Comment: The effect of post-conflict transition on deforestation in protected areas in Colombia

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ABSTRACT

A recent study on Colombian protected areas has found an increase in deforestation after ending armed conflict. The authors propose several drivers behind this trend and take their findings as proof of how these drivers specifically affect protected areas and render them particularly vulnerable to deforestation during post-conflict transition. However, after conducting an extended analysis of the data, we show that the original study merely noticed a national trend of increased deforestation in Colombia, and that forests in national protected areas are actually less affected by the transition than other forests in Colombia. Given these results, the proposed drivers and conservation lessons of the original study can only be regarded as speculative. In this comment, we point out the conceptual and statistical shortcomings of the original study to discuss how to improve forest change analyses regarding policy relevance.

Introduction

In their study[1] on Colombian national protected areas, Clerici et al. investigated how deforestation is influenced by armed conflict. The authors evaluated the change in forest loss in and around 39 protected areas before and after a peace agreement was reached to end military conflict between the Colombian government and the guerrilla groups of the *Fuerzas Armadas Revolucionarias de Colombia* (FARC). The authors present their observations regarding increase in forest loss, then propose several drivers that are related specifically to protected areas, and finally argue that these drivers are responsible for forest loss observed in protected areas.

After replicating the original study[1] and conducting an extended statistical analysis, we found that the interpretations of the authors are not supported by their data. The analysis and conclusions presented in the study[1] appear to be affected by three key conceptual and statistical shortcomings: (1) no reference trend (or "control") was presented against which deforestation rates can be compared; (2) no counterfactual[2] (i.e. a scenario in which the hypothesized effects are absent) was formulated to evaluate change in protected area effectiveness; (3) no statistical model was employed to assess the potential relationship between conflict periods and forest loss; and (4) only relative change in rates of forest loss was assessed, which does not account for the fact that the same relative change can lead to markedly different deforestation trajectories, depending on the initial deforestation rates. In our reanalysis of the data, we found that forests in national protected areas are actually less vulnerable than other forests in the face of post-conflict transition. The original study only happens to notice a national trend of increased forest loss that is also present in protected areas, albeit to a much smaller degree. In addition, we find it concerning that none of the variables that the authors present as causal drivers for deforestation in protected areas are actually included in their statistical analysis. In the following, we present the results of our reanalysis and the implications for investigating – and acting on – deforestation in protected areas.

Reanalysis

We structured our reanalysis into two parts. In the first part, we replicated the original analysis, but also compared the relative change in forest loss (between the periods "before" and "after" the peace agreement) to a reference trend. In the second part, we conducted a more comprehensive statistical analysis to also address the other shortcomings identified above. Following the methods by Clerici et al.[1], the extent of forest loss in our replication (Supplementary Tables S1, S2) closely matched that reported in the original study (Pearson's $r > 0.99$). In addition, we calculated a national-level reference trend of forest loss observed outside the assessed protected areas and buffer zones. The percentage increase of forest loss within national protected areas (median: 121.7 %, range: 790.2 %) is different from zero (sign test, $k = 31$, $n = 39$, $p < 0.01$), but it is not significantly different (sign test, $k = 19$, $n = 39$, $p > 0.99$) from the reference trend (116 %). The percentage increase within 10-kilometre buffer zones around protected areas (median: 158,0%, range: 698,6%) also does not differ significantly from the reference trend (sign test, $k = 23$, $n = 39$, $p = 0.34$). Therefore, forests in national protected areas (and their buffer zones) do not appear to be more heavily affected by post-conflict transition than forests elsewhere in Colombia, contrary to the conclusions of Clerici et al.[1].

For the second part of our reanalysis, we formulated a generalized linear mixed model (Supplementary methods; Supplementary Tables S3 – S5) to assess the effect of post-conflict transition on forest loss (Fig. 1). To compare deforestation trajectories, we used proportional forest loss, which expresses forest area lost as a percentage of total forest area (see Supplementary methods, Supplementary Tables S1, S2). In addition to the national reference trend, we used a counterfactual stated as: "the proportion of forest area lost within protected areas and buffer zones increases by the same amount as in Colombian forests outside these areas". We consider this the simplest counterfactual in the context of the original study, but other types of counterfactuals can surely be formulated[3,4].

