Colombia’s transition to peace is enhancing coca-driven deforestation

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Abstract

Forests cover 70% of the Colombian territory, which includes part of the Amazon. Recent studies have examined how the country’s tree cover dynamics are affected by coca cultivation and its internal armed conflict. In light of Colombia’s recent peace agreement, this study examines whether the impact of coca cultivation on forest loss is conditional on the conflict (i.e. whether the impact varies across different levels of conflict intensity). This conditional association is supported by a state-of-the-art spatial panel data analysis, covering the entire territory throughout 2006–2019. As the conflict becomes less intense, each hectare of coca is associated with a larger extension of forest loss.

1. Introduction

Colombia is the size of France and Spain combined. As of 2019, tree cover occupied 70% of its land area (vegetation taller than 5 meters in height), and 98% of its tree cover loss occurred within natural forest (WRI 2020, GFW 2020, Hansen et al 2013). It is also estimated that Colombia currently hosts 10% of the world’s biodiversity (CBD 2020).

Researchers have identified numerous environmental, demographic, and socio-economic factors associated with forest loss in Colombia (e.g. Negret et al 2019, Armenteras et al 2013, Sánchez-Cuervo and Aide 2013). Among the various challenges that Colombia faces and which may affect deforestation, the following two have received considerable attention: its decades-long internal armed conflict and coca cultivation.

Colombia has experienced an internal conflict with different armed groups since the 1960s (Guáqueta 2005). The conflict has been characterized by different types of violence, such as combats, kidnapping, the use of landmines, attacks on infrastructure, and human displacement (UNOCHA 2020).

Landholm et al (2019) provide an elaborate explanation of the various mechanisms through which conflict intensity can lead to forest change. The rationale is that the impact of the armed conflict is mainly indirect: the conflict first affects drivers of land use change (e.g. land grabbing for cattle ranching), and these drivers in turn affect forest change. For example, the impact is expected to be positive (forest gain) if the conflict leads to land abandonment or the isolation of strategic areas for transport or hiding (a phenomenon often referred to as ‘gunpoint conservation’; Alvarez 2003). Conversely, the impact is expected to be negative (forest loss) if the conflict is financed by — or leads to land grabbing associated with — illegal mining, logging, or crop production.

In line with this conceptualization, sophisticated analyses have helped uncover the complexity of the various localized associations between the Colombian armed conflict and forest change (Castro-Nunez et al 2017, Sánchez-Cuervo and Aide 2013). Notably, the analysis by Landholm et al (2019), which covers the period 1992–2015, indicates that conflict areas have been predominantly associated with forest loss. A separate analysis, covering the period 2000–2015, also indicates that the effect of conflict intensity on forest loss is significant, yet relatively small (Negret et al 2019).

The intensity of the Colombian conflict has varied not only across locations, but also across the years. In 2012, the Colombian government and the largest insurgent group started a peace negotiation process, which concluded with the signature of a peace agreement in 2016. This process motivated recent calls for research on the potential unintended effects of peace on Colombia’s unique environment (Baptiste et al 2017, Salazar et al 2018, Eufemia et al 2019). One
major concern is that the transition to peace is likely accompanied by, for example, investments in new infrastructure, migration, and a combination of legal and illegal mining and agricultural activities, which can enhance forest fragmentation, degradation, or loss.

New evidence feeds this concern. After the peace agreement, forest loss has increased in former conflict areas (Prem et al 2020), protected areas (Clerici et al 2020), and the Andes–Amazon Transition Belt (Murillo-Sandoval et al 2020). Acknowledging that the conflict has contributed to complex cycles of conversion, abandonment, and unplanned preservation (Prem et al 2020), the net effect after the peace agreement appears to be localized forest loss.

This negative impact of the peace agreement (after 2016) is not necessarily at odds with the negative impact of the armed conflict (Landholm et al 2019, Negret et al 2019, until 2015). It is important to note that these studies focus on different periods and locations, and that the impact of the armed conflict until 2015 is small in comparison to other drivers (Negret et al 2019). Even if the conflict has contributed to forest loss, the end of the conflict might be exacerbating the impact of other forest loss drivers, such as land grabbing for cattle ranching and coca cultivation (Murillo-Sandoval et al 2020, Clerici et al 2020).

