An investment strategy to address biodiversity loss from agricultural expansion

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The landmark 2019 IPBES Global Assessment cited land-use change as the primary driver of biodiversity loss. A 2016 peace agreement in Colombia has led to increasing agricultural expansion into biodiversity-rich forests. We focus on the case of Colombia to demonstrate an approach to maximize the biodiversity benefits from limited conservation funding while ensuring that landowners maintain economic returns equivalent to agriculture. We apply a quantitative model that relates conservation investment to national biodiversity outcomes. Then we identify six regions with high potential return on investment by spatially modeling the risk of forest conversion and

the expected impact of conservation actions. Our results suggest that agricultural expansion, left unchecked, would increase national biodiversity loss by 38-52% by 2033, and that doubling investment is necessary to counteract this loss. Our approach can be broadly used to target investment to weigh development and biodiversity goals. We demonstrate the approach in Colombia with its accelerated social and environmental changes and show how the efficiency of conservation options can be improved by considering opportunity cost of conservation to communities whose livelihoods depend on agriculture. This approach can be applied to other contexts to examine development and policy priorities to estimate financial needs for achieving biodiversity goals.

Introduction

The United Nations Sustainable Development Goals (SDGs) aim to promote sustainable development, including biodiversity conservation[1]. However, biodiversity is declining globally[2–4], we have not succeeded in achieving the SDGs[5], and the COVID-19 pandemic has further delayed progress[6]. These problems compound the need for approaches that enable careful planning for biodiversity conservation while balancing development needs.

The 2016 peace agreement in Colombia[7] represents an opportunity for government, private, and civil society actors to examine interactions between biodiversity conservation (SDG 15) and human development (SDG 1). Colombia is a highly biodiverse country facing accelerated biodiversity loss after the end of five decades of armed conflict[7]. Socioeconomic changes caused by the peace agreement with the Revolutionary Armed Forces of Colombia (FARC) makes optimal allocation of conservation funds especially critical. The presence of FARC, and other armed groups, reduced human pressures on forests by preventing economic activities[8]. The withdrawal of FARC members from forests led to increased agricultural expansion and other legal and illegal activities, such as mining, oil extraction, infrastructure development and logging[8–13]. Indeed, the deforestation rate rose by 44% after the peace agreement[14] and a majority of Protected Areas (PAs) experienced increased deforestation rates[15]. With already high deforestation levels[9], this pressure has only heightened the importance of curbing the loss of biodiversity.

The economy in Colombia relies on large-scale agriculture, which has broad implications for sustainable development and biodiversity conservation. For example, trade agreements and agricultural subsidies favor large-scale oil palm cultivation, which represent a threat to biodiversity[16,17]. Additionally, the management of natural resources suffers from insufficient funding and unstable regulation[18,19]. A national focus on effective conservation planning, together with appropriate implementation, can help decision-makers balance agricultural expansion with forest preservation.

An estimate of the financial needs to protect Colombia's biodiversity is necessary to understand the tradeoffs inherent to decisions about biodiversity conservation and sustainable development. Understanding the economic costs of possible alternative decisions allows policy-makers to explore how funding choices could harmonize social and biodiversity needs. In this paper, we apply a quantitative model to predict Colombia's conservation funding needs. We expand a model used by Waldron et al. to predict biodiversity declines under various scenarios of human development, and how changes in financial resourcing of conservation can reduce these declines[20]. We demonstrate how to operationalize this model so decision-makers can use the relationship to determine how to address the timely and relevant conservation issue of post-FARC agricultural expansion.

We then identify how Colombia can target conservation funding while ensuring that landowners maintain economic returns to agriculture. In particular, we estimate the opportunity cost of agriculture as a proxy for the costs of conservation actions. By integrating our results with the STAR metric[21], a spatially explicit estimate of species recovery potential, we develop a prioritization map that permits policy-makers to target conservation actions toward regions where conservation benefits are high and economic impacts are low. Our approach demonstrates how to use the STAR metric as a benefit layer in a return-on-investment analysis, together with a proxy of conservation costs, to inform biodiversity conservation spending while ensuring economic benefits of agriculture.

Results

Predicting Colombia´s conservation funding needs post-FARC

We found that the expected biodiversity decline in Colombia post-FARC is 38%-52% greater than before the peace agreement, for the best-case and worst-case scenario of deforestation, respectively. To avoid this additional biodiversity loss, Colombia would have to invest 37-39 million USD annually in the best and worst-case scenarios of deforestation, respectively (Tables S1-S2). This means an increase in its conservation spending of 7.69-10.16 million USD per year. Avoiding this decline (preventing further loss) would require 61-63 million USD annually, which is more than twice the conservation spending before the peace agreement. These estimates are based on projections of agriculture and economic growth in Colombia, which permitted us to consider the biodiversity impacts of expected agricultural expansion and propose funding needs given a target level of biodiversity loss (see Methods).

