



Large differences between observed and expected Ecuadorian deforestation from 2001 to 2009: a counterfactual simulation approach

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Abstract

Ensuring the integrity of the world's forests is indispensable for mitigating climate change, combatting biodiversity loss, and protecting the livelihoods of rural communities. While many strategies have been developed to address deforestation across different geographic scales, measuring their impact against a fluctuating background of market-driven forest loss is notoriously challenging. In this article, we (1) assess deforestation in Ecuador using a dynamic, counterfactual baseline that excludes non-market factors, (2) identify periods of reduced and excess deforestation, and (3) assess the economic consequences of associated CO₂ emissions using the social cost of carbon metric. We construct a counterfactual market-forces-only reference scenario by simulating heterogeneous profit-seeking agents making satisficing land-use allocation decisions under uncertainty. The model simulates a reference scenario for 2001–2022, a period encompassing dollarization, the beginning of a constitution granting inalienable rights to nature, and the launch of the largest payments for ecosystem services program in Ecuador's history. On this period, total deforestation was approximately 20% lower than expected in a market-forces-only scenario (9540 vs. 12,000 km²). The largest deviation occurred in 2001–2009, when observed deforestation was 43.6% lower than expected (3720 vs. 6590 km²). From 2010 onwards, deforestation appears to be market-driven. We assess the economic value of avoided CO₂ emissions at US \$5.7 billion if the reduction is permanent, or US \$3.1 billion considering a 1% risk of loss from 2022 onwards. We discuss contributing factors that likely shaped periods of reduced and excess deforestation and stress the need to use realistic baselines.

Keywords Deforestation · Social cost of carbon · Ecuador · Counterfactual modelling

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Introduction

Global forest area has decreased by roughly 10% in the last 60 years, with the most serious losses occurring in the tropics (Hansen et al. 2013; Estoque et al. 2022). In addition to their intrinsic value, tropical forests account for more than half of Earth's terrestrial biodiversity (FAO 2022), provide local ecosystem services to approximately 1.5 billion people (Lewis et al. 2015), and generate global benefits like carbon sequestration and climate stabilization (Fuss et al. 2021). Unfortunately, gross carbon loss from tropical forests is accelerating, with a doubling from 2001 to 2019 that appears to be driven mainly by agricultural expansion (Feng et al. 2022). South America is a leading contributor (Hansen et al. 2013; Feng et al. 2022).

The integrity of the world's forests, tropical and otherwise, depends heavily on how we interact with and use them (Díaz et al. 2019; Purvis et al. 2019; IPCC 2022). In recent decades, various initiatives operating at international, regional, and local levels have been developed to combat deforestation and mitigate its impacts, such as the UN-REDD+ Program, LEAF Coalition, Zero-Deforestation agreements, and Ecuador's Socio Bosque program (de Koning et al. 2011; Un-REDD programme 2016; Pasiecznik and Savenije 2017; LEAF Coalition 2023). However, these schemes often lack explicit criteria for monitoring and assessment, making it difficult to evaluate their effectiveness (Garrett et al. 2019). Even when systematic assessments are employed, such as the Monitoring, Reporting, and Verification (MRV) system used by REDD+ projects, they are typically based on static before-after comparisons of carbon stocks and emissions (IPCC 2022), an approach which neglects existing trends and shifting drivers of forest loss. Although it is well-established that using inappropriate baselines can significantly overestimate emissions reductions (West et al. 2020; West et al. 2023), defining sound "business-as-usual" baselines can be immensely challenging, especially on forest-relevant timescales. As a result, most assessments lack plausible counterfactual reference scenarios that clearly describe what would have happened in the absence of an intervention (Köthke et al. 2014; Bos et al. 2017; Gifford 2020).