Colombia is one of the top two producers of coca leaf in the world, the base ingredient of cocaine (UNODC 2020). Coca cultivation is a complex phenomenon not only because it is influenced by market, state presence, and social dynamics factors, but also because it is an activity performed by distinct groups of actors, such as farmers, armed groups, and indigenous communities (Dion and Russler 2008, Rincón-Ruiz et al 2016).

Economic theory is often used to explain the possible direct association between coca cultivation and forest loss. The rationale is that poverty and high economic gains motivate farmers to clear the forest to grow coca (Thoumi 2002; for discussions on this and alternative views, see Dávalos and Dávalos 2020, Dávalos et al 2016). Acknowledging that there can be other social, cultural, and political factors at play, economic motivations appear to be relevant: coca cultivation has been recognized as a lucrative activity for farmers (Ibanez and Carlsson 2010, Rincón-Ruiz et al 2016), a means of subsistence for impoverished indigenous and Afro-Colombian communities (Sánchez-Cuervo and Aide 2013, Dávalos et al 2009), and major source of finance to armed groups (Cornell 2005).

Interestingly, the association between coca cultivation and forest loss can also be indirect. For example, Dávalos et al (2011) posit that coca cultivation can (i) attract new coca growers, driving the expansion of the existing cultivated area; (ii) fuel the armed conflict in the area, forcing coca growers to relocate; or (iii) be subject to eradication actions (aerial spraying), which may not only force coca growers to relocate, but also cause direct deforestation.

Indeed, the evidence indicates that the association between coca cultivation and forest loss can be direct (Negret et al 2019, Chadid et al 2015, Viña et al 2004, Armenteras et al 2013, Dávalos et al 2011) as well as indirect (e.g. mediated by eradication or migration factors; Rincón-Ruiz et al 2016, Rincón-Ruiz and Kallis 2013).

1.1. Conflict intensity and coca-driven deforestation

These theories and findings lead to the question of whether the impact of coca cultivation on forest loss has been conditional on the intensity of the conflict. Some forests and forest buffer zones may have been protected by landmines, threats, and the enforcement of the armed group’s rules about land use (‘gunpoint conservation’; Murillo-Sandoval et al 2020). Other forests and forest buffer zones may have been protected by actual conflict-related violence (combats, bombings). In either case, a high level of conflict intensity can deter coca growers (as well as other actors) from opening the forest frontier.

These barriers are lowered as the conflict becomes less intense. In particular, recent interviews with farmers suggest that the peace agreement has opened previously inaccessible forests to cattle ranching, coca cultivation, and ‘licit’ agricultural activities (Van Dexter and Visseren-Hamakers 2019, Murillo-Sandoval et al 2020).

The objective of the present study, therefore, is to test whether conflict intensity mitigates coca-driven deforestation. The analysis is not designed to test whether the transition to peace has enhanced coca cultivation in itself, or has enhanced coca cultivation more than other forest loss drivers (i.e. it does not treat conflict intensity as the predictor and coca cultivation as the outcome variable). Instead, the analysis is designed to test whether the association between coca cultivation and forest loss varies depending on the level of conflict intensity (i.e. it treats coca cultivation as the predictor, conflict intensity as the moderator, and forest loss as the outcome variable). A statistical analysis examining the independent (main) effects of coca cultivation, conflict intensity, and other relevant factors operates under the assumption that the impact of coca cultivation on forest loss is constant across different levels of conflict intensity. This can be problematic, however, as excluding the possible interaction (moderating) effect of conflict intensity could bias the results.

This moderation hypothesis is tested using a state-of-the-art spatial panel data analysis technique (i.e. a fixed effects generalized moments estimation accounting for spatial error correlation and spatial autocorrelation), using municipality level observations for the period 2006–2019 ($N = 14,868$ municipality-year observations). The results support
the expected moderation association: as the conflict becomes less intense, each hectare of coca cultivation is associated with a larger extension of forest loss.

This study contributes to the literature in three ways. First, it joins the emerging group of studies responding to calls for research on the possible unintended effects of Colombia’s peace on the environment (Baptiste et al 2017, Salazar et al 2018, Eufemia et al 2019), and presents evidence indicating that the transition to peace is enhancing coca-driven deforestation. Second, it elaborates on how the armed conflict or the peace process can be conceived not only as predictors, but also as moderator variables, which can weaken or strengthen well-established direct associations between forest loss drivers and forest loss. This study could motivate new research on how conflict intensity mitigates or enhances the impact of, for example, large agricultural projects or mining activities. Finally, this study illustrates how it is possible to combine spatio-temporal data from different data sources in order to analyze forest loss dynamics, using a modern spatial panel data analysis technique.