Targeting funding to avoid additional biodiversity decline

Our strategy for targeting conservation funding involves first identifying regions with a high risk of forest conversion to agriculture. We used a two-step modeling process to estimate: 1) the general risk of forest conversion, and 2) the probability of forest conversion to different types of agricultural activities, if a parcel were transformed to agriculture. The types of agricultural activities that we considered are illegal coca cultivation and cattle ranching or other crops. Forecasting accuracy, tested by overall accuracy, was relatively high for both logistic regression models (83.69% and 73.10%, respectively). We checked for spatial autocorrelation using spatial correlograms (see Methods and Fig.S1).

For the first stage, we modeled the odds as the probability of forest conversion divided by the probability of the parcel remaining as forest (Fig.1a-c, continuous line over dashed line). For example, every additional km away from a road decreases the ratio of probabilities by 0.43%, but the change in the probability is smaller with every km, meaning that the effect of distance to roads is stronger for shorter distances. For the second stage of the model, the odds describe the ratio of the probability of forest conversion to coca crops to the probability of forest conversion to cattle and other crops (Fig.1d-e, green line over orange line).

We find that the odds of deforestation increase 3.05% with each additional inhabitant per km^2 and increase 21.29% for each km closer to an already deforested area, and 0.43% with each km closer to a road (Table 1). These results are particularly worrying in the current post-conflict context. As part of the peace agreement, a rural land reform has been proposed that will likely increase access to forest, including road development, to encourage agricultural development and extractive activities[22]. Our results highlight the need for careful zoning planning to lower deforestation impacts of development programs[11].

For deforested areas, we find that the odds (ratio of probabilities) of forest conversion to coca crops over cattle and other crops increases 3.29% for each additional inhabitant per km^2. This result is consistent with previous work on deforestation in coca-growing municipalities[23]. We find that the odds increase 6.47% for each additional km from a road. This means that *if* a parcel *were* deforested *to one of these* agricultural uses, the probability of transformation to cattle and other crops decreases with distance to roads, while the probability of transformation to coca increases. These results suggest that coca crops are grown in more isolated areas, away from roads, compared with cattle.

The presence of FARC was the most influential variable determining the fate of the deforested area, as the odds of forest conversion to coca crops over conversion to cattle or other crops in areas with presence of FARC is 308.04% higher than the odds in areas without FARC. This means that the relationships between predictors and probabilities of conversion to coca or cattle and other crop have the same direction for both types of agricultural activities, but the probability of conversion to coca cultivation, compared with cattle and other crops, is greater for parcels with FARC presence (Fig.1d-f).

We did not detect a significant difference in the odds of general forest conversion, or in the type of agricultural land use, for areas inside or outside a PA. This result is consistent with previous work which reports that national PAs do not prevent deforestation in remote areas, and that they can even increase coca crops, particularly in the Amazon and Pacific regions[9]. Indeed, previous work has reported higher deforestation levels inside PAs, especially after the peace agreement[8,15]. A lack of state presence that accompanies the withdraw of FARC and prevents illegal activities could explain this result[8,9,11,15].

Using our probability models and projected data on land use change and population density, we found that 20.46% of the forest in Colombia is at high risk ($P_{def} \geq 0.67$) of conversion in the post-conflict period, 16.31% is at medium risk ($0.33 \leq P_{def} < 0.67$), and 63.22% is at low risk ($P_{def} < 0.33$) (Fig.2a) (see Methods). We were able to predict forest conversion for 50.33% of land area of the country, encompassing the majority of the forested area in 2017, just after the peace agreement was signed.

High concentrations of forests at high risk of conversion were in the center and north of the country in the Andean and Caribbean natural regions, both densely inhabited regions with low percentage of forest coverage. The Pacific/Chocó natural region at the west of the country, a biodiversity hotspot, includes habitats with both high and low forest conversion risk. The low-risk areas largely occur in the south in the Amazon region, which is mostly covered in tropical rainforest and is not heavily populated (Table 2). These results by natural regions should be used with caution because deforestation patterns are highly heterogenous[24] and spatial variability can be masked by this aggregation. For example, the Amazon region have extensive areas of low risk and also small regions of high risk of deforestation[11].

We estimated the spatial variation of the cost of potential conservation interventions by calculating the Opportunity Cost of Conservation (OCC) as an approximation of the expected cost of compensating a land owner for avoiding conversion of their property[25]. We assumed that the sale value of a parcel is equal to its expected future cash flow, discounted to reflect the risk of these cash flows[26] (see Methods). We paired the outputs of our models of forest conversion and agricultural use(Fig.2b) with the expected annual returns of each agricultural activity to find that the great majority of forested area (85%) has a low level of OCC (< 3,174 USD/ha at 10% discount rate), 14.04% a medium level (> 3,174 and <6,348 USD/ha) while only 0.88% of the forest area has a high level of OCC (> 6,348USD/ha) (Table 4).

Consistent with the probability of forest conversion predictions, we found that the Andean region contains the highest mean OCC, reflecting the strong probability of agricultural conversion of the remaining forests. Following closely are the Pacific, the Caribbean and the Orinoquia regions. The Amazon region, the one with the lowest mean probability of agricultural conversion, the greatest forest cover percentage and the greatest forest area, has a lower OCC (Table 2).