Two main results arise from the regression analysis. First, protected areas show far less forest loss than other forested areas in Colombia, both "before" and "after" peace negotiations (Fig. 1). This is a key aspect missing from the original analysis: it essentially explains why, for protected areas, a similar relative change over time translates to a deforestation trajectory that is substantially different from both the reference trend and counterfactual (Table 1). As a second result, the difference in proportional forest loss between protected areas and the counterfactual (Table 1) has widened during post conflict transition – which means that the proportion of forest area spared from deforestation has increased compared to the counterfactual and reference trend. In contrast, the trajectory for buffer zones closely tracks the counterfactual (Fig. 1). These results show that protected areas are more effective at reducing deforestation compared to forests elsewhere. It can even be argued that their effectiveness has *increased* relative to other forested areas. Some caution is warranted when interpreting these trends, however, as much of the variation in forest loss remains unexplained by our model (total deviance explained: 19.7%; Supplementary Tables S4, S5).

In summary, whatever drivers act upon forests in Colombian national protected areas during post-conflict transition, their overall effect leads to these forests being *less affected* by the transition than other forests. In the original study[1], the authors repeatedly point to weak institutions and a higher incidence of illicit crops as the drivers that specifically affect protected areas, and argue that these drivers cause protected areas to be particularly prone to deforestation during post-conflict periods. However, their statistical analysis does not actually include the drivers they propose. Taken together, this omission and the results of our reanalysis indicate that the argument in the original study[1] – i.e. attributing deforestation under post-conflict transition to the purported drivers – is not supported by the available data and therefore remains entirely speculative. The same must thus be said about the conservation implications that were derived from this argument. For example: when extending beyond the Colombian situation, the authors argue in favour of an increased presence of a central government during post-conflict transition. However, their analysis does not provide evidence for why this strategy could be effective, or why it should be preferred over alternative (or complementary) strategies such as strengthening local indigenous or community-level institutions[5–7].

Implications for forest change research and policy

Deforestation is the result of multiple interacting drivers[8,9] (which is also acknowledged by Clerici et al.[1]). And like the original study, our reanalysis remains strongly limited in identifying causal drivers, as only one potential driver (the cessation of armed conflict) is included as a predictor variable, without controlling for other (and potentially confounding) variables. In comparing forest loss inside protected areas to the simple counterfactual we defined, we have used a rather coarse measure of protected area effectiveness, and other indicators would be needed to judge performance regarding ecosystem service provision and well-being of the local population[10,11]. In addition to weak conservation institutions and presence of illicit crops (as proposed by Clerici et al.[1]), forest loss in protected areas could be influenced by numerous biophysical and social variables, such as distance to roads, terrain ruggedness, soil fertility, population density, and availability of alternative income sources for the local population, to name but a few. For some of these factors, geospatial information is readily available and can be integrated into statistical models. Others, however, may require detailed ground surveys or in-depth interviews. Understandably, the latter are difficult to obtain in situations of armed conflict. Nonetheless, if a certain factor is absent from the analysis, we strongly suggest that its effect on forest loss be treated as a hypothesis rather than a demonstrated cause. For example, while it is entirely possible that institutions related to protected area governance are weak – contributing to increased deforestation relative to non-protected areas – it is also possible that other factors (such as remoteness) produce counteracting effects strong enough to result in reduced deforestation, relative to non-protected areas, as we have observed for Colombia. Teasing apart a set of spatially concurrent drivers based on well-defined hypotheses thus remains important for arriving at the right "lessons" for conservation[12].