2. Methods

2.1. Variable measurement

2.1.1. Forest loss, coca cultivation, and conflict intensity

Forest loss is treated as the outcome variable, and is measured as the number of hectares of stand level replacement of vegetation taller than 5 meters in height, using a canopy density threshold of 30% (GFW 2020, Hansen et al 2013). This measure is based on the data source’s analysis of Landsat satellite images at a 30 x 30 meter resolution. Recent research employs the same definition of forest loss (Negret et al 2019).

Coca cultivation is treated as the predictor variable, and is measured as the number of hectares of coca crops, based on the data source’s analysis of Landsat satellite images at a 15 x 15 meter resolution (ODC 2020). Conflict intensity is treated as the moderator variable, and is measured as the number of victims of the armed conflict (thousands of victims of, e.g. terrorist acts, torture, homicide, human displacement, landmines), based on official data (RNI 2020). The analysis includes an alternative test focusing on internally displaced persons only, as this has been identified as a suitable indicator of the varying degrees of conflict intensity in Colombia (Landholm et al 2019).

2.1.2. Covariates

The analysis includes the following covariates: population size, manual eradication, agricultural land, aerial spraying, and poverty. These covariates are incorporated because they can relate to both coca cultivation and forest loss, acting as potential confounds. Forest loss is associated with agricultural plantations (e.g. Prem et al 2020), manual eradication and aerial spraying (Rincón-Ruiz and Kallis 2013), and population size and poverty (Armenteras et al 2013, Sánchez-Cuervo and Aide 2013). The objective of manual eradication and aerial spraying is to reduce coca cultivation directly. Coca cultivation can also be influenced by poverty (Dávalos and Dávalos 2020). Due to its illegal nature, coca cultivation may take place in less densely populated areas, and to some extent, it may compete against alternative ‘licit’ agricultural projects (Van Dexter and Visseren-Hamakers 2019).

Population size is measured as the number of permanent inhabitants (in thousands; DANE 2020a). Agricultural land is measured as the number of hectares of cultivated area, combining permanent and transitional crops (AGRONET 2020). Manual eradication is measured as the number of hectares that have been eradicated by hand, and aerial spraying is measured the number of hectares of coca crops sprayed with glyphosate herbicide (UNODC 2020). Poverty is measured as the percentage of the population with a household income per capita below the poverty line (DANE 2020a). A summary of all these measures is presented in table S1 in the supplementary material (SM) available online (stacks.iop.org/ERL/15/104071/mmedia).

2.2. Sample

Each measure employs publicly available observations, which are reported by year and at the municipality level (second level administrative divisions). The forest loss data set makes use of the Global Administrative Areas database, which recognizes 1,065 divisions for Colombia (GFW 2020, GADM 2020). One division is unnamed and has no forest loss data, so it is excluded from the analysis. Two divisions are not second but third level divisions (San José de Ocune and Santa Rita in the department of Vichada), so they are merged together with the municipality they belong to (Cumaribo). The resulting data set contains 1,062 divisions, which cover the entire Colombian territory.

The other data sets make use of the official nomenclature, which currently includes 1,121 second level divisions (DANE 2020b). The map of the GFW (2020) portal is used to identify how the remaining 59 divisions are contained within the divisions of the forest loss data set. The list of these 59 divisions and the GADM divisions that contain them is presented in table S2 in SM. This list is used to aggregate the observations in each data set, so that all data sets can be merged using the same 1,062 divisions. It is important to note that the tests yield the same pattern of results either by following this procedure or by excluding these 59 divisions from the analysis.

Agricultural land is available from 2006, so this year sets the lower boundary of the covered period. Aerial spraying was interrupted in 2015, just before the peace agreement, which means that the absence of
aerial spraying throughout 2016–2019 is highly correlated with a reduction in conflict intensity, raising concerns about multicollinearity. For this reason, aerial spraying is excluded from the baseline model and incorporated into an alternative test. Poverty is available for 2010–2018, and is reported at the municipality level for each department’s capital city, and at the department level for all other municipalities (first level administrative divisions are referred to as departments). For these reasons, poverty is excluded from the baseline model and incorporated into an alternative test.