Prioritizing areas to prevent forest conversion

We then paired our spatially explicit expected conservation cost (OCC) with estimates of expected benefit to explore how conservation investment could be prioritized in regions with the greatest expected return. We used the "Species Threat Abatement and Restoration" (STAR) metric[21], which is a spatially explicit measurement of the potential benefit for threatened species of actions to reduce threats and restore habitat for amphibians, birds and mammals[21] (see Methods). We used the agriculture-related threats portion of the STAR threat-abatement score ($\mathrm{STAR_T}$) to construct a benefit layer for our return-on-investment analysis.

We mapped STAR scores to areas of the country which were forested in 2017, the year immediately after the peace agreement was signed. We found that 63% of this area has low STAR scores, 30.80% has medium scores and only 6.03% has high scores (Table 4, see Methods) suggesting small regions of concentrated conservation benefit.

Similar to the distribution of conversion risk and OCC, higher STAR scores are concentrated in the Caribbean and Andean regions where the total forest area and percentage of forest is lower. This suggest that these regions are currently under high levels of agricultural threats and have great potential benefit from abating these agricultural threats. The very biodiverse Pacific region also has a high STAR score, especially in the border with the West Andes. Low STAR scores dominate in the Amazon and Orinoquia regions, where the mean risk of agricultural conversion is lowest.

We selected municipalities at high risk of forest conversion ($probability \geq 0.67$) that had more than 45% of their area in forested land to identify the top six focal zones of conversion risk in the three natural regions with the highest probability of forest conversion: Andean, Caribbean and Pacific (Table 3). Two of these focal zones are mountain formations in the Caribbean and Andean regions: Serranía de San Lucas, a forested massif; and Sierra Nevada de

Santa Marta, an isolated mountain range. The other focal zones are Western Antioquia, Telembí-Pacífico Sur, Buenaventura and Catatumbo. Some of these regions were previously FARC territories and are now suffering increased violence due to the lack of governance, which have the potential to increase deforestation rates[11] and difficult the implementation of conservation actions[8,12].

Within our six focal areas of high forest conversion risk, despite their high probability of conversion, only Buenaventura in the Pacific region has a high level of OCC. The lowest OCC are found in Western Antioquia in the Andean region, and in the mountain formations of Serranía de San Lucas and Sierra Nevada de Santa Marta in the Caribbean. The two remaining focal zones, Telembí-Pacífico Sur and Catatumbo, have medium levels of OCC (Table 3).

Contrary to the patterns found in forest conversion risk and OCC, the two mountain formations in our six focal areas of agricultural conversion risk have very different STAR scores. Sierra Nevada de Santa Marta shows the highest mean score, while Serranía de San Lucas has the lowest, even though both have similar probabilities of forest conversion. The areas with the highest conversion risk, Buenaventura and Western Antioquia, show the greatest STAR scores after Sierra Nevada de Santa Marta, although the score in Western Antioquia is much higher than that in Buenaventura.

To identify priority candidates for conservation investment, we classified each municipality with forest area in 2017 into one of nine groups according to its mean STAR score and OCC (Fig.2c). We also considered the percentage and absolute forested land area to cover the greatest area of forested land (Fig.S2a). The highest priority candidate areas are those that would yield high STAR gains at low OCC.

We found that two of the three focal zones with high STAR score municipalities have the least percentage and absolute area of forested land. These regions, Sierra Nevada de Santa Marta and Western Antioquia, also have all municipalities with low levels of OCC, indicating significant benefit to conservation investments. In contrast, Buenaventura, the third focal zone with high STAR scores municipalities, has the biggest percentage of forested land, which makes it advisable for conservation action, but also the highest OCC. From these regions, it appears that a counterbalance exists between forest area and level of OCC at the municipality level.

Telembí-Pacífico Sur shows a similar but less marked pattern. In this area, municipalities with medium to high STAR scores have a significantly large area of forest (less than Serranía de San Lucas) and percentage of forested land (less than Buenaventura) and show medium levels of OCC across all municipalities.

We found that the patterns between forest area and OCC does not apply to the focal zones in municipalities with medium STAR scores. Catatumbo and Serranía de San Lucas have similar proportions of municipalities with medium and low OCC despite the significant difference in its total forested land. The absolute forest area in Catatumbo is half of the forest area in Serranía de San Lucas, although its percentage area is just slightly smaller. Given the similarities in STAR scores and OCC and the variation in forest area, Serranía de San Lucas could be a better target of conservation action.

We calculated the funding that would be needed to protect the forested land in our focal zones of high agricultural conversion risk in order to compare it with the estimated national level of conservation investment needed to avoid the expected increase in biodiversity loss (Table 3 and Fig.S2c).

We found that Western Antioquia and Sierra Nevada de Santa Marta have the highest STAR scores and are the cheapest to protect (127 and 747 million USD, respectively), which makes them excellent candidates for conservation investment from a return-on-investment point of view. The total OCC in both areas together accounts for only a quarter of the necessary amount to avoid forest conversion in Telembí-Pacífico Sur or Buenaventura (3,303 and 3,280 million USD, respectively). Also, mean STAR scores within these both regions are high, or at least medium-high scores, but are either at a much higher risk or have much more forested land, resulting in higher OCC.

