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An investment strategy to address biodiversity loss from agricultural expansion

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The landmark 2019 Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES) Global Assessment cited land-use change as the primary driver of biodiversity loss. The 2016 peace agreement in Colombia has led to increasing agricultural expansion into biodiversity-rich forests. We have focused 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 applied a quantitative model that relates conservation investment to national biodiversity outcomes. Then we identified six regions with high potential return on investment by spatially modelling 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.

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[1], and the COVID-19 pandemic has further delayed progress[5]. These problems compound the need for approaches that enable careful planning for biodiversity conservation while balancing development needs.

The 2016 peace agreement in Colombia[6] 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[6]. 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[7]. 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[7–12]. Indeed, the deforestation rate rose by 44% after the peace agreement[13] and a majority of protected areas (PAs) experienced increased deforestation rates[14]. With already high deforestation levels[8], 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 favour large-scale oil palm cultivation, which represents a threat to biodiversity[15,16]. Additionally, the management of natural resources suffers from insufficient funding and unstable regulation[17,18]. 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 trade-offs 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 study, we applied a quantitative model to predict Colombia's conservation funding needs. We expanded 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[19]. We demonstrate here 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 identified how Colombia can target conservation funding while ensuring that landowners maintain economic returns to agriculture. In particular, we estimated the opportunity cost of agriculture as a proxy for the costs of conservation actions. By integrating our results with the species threat abatement and restoration (STAR) metric[20], a spatially explicit estimate of species recovery potential, we have developed 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

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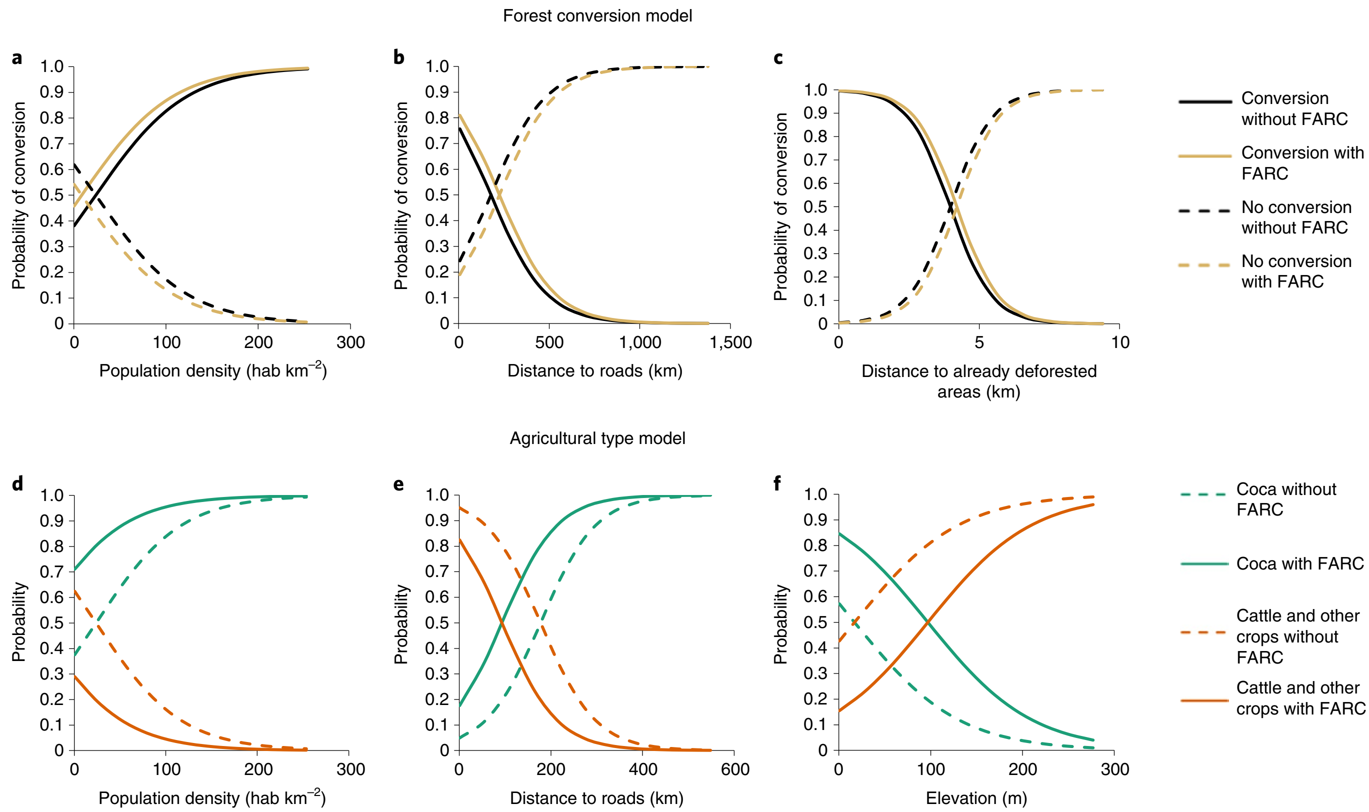