The resulting integrated panel data set for the baseline model contains 14,868 municipality-year observations (1,062 municipalities x 14 years). Each step of the sample selection procedure is described in tables S3 and S4 in SM.

2.3. Empirical strategy

For robustness, the expected moderation association is tested using five different models. All models treat coca cultivation, conflict intensity, and forest loss as the predictor, moderator, and outcome variables. They also include the product of coca cultivation and conflict intensity as the interaction term. Model 1 is used as the baseline model and incorporates the following covariates: agricultural land, manual eradication, and population size. Model 2 excludes all the municipalities that had zero coca cultivation during 2006–2019, as coca crops tend to be clustered in certain locations. Model 3 employs human displacement as an alternative indicator of conflict intensity (Landholm et al 2019). Models 4 and 5 include aerial spraying and poverty, respectively.

The model specification strategy follows current advances in spatial panel data econometrics (Croissant and Millo 2019, Elhorst 2014). A standard (aspatial) panel data analysis fails to account for the spatial dependency of the municipalities, and this can bias the results. A spatial panel data analysis controls for the space-specific time-invariant variables omitted in the standard analysis (Elhorst 2014), and for this reason, can be considered appropriate for this study. Indeed, it is recommended to account for spatial effects when analysing forest loss data (Mets et al 2017).

The procedure is as follows. Municipality coordinates are used to generate a spatial weights matrix, which captures the spatial influence between locations (based on distance). This matrix is then converted into a weighted list, which is required by the spatial panel regression. To select the appropriate model specification (i.e. whether to account for spatial effects, and for fixed vs. random effects), it is recommended to test for spatial autocorrelation and spatial error correlation, and also to conduct a spatial Hausman test (Croissant and Millo 2019). These tests are conducted using the baseline model, using standardized variables in order to avoid computational issues in the presence of dissimilar variable scales (e.g. computations of values with numerous decimal places that approximate zero). The results of these tests are presented in table S5 in SM, and indicate that a fixed effects generalized moments estimation — accounting for spatial autocorrelation and spatial error correlation — is appropriate in this case (Croissant and Millo 2019, Millo and Piras 2012).

There are two possible estimations. As compared to a maximum likelihood estimation, the generalized moments method is advantageous in this context, as it works well with large samples, does not require assumptions about the distribution of the residuals, and is computationally more efficient (Fuhrer et al 1995, Millo and Piras 2012).

3. Results

Figure 1 depicts magnitudes and locations for forest loss, coca cultivation, and conflict intensity. The series of the annual country level totals reveals recent spikes in forest loss and coca cultivation (around 2017), and a fluctuating downward trend in conflict intensity since 2006. The sharp increase in forest loss and coca cultivation levels coincides with the end of the peace negotiation process, prior to the 2016 peace agreement, and hints at a possible association between the three variables.

The maps depict mean values at the municipality level (sum totals divided by the number of years). Although the variables’ levels and locations have not remained constant throughout the period, these maps provide a rough indication of where these phenomena have taken place. They have been to some extent peripheral to the Andean mountains, which are located at the center of the territory and host the capital city and other major urban centers. The municipalities below the Andean mountains have been affected by the three phenomena, particularly by high levels of forest loss (figure 1(d)). Some areas near the Ecuadorian border (at the South-West) have been affected by high levels of both coca cultivation and conflict intensity (figure 1(e) and (f)). The partial overlaps in locations could also hint at a possible association between these variables.

3.1. The mitigating effect of conflict intensity

To formally assess the expected association, the analysis includes five models (a baseline model plus four alternative tests). The results are presented in table 1, and provide support for the expected association. Each model reveals a positive and significant association between coca cultivation and forest loss (a positive main effect), which is significantly weakened by the intensity of the armed conflict (a negative moderation effect). This indicates that, as the conflict becomes less intense, each hectare of coca is associated with a larger extension of forest loss.
This mitigating effect of conflict intensity (the significant interaction term) is observed using all the available observations for the variables included in this analysis (Model 1), excluding municipalities without coca crops (Model 2), using human displacement as an alternative conflict intensity indicator (Model 3), and controlling for aerial spraying (Model 4) and poverty (Model 5). This significant moderation effect is not only observable over and above the potential influence of the covariates and fixed municipality characteristics (which may relate to, e.g. altitude, slope), but also while accounting for spatial autocorrelation and spatial error correlation.