For regions with medium STAR scores, the protection of the forest in Catatumbo requires a smaller level of investment than in Serranía de San Lucas (1,478 and 2,476 million USD, respectively). However, Serranía de San Lucas contains a significantly larger area of forested land. Provided that the presence of FARC dissidents and deserters in Catatumbo is stronger, conservation actions could be more difficult to implement.

To maximize the impact of limited funding available for conservation, our return-on-investment analysis suggests that Sierra Nevada de Santa Marta and Western Antioquia, in the Caribbean and Andean natural regions, are priority targets for conservation spending within the country. These territories have the highest risk of expected forest conversion, while also being the regions with the lowest OCC and highest STAR scores without current presence of FARC dissidents and deserters. It should be recognized, however, that conservation investment in the other parts of Colombia will deliver additional reductions in species extinction risk that cannot be achieved by investing in conservation in Sierra Nevada de Santa Maria and Western Antioquia alone.

Discussion

Decision support approaches that facilitate biodiversity conservation and also consider development goals are urgently needed. We combine two recent high-profile theoretical approaches to conservation decision support, the Waldron model[20] of conservation investment and the STAR metric[21] of biodiversity impacts and demonstrate how a country could explore the biodiversity and economic consequences of potential investments. Focusing on Colombia, our approach shows how to maximize the biodiversity benefits from limited conservation funding while ensuring that landowners maintain returns equivalent to agriculture. In doing so, we provide a template for how national level decision makers can use available theory and data to consider the social and biodiversity consequences of their actions as they strive for a sustainable future.

Policy Implications and Challenges

Colombia has been identified as a high priority[28] but underfunded country for biodiversity conservation[18,19,29]. We show that due to the expected increased agricultural expansion and economic growth, the human pressures on the forests will likely accelerate biodiversity loss. To counteract this loss, Colombia would need to substantially increase its conservation spending. While our analyses are specific to Colombia, our approach can be applied to other landscapes. National and regional governments, private companies or landowners could use our approach to examine alternative development trajectories and estimate financial investment needs to achieve particular objectives (e.g. SDG goals), or cost of alternative land management scenarios.

Agricultural land cover has been projected to dramatically increase by 2050, driving severe loss of biodiversity[35]. The methods developed here offer an approach to identifying areas of greatest conservation returns on investment by balancing cost of conservation action, measured as opportunity cost for agriculture, and biodiversity impacts. Given the current need and opportunities for improved land management in Colombia, this approach is a powerful tool to harmonize increasing human development with conservation planning at this decisive moment of social and ecological transition.

Our results can help balance conservation costs with biodiversity protection needs in a rapidly changing context and inform funding choices. In a post-war context, the environment is at high risk of degradation because infrastructure is often prioritized, which can lead to environmental degradation, endangering the durability of peacebuilding efforts [31]. Our methodology can be adjusted to analyze potential consequences in biodiversity conservation costs of infrastructure development plans, which attracts extractive activities and agricultural expansion.

Our results can also assist in the planning of PAs. Currently in Colombia, the National Natural Park System is working to declare five new PAs, and to expand three more[32]. Evidence shows that more effective and lasting conservation outcomes are achieved when governance empowers local communities and support their environmental stewardship[33]. In fact, collective lands in Colombia, like indigenous reserves and Afro-Colombian lands, have already proved to be more effective in controlling deforestation than strict-use PAs[9]. Using our results, decision-makers can identify PAs that are currently failing to protect the biodiversity they hold, yet have great potential conservation impacts, and could benefit from a change in their governance scheme to indigenous and Afro-Colombian communities. By adapting our methodology to other contexts with particular goals, our methodology could be implemented to identify areas with high conservation costs and low potential biodiversity benefits. For example, it could be used in planning food-security corridors in tropical Africa as a way to balance forest conservation and livelihood needs of local communities that depend on agriculture[34], while preserving sites of low return on investment for farmers to biodiversity protection.

In conclusion, our novel approach to integrate spatially explicit methods of biodiversity risk with estimates of cost can be broadly applied to other contexts. The approach can be used to examine development trajectories and goals of a country to estimate gross financial needs to achieve biodiversity goals. It can also be useful in evaluating trade-offs in sustainable development and biodiversity goals to improve the efficiency of PA networks by considering opportunity cost of conservation to communities whose livelihoods depend on agriculture.

Methods

To estimate the potential increase in biodiversity decline and the national level of conservation investment needed to counteract it in post-conflict Colombia, we used a model developed by Waldron et al.[20]. This quantitative model predicts national biodiversity status change (the "biodiversity decline score" BDS) based on investment in conservation actions, in relation to human development pressures. The model uses seven predictors related to the economy of each country, its biodiversity status or dynamics and its conservation spending (see Waldron et al.[20]).

Scenarios

We used the Waldron et al. model to predict: 1) the expected increase in biodiversity decline immediately after the peace agreement (post-conflict period), 2) the conservation funding needed to prevent this additional decline, and 3) the investment necessary to avoid biodiversity decline. We used four scenarios to examine our questions.