Fig. 1 | Probability of forest conversion and agricultural land-use models. a–f, Main variables considered to evaluate the probability of forest conversion (**a**–**c**) and conversion to agricultural land-use (**d**–**f**) models: population density (**a**,**d**), distance to roads (**b**,**e**), distance to already deforested areas (**c**) and elevation (**f**). For a given plot, only the variable in the horizontal axis varies. All other predictor variables are set at the mean. hab, inhabitant.

conservation costs, to inform biodiversity conservation spending while ensuring the 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- and worst-case scenarios of deforestation, respectively. To avoid this additional biodiversity loss, Colombia would have to invest US$37–39 million annually in the best- and worst-case scenarios of deforestation, respectively (Supplementary Tables 1 and 2). This means an increase in its conservation spending of US$7.69–10.16 million per year. Avoiding this decline (preventing further loss) would require US$61–63 million 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 modelling 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 Extended Data Fig. 1).

For the first stage, we modelled the odds as the probability of forest conversion (P_{def}) divided by the probability of the parcel remaining as forest (Fig. 1a–c, continuous line over dashed line). For example, every additional kilometre away from a road decreases the ratio of probabilities by 0.43%, but the change in the probability is smaller with every kilometre, 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–f, green line over orange line).

We found that the odds of deforestation increase 3.05% with each additional inhabitant per square kilometre, 21.29% for each kilometre closer to an already deforested area and 0.43% with each kilometre 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[21]. Our results highlight the need for careful zoning planning to lower deforestation impacts of development programs[10].

For deforested areas, we found 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 square kilometre. This result is consistent with previous work on deforestation in coca-growing municipalities[22]. We found that the odds increase 6.47% for each additional kilometre 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

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	2.03×10^{-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	6.83×10^{-7}*	2.2182	0.18078
Distance to roads	−0.9069	0.00146*	2.2892	0.01818*
Overall accuracy after tenfold cross-validation (%)	83.69		73.10	

*$P<0.05$, **$P<0.1$.

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 deforested areas, as the odds of forest conversion to coca crops over conversion to cattle or other crops in areas with the 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 crops 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 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[8]. Indeed, higher deforestation levels inside PAs, especially after the peace agreement, have been previously reported[7,14]. A lack of state presence accompanying the withdrawal of FARC and preventing illegal activities could explain this result[7,8,10,14].

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 of conversion ($P_{def}\geq0.67$) 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 also the Methods). We were able to predict forest conversion for 50.33% of the 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 centre and north of the country in the Andean and Caribbean natural regions, both densely inhabited regions with a low percentage of forest coverage. The Pacific natural region in 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 heterogeneous[23] and spatial variability can be masked by this aggregation. For example, the Amazon region has extensive areas at low risk and also small regions at high risk of deforestation[10].

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[24]. 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[25] (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 (<US\$3,174 ha^{-1} at 10% discount rate (δ)), 14.04% at a medium level of OCC (>US\$3,174 ha^{-1} and <US\$6,348 ha^{-1}), while only 0.88% of the forest area has a high level of OCC (>US\$6,348 ha^{-1}; Table 3).

Consistent with the probability of forest conversion predictions, we found that the Andean region has 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, with the lowest mean probability of agricultural conversion, the greatest forest cover percentage and the greatest forest area, has the lowest 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 STAR metric[20], 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[20] (see Methods). We used the agriculture-related threats portion of the STAR threat-abatement score ($STAR_T$) to construct a benefit layer for our return-on-investment analysis.