Ecuador stands out as one of the world's most fascinating case studies in forest and biodiversity protection (Coral et al. 2021). Situated at the biogeographic confluence of the Andes, the Amazon basin, and the Tumbes-Chocó-Magdalena hotspot (Iturralde-Pólit et al. 2017), Ecuador is a megadiverse country (Kleemann et al. 2022) that for decades recorded the highest deforestation rates in South America, losing more than half of its forest area since the 1970s (Bilborrow et al. 2004; Tapia-Armijos et al. 2015). Figure 1 compares the forest conditions in 1990

and in 2022 based on public data from the Ministerio del Ambiente, Agua y Transición Ecológica (2024). The figure illustrates a substantial reduction in the extent of natural forest cover over the 32-year period, as well as the spatial distribution of the forest loss. Deforestation hotspots are concentrated in the Ecuadorian Amazon basin, particularly along the so-called *Troncal Amazónica*, a major road that crosses the region from north to south. Additionally, two other affected areas were identified along the northern and southern borders in this region. Intense deforestation was also observed in the northern coastal region, while the remaining forests in the central and southern coastal areas, as well as in the western Andean mountain range, experience comparatively lower levels of deforestation. The country has a disproportionately high share of species on the IUCN red list (Rodrigues et al. 2014). Although logging, mining, and oil concessions all make significant contributions (Ojeda Luna et al. 2020; Sierra et al. 2021), agricultural expansion (pasture and croplands) remains the primary driver of deforestation and biodiversity loss in Ecuador (Mena et al. 2011; Knoke et al. 2016).

Following overlapping periods of economic upheaval and nearly a decade (1997–2008) of decentralized natural resource management reform which occurred mainly at the canton (a spatial administrative unit similar to a county) level (Kauffman and Terry 2016), in 2008, Ecuador became the first country in the world to constitutionally guarantee specific, legally enforceable rights to nature (Asamblea constituyente del Ecuador 2008; Tanasescu 2013; Kotzé and Villavicencio Calzadilla 2017). These include the right to exist and persist (Article 71), to restoration (Article 72), and to provide environmental benefits to people and communities (Article 74) (Kotzé and Villavicencio Calzadilla 2017; Nieto Sanabria 2017).

Empowered by this last provision in particular, Ecuador's Environmental Ministry swiftly implemented a program, Socio Bosque, with the dual goals of conservation and poverty alleviation (de Koning et al. 2011; Nieto Sanabria 2017). This program offers economic incentives to private owners and communities who willingly pledge to conserve and restore forest and *páramo* for at least 20 years (Vanacker et al. 2018). As of May 2023, nearly 17,000 km² have been enrolled, representing more than 6% of continental Ecuador's total land area, and payments have been disbursed to some 120,000 beneficiaries (Ministerio del Ambiente, Agua y Transición Ecológica 2023).

Taken together, it is a remarkable story. A nation that suffered from an economic crisis and was unable to halt the decline of its natural forests decided to undertake a bold legal experiment to constitutionally recognize the rights of nature. The country succeeded in implementing it and immediately launched the largest-ever payments for