The War BDS scenario was the baseline scenario that estimated the BDS of the last 12 years of the conflict, before the peace agreement in 2016. Predictor variables related to human pressures were from 4-5 years before to appropriately represent the lag in modeled effect[20]. We used the most recent available value of "strict-sense" conservation investment[20]. The next three scenarios examined post-conflict options and were compared to this War BDS scenario.

The Peace BDS scenario predicted the BDS for a 12-years period post-conflict. The predictor variables related to human pressures were from the 11-year period immediately after the peace agreement. We assumed the same conservation spending as for the War BDS. The Lower BDS scenario estimated the necessary investment to achieve the War BDS. This represented a situation where the biodiversity loss during the conflict did not change post-conflict. For this scenario, we held human pressures variables the same as in the Peace BDS scenario. The Prevented BDS scenario was exactly like the Lower BDS scenario, but we set a target of no biodiversity decline (BDS = 0).

We used the War and Peace BDS estimates to calculate the expected additional biodiversity decline post-conflict. Then, we used the model with data from Lower BDS scenario to calculate the investment needed to prevent any additional biodiversity decline post-conflict. Finally, we used data from the Prevented BDS scenario to estimate the conservation investment necessary to halt biodiversity decline in the post-conflict period.

Data for predictor variables

We modified the predictors related to agriculture and economic growth to examine anticipated changes in human pressures. This revision allowed us to consider the expected agricultural expansion, in the form of percentage of agricultural land and growth, and economic growth, as the Gross Domestic Product(GDP) and GDP growth. We also modified the function so that we could use it to estimate funding needs given a target BDS.

For the War BDS scenario data on GDP, GDP growth, and agricultural land area and growth was either available or easily computed. Data for GDP and percentage of agricultural land from 2001-2012 were obtained from The World Bank[35]. The agricultural land growth was calculated as the difference in the percentage of agricultural land between consecutive years. GDP growth was calculated with the GDP per capita from The World Bank[35].

For the Peace, Lower and Prevented BDS scenarios, we made projections about the predictors. For the GDP we used projections for 2017-2019, and for GDP growth for 2019-2022[36], and then selected an annual increase of the GDP growth of 0.3 percentage points for the remaining 5 years, corresponding to the most conservative estimate found in ref.[37]. We then used our estimates of GDP growth for the whole time period to calculate the GDP per capita for the last 10 years and used population projection to compute the GDP for the next 10 years.

To estimate the agricultural land and growth for the Peace, Lower BDS and Prevented BDS scenarios, we used projections on deforestation. We developed our model to reflect the immediate consequences in agricultural expansion and deforestation post-conflict. Thus, we estimated the percentage agricultural land area using projected values of deforestation[38]. We support this approach based on two observations. First, at least 90% of deforested land was transformed to agriculture during past years[39]. Second, forest transformation to agriculture has been more aggressive since the peace agreement[8,11,12]. Thus, the processes that fuel agricultural conversion are stronger. For each year we added the deforested area to the previous agricultural land area. We then calculated the yearly percentage agricultural land area and computed the agricultural growth as the difference between the agricultural growth of consecutive years. We took the minimum and maximum values of deforestation projections to create a best-case and a worst-case scenario.

We acknowledge that our use of the Waldron et al. model has limitations because we did not update all the predictors. Specifically, two “inertia” terms that account for the effect of biodiversity decline occurring immediately before the time period of interest[20]. The coefficients associated with these terms have a positive effect on the BDS, which means that a more intense decline in the past will increase the predicted biodiversity decline. Given the human pressures increase, the actual inertia terms are probably larger than the ones we used. Thus, the Peace BDS and the actual increase in biodiversity decline post-FARC may be larger.

The Model

To create a broad proxy for the expected cost of potential conservation interventions across Colombia, we estimated the opportunity cost of conservation (OCC) for agriculture at the 1 km^2 scale. We estimated OCC by building a spatially explicit probability model of forest conversion to agriculture and then paired it with the net present value of the expected return of different agricultural activities.

We calculated the OCC following the methodology proposed by ref.[25]. Their approach models the expected net present value of potential net rents resulting from agricultural uses of a forested parcel, while accounting for the probability of conversion to agriculture. Provided that each agricultural use k has its own annual expected return per area of land R_k, and that each parcel i has a probability of conversion P_{ik} from forest to agricultural use k, the expected value for a given discount rate δ is

$$\mathrm{OCC} = \sum_{i=1}^{\mathrm{I}} \sum_{k=1}^{\mathrm{K}} \mathrm{P}_{i,k} \frac{\mathrm{R}_k}{\delta} \qquad \text{Equation 1.}$$

Thus, the OCC of an area composed of several parcels is equal to the sum of the expected returns of the probable agricultural uses, weighted according to their own probability of conversion, in each of the parcels, summed across all of the parcels.

We calculated the OCC for forested areas in three steps. First, we built a probability model to obtain the general risk of forest conversion ($\mathrm{P}_{\mathrm{def}}$). Next, we built a second model that, given that a parcel had been transformed, predicted the probability of forest conversion to different types of agricultural activities ($\mathrm{P}_{\mathrm{ag}_k}$). We used both models to compute the total probability of conversion to each type of agricultural activity k in a parcel i ($\mathrm{P}_{ik} = \mathrm{P}_{\mathrm{def}_i} * \mathrm{P}_{\mathrm{ag}_{i,k}}$). We then estimated net present value of the expected return of each agricultural activity (R_k/δ) using literature and commercial prices and costs of agricultural products.