We mapped STAR scores to areas of the country that 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 3, see also 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 are lower. This suggests that these regions are currently under high levels of agricultural threat 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 region 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 ≥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 4). 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 has the potential to increase deforestation rates[10] and make difficult the implementation of conservation actions[7,11].

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 OCCs 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 4).

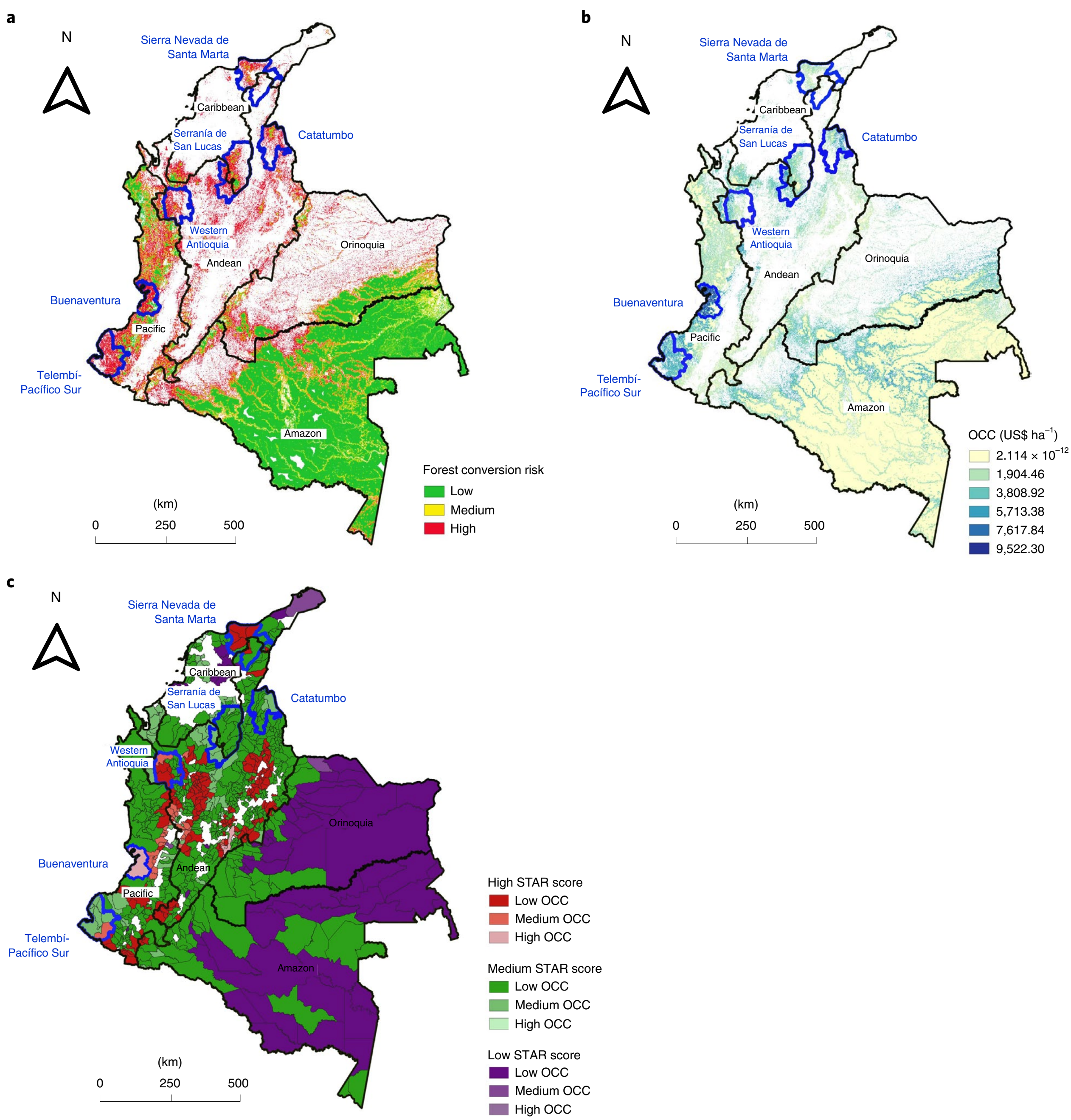

Fig. 2 | Results from the forest conversion and opportunity cost for conservation model to target conservation funding accross Colombia. a–c, Maps of forest conversion risk in Colombia (**a**), OCC at 10% discount rate (**b**) and classification of municipalities by STAR scores and OCC (**c**).