Combining forest change data (such as provided by Hansen et al.[13]) with other geospatial information can provide important insights into deforestation patterns. To fully leverage these data while accounting for different drivers of forest loss, we suggest that studies follow a more rigorous statistical approach and, whenever possible, use statistical models to quantify relationships between deforestation and its potential drivers. While a comprehensive discussion of these methods is beyond the scope of this comment, we suggest that at least the following aspects be taken into account. First, to fully take advantage of high-resolution forest loss data (e.g. at 1 arc-second), we suggest using observations at the level of single raster cells. The observed response will then be a binary variable ("no forest loss" or "forest loss") for a given location (i.e. raster cell) in a given year (or otherwise defined time period). Alternatively, patches of several raster cells may be aggregated (e.g. patches of 3×3 cells) and forest loss events counted per patch, with the response now becoming a count variable. Both methods avoid having to spatially aggregate forest loss for areas that differ widely in size (which is often the case for protected areas). In addition, data on forest loss is then structured similar to species presence-absence data (or abundance data in the aggregated case), taking advantage of the rich toolbox that has been developed for analyzing them[14–16]. Conceptualizing forest loss in this way also provides vastly more observations, which means (in principle) that more potential drivers of forest loss can be included as predictors in statistical models. Second, the selection of variables that may be linked to deforestation should be informed both by *a priori* hypotheses, and by a systematic literature review for the location of interest, in order to identify potential confounding variables. Finally, as drivers of forest loss may not be independent, any collinearity between predictors should be accounted for[17], and its effects should be discussed when causal interpretation of the predictor variables is attempted. In the context of Colombian forests, a good example for a more rigorous statistical approach is given by a recent study demonstrating a link between deforestation and forest fires[18]; whereas another recent study on drivers of deforestation[19] does not take the aforementioned aspects into account and is affected by most of the shortcomings discussed above.

With this comment we would like to encourage researchers to use readily available geospatial information on deforestation and its potential drivers to investigate policy-relevant questions, such as Clerici et al.[1] have done. We greatly appreciate that the authors have brought this concerning trend of increased deforestation in Colombia to our attention, and we believe that more studies on underlying causes of deforestation are needed to improve forest governance. For future studies on forest change to be most relevant for policymaking, however, they should aim to provide the strongest supporting evidence achievable – given the available data and the question at hand. This requires that analytical concepts and statistical methods be as robust as possible, and interdependencies and uncertainties related to potential drivers of forest loss be clearly communicated.

Data availability

The analysis scripts used in this study are available as a git repository (`https://www.github.com/dschoenig/ForestchangeColPA`) and have been archived with DOI 10.5281/zenodo.3984087.

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Ackowledgements

The work of DS is supported by the *Natural Sciences and Engineering Research Council of Canada* (NSERC) as part of the CREATE programme *Biodiversity Ecosystem Services and Sustainability* (BESS).

Author contributions statement

DS replicated the original study, performed additional statistical analyses, and lead writing of the manuscript. CM and JD contributed to discussing and writing the manuscript.

Additional information

Competing interests

The authors declare no competing interests.