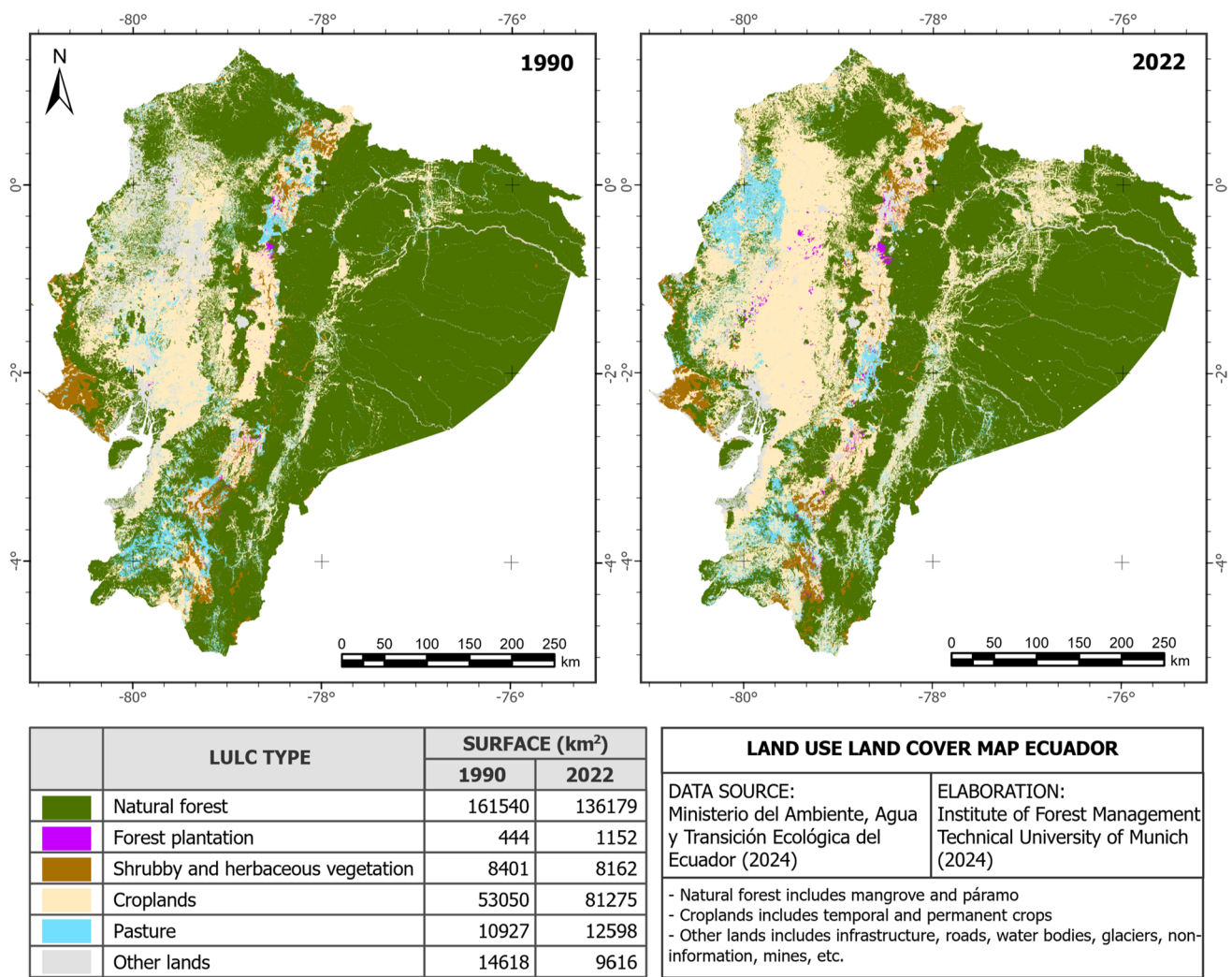


Fig. 1 Land-use land-cover (LULC) map of Ecuador illustrating the status of natural forest in 1990 and 2022. Based on data from Environmental, Water and Ecological Transition Ecuadorian Ministry (Ministerio del Ambiente, Agua y Transición Ecológica 2024)

ecosystem services program in its history. Despite garnering well-deserved attention from scholars, policymakers, and the media, relatively few efforts have been made to systematically quantify the aggregate impact of these changes on national-scale deforestation trends (but see Mohebalian and Aguilar 2016; Eguiguren et al. 2019; Fischer et al. 2021).

In this study, we apply a new method to assess deforestation trends in Ecuador against a dynamic counterfactual baseline, and assess the economic value associated with periods of excess (i.e. above-baseline) and reduced (below-baseline) deforestation using published estimates of the social cost of carbon (SCC). The baseline scenario is designed to reflect the level of deforestation attributable to market forces only (i.e. what would have occurred in a counterfactual scenario where external factors, such as policy interventions, are absent). Deviations between the market-forces-only baseline and observed deforestation levels are

assumed to result from these external factors. We investigate the following questions:

- Q1 Does the observed deforestation deviate from the market-oriented deforestation trajectory?
- Q2 Are the deviations between observed and counterfactual deforestation associated with non-market factors at the country scale?
- Q3 What is the economic value of CO₂ emissions associated with excess or reduced deforestation relative to the counterfactual market-forces-only baseline?