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 highest 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 of forested land in each municipality to cover the greatest area of forested land (Extended Data Fig. 2a). 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 lowest 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 notable benefit to conservation investments. In contrast, Buenaventura, the third focal zone with high STAR score 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

Table 2 | Probability of forest conversion, OCC at 10% discount rate and STAR score for the five natural regions in Colombia

Region	Probability of forest conversion		OCC (US$ ha^{-1}), $\delta = 10\%$		STAR score	
	Mean	s.d.	Mean	s.d.	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 | Classification of OCC and STAR scores

Group	OCC (US$ ha^{-1})			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

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 do 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 considerable difference in their 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 for conservation action.

We calculated the funding that would be needed to protect the forested land in our focal zones of high agricultural conversion risk to compare with the estimated national level of conservation investment needed to avoid the expected increase in biodiversity loss (Table 4 and Extended Data Fig. 2c).

We found that Western Antioquia and Sierra Nevada de Santa Marta have the highest STAR scores and are the cheapest to protect (US$127 million and US$747 million, 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 (US$3,303 million and US$3,280 million, respectively). Also, the mean STAR scores within both these regions are high, or at least medium-to-high, but are either at a much higher risk or have much more forested land, resulting in a higher OCC.

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

To maximize the impact of the 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, respectively, 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 have combined two recent high-profile theoretical approaches to conservation decision support, the Waldron model[19] of conservation investment and the STAR metric[20] of biodiversity impacts, and demonstrated 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[26] but underfunded country for biodiversity conservation[17,18,27]. We have shown that due to the expected increased agricultural expansion and economic growth, human pressures on the forests will likely accelerate biodiversity loss. To counteract this loss, Colombia would need to substantially increase its conservation spending. Although 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 the financial investment needs to achieve particular objectives (for example, SDGs) or the cost of alternative land management scenarios.

Agricultural land cover has been projected to dramatically increase by 2050, driving severe biodiversity loss[28]. The methods developed here offer an approach to identifying areas of greatest conservation returns on investment by balancing the cost of conservation action, measured as the 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 for harmonizing 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[29]. Our methodology can be adjusted to analyse the 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[30]. Evidence shows that more effective and lasting conservation outcomes are achieved when governance empowers local communities and supports their environmental stewardship[31]. In fact, collective lands in Colombia, such as indigenous reserves and Afro-Colombian lands, have already proved to be more effective in controlling deforestation than strict-use PAs[8]. Using our results, decision-makers can

Table 4 | Probability of forest conversion, mean 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 (US$ ha^{-1})	Mean STAR score	Forest area (%)	Forest area (10^3 ha)	Total OCC (US$ million), $\delta = 10\%$
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

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 to plan food-security corridors in tropical Africa as a way to balance forest conservation and the livelihood needs of local communities that depend on agriculture[32], while preserving sites of low return on investment for farmers to biodiversity protection.

In conclusion, our novel approach to integrating spatially explicit methods of biodiversity risk assessment with estimates of cost can be broadly applied to other contexts. The approach can be used to examine the development trajectories and goals of a country to estimate the gross financial needs to achieve biodiversity goals. It can also be useful for evaluating trade-offs in sustainable development and biodiversity goals to improve the efficiency of PA networks by considering the OCC 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.[19]. 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[19].

Scenarios. We used the Waldron et al.[19] model to predict (1) the expected increase in biodiversity decline immediately after the peace agreement (the 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 baseline scenario was the War BDS scenario, which 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 the modelled effect[19]. We used the most recent available value of 'strict-sense' conservation investment[19]. The following three scenarios examined post-conflict options and were compared with this War BDS scenario.