Figure 2 shows the varying marginal effect of coca cultivation on forest loss, based on the estimates of Model 1. When conflict intensity is particularly high (8,000–10,000 victims in one municipality), coca cultivation is not associated with forest loss. When conflict intensity is low (in peaceful locations), one hectare of coca cultivation is associated with approximately 0.19 hectares of forest loss. The estimates of Models 2-3 also indicate that the marginal effect of coca cultivation in peaceful locations approximates 0.19 hectares. Model 4, which covers the period 2006–2015 and excludes the years after the peace agreement, yields a lower estimate (0.106 hectares). This result provides an additional indication that the peace agreement enhances the impact of coca cultivation (the impact appears to be weaker before 2016). The estimate of Model 5 indicates that the marginal effect for zero conflict intensity could be even larger (0.271 hectares). The results of Model 5 should be interpreted with caution, however, as the poverty measure is mainly available at the department level, and this model covers fewer years.
Table 1. Spatial panel fixed effects generalized-moments (GM) estimation of forest loss: baseline model and alternative tests.

|                          | Outcome variable: Forest loss |
|--------------------------|-------------------------------|
|                          | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
| Coca cultivation         | 0.192*** | 0.189*** | 0.185*** | 0.106*** | 0.271*** |
|                          | (0.015)  | (0.028)  | (0.014)  | (0.030)  | (0.019)  |
| Conflict intensity       | −9.633   | −2.087   | −10.004  | 11.073   | −5.296   |
|                          | (6.613)  | (14.104) | (7.373)  | (5.738)  | (7.674)  |
| Coca cultivation x Conflict intensity | −0.020*** | −0.018*** | −0.022*** | −0.011*** | −0.021*** |
|                          | (0.002)  | (0.005)  | (0.003)  | (0.003)  | (0.003)  |
| Population size          | −0.210   | −0.838   | −0.210   | −0.391   | 0.004    |
|                          | (2.97)   | (2.108)  | (2.297)  | (3.357)  | (0.524)  |
| Manual eradication       | −0.004   | −0.024   | −0.007   | −0.026*  | 0.056**  |
|                          | (0.012)  | (0.024)  | (0.012)  | (0.013)  | (0.020)  |
| Agricultural land        | 0.006*** | 0.001    | 0.006*** | 0.001    | 0.010*** |
|                          | (0.002)  | (0.004)  | (0.002)  | (0.002)  | (0.002)  |
| Aerial spraying          | −0.002   | −0.002   | −0.002   | 0.004    | 0.015    |
|                          | (0.011)  | (0.011)  | (0.011)  | (0.011)  | (0.011)  |
| Poverty                  | 4.188**  | 4.188**  | 4.188**  | 4.188**  | 4.188**  |
|                          | (1.372)  | (1.372)  | (1.372)  | (1.372)  | (1.372)  |

Notes. Model 1 is used as the baseline model. Model 2 excludes municipalities with zero coca cultivation across 2006–2019. Model 3 uses human displacement as the conflict intensity indicator. Models 4 and 5 include aerial spraying and poverty as covariates, respectively. Coef. stands for coefficient. The GM estimation does not provide a significance test for the spatial autoregressive coefficient ($\rho$). Standard errors are in parentheses. ***p < 0.001; **p < 0.01; *p < 0.05.

Figure 2. Marginal effect of coca cultivation on forest loss as conflict intensity varies (based on the results of Model 1 in table 1). The outer lines represent the upper and lower bounds of a 95% confidence interval.

In line with prior findings, some of these models indicate that forest loss is positively associated with manual eradication (e.g. Rincón-Ruiz and Kallis 2013, Reyes 2014), agricultural land (e.g. Etter et al 2006, Sánchez-Cuervo and Aide 2013), and poverty (e.g. Armenteras et al 2013).

4. Discussion

This study joins the emerging group of studies responding to calls for empirical research on the possible unintended effects of Colombia’s transition to peace on the environment, particularly on forest loss.
 gave serious concerns about the impact of the transition to peace on, for example, the Andes–Amazon biodiversity bridge (Clerici et al. 2019), and emerging evidence already indicates that, after the peace agreement, forest disturbances have increased in this area (Murillo-Sandoval et al. 2020). Protected areas across the country may be suffering a similar fate (Clerici et al. 2020).