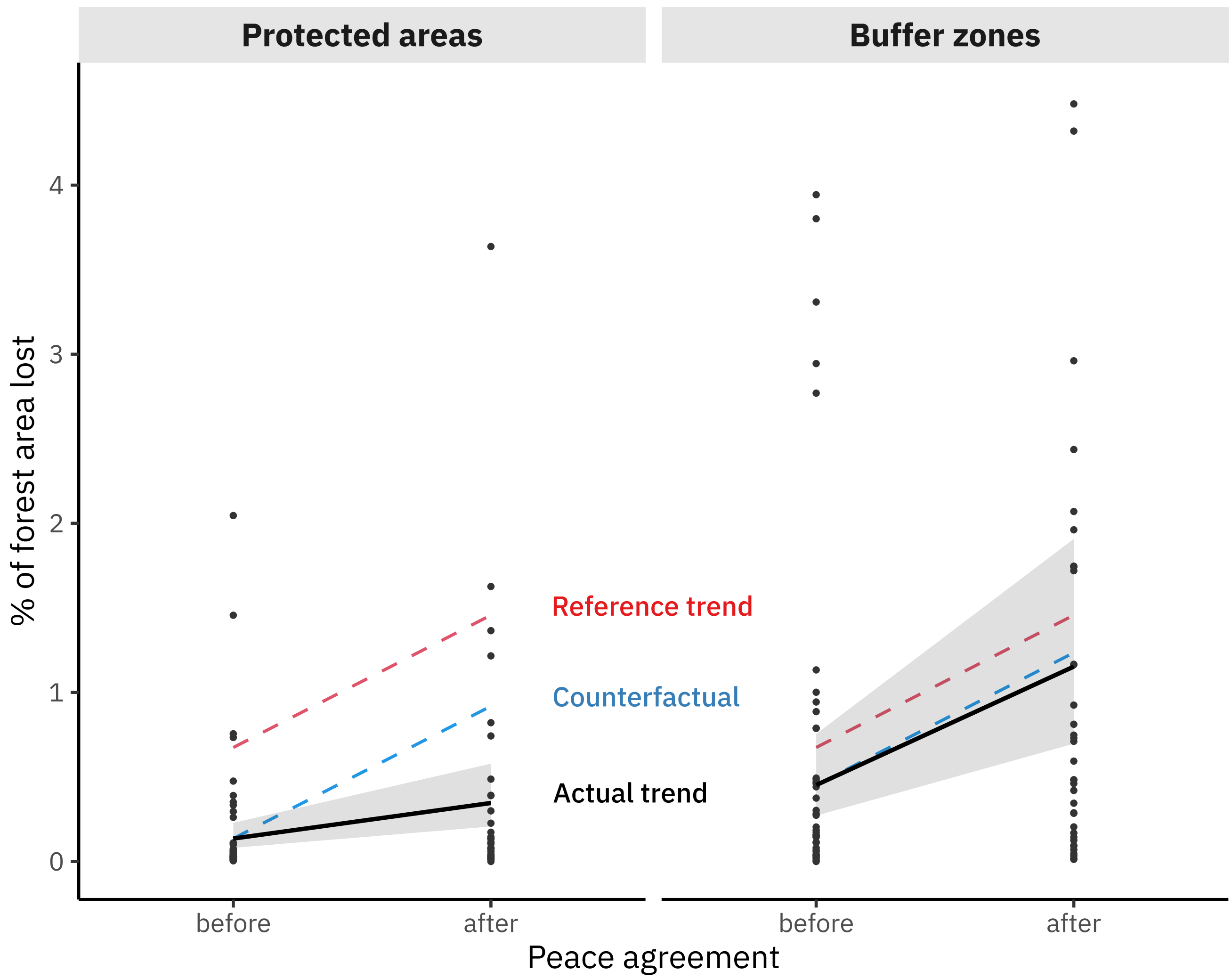

Figure 1. **Comparison of forest loss before and after the peace agreement.** While post-conflict transition coincides with a general increase in deforestation at the national level, national protected areas suffered only a relatively small increase in forest loss. The black line shows the predictions of a generalized linear mixed model (Supplementary Information) fitted on these observations. 95% confidence intervals are shown in grey. The red dashed lined corresponds to the percentage of forest area lost for Colombian forested land lying outside the assessed protected areas and buffer zones. The blue dashed line represents a hypothetical scenario in which forest loss increases at the same rate as outside protected areas and their buffer zones, but starting at the level of the actually observed forest loss before the peace agreement. Individual observations for national protected areas and their 10-kilometre buffer zones, respectively, are shown as black points. Observations for one protected area and three buffer zones in the period *after* the peace agreement are not shown due to high rates of forest loss (> 7.3% of forest area lost), but they have been included in the regression model.

Table 1. Model predictions compared to reference trend and counterfactual.