The Peace BDS scenario predicted the BDS for a 12-year 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 the human pressure variables the same as in the Peace BDS scenario. The Prevented BDS scenario was exactly the same as 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 the 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, agricultural land area and agricultural land area growth were either available or easily computed. The data for GDP and the percentage of agricultural land from 2001–2012 were obtained from The World Bank[28]. The agricultural land growth was calculated as the difference between the percentage of agricultural land of consecutive years, and GDP growth was calculated from the GDP per capita data from The World Bank[28].

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 the GDP growth projections for 2019–2022 (ref. [33]), and then selected an annual increase in the GDP growth of 0.3 percentage points for the remaining 5 years, corresponding to the most conservative estimate found in ref. [34]. 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 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[35]. We support this approach based on two observations. First, at least 90% of deforested land was transformed to agriculture during past years[36]. Second, forest transformation to agriculture has been more aggressive since the peace agreement[7,10,11]. 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 percentage difference between the agricultural land area of consecutive years. We took the minimum and maximum values of deforestation projections to create best- and worst-case scenarios.

We acknowledge that our use of the Waldron et al.[19] 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[19]. 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 increase in human pressures, 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 OCC for agriculture at the 1 km^2 scale. We estimated the 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 Naidoo and Adamowicz[24]. 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

$$\mathrm{OCC} = \sum_{i=1}^{I} \sum_{k=1}^{K} P_{i,k} \frac{R_k}{\delta} \tag{1}$$

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 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 (P_{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 (P_{ag_k}). We used both models to compute the total probability of conversion to each type of agricultural activity k in a parcel i ($P_{ik} = P_{\mathrm{def}_i} \times P_{\mathrm{ag}_{i,k}}$). We then estimated the net present value of the expected return of each agricultural activity (R_k/δ) using literature and commercial prices and the costs of agricultural products.

Types of agricultural land use modelled. 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[11]. This activity has accounted for 50% of deforestation, in the form of forest conversion to pasture, in past years[36], and has considerably expanded post-conflict[7].

Illegal coca crops are expected to be, and have been observed to be, an important driver of post-conflict deforestation[12]. 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 gaining control of such crops in the territory[7,11,12]. Indeed, evidence shows that deforestation associated with coca cultivation increased as the conflict became less intense[37].

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%) compared with cattle ranching and coca crops (47 and 50%, respectively). 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. The 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[38]. Oil palm is important owing to its steep increase in cultivation during the last few years[12], to the point that Colombia is now the largest producer in South America[39]. The relevance of coffee resides in its impact on the rural population, given that coffee crops are the only source of income for approximately 563,000 families and generates over 726,000 rural jobs[40].

Landscape features data. We selected ten 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[23], elevation, proximity to deforested areas, to rivers, to mining areas and to oil wells, and belonging to national and regional PAs[10]. 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[8,41]. We did not include indigenous reserves or Afro-Colombian lands.

We used deforested areas from 1990 to 2000 from the Instituto de Hidrología, Meteorología y Estudios Ambientales (IDEAM)[42], the water bodies map from the Department of Environment and Sustainable Development[43] and maps from the Instituto Geográfico Agustín Codazzi (IGAC)[44] to calculate the distance to already deforested areas, rivers, roads, mining areas and oil wells. The elevation map was obtained from NASA's (National Aeronautics and Space Administration's) Land Topography digital images[45], and we calculated the slope using the elevation map. We computed population density as the mean value of the 32 mainland administrative departments from 2000 to 2012 using data from the Departamento Administrativo Nacional de Estadística[46] (DANE; see Supplementary Table 3 for dataset details). We obtained a map showing the presence of FARC from the Fundación Paz y Reconciliación (PARES)[47]. All spatial data calculations were performed using software QGIS (https://www.qgis.org/en/site/, version 3.12.2) and R (https://www.r-project.org/, version 3.6.2).

Forest conversion and agricultural use model. We used a two-stage modelling process. First, we modelled 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 modelled 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 to 2012 across the country, available from IDEAM[42], and reclassified each pixel cell as forested or transformed. We used the bayesglm function from the R arm package[48].

For our agricultural use model, we built a second binomial logistic regression model to estimate P_{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 the Sistema Integrado de Control de Cultivos Ilícitos (BIESIMCI)[49]. For the cattle ranching map, we used forested areas converted to pasture. Our other crop data contained temporary and permanent crops obtained from a land cover map[43].