These new studies examine the overall effect of the peace agreement on forest loss using ‘before and after’ comparisons, and while focusing on specific locations (Prem et al. 2020, Clerici et al. 2020, Murillo-Sandoval et al. 2020). They also provide indications of the possible mechanisms that may be at play. The analysis of ethnographic data points at land grabbing (Murillo-Sandoval et al. 2020), and a differences-in-differences analysis points at land intensive economic activities and limited state presence (Prem et al. 2020).

The present study contributes to the literature by focusing on one forest loss driver in particular (coca cultivation), and by assessing how its impact varies depending on the intensity of the conflict. The results indicate that, as Colombia transitions to peace, each hectare of coca is associated with a larger extension of forest loss. In the absence of a powerful actor that controlled part of the territory, the transition to peace can exacerbate the effects of various forest loss drivers (Clerici et al. 2020). The present analysis suggests that coca cultivation is one of them. In this sense, this study responds to the above-mentioned calls for research by examining not whether the transition to peace is affecting deforestation, but how (by exacerbating the impact of coca cultivation).

This study presents a country-wide analysis, which complements findings focused on protected areas (Clerici et al. 2020) or municipalities previously affected by the conflict (Prem et al. 2020). Instead of comparing periods, it treats conflict intensity as a continuous variable, which can vary across years and locations (in line with Landholm et al. 2019). Although the peace process has significantly reduced the intensity of the conflict at a national level, some municipalities were peaceful before the peace agreement, and others have been experiencing increased conflict intensity after the peace agreement. A continuous conflict intensity indicator has the advantage of capturing this type of nuances and exceptions across years and locations.

The results are robust to alternative model specifications. The analysis covers 14 years and the entire Colombian territory, includes relevant covariates, and accounts for spatial effects. With the available data, however, the possibility that the results are affected by unobserved factors cannot be fully ruled out. Researchers have identified several forest loss drivers for Colombia (e.g. Sánchez-Cuervo and Aide 2013, Armenteras et al. 2013), and some of them could act as confounds by simultaneously influencing coca cultivation and forest loss. For example, some farmers are opting for cattle ranching to substitute coca crops (Murillo-Sandoval et al. 2020), but due to panel data limitations, pastures and cattle ranching indicators are not included in this analysis. As panel data at the municipality level become more available, future studies can incorporate these potential confounds to better assess the magnitude of the hypothesized effect.

Another limitation relates to the level of analysis. Municipality level data aggregate granular observations at a larger scale. This means that, for some observations, coca cultivation and forest loss may occur in the same municipality but not necessarily at the same location (false positives). There is an additional loss in measurement precision for the subset of GADM (2020) divisions containing smaller municipalities within their boundaries (listed in table S2 in SM). Future research may use more precise spatio-temporal observations (as in Murillo-Sandoval et al. 2020) to further analyse the proposed moderation association.

One key point of discussion relates to the theory of how the three main variables can relate. One possibility is to conceive conflict intensity as a predictor, coca cultivation as a mediator, and forest loss as the outcome variable. However, formulating a hypothesis on how conflict intensity causes coca cultivation can be challenging. The conflict may partially explain coca cultivation (e.g. as a source of finance for insurgent groups), but not all coca cultivation is related to the conflict. Similarly, it is not easy to argue that the transition to peace — in and by itself — causes coca cultivation; the motivations to grow coca lie elsewhere (Dávalos and Dávalos 2020).

This leads to a second possibility, which is to conceive coca cultivation as a predictor, and conflict intensity as a moderator that weakens or strengthens the potential effect of coca cultivation on forest loss. If coca cultivation causes deforestation, as prior research suggests (e.g. Negret et al. 2019, Chadid et al. 2015), where would this be more likely to happen: in more peaceful or more violent locations? The decision of whether to expand the forest frontier to grow coca could thus depend on intensity of the conflict. The hypothesis that follows, therefore, is that conflict intensity moderates the association between coca cultivation and forest loss.