<u>Types of agricultural land use we modeled</u>

Our OCC model needed to represent relevant agricultural activities. Below we justify our selection of three types of agricultural land uses: cattle ranching, coca crops and other crops.

Cattle ranching is expected to be a major driver of post-conflict deforestation[12]. This activity has accounted for 50% of deforestation, in the form of forest conversion to pasture, in past years[39], and has significantly expanded post-conflict[8].

Illegal coca crops are expected to be, and have been observed to be, an important driver of post-conflict deforestation[13]. This activity is at risk of increase where the withdrawal of FARC and the absence of state presence left a "power vacuum" that facilitated other illegal groups to gain control of such crops in the territory[8,12,13]. Indeed, evidence shows that deforestation associated with coca cultivation increased as the conflict became less intense[40].

Other crops were grouped into a single category with cattle ranching due to their small percentage contribution to forest conversion in our time frame (3%), relative to cattle ranching and coca crops (47% and 50%). We proxy for the extent of all other crops by using data on the distribution of three relevant agricultural products in the post-conflict period: cacao, oil palm and coffee. Cacao crop has high potential in most of the key post-conflict areas in Colombia, so it could have a major role in the peace transition[41]. Oil palm is important for its steep increase during the last few years[13], to the point that Colombia is now the largest producer in South America[42]. The relevance of coffee resides in its impact on rural population, given that coffee crops are the only source of income to approximately 563,000 families and generates over 726,000 rural jobs[43].

Landscape features data

We selected 10 factors relevant to deforestation in Colombia to model the probability of forest conversion: proximity to roads, presence of FARC (binary: presence or no presence), population density, slope[24], elevation, proximity to deforested areas, proximity to rivers, to mining areas, and to oil wells, and belonging to national and regional PAs[11]. National PAs restrict economic activities and are managed by the System of National Natural Parks, while regional PAs allow multiple-use activities and are managed by regional environmental authorities[9,44]. We did not include indigenous reserves or Afro-Colombian lands.

We used deforested areas from 1990-2000 from IDEAM[45], the water bodies map from the Department of Environment and Sustainable Development[46], and maps from IGAC[47] to calculate distance to already deforested areas, rivers, roads, mining areas and oils wells. The elevation map was obtained from NASA's Land Topograghy digital images[48]. We calculated the slope using the elevation map. We computed population density as the mean value from 2000-2012 of the 32 mainland administrative departments from DANE[49] (see Table S3 for dataset details). We obtained a presence of FARC map from PARES[50]. All spatial data calculations were performed in QGIS 3.12.2 and R 3.6.2.

Forest conversion and Agricultural use model

We used a two-stage modeling process. First, we modeled the probability of an area being deforested by any driver (not exclusively due to agricultural expansion), using the total deforested area in the country in a 12-year period to parametrize our model(forest conversion model). Second, we modeled the probability that the deforestation was due to a particular agricultural activity(agricultural use model). To parametrize this second model, we used patches of land that were indeed transformed to an agricultural use in this same 12-year period. We combined these two models to obtain the probability that a patch of land was deforested to a particular agricultural activity.

We used a binomial logistic regression model to build our forest conversion model, which estimates the probability of forest conversion (P_{def}). We used the land cover change from

2000-2012 across the country, available from IDEAM[45], and reclassified each pixel cell as forested or transformed. We used bayesglm function from the R arm package[51].

For our agricultural use model, we built a second binomial logistic regression model to estimate $\mathrm{P}_{\mathrm{ag}_k}$, the probability of conversion to each type of agricultural activity(cattle and other crops or coca crops) for a parcel that had been transformed. We employed data on forested areas in 2000 that had been converted by 2012. The coca crops cover map was obtained from BIESIMCI[52]. For the cattle ranching map we used forested areas converted to pastures. Our other crops data contained temporary and permanent crops from land cover map[46].

It should be noted that in logistic regression models the probability of conversion does not change in a linear fashion, but the ratio of probabilities(odds) does. For the agricultural model, the odds describe the probability of conversion to coca crops over the joint probability of conversion to cattle and other crops. This implies that the variation between the probabilities, not the probability itself, changes constantly.

To check for spatial autocorrelation, we plotted spatial correlograms of the models' residuals with Moran's I. Since spatial patterns were present, we subsampled for pixel cells at a minimum distance of 20 km between points, which reduced the spatial effects adequately for our purposes, although it was most effective for the forest conversion model (Fig.S1). We checked for collinearity in the predictor variables using variance inflation factor scores and removed the variables with a value > 3 (distance to mines and oil wells) (Tables S4 and S5). We performed tenfold cross-validation to test the predicting accuracy of the models. This process splits the data into ten subsets and repeatedly fits the model with the data of nine of the subsets to compare its predictions with the remaining subset. We calculated the percentage of correct prediction (overall accuracy) each time and computed the mean as the final forecasting accuracy indicator.