To construct a dynamic, counterfactual baseline, we adopt an approach recently introduced by Knoke et al. (2023) consisting of a behaviourally consistent land-use allocation model in which profit-seeking agents make satisficing decisions under future uncertainty. This approach is based on

three assumptions: (a) forest loss is driven by the transformation of land use, mainly into agriculture; (b) decision-makers seek satisfactory and sufficient (“satisficing”), rather than maximal, profits; and (c) the individual expectations of land managers drive land-use allocation decisions. Building on heterogeneous expectations of land managers about market prices, agricultural productivity, and corresponding profits, this approach establishes a suitable deforestation baseline for estimating the social value of excess and avoided deforestation.

Material and methods

We compare observed forest cover losses for Ecuador (2000–2022) from Global Forest Watch (2024) with simulated forest losses from a market-oriented counterfactual land-use allocation model. Because Ecuador’s forest cover is dominated by natural forest, we interpret any forest loss as a permanent removal, neglecting that some forests might re-establish naturally or be replanted on previously cleared lands (see Bos et al. 2017 for a similar assumption and Feng et al. 2022 for empirical support).

Background and expected deforestation trends

Between 1990 and 2000, Ecuador experienced a series of interlinked economic crises (Beckerman 2001) and political instability (Conaghan and La Torre 2008; Kauffman and Terry 2016), culminating in a strong currency depreciation and the adoption of the US dollar as the national currency (“dollarization”). Because currency depreciations and political instability tend to enhance deforestation in developing countries (Didia 1997; Arcand et al. 2008), it is reasonable to assume that this period featured higher deforestation levels than would be expected from purely microeconomic land-use allocation decisions. Conversely, however, this period of national political instability created space for a series of local, canton-level natural resource management reforms, such as measures to combat deforestation in rural watersheds, which were pursued from 1997 to 2008. Kauffman and Terry (2016) showed that these reforms were attempted by 94 of Ecuador’s 221 cantons, collectively representing about 50% of the country’s area (see Fig. 1 in Kauffman and Terry 2016). Combined with the currency stabilization from 2000 onwards, the reforms may have caused reduced deforestation.

In 2006, the election of president Rafael Correa marked a turning point in Ecuador’s political landscape (Conaghan and La Torre 2008). Among other things, it opened the door to ratifying a new constitution granting inalienable rights to nature and establishing the Socio Bosque conservation program, both in 2008 (Krause and Loft 2013). Intuitively,

one would expect these developments to exert a downward pressure on deforestation rates. However, the 2007–2020 period featured a novel combination of large-scale conservation incentives alongside an expansion of “neo-extractivist” activities (Coral et al. 2021), opposing trends that may have counteracted one another.

Counterfactual land-use allocation to model expected deforestation

We adopted an approach to counterfactual land-use allocation modelling recently introduced by Knoke et al. (2023), which aims to support evaluations of broad country-scale non-market drivers of deforestation by simulating plausible reference scenarios corresponding to deforestation levels that would be expected in the absence of any policy intervention (i.e. if land-use allocation decisions were driven exclusively by microeconomic factors). The broad country-level counterfactual deforestation simulation is non-spatial. We simulate land-use allocation decisions (including forest conversion to alternative LULC types) for hypothetical regions of Ecuador, assuming groups of agents with heterogeneous expectations concerning economic profits and uncertainties. These simulations are likely to be really independent from observed deforestation and would thus be well-suitable as reference scenarios. We start with the premise that land-use allocation processes at the regional level, even when agents act individually, are often influenced by suggestions and advice from others. Salas-Molina et al. (2023) have recently described such simulation approaches in general. Our model is parsimonious in that it uses only input information on agricultural productivity and market prices and costs. The possible variation of the expectations of different land managers is simulated based on random Monte Carlo simulations, assuming that individual land managers perceive future productivities and profits differently. The random process assigns more or less pessimistic profit expectations to more or less risk-averse land managers, so that decision-makers’ heterogeneity is represented. The core principle of our simulation uses a distance function expressing the current economic dissatisfaction of the individual members of a group of agents. We minimize this function across multiple heterogeneous expectations concerning the current and future land-use profits by simulating an appropriate land-use re-allocation.