Period [a]	Forest loss *(% of total forested area)* [b]	Difference in forest loss *vs.* [c]	
		Reference trend [d]	Counterfactual [e]
Protected areas			
before	0.136 (0.080, 0.229)	-0.584 (-0.639, -0.491)	0 (-0.055, 0.093)
after	0.346 (0.207, 0.579)	-1.208 (-1.347, -0.975)	-0.624 (-0.763, -0.391)
Buffer zones			
before	0.452 (0.271, 0.754)	-0.268 (-0.449, 0.034)	0 (-0.181, 0.302)
after	1.153 (0.696, 1.908)	-0.401 (-0.858, 0.354)	-0.133 (-0.590, 0.622)

[a] Refers to the three-year periods before (2013 – 2015) or after (2016 – 2018) the peace agreement was reached.
[b] Total forested area was defined as the combined area of all raster cells with at least 50% tree cover in the year 2000, and with no forest loss recorded prior to 2013. 95% confidence intervals are given in parentheses.
[c] Absolute difference. Negative values indicate that estimated proportional forest loss is *lower* than the reference trend or counterfactual, respectively. 95% confidence intervals are given in parentheses.
[d] Defined as the percentage of forest area lost outside the assessed protected areas and buffer zones in Colombia.
[e] Hypothetical scenario defined as: "the proportion of forest area lost within protected areas and buffer zones, respectively, increases by the same amount as in Colombian forests outside these areas".

SUPPLEMENTARY INFORMATION

Comment: The effect of post-conflict transition on deforestation in protected areas in Colombia

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1 Supplementary methods

We generally followed the methods of the original study (as documented in the main text and the supplementary information) and used the data sources documented therein. The analysis scripts and final results have been archived under DOI 10.5281/zenodo.3984087.

Geospatial analysis

The global forest change data sets (referenced in the main text) provide, for each raster cell, tree cover estimates in percent for the year 2000. In the original study, the authors do not report whether they used a tree cover threshold to exclude barely forested land from their analysis. We therefore decided to chose a threshold ourselves and included only raster cells with at least 50% tree cover. For absolute forest loss in the periods before and after the peace agreement, we assessed agreement between our replication and the original study by calculating correlation coefficients (Pearson's r).

In addition to forest loss, we also calculated the total forested area for each protected area and buffer zone. We defined total forested area as the combined extent of all raster cells with at least 50% tree cover in the year 2000, and with no forest loss recorded prior to 2013. This is a conservative estimate of total forested area as it does not include newly planted or regenerating forests in areas that were below the tree cover threshold in the year 2000. To calculate forest loss and total forest area for Colombia, we applied the same methods we used for protected areas and buffer zones. Forest loss outside protected areas and buffer zones was then obtained by subtracting forest loss calculated for protected areas and buffer zones from the national total. We took this as the reference trend (or "control") against which to compare deforestation rates in individual protected areas and their buffer zones.

The relative change (expressed in percent) between the three-year periods before (2013 – 2015) and after (2016 — 2018) the peace agreement are calculated in the same way as in the original study:

$$100 \times \frac{\textit{forest loss before} \;-\; \textit{forest loss after}}{\textit{forest loss before}}$$

For each region of interest (i.e. protected areas, their buffer zones, and Colombia as a whole), we also expressed forest loss as a percentage of total forested area (as defined above) in the respective region, calculating for each period separately:

$$100 \times \frac{\textit{forest loss over period}}{\textit{total forested area}}$$

Proportional forest loss allows to better compare deforestation between different areas, because it includes differences in initial deforestation rates. This is important because areas that experience the same relative change in deforestation can move along strongly diverging trajectories according to the initial amount of forest loss.

Replication of original analysis

In our replication of the original study, we tested whether the observed relative change of deforestation is different from zero, separately for protected areas, and their buffer zones. In addition, we also tested whether the observed change was different from the relative change observed for Colombian forests outside the assessed protected areas and buffer zones. Given that the relative changes in forest loss are distributed asymmetrically around the median, we consider the *Wilcoxon signed-rank test* – as used in the original study – an inadequate choice, and instead used the more general *sign-test*.