Estimation of annual net rent

We estimated net present values of the expected return of each agricultural activity to estimate the OCC of forested areas in Colombia. For cattle, we used annual net rent from a beef company[53]. Total annual net rent for other crops was calculated as the weighted average of the net rents for oil palm, cacao and coffee proportional to their land area in 2016 and 2017[54–56]. For coca crops we used the average net profit for farmers who sell coca leaves[57]. We selected three values of discount rate: 5%, 10% and 20% (Tables S6 and S7).

Predicting forest conversion and OCC

To predict the probability of forest conversion, we updated our spatial information about roads, deforested areas from 2007 to 2017[45], FARC presence as the presence of FARC dissidents and deserters in 2017[50], and population density as the mean population density by departments from 2017 to 2023[58]. Together with the annual net rent for each agricultural activity, we used the probabilities of conversion of the two models to compute the OCC, or expected land value, of each forested pixel cell for the three discount rates, using eq. 1.

We recognize that the simplified national context of social violence when predicting the probability of forest conversion can limit the application of our results. Our models included FARC presence, and we used the presence of dissidents and deserters in this forecasting stage. However, this ignores other criminal groups that might influence the risk of forest conversion, particularly into coca crops, due to the “power vacuum” left by the withdraw of FARC and lack of state presence[12]. Since we overlooked the potential impact of other criminal groups, the probability of forest conversion, particularly into coca crops, could have been underestimated.

This would imply an underestimation of the OCC in the areas with presence of these other criminal groups.

We used the rural cadastral values[59] to validate our OCC results by comparing our predicted mean land values by administrative departments in the country. Although rural cadastral values might not reflect the illegal coca crops values, it was, to the best of our knowledge, the best available data for our purposes.

The STAR metric

The STAR metric is a measurement of the potential benefit to threatened and Near Threatened species of actions aimed at reducing threats and restoring habitat[21]. The metric can be disaggregated spatially using the area of habitat for each species, showing the proportional potential contributions of conservation actions in particular regions. We focused on the STAR threat-abatement score ($STAR_T$) only. This $STAR_T$ can be further disaggregated by threat according to the contribution of each threat to the species' risk of extinction, which allows analysis of potential abatement of species extinction risk by particular activities at particular locations. We took advantage of this trait and used the $STAR_T$ metric in a specialized way, focusing on the threats posed by agriculture only of all the species with area of habitat in Colombia. This resulted in 475 species considered (246 amphibians, 172 birds and 57 mammals), of which 169 are Vulnerable, 124 Near Threatened, 130 Endangered, and 52 Critically Endangered. Agriculture accounted for 52% of the total $STAR_T$. This focus on agriculture includes annual and perennial non-timber crops, wood and pulp plantations, and livestock farming and ranching, so we treated land converted to cattle and crops in the same way even though each land use type has different impacts on species.

The use of the STAR metric has some limitations associated with the spatial distribution of the threat due to agriculture. First, STAR is based on documented ongoing and expected future threats to the species according to the IUCN Red List. The majority of documented threats are ongoing, thus the majority of species threatened by agriculture are already being negatively impacted. This causes uncertainty in the assumption that avoiding further agricultural conversion will reduce species extinction risk, as additional activities to mitigate the impact of current agricultural activities on the species may also be required. Nevertheless, species assessed as threatened by agriculture are known to be vulnerable to this pressure, meaning that they would almost certainly suffer negative impacts under future agricultural expansion.

Second, there is uncertainty in the potential spatial distribution of agricultural expansion. Therefore, the STAR metric as we used it helped us identify sites with urgent potential benefits of avoiding agriculture. This could underrepresent territories of great biodiversity value that are not currently impacted by agriculture, like the Amazon region.

Prioritization maps

We wanted to achieve a coarse methodology that could help decision makers focus national conservation funding to the territories with the most potential benefits of halting forest conversion to agriculture. To pair the STAR scores with our modeled OCC, we divided the total range of STAR scores and OCC into high, medium and low values. Given the distribution of STAR scores, we divided the total range in logarithmic scale. We classified each forested pixel cell into one of nine combinations of STAR scores and OCC. This analysis was later translated to the municipality resolution by calculating the mean STAR score and mean OCC of all forested pixel cells in each municipality, and applying the same classification systems used at the pixel resolution. The distributions of aggregated STAR scores and OCC at the municipality resolution follow a similar pattern to the distribution by pixel cell, with small differences due to the grouping of the values in means (see Fig. S2 b-c).