To address such decision processes, including multiple decision-making agents at the regional scale, we generated counterfactual reference scenarios by simulating a large number of land-use allocation decisions made by heterogeneous groups of agents responding to microeconomic signals. The difference between the empirical (actually observed) deforestation levels and the reference (i.e. simulated counterfactual baseline) represents reduced or excess deforestation, which

we use as a basis for calculating the economic value of both avoided and additional carbon emissions, using published estimates for SCC (see Supplementary Methods 4.2 and Supplementary Table 8 in Knoke et al. 2023). We used an emission factor of 108 Mg C hectare⁻¹ (derived from data in Harris et al. 2012).

In this application, agents represent land manager groups making satisficing decisions under uncertainty in response to subjective profit expectations. Uncertainty encompasses volatility of market prices, productivity fluctuations, and potential crop losses caused by natural hazards and sudden political changes. In our model, Ecuadorian land managers would consider multiple possible future profits. Our approach implies satisficing decisions, which means that land managers gradually improve their current land-use profits by seeking a compromise land-use allocation that promises “sufficient” outcome levels in all possible future states of the world. To achieve this, an individual land manager would consider two types of information: (1) expected profits under the current land-use allocation and (2) the best achievable profits expected under a different allocation (for multiple possible future profit scenarios). The potential for improvement is represented by the difference between (2) and (1), which shows the degree of land manager dissatisfaction with current profits. In contrast to a previous non-stochastic model (Knoke et al. 2020), we use a wide range of stochastic profit scenarios to account for the heterogeneity of individual expectations (Grêt-Regamey et al. 2019). This implies that not all land managers would contribute equally to LULC changes, but mainly those who perceive the greatest potential for improving their profits (i.e. those who experience the largest dissatisfaction with their current profits). Individual land managers are clustered into groups to represent potential regional heterogeneity, and we assume that such groups arrange their land-use allocation to minimize their maximum dissatisfaction across multiple future profit expectations over time, considering their heterogeneous profit expectations. Individual land managers’ subjective economic expectations are represented as profit scenarios p , consisting of a profit vector for seven LULC types generated using Monte Carlo simulation (i.e. random draws from regionally simulated profit probability distributions).

$$R_{...p} = E(R_{...}) + u \cdot sd - r_{\#} \cdot (u + l) \cdot sd \tag{1}$$

where $R_{...p}$ represents the random profits of a specific LULC type under profit scenario p in a given period, $E(R_{...})$ denotes the mathematical expectation value of the profit expressed in US\$ per hectare, the variable u is a multiplier to obtain the upper interval limit ($u = 1$), while sd represents the standard deviation of the profits, $r_{\#}$ a uniformly distributed random number ($0 \leq r_{\#} \leq 1$), and l acts as second multiplier to obtain lower interval limit ($l = 2$).

The standard deviations sd were derived empirically as root means square errors (RMSE) of regression trend lines, parameterized using FAO data on gross production values. The decisions made by landowner groups are satisficing because they do not aim to maximize profits under expected conditions but instead seek a satisfactory and sufficient land-use allocation even under worst-case conditions across multiple future expectations. Satisficing allocations are identified using a modified version of the robust optimization approach described by Knoke et al. (2020), adjusted to incorporate heterogeneous and stochastic profit expectations. Each land manager group’s objective function minimizes a measure we call dissatisfaction D_p , defined as the difference between the highest potential profit R_p^* (\$ ha⁻¹) under assumed best-case conditions in one specific profit scenario p , and the assumed actually achievable profit obtained through a given future LULC composition R_p , being R_{p*} the lowest individually assumed profit (\$ ha⁻¹)

$$D_p = \frac{R_p^* - R_p}{R_p^* - R_{p*}} \cdot 100 \tag{2}$$

R_p is obtained as follows,

$$R_p = N_{Ti}R_{Np} + Df_{Ti}R_{Dp} + P_{Ti}R_{Pp} + C_{Ti}R_{Cp} + H_{Ti}R_{Hp} + S_{Ti}R_{Sp} + O_{Ti}R_{Op} \tag{3}$$

with $N_{Ti} + Df_{Ti} + P_{Ti} + C_{Ti} + H_{Ti} + S_{Ti} + O_{Ti} = 1$ (negative area proportions excluded)