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*. Because 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 (Extended Data Fig. 1). 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; Supplementary Tables 4 and 5). We performed tenfold cross-validation to test the prediction 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 predictions (overall accuracy) each time and computed the mean as the final forecasting accuracy indicator.

Estimation of annual net rent. We estimated the 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[50]. The 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 (refs. [51–53]). For coca crops, we used the average net profit for farmers who sell coca leaves[54]. We selected three discount rate values: 5, 10 and 20% (Supplementary Tables 6 and 7).

Predicting forest conversion and OCC. To predict the probability of forest conversion, we updated our spatial information on roads, deforested areas from 2007 to 2017 (ref. [42]), FARC presence as the presence of FARC dissidents and deserters in 2017 (ref. [47]), and population density as the mean population density by department from 2017 to 2023 (ref. [55]). 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 to coca crops, due to the 'power vacuum' left by the withdrawal of FARC and lack of state presence[11]. Because we overlooked the potential impact of other criminal groups, the probability of forest conversion, particularly to 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[56] to validate our OCC results by comparing our predicted mean land values by administrative department in the country. Although rural cadastral values might not reflect the value of illegal coca crops, they were, 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[20]. 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 ($\mathrm{STAR_T}$) only. The $\mathrm{STAR_T}$ score 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 $\mathrm{STAR_T}$ metric in a specialized way, focusing on the threats posed by agriculture only on all the species with an 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 $\mathrm{STAR_T}$. 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, the STAR metric is based on documented ongoing and expected future threats to the species according to the International Union for Conservation of Nature 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 under-represent 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 direct national conservation funding to the territories with the most potential benefits of halting forest conversion to agriculture. To pair the STAR scores with our modelled 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 the 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 system 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 (Extended Data Fig. 2b,c).

Reporting Summary. Further information on research design is available in the Nature Research Reporting Summary linked to this article.

Data availability

We used data from Waldron et al.[19] to predict Colombia´s conservation funding needs post-FARC. We used data from Mair et al.[20] 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). Maps of forest cover and deforested areas were obtained from the Sistema de Monitoreo de Bosques y Carbono (SMBYC; http://smbyc.ideam.gov.co/MonitoreoBC-WEB/reg/indexLogOn.jsp). Maps of rivers, cattle ranching and other crops, roads, mining areas and oil wells were obtained from the Department of Environment and Sustainable Development and 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 BIESIMCI (https://www.biesimci.org/index.php?id=124). PA maps were obtained from the Sistema de la Información Ambiental de Colombia (SIAC; http://www.siac.gov.co/catalogo-de-mapas). Source data are provided with this paper.

Code availability

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

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Author contributions

C.G.-P. and G.D.I. led on analysis, development and manuscript drafting. L.M. and L.R.G. contributed to the conceptual development and data acquisition. F.H. and J.S. contributed to the acquisition of STAR data. D.M. contributed to the conceptual development of the work and provided the model data of Waldron et al.[19]. All authors edited and revised the manuscript.

Competing interests

The authors declare no competing interests.