The use of interactions is not unique to this study. For example, the recent difference-in-differences analysis by Prem et al. (2020) includes interaction terms (noting that a coca-related indicator is not included in the interaction terms). In line with the present study, they report an increase in deforestation after the ceasefire in municipalities with a higher ‘coca suitability’ index (i.e. soil and climate suitable for coca cultivation). The present analysis expands this finding by formally formulating and testing the effect of the interaction between coca cultivation and conflict intensity on forest loss.
After the peace agreement, preventing the exacerbation of deforestation factors is crucial. The question is how. There is not only a need for stronger government and institutional frameworks to protect the forests (Prem et al. 2020, Clerici et al. 2020, Murillo-Sandoval et al. 2020), but also a need for true coordination between anti-drug, forest protection, and social and economic development policies. If farmers continue to see coca cultivation as a means to escape poverty (Dávalos and Dávalos 2020), and the forests represent opportunities to do so (Van Dexter and Visseren-Hamakers 2019), it is critical to implement not separate but rather integrated strategies. For instance, the Colombian government is currently planning to resume aerial spraying. If this type of enforcement actions ignore social and environmental factors, an increase in the number of destroyed crops may be a win in the war against drugs, but not necessarily in terms of sustainable development.

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Data availability statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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References

AGRONET 2020 Ministerio de Agricultura – Evaluaciones agropecuarias del sector agropecuario (https://www.agronet.gov.co/estadistica/Paginas/home.aspx?cod=59)
Alvarez M D 2003 Forests in the time of violence: conservation implications of the Colombian war J. Sustainable Forestry 16 47–68
Armenteras D, Cabrera E, Rodríguez N and Retana J 2013 National and regional determinants of tropical deforestation in Colombia Regional Environ. Change 13 1181–93
Baptiste B, Pinedo-Vásquez M, Gutierrez-Velez V H, Andrade G I, Viera P, Estupi n-Suárez L M, Londo no M C, Laurance W and Lee T M 2017 Greening peace in Colombia Nat. Ecol. Evolution 1 1–3
Castro-Nunez A, Mertz O, Buritica A, Sosa C C and Lee S T 2017 Land related grievances shape tropical forest-cover in areas affected by armed-conflict Appl. Geogr. 85 39–50
CBD 2020 The Convention on Biological Diversity – Colombia: Country Profile (https://www.cbd.int/countries/profile/default.shtml?country=CO)
Chad M, Dávalos L, Molina J and Armenteras D 2015 A Bayesian spatial model highlights distinct dynamics in deforestation from coca and pastures in an Andean biodiversity hotspot Forests 6 3828–46
Clerici N et al 2020 Deforestation in Colombian protected areas increased during post-conflict periods Sci. Rep. 10 1–10
Clerici N, Salazar C, Pardo-Díaz C, Jiggins C D, Richardson J E and Linares M 2019 Peace in Colombia is a critical moment for Neotropical connectivity and conservation: Save the northern Andes–Amazon biodiversity bridge Conservation Lett. 12 e12594
Cornell S E 2005 The interaction of narcotics and conflict J. Peace Res. 42 751–60
Croissant Y and Millo G 2019 Panel Data Econometrics With R (New York: Wiley)
DANE 2020a Departamento Administrativo Nacional de Estadística – Estadísticas por tem a (https://www.dane.gov.co/index.php/estadisticas-por-tema)
DANE 2020b Geovisor de Consulta de Codificación de la Divi pola (https://geoportal.dane.gov.co/)
Dion M L and Russler C 2008 Eradication efforts, the state, displacement and poverty: Explaining coca cultivation in Colombia during Plan Colombia J. Latin Am. Studies 40 399–421
Dávalos and Dávalos 2020 Social investment and smallholder coca cultivation in Colombia J. Development Studies 56 1118–40
Dávalos I M, Bejarano A C and Correa H L 2009 Disabling cocaine: Pervasive myths and enduring realities of a globalised commodity Int. J. Drug Policy 20 361–6