where $N_{Ti}R_{Np}$ represents the future proportion of *natural forest* multiplied by the profits of natural forest in profit scenario p , subject to the condition $0 \leq N_{Ti} \leq N$, where N denotes the current proportion of natural forest. $Df_{Ti}R_{Dp}$ describes the future proportion of *deforested* areas (forest conversion to agriculture) multiplied by the profits of deforestation in profit scenario p ($0 \leq Df_{Ti} \leq N$). $P_{Ti}R_{Pp}$ is the future proportion of *pasture* multiplied by the profits of pasture in profit scenario p , $C_{Ti}R_{Cp}$ is the future proportion of *cropland* (annual crops) times profits of cropland in profit scenario p , $H_{Ti}R_{Hp}$ stands for the future proportion of *permanent crops* times profits of permanent crops in profit scenario p , $S_{Ti}R_{Sp}$ denotes the future proportion of *forest plantations* multiplied by the profits of forest plantations in profit scenario p , and $O_{Ti}R_{Op}$ signifies the future proportion of *other land* times the profits of other land (profits are assumed to be zero for other land-use types).

Because each land manager-member in a group is assigned several random profit scenarios, their dissatisfaction with a given land allocation also varies. The simulation-optimization model selects a target land-use portfolio that minimizes the maximum dissatisfaction D_p for the group as a whole. The current land-use allocation is then incrementally adjusted over the course of a 30-year time

horizon to approach the target portfolio. Agents consider allocations across seven LULC types, including natural (i.e. non-plantation) forest N_{Ti} . Conversions away from natural forests N_{Ti} are counted as forest loss L_i . To obtain overall reference deforestation levels L_t , we average L_i across all 50 groups for each year of the simulation.

$$L_t = (1 \div 50) \cdot \sum_i L_i \tag{4}$$

$$L_i = A \cdot (N - N_{Ti}) \cdot k \tag{5}$$

where L_i represents the area of natural forest lost for land manager group i (ha year⁻¹), A stands for the total land area of a country (ha), and N_{Ti} signifies the desired future proportion of natural forest after T years, with the condition $0 \leq N_{Ti} \leq N$, being N the current proportion of natural forest (with $0 \leq N \leq 1$). k represents a factor that takes into account for the planning horizon ($k = 1 \div T$), and T is the planning horizon, assumed to be 30 years ($T = 30$).

For each year of the study period, we simulated decisions by $n = 50$ land manager groups, each consisting of individual members, who are differentiated from one another by the profit scenarios they have been assigned.

After calibrating the model using historical FAO deforestation data for 1990–2000 (FAO Statistics 2022), we compared model predictions with empirical forest loss data for the study period to identify deviations between observed deforestation levels and the reference levels that would be expected to arise from microeconomic decision-making alone (see Knoke et al. 2023 and their supplementary information for more details).

As the calibration period coincided with a period of pronounced political and currency instability in Ecuador, our model was calibrated conservatively. Tables 1 and 3 provide the upper and lower ranges of profit expectations (numbers with standard deviation as units) and the coefficients of variation used for deforestation and natural forest areas that we obtained as a result of calibration.

Table 1 Calibration. First two periods (1990–1994; 1995–1999) were used to calibrate the model by varying u , l , and the variation coefficient, vc , for the profits from deforestation areas and natural forest in order to achieve an acceptable fit of reported and simulated forest losses. u and l define the

Upper limit (standard deviations)	Lower limit (standard deviations)	Variation coefficient vc in %		Maximum proportion in % in 2049 (proportion 2019 in parentheses)
u	l	Deforestation	Forest	$(C + H)^{max}$
1	2	50	35	13.8 (10.1)