Additional information

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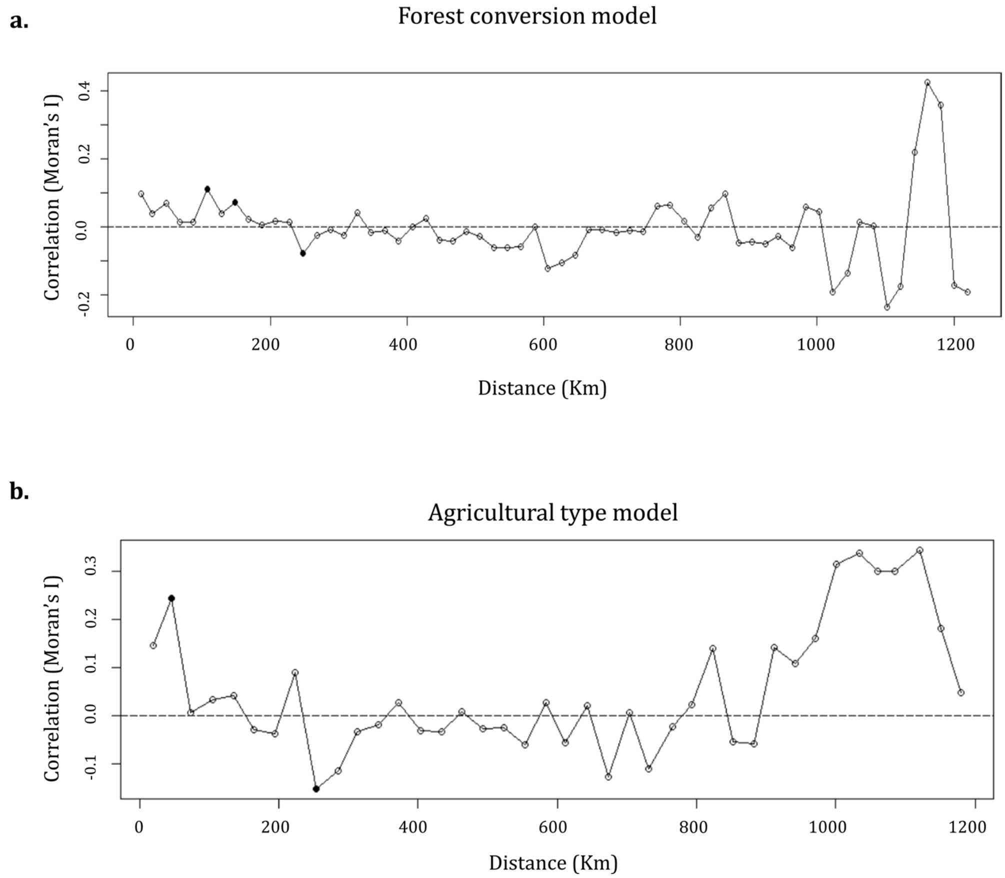
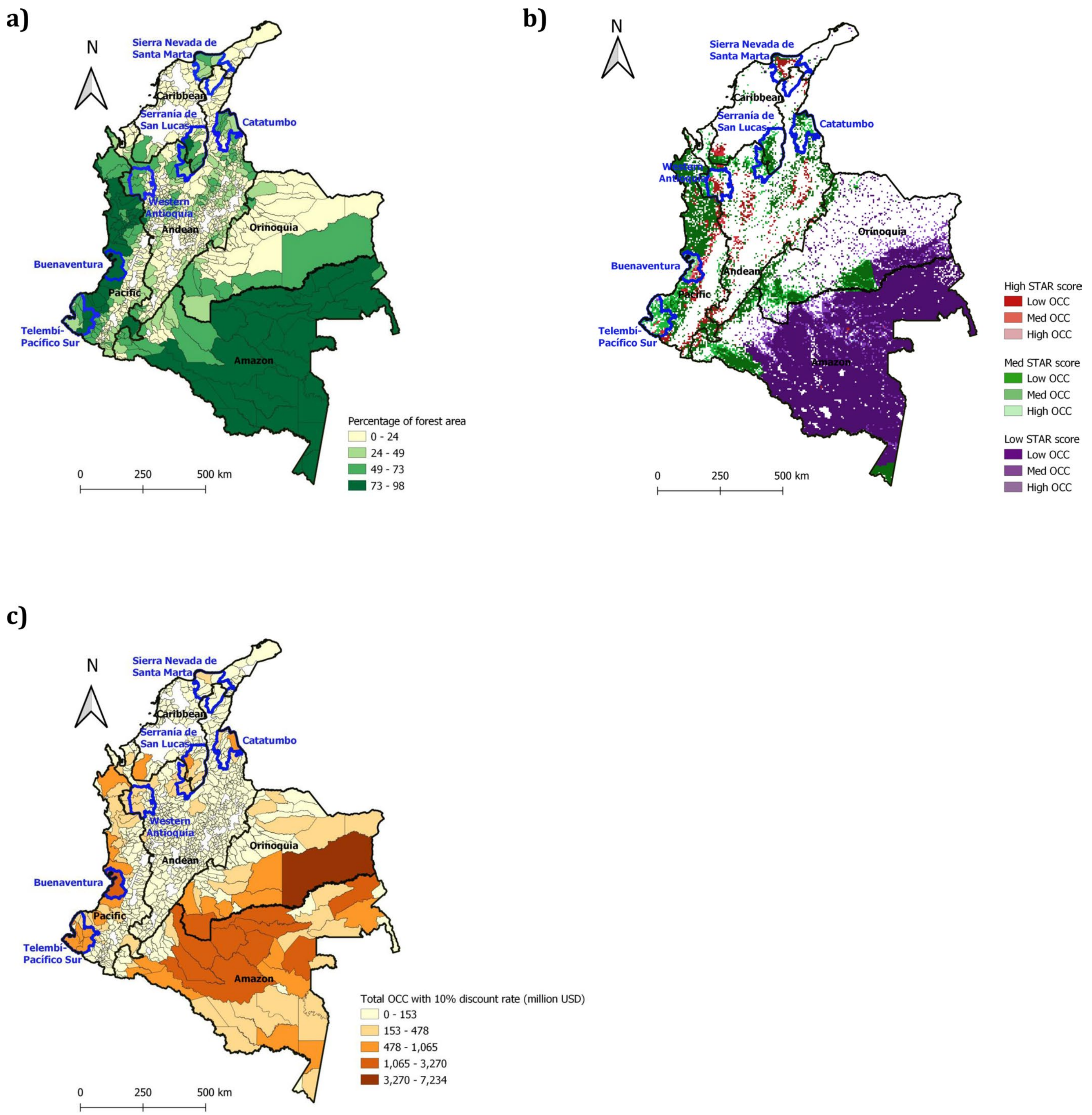