Extended statistical analysis

We analyzed deforestation trajectories by formulating regression models on the percent of forest area lost as the response variable. Given that each buffer zone pertains to a specific protected area (i.e. buffer zones and protected areas are not independent). We therefore included both types of areas in our models, and formulated two grouping variables: the *type* of area ("buffer zone" or "protected area") and the *protected area ID* to indicate which protected area and buffer zone are paired. We formulated four models differing in the linear combination of their predictor variables (Supplementary Table S3): (1) an intercept-only model; (2) a model based on *conflict period* ("before" or "after") and *type*; (3) same as the second model but including a random intercept based on *protected area ID*; (4) same as the third model but also containing an interaction term between *conflict period* and *type*. Inspection of the data suggested that an adequate distribution for the percentage of forest area lost would have to be heavy-tailed (towards the upper end) and be able to accommodate a concrete probability mass at zero. We therefore chose the *Tweedie* distribution, with scale parameter ϕ and power parameter p to be estimated as part of the fitting process. As link function we used the natural logarithm. We used *Akaike's information criterion* (corrected for small sample size) to select the final model out of the four candidate models, and did not perform further variable selection. For fixed effects, p-values were computed based on Wald tests in which the Bayesian covariance matrix was used[20]; for the random intercept term, p-values are based on a likelihood ratio statistic[21].

Software

For data handling and geospatial analyses we used the GDAL[22] command line utilities and the following packages for *R*[23] (version 4.0.2): *gdalUtils*[24], *stars*[25], *sf*[26], *lwgeom*[27], *units*[28] and the *tidyverse*[29] packages. For statistical analyses we used the *mgcv*[30] and *MuMIN*[31] R packages.

2 Supplementary tables

Table S1. Forest loss in Colombian national protected areas and national nature reserves.

ID	Name	Initial forest area [a] (km^2)	Absolute forest loss (km^2)		Proportional forest loss (*% of initial forest area*)	
			before [b]	after [c]	before [b]	after [c]
1	Alto Fragua - Indi Wasi	752.972	0.365	0.586	0.048	0.078
2	Amacayacu	2,619.180	0.799	1.718	0.031	0.066
3	Cahuinarí	5,487.014	0.386	1.401	0.007	0.026
4	Catatumbo Barí	1,561.293	11.793	56.783	0.755	3.637
5	Chingaza	466.523	0.078	0.618	0.017	0.133
6	Complejo Volcánico Doña Juana Cascabel	619.749	0.083	0.248	0.013	0.040
7	Cordillera de los Picachos	2,754.313	10.745	33.486	0.390	1.216
8	Cueva de los Guácharos	70.699	0.004	0	0.005	0
9	El Cocuy	1,621.238	0.348	2.221	0.021	0.137
10	El Tuparro	937.267	0.647	2.804	0.069	0.299
11	La Paya	4,327.761	20.574	32.127	0.475	0.742
12	Las Hermosas	680.614	0.260	0.522	0.038	0.077
13	Las Orquídeas	280.539	0.212	1.092	0.076	0.389
14	Los Farallones de Cali	1,898.444	0.550	1.470	0.029	0.077
15	Los Katíos	662.541	0.365	1.144	0.055	0.173
16	Los Nevados	101.206	0.020	0.010	0.020	0.010
17	Macuira	52.215	0.154	0.030	0.295	0.058
18	Munchique	457.022	1.193	2.226	0.261	0.487
19	Nevado del Huila	1,220.238	0.350	0.240	0.029	0.020
20	Nukak	8,615.641	9.384	19.499	0.109	0.226
21	Paramillo	4,889.628	17.180	40.128	0.351	0.821
22	Pisba	177.134	0.046	0.258	0.026	0.146
23	Puinawai	10,833.330	6.358	11.814	0.059	0.109
24	Puracé	728.412	0.120	0.295	0.016	0.041
25	Río Puré	9,856.320	0.380	1.564	0.004	0.016
26	Sanquianga	484.177	0.532	0.678	0.110	0.140
27	Selva de Florencia	98.894	0.031	0.031	0.032	0.031
28	Serranía de Chiribiquete	27,217.876	3.590	3.765	0.013	0.014
29	Serranía de los Churumbelos - Auka Wasi	967.892	0.427	0.357	0.044	0.037