Economic valuation using the social cost of carbon

In the final step, we analyzed deviations between observed and expected deforestation as additional or avoided carbon emissions, which we valued economically using published SCC estimates. Following Groom and Venmans (2023), we define SCC as the present value of the social cost of climate damages associated with an additional tonne of emitted CO₂:

$$SCC_t = \sum_t^\infty (1 + r)^{-t} \cdot D_t \tag{6}$$

where D_t is the temperature-dependent marginal damage in USD associated with an additional unit of CO₂ emitted and r is a constant discount rate. We adopted conservative SCC_t estimates from the United States Government (2021) for $r = 0.03$ and assume D_t to increase at a constant annual rate of 0.0202 (United States Government 2021); see Knoke et al. (2023) and their supplementary material for details. We calculate the present value of avoided emissions (Groom and Venmans 2023) over time horizon T as:

$$V = \sum_{t=0}^{T=19} (1 + r)^{-t} \cdot E_t \cdot SCC_t = \sum_{t=0}^\infty (1 + r)^{-t} \cdot S_t \cdot D_t \tag{7}$$

where E_t represents the social benefit (cost) associated with reduced (excess) deforestation, and S_t represents the aggregate avoided (additional) emissions, assumed to stabilize at the end of T :

$$S_t = \sum_0^t E_t \tag{8}$$

We account for the climate benefits associated with delayed (rather than absolutely avoided) emissions by assuming a constant annual probability ρ (here, 1%) that carbon stocks will revert to their initial values after T :

$$V^* = \sum_{t=0}^{T=19} (1 + r)^{19-t} \cdot S_t \cdot D_t + \sum_{t=20}^\infty (1 + r)^{-(t-19)} \cdot (1 + \rho)^{-(t-19)} \cdot S_t \cdot D_t \tag{9}$$

Although the social value of avoided emissions accrues at the global level, the opportunity costs associated with

upper and lower limits, which include the random profits, $R_{...p}$, with $E(R_{...}) - l \cdot sd \leq R_{...p} \leq E(R_{...}) + u \cdot sd$. sd is the standard deviation of the profit and $(C + H)^{max}$ is the upper limit for the target proportion of total cropland area (land proportion covered by annual crops, C , and permanent crops, H)

retaining natural forest rather than converting it to more profitable (typically agricultural) LULC are typically incurred by individual landowners. However, these opportunity costs vary substantially over the study period due to market fluctuations. We calculate their cumulative present value as:

$$C = \sum_{t=0}^{\infty} (1+r)^{-t} \cdot S_t^{\Delta L} \cdot O_t \tag{10}$$

where $S_t^{\Delta L}$ is the cumulative change in the total forest area and O_t represent the time-dependent land opportunity costs.

$$S_t^{\Delta L} = \sum_0^t \Delta L_t \tag{11}$$

ΔL_t represents the deviation in observed deforestation relative to the simulated market-only counterfactual reference level. As with climate benefits, we consider non-permanence by accounting for a constant annual probability that opportunity costs will revert to the reference level after the study period, using the same parameter values as above:

$$C^* = \sum_{t=0}^{T=19} (1+r)^{19-t} \cdot S_t^{\Delta L} \cdot O_t + \sum_{t=20}^{\infty} (1+r)^{-(t-19)} \cdot (1+\rho)^{-(t-19)} \cdot S_t^{\Delta L} \cdot O_t \tag{12}$$

Depending on the period considered, the land opportunity costs ranged between 137 and 153 US\$ per hectare per year (Table 2).

Data sources

Data for observed forest losses were obtained from Global Forest Watch (2024) and FAOSTAT (FAO Statistics 2022). FAO-documented data were used to represent observed forest losses for the calibration of the counterfactual model (1990–2000), as remotely sensed forest losses were not available for this period. Profit data, used as input in the land-use allocation model, were derived from gross production values published in FAOSTAT and from previously published materials (Table 3).

Gross profits were calculated by dividing gross production values (constant 2014–2016 US\$) by the area harvested for crops or area of LULC type (milk and meat). For forest LULC types, we used the timber volume harvested

per hectare multiplied by the price derived from export value for naturally regenerating forests, or used modelled volumes (Knoke et al. 2014) multiplied by timber prices adopted from the Global Forest Products model for planted forests (Buongiorno 2003). Variation coefficients, vc , were adopted to obtain standard deviations of profits, sd . The variation coefficient was built on the RMSE of fitted trend lines, $vc = rmse/\bar{R} \cdot 100$. The LULC category “Deforestation” had the same coefficients as “Permanent meadows & pastures” but a different vc (Table 3). Following Knoke et al. (2023, supplementary material) we assumed that the upfront profits from clearing the natural forest were high enough to finance the new establishment of new pasture.