Extended Data Fig. 1 | Spatial correlograms. Spatial correlograms of probability of forest conversion to agriculture models' residuals after correcting for spatial patterns.



Extended Data Fig. 2 | Maps. Maps of (a) Percentage of forest area by municipality, (b) Classification at the pixel cell level based on OCC and STAR score, and(c) Total OCC necessary to protect all the remaining forest by municipality.

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Ecological, evolutionary & environmental sciences study design

All studies must disclose on these points even when the disclosure is negative.

Study description	We modeled biodiversity decline within Colombia using an existing quantitative model that predicts national improvements in biodiversity decline based on investment in conservation actions, in relation to human development pressures. We estimated the opportunity cost of agriculture by building a spatially explicit probability model (using a binomial logistic regression model) of forest conversion to agriculture and then paired it with the net present value of the expected return of different agricultural activities. We paired these results with estimates of species recovery potential to inform a prioritisation map.
Research sample	For the spatial analysis, we used existing datasets. GDP, GDP growth and agricultural land area maps were obtained from The World Bank Open Data. Elevation maps were obtained from NASA's catalog of images. Forest cover and deforested areas maps were obtained from Sistema de Monitoreo de Bosques y carbono -SMBYC-. 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-. Population density was obtained from the National Departmen of Statistics-DANE-. Coca crops maps were obtained from Sistema Integrado de Control de Cultivos Ilícitos-BIESIMCI-. Protected Areas maps were obtained from Sistema de la Información Ambiental de Colombia -SIAC-.
Sampling strategy	We did not use statistical test to pre-determine sample size, since the study analyses a whole country. However, we used spatial correlograms of the models' residuals to confirm that there was no spatial autocorrelation in the sample.
Data collection	Not applicable to our study, since we used existing datasets.
Timing and spatial scale	Not applicable to our study, since we used existing datasets.
Data exclusions	No data were excluded from the analysis.
Reproducibility	Since we studied opportunity cost of agriculture and forest conversion risk in Colombia, no replication was performed.
Randomization	Not applicable to our study, which predicts forest conversion risk and opportunity cost of agriculture.
Blinding	Not applicable to our study.

Did the study involve field work? ☐ Yes ☒ No

Reporting for specific materials, systems and methods

We require information from authors about some types of materials, experimental systems and methods used in many studies. Here, indicate whether each material, system or method listed is relevant to your study. If you are not sure if a list item applies to your research, read the appropriate section before selecting a response.

Materials & experimental systems

n/a	Involved in the study	
☒	☐	Antibodies
☒	☐	Eukaryotic cell lines
☒	☐	Palaeontology and archaeology
☒	☐	Animals and other organisms
☒	☐	Human research participants
☒	☐	Clinical data
☒	☐	Dual use research of concern

Methods

n/a	Involved in the study	
☒	☐	ChIP-seq
☒	☐	Flow cytometry
☒	☐	MRI-based neuroimaging