Republic of the Congo. Third World Q. 31 (3), 401–413.

Miguel, E., Styanath, S., Sergenti, E., 2004. Economic shocks and civil conflict: an instrumental variables approach. J. Polit. Econ. 112, 725–753.

Mittermeier, R.A., Gil, P.R., Mittermeier, C.G., 1999. Megadiversity: Earth's Biologically Wealthiest Nations. Conservation International.

Nackoney, J., Molinario, G., Potapov, P., Turubanova, S., Hansen, M.C., Furuichi, T., 2014. Impacts of civil conflict on primary forest habitat in northern Democratic Republic of the Congo, 1990–2010. Biol. Conserv. 170, 321–328.

Nellemann, C., Redmond, I., Refisch, J. (Eds.), 2010. The Last Stand of the Gorilla — Environmental Crime and Conflict in the Congo Basin. United Nations Environmental Programme.

Nelson, A., Chomitz, K.M., 2011. Effectiveness of strict vs. multiple use protected areas in reducing tropical forest fires: a global analysis using matching methods. PLoS One 6, e22722.

Nepstad, D.C., McGrath, D.G., Soares-Filho, B., 2011. Systemic conservation, REDD, and the future of the Amazon Basin. Conserv. Biol. 25, 1113–1116.

Nunn, N., Puga, D., 2012. Ruggedness: the blessing of bad geography in Africa. Rev. Econ. Stat. 94, 20–36.

O'Loughlin, J., Witmer, F.D.W., Linke, A.M., Laing, A., Gettelman, A., Dudhia, J., 2012. Climate variability and conflict risk in East Africa, 1990–2009. Proc. Natl. Acad. Sci. U. S. A. 109, 18344–18349.

Olofsson, P., Foody, G.M., Herold, M., Stehman, S.V., Woodcock, C.E., Wulder, M.A., 2014. Good practices for estimating area and assessing accuracy of land change. Remote Sens. Environ. 148, 42–57.

Ostrom, E., Nagendra, H., 2006. Insights on linking forests, trees, and people from the air, on the ground, and in the laboratory. Proc. Natl. Acad. Sci. 103, 19224–19231.

Phalan, B., Bertzky, M., Butchart, S.H.M., Donald, P.F., Scharlemann, J.P.W., Stattersfield, A.J., Balmford, A., 2013. Crop expansion and conservation priorities in tropical countries. PLoS One 8, e51759.

Potapov, P.V., Turubanova, S.A., Hansen, M.C., Adusei, B., Broich, M., Altstatt, A., Mane, L., Justice, C.O., 2012. Quantifying forest cover loss in Democratic Republic of the Congo, 2000–2010, with Landsat ETM + data. Remote Sens. Environ. 122, 106–116.

Prunier, G., 2004. Rebel movements and proxy warfare: Uganda, Sudan and the Congo. Afr. Aff. 103 (412), 359–383.

Prunier, G., 2008. Africa's World War: Congo, the Rwandan Genocide, and the Making of a Continental Catastrophe. Oxford University Press.

Radeloff, V.C., Beaudry, F., Brooks, T.M., Butsic, V., Dubinin, M., Kuemmerle, T., Pidgeon, A.M., 2013. Hot moments for biodiversity conservation. Conserv. Lett. 6, 58–65.

Raleigh, C., Linke, A., Hegre, H., Karlsen, J., 2010. Introducing ACLED: an armed conflict location and event dataset: special data feature. J. Peace Res. 47, 651–660.

Reno, W., 1998. Warlord Politics and African States. Lynne Reiner, London.

Rustad, S.C.A., Rød, J.K., Larsen, W., Gleditsch, N.P., 2008. Foliage and fighting: forest resources and the onset, duration, and location of civil war. Polit. Geogr. 27, 761–782.

Saatchi, S.S., Harris, N.L., Brown, S., Lefsky, M., Mitchard, E.T.A., Salas, W., Zutta, B.R., Buermann, W., Lewis, S.L., Hagen, S., Petrova, S., White, L., Silman, M., Morel, A., 2011. Benchmark map of forest carbon stocks in tropical regions across three continents. Proc. Natl. Acad. Sci. U. S. A. 108, 9899–9904.

Seto, K.C., Güneralp, B., Hutyra, L.R., 2012. Global forecasts of urban expansion to 2030 and direct impacts on biodiversity and carbon pools. Proc. Natl. Acad. Sci. U. S. A. 109, 16083–16088.

Shearman, P.L., Ash, J., Mackey, B., Bryan, J.E., Lokes, B., 2009. Forest conversion and degradation in Papua New Guinea 1972–2002. Biotropica 41, 379–390.

Shearman, P., Bryan, J., Laurence, W., 2012. Are we approaching “peak timber” in the tropics? Biol. Conserv. 17–21.

Sims, K.R.E., 2010. Conservation and development: evidence from Thai protected areas. J. Environ. Econ. Manag. 60, 94–114.

Stehman, S.V., Wickham, J.D., 2011. Pixels, blocks of pixels, and polygons: choosing a spatial unit for thematic accuracy assessment. Remote Sens. Environ. 115, 3044–3055.

Stevens, K., Campbell, L., Urquhart, G., Kramer, D., Qi, J., 2011. Examining complexities of forest cover change during armed conflict on Nicaragua's Atlantic Coast. Biodivers. Conserv. 20, 2597–2613.

Sunderlin, W.D., Dewi, S., Puntodewo, A., Müller, D., Angelsen, A., Epprecht, M., 2008. Why forests are important for global poverty alleviation: a spatial explanation. Ecol. Soc. 13.

The World Bank, 2008. Democratic Republic of Congo Growth With Governance in the Mining Sector.

Themner, L., Wallensteen, P., 2012. Armed conflicts, 1946–2011. J. Peace Res. 49, 565–575.

Tollefsen, A.F., Strand, H., Buhaug, H., 2012. PRIO-GRID: a unified spatial data structure. J. Peace Res. 49, 363–374.

Tyukavina, A., Stehman, S.V., Potapov, P.V., Turubanova, S.A., Baccini, A., Goetz, S.J., Laporte, N.T., Houghton, R.A., Hansen, M.C., 2013. National-scale estimation of gross forest aboveground carbon loss: a case study of the Democratic Republic of the Congo. Environmental Research Letters 8. IOP Publishing, p. 044039.

UNEP., I., 2009. The World Protected Areas Database.

World Bank, 2009. News & Broadcast — World Bank Board approves GEF Grant to support rehabilitation of protected areas in Congo [WWW Document]. URL, http://web.worldbank.org/WBSITE/EXTERNAL/NEWS/0, contentMDK:22128101~menuPK:34463~pagePK:34370~piPK:34424~theSitePK:4607,00.html (accessed 7.25.13).

World Bank, 2013. FAQs — Forests in the Democratic Republic of Congo [WWW Document]. URL, http://web.worldbank.org/WBSITE/EXTERNAL/EXTSITETOOLS/0, contentMDK:22322346~pagePK:98400~piPK:98424~theSitePK:95474,00.html#3 (accessed 7.25.13).