(continued on next page)

Table S1. (continued)

ID	Name	Initial forest area [a] (km^2)	Absolute forest loss (km^2)		Proportional forest loss (*% of initial forest area*)	
			before [b]	after [c]	before [b]	after [c]
30	Serranía de los Yariguies	589.256	0.216	0.615	0.037	0.104
31	Sierra de la Macarena	5,748.020	42.160	93.483	0.733	1.626
32	Sierra Nevada de Santa Marta	2,342.431	7.809	31.975	0.333	1.365
33	Sumapaz	985.404	0.172	0.309	0.017	0.031
34	Tamá	426.736	0.423	1.670	0.099	0.391
35	Tatamá	420.414	0.123	0.104	0.029	0.025
36	Tayrona	114.337	1.665	0.019	1.456	0.017
37	Tinigua	1,855.491	37.963	161.290	2.046	8.693
38	Utría	513.499	0.147	0.582	0.029	0.113
39	Yaigojé Apaporis	10,321.017	6.633	8.283	0.064	0.080

[a] Defined as the combined area of all raster cells with at least 50% tree cover in the year 2000 (see Supplementary methods), and with no forest loss recorded prior to 2013.
[b] The three-year period 2013 – 2015.
[c] The three-year period 2016 – 2018.

Table S2. Forest loss in 10-kilometre buffer zones of Colombian national protected areas and national nature reserves.

ID	Corresponding protected area	Initial forest area [a] (km^2)	Absolute forest loss (km^2)		Proportional forest loss (*% of initial forest area*)	
			before [b]	after [c]	before [b]	after [c]
1	Alto Fragua - Indi Wasi	832.894	8.337	14.325	1.001	1.720
2	Amacayacu	2,577.405	3.714	3.217	0.144	0.125
3	Cahuinarí	3,664.800	0.748	1.211	0.020	0.033
4	Catatumbo Barí	1,453.194	42.793	108.271	2.945	7.451
5	Chingaza	1,276.829	0.538	1.202	0.042	0.094
6	Complejo Volcánico Doña Juana Cascabel	1,281.750	1.893	3.651	0.148	0.285
7	Cordillera de los Picachos	1,930.671	9.523	57.173	0.493	2.961
8	Cueva de los Guácharos	127.389	0.598	2.220	0.469	1.743
9	El Cocuy	2,075.424	1.668	7.155	0.080	0.345
10	El Tuparro	769.214	3.395	7.113	0.441	0.925
11	La Paya	2,587.724	71.681	115.940	2.770	4.480
12	Las Hermosas	1,614.442	2.509	7.804	0.155	0.483
13	Las Orquídeas	1,162.301	1.994	9.431	0.172	0.811

(continued on next page)

Table S2. (continued)