Data availability

We used data from Waldron et al. (2017)[20] to predict Colombia´s conservation funding needs post-FARC. We used data from Mair et al. (2021)[21] for the STAR metric in Colombia for agriculture. All other datasets were derived from the following public domain resources: GDP, GDP growth and agricultural land area maps were obtained from The World Bank Open Data, https://data.worldbank.org/. Elevation maps were obtained from NASA's Land Topography, https://visibleearth.nasa.gov/images/73934/topography. Forest cover and deforested areas maps were obtained from Sistema de Monitoreo de Bosques y carbono -SMBYC-, http://smbyc.ideam.gov.co/MonitoreoBC-WEB/reg/indexLogOn.jsp. Rivers, cattle ranching and other crops, roads, mining areas and oils wells maps were obtained from the Department of Environment and Sustainable Development and Instituto Geográfico Agustín Codazzi-IGAC-, http://www.siac.gov.co/catalogo-de-mapas. Population density was obtained from the National Department of Statistics-DANE-, https://www.dane.gov.co/index.php/estadisticas-por-tema/demografia-y-poblacion/censo-general-2005-1#estimaciones-demograficas-linea-base-2005 and https://www.dane.gov.co/index.php/estadisticas-por-tema/demografia-y-poblacion/proyecciones-de-poblacion. Coca crops maps were obtained from Sistema Integrado de Control de Cultivos Ilícitos-BIESIMCI-, https://www.biesimci.org/index.php?id=124. Protected Areas maps were obtained from Sistema de la Información Ambiental de Colombia -SIAC-, http://www.siac.gov.co/catalogo-de-mapas.

Code availability

Code that supports the findings of this study is available at https://github.com/camilagupi/Colombia_AISTABLFAE_2020_2.git.

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Author contributions Statement

C.G.P. and GD.I. led on analysis, development and manuscript drafting. L.M. and L.R.G. contributed to conceptual development and data acquisition. F.H. and J.S. contributed to the acquisition of the STAR data. D.M. contributed to the conceptual development of the work and provided Waldron et al. model data. All authors edited and revised the manuscript.

Competing Interests Statement

The authors declare no competing interests.

Tables

Table 1. Variables used in binomial logistic regression analysis of forest conversion to agriculture in Colombia.

	Forest conversion		Agricultural use	
Predictor	Coefficient	p-value	Coefficient	p-value
Intercept	-4.6565	2.03 e-6*	2.5735	0.01162*
FARC presence	0.3147	0.48800	1.4062	0.01089*
Population density	0.7438	0.00443*	0.7833	0.00273*
Elevation	-0.1697	0.40661	-0.4872	0.06274**
Distance to deforested areas	-6.3053	6.83 e-7*	2.2182	0.18078
Distance to roads	-0.9069	0.00146*	2.2892	0.01818*
Tenfold cross-validation				

Overall accuracy	83.69%	73.10%

Table 2. Probability of forest conversion, Opportunity Cost of Conservation at 10% discount rate, and STAR score for the five natural regions in Colombia.

	Probability of forest conversion		OCC, $\delta = 10\%$ (USD/ha)		STAR score	
Regions	Mean	St.deviation	mean	St.deviation	mean	range
Andean	0.729	0.193	2,500	1,279	3.66	0-201.68
Caribbean	0.648	0.246	2,400	1,012	4.18	0-76.82
Pacific	0.517	0.294	2,400	2,000	2.36	0-242.79
Orinoquia	0.391	0.297	2,000	1,598	0.15	0-31.39
Amazon	0.113	0.199	800	1,297	0.06	0-22.22

Table 3. Probability of forest conversion, mean Opportunity Cost of Conservation (OCC) at 10% discount rate, STAR score, absolute and percentage forested area and total OCC necessary to cover the total forested area for focal areas of forest conversion risk in Colombia.

Focal zone	Natural region	Mean Probability of conversion	Mean OCC (USD/ha)	Mean STAR score	Forest area (%)	Forest area (thousand ha)	Total OCC, $\delta =$ 10% (million USD)
Buenaventura	Pacific	0.76	6,534	3.17	79.99	502	3,280
Telembí-Pacífico Sur	Pacific	0.74	4,286	1.04	65.09	771	3,303
Western Antioquia	Andean	0.72	2,664	9.58	45.80	453	127
Serranía de San Lucas	Caribbean and Andean	0.69	2,967	0.43	48.39	834	2,476
Catatumbo	Andean	0.69	3,350	0.57	44.42	441	1,478
Sierra Nevada de Santa Marta	Caribbean	0.67	1,874	13.61	27.74	399	747

Table 4. Classification of Opportunity Cost of Conservation and STAR scores.

Group	OCC (USD/ha)			Total STAR score
	$\delta = 5\%$	$\delta = 10\%$	$\delta = 20\%$	
Low	0 – 6,348	0 – 3,174	0 – 2,116	0 – 0.026
Medium	6,348 – 12,696	3,174 – 6,348	2,116 – 4,232	0.026 – 2.51
High	12,696 – 19,045	6,348 – 9,523	4,232 – 6,349	2.51 – 242

Figure Legends

Figure 1. Main variables for the probability of forest conversion and conversion to agricultural land uses models. For a given plot, only the variable in the horizontal axis varies.

All other predictor variables are set at the mean. Solid yellow and black lines (a-c) represent the probability of forest conversion, with and without FARC, respectively. Orange and green lines (d-f) represent the probability of forest conversion to particular agricultural, dashed lines for parcels without FARC presences and solid lines for parcels with FARC presence.

Figure 2. Maps of (a) Forest conversion risk in Colombia, (b) Opportunity Cost of Conservation (OCC) at 10% discount rate, and (c) classification of municipalities by STAR scores and OCC.

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