Dávalos I M, Bejarano A C, Hall M A, Correa H L, Corthals A and Espo o J 2011 Forests and drugs: Coca-driven deforestation in tropical biodiversity hotspots Environm. Sci. Technol. 45 1219–27
Dávalos I M, Sanchez K M and Armenteras D 2016 Deforestation and cocoa cultivation rooted in twentieth-century development projects Bioscience 66 974–82
Elhorst J P 2014 Spatial Panel Data Models (Berlin: Springer) pp 37–93
Etter A, McAlpine C, Wilson K, Phinn S and Possingham H 2006 Regional patterns of agricultural land use and deforestation in Colombia Agriculture Ecosyst. Environ. 114 369–86
Eufemia L, Bonatti M, Castro-Nunez A, Lana M, Morales H and Sieber S 2019 Colombia’s inadequate environmental goals. Science (New York, NY) 364 444–5
Fuhrer J C, Moore G R and Schuh S D 1995 Estimating the linear-quadratic inventory model maximum likelihood versus generalized method of moments J. Monetary Economics 35 115–57
GADM 2020 Administrative boundaries: Global Administrative Areas database, version 3.6. (https: //gadm.org/)
GFW 2020 Global Forest Watch – Natural forest in Colombia (https://www.globalforestwatch.org)
Guáqueta A 2005 Change and continuity in US–Colombian relations and the war against drugs J. Drug Issues 35 27–56
Hansen M C et al 2013 High-resolution global maps of 21st-century forest cover change Science 342 850–3
Ibanez M and Carlsson F 2010 A survey-based choice experiment on cocoa cultivation J. Development Economics 93 249–63
Landholm D M, Pradhan P and Kropp J P 2019 Diverging forest land use dynamics induced by armed conflict across the tropics Glob. Environ. Change 56 86–94
Metcalfe D, Armenteras D and Dávalos I M 2017 Spatial autocorrelation reduces model precision and predictive power in deforestation analyses Ecosphere 8 1–18
Millo G and Piras G 2012 spm: Spatial panel data models in R J. Stat. Software 47 1–38
Murillo-Sandoval P J, Van Dexter K, Van Den Hoek J, Wrathall D and Kennedy R E 2020 The end of gunpoint conservation: Forest disturbance after the Colombian peace agreement Environ. Res. Lett. 15 034033
Negret P J, Sonter L, Watson J E, Possingham H P, Jones K R, Suarez C, Ochoa-Quintero J M and Maron M 2019 Emerging evidence that armed conflict and coca cultivation influence deforestation patterns Biol. Conservation 239 1–8
ODC 2020 Observatorio de Drogas de Colombia – Sistema de Información de Drogas de Colombia (www.odc.gov.co/sidco)
Prem M, Saavedra S and Vargas J F 2020 End-of-conflict deforestation: Evidence from Colombia’s peace agreement *World Development* 129 1–11
Reyes L C 2014 Estimating the causal effect of forced eradication on coca cultivation in Colombian municipalities *World Development* 61 70–84
Rincón-Ruiz A, Correa H L, León D O and Williams S 2016 Coca cultivation and crop eradication in Colombia: The challenges of integrating rural reality into effective anti-drug policy *Int. J. Drug Policy* 33 56–65
Rincón-Ruiz A and Kallis G 2013 Caught in the middle, Colombia’s war on drugs and its effects on forest and people *Geoforum* 46 60–78
RNI 2020 Red Nacional de Información – Unidad para la Atención y la Reparación Integral a las Victimas (https://cifras.unidadvictimas.gov.co/Reporteador)
Salazar A et al 2018 The ecology of peace: Preparing Colombia for new political and planetary climates *Front. Ecol. Environ.* 16 525–31
Sánchez-Cuervo A M and Aide T M 2013 Consequences of the armed conflict, forced human displacement and land abandonment on forest cover change in Colombia: A multi-scaled analysis *Ecosystems* 16 1052–70
Thoumi F E 2002 Illegal drugs in Colombia: from illegal economic boom to social crisis *Annals Am. Acad. Political Social Sci.* 582 102–16
UNOCHA 2020 United Nations Office for the Coordination of Humanitarian Affairs – Colombia: Monitor – Mapa de Afectados (https://monitor.salurhantaria.co)
UNODC 2020 United Nations Office on Drugs and Crime – Alternative Development: Colombia (https://www.unodc.org/unodc/en/alternative-development/columbia.html)
Van Dexter K and Visseren-Hamakers I 2019 Forests in the time of peace *J. Land Use Sci.* 15 1–16
Viña A, Echarvarria F R and Rundquist D C 2004 Satellite change detection analysis of deforestation rates and patterns along the Colombia–Ecuador border *AMBIO: J. Human Environ.* 33 118–26
WRI 2020 Spatial database of planted trees (https://www.wri.org/publication/planted-trees)