ID	Corresponding protected area	Initial forest area [a] (km^2)	Absolute forest loss (km^2)		Proportional forest loss (*% of initial forest area*)	
			before [b]	after [c]	before [b]	after [c]
14	Los Farallones de Cali	1,977.895	3.671	5.693	0.186	0.288
15	Los Katíos	899.553	7.970	38.860	0.886	4.320
16	Los Nevados	1,141.070	4.275	5.505	0.375	0.482
17	Macuira	1.598	0	0.001	0	0.047
18	Munchique	1,301.171	10.247	25.521	0.788	1.961
19	Nevado del Huila	2,541.519	7.173	18.990	0.282	0.747
20	Nukak	5,433.456	8.462	39.661	0.156	0.730
21	Paramillo	3,767.065	29.706	91.779	0.789	2.436
22	Pisba	803.174	0.475	3.373	0.059	0.420
23	Puinawai	5,013.538	1.836	3.494	0.037	0.070
24	Puracé	1,686.545	0.597	1.545	0.035	0.092
25	Río Puré	3,686.698	0.288	0.631	0.008	0.017
26	Sanquianga	799.613	3.870	4.746	0.484	0.594
27	Selva de Florencia	614.650	2.833	10.735	0.461	1.746
28	Serranía de Chiribiquete	10,187.658	2.458	1.291	0.024	0.013
29	Serranía de los Churumbelos - Auka Wasi	1,320.814	12.456	23.052	0.943	1.745
30	Serranía de los Yariguies	1,461.122	2.979	17.000	0.204	1.163
31	Sierra de la Macarena	3,238.298	107.147	295.494	3.309	9.125
32	Sierra Nevada de Santa Marta	2,675.664	30.311	55.384	1.133	2.070
33	Sumapaz	2,092.728	1.401	4.276	0.067	0.204
34	Tamá	734.966	2.008	5.221	0.273	0.710
35	Tatamá	1,314.390	3.972	15.330	0.302	1.166
36	Tayrona	245.020	9.314	1.130	3.801	0.461
37	Tinigua	788.178	31.080	104.846	3.943	13.302
38	Utría	909.286	1.017	1.530	0.112	0.168
39	Yaigojé Apaporis	5,875.261	6.694	8.399	0.114	0.143

[a] Defined as the combined area of all raster cells with at least 50% tree cover in the year 2000, and with no forest loss recorded prior to 2013.
[b] The three-year period 2013 – 2015.
[c] The three-year period 2016 – 2018.

Table S3. Regression models considered.

Model [a]	Effects				Distribution	Link
	Conflict period [b]	Type [c]	Conflict period × type [d]	Protected area ID[e] (random intercept)		
1					*Tweedie*	*log*
2	X	X			*Tweedie*	*log*
3	X	X		X	*Tweedie*	*log*
4	X	X	X	X	*Tweedie*	*log*

[a] All models are based on $n = 156$ observations, and the response variable is the percentage of forest area lost. For calculation of forest loss and total forested area, see supplementary methods. All models were estimated using restricted maximum likelihood (REML).
[b] Either the three-year period *before* (2013 – 2015) or *after* (2016 – 2018) the peace agreement was reached.
[c] Either *protected area* or *buffer zone*.
[d] Interaction term.
[e] Grouping variable to identify which buffer zone corresponds to which protected area. Estimated as a penalized smooth term.

Table S4. Model selection.

Model	Distribution parameters [a]	DF [b]	Dev. expl. [c]	R^2 (adj.)	AIC_c [d]
1	$Tweedie(\phi = 2.211,\ p = 1.920)$	3	< 0.1%	0	199.3
2	$Tweedie(\phi = 1.851,\ p = 1.906)$	5	16.9%	0.087	163.5
3 (selected)	$Tweedie(\phi = 1.795,\ p = 1.904)$	5.97	19.7%	0.100	**158.2**
4	$Tweedie(\phi = 1.803,\ p = 1.905)$	6.97	19.8%	0.095	160.3

[a] The scale parameter ϕ and Tweedie power parameter p were estimated during the fitting process.
[b] Model degrees of freedom.
[c] Deviance explained.
[d] Akaike information criterion corrected for small sample size.

Table S5. Parameter estimates of the final model.

Parameter	Fixed effect			Random effect	
	Coef.	SE [a]	95% CI [b]	SD [c]	95% CI [b]
Intercept	-1.998^{***}	0.267	-2.521, -1.476		
After conflict	0.936^{***}	0.220	0.505, 1.368		
Buffer zone	1.204^{***}	0.220	0.772, 1.635		
Protected area ID				0.021^{*}	0.004, 0.106

Significance levels: * p<0.05; ** p<0.01; *** p<0.001

[a] Standard error of the coefficient estimate.
[b] Point-wise confidence intervals for the regression coefficient (for fixed effects) or standard deviation (for random effects).
[c] Standard deviation.

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