Results

Simulated counterfactual deforestation rate

The overall average annual deforestation rate for 1990–2022 predicted by the counterfactual market-oriented land-use allocation model was 0.47%, with a maximum of 0.58% p.a. in the period 2005–2009 (a period with very high crop prices) and a minimum of 0.35% p.a. in the periods 2010–2014 and 2015–2022 (a period of declining crop prices). In this section, we use random 5-year periods to convey overall overview of deforestation (Table 3).

The frequency distribution of simulated counterfactual deforestation rates followed a negative exponential distribution (Fig. 2) with a median deforestation rate of 0.32% p.a. The average simulated forest loss without the influence of non-market factors is 605 km² per annum in the period 1990–2022, including the calibration period (1990–2000). For 2001–2022, we obtained an expected deforestation reference level of 545 km² p.a., while the observed deforestation was 434 km² p.a.

Deforestation trends

We calibrate our non-spatial model conservatively to stablish reference deforestation levels slightly below those reported by the FAO (Fig. 3). These reference levels capture natural

Table 2 Opportunity costs land managers face when avoiding deforestation in Ecuador and shares of replacement land-use/land-cover types (LULC), obtained from counterfactual model

% of land-cover shares of LULC types of converted natural forest				Where agricultural establishment failed; estimated based on Knoke et al. (2009)	Opportunity costs [US\$ per hectare per year] considering the years 2000 to 2022 (agricultural net benefits minus natural forest net benefits)
Planted forest (S)	Arable land (C) and permanent crops (H)	Perm. meadows and pastures—cultivated (P)			
5	26	48	21	135–153	

Table 3 Profit data used as input information for the land-use allocation model. *LULC*, land-use/land-cover type; *vc*, variation coefficient; periods 0–6: 1990–1994, ..., 2015–2019, 2020–2022

LULC	Crops/goods used for parameterization	Expected profits, $E(R_{...})$, from fitted trend lines [US\$ per hectare per year] in period z							<i>vc</i> [%]	Further input information (e.g. costs) adopted from
		0	1	2	3	4	5	6		
Other land (O)	-	-	-	-	-	-	-	-	-	-
Planted forest (S)	Timber	98	119	138	157	174	191	218	40	Knoke et al. (2014)
Arable land (C)	Maize	379	284	299	369	439	451	352	26	Meade et al. (2016)
Permanent crops (H)	Bananas, palm oil	1119	1241	1285	1231	1138	947	678	43	Chrisendo et al. (2021)
Perm. meadows and pastures—cultivated and natural (P)	Meat, milk	95	141	173	191	195	185	161	10	Feltran-Barbieri and Féres (2021), Knoke et al., (2020)
Deforestation (Df)	Meat, milk	95	141	173	191	195	185	161	50%, calibrated (Knoke et al. 2014; Knoke et al. 2009)	
Naturally regenerating forest (N)	Timber	30	44	58	71	83	95	126	35%, calibrated (Knoke et al. 2009)	

forest losses that would have been expected to occur in the absence of external factors like policy interventions.

The results show large negative deviations between observed and expected counterfactual deforestation for 2001–2009 (Fig. 3). This period overlaps with canton-level “reforms of natural resource management” (1997–2008) and starts 1 year after the currency change (“dollarization” in 2000). Our counterfactual market-only scenario thus predicts a trend change of forest losses from 2000 to 2009 in which much less deforestation actually occurred than expected. From 2005 to 2009 in particular, high crop prices led our counterfactual model to predict accelerating deforestation,

a trend that did not materialize on the ground. When crop prices declined from 2010 onwards, the observed and expected deforestation do not show systematic deviations, suggesting a period with market-oriented deforestation.

Social value of the deforestation trend

The estimated cumulative avoided emissions from 2000 to 2010 are + 0.114 gigatonnes CO₂ (Fig. 4a). To calculate the economic value of these avoided emissions, we use conservative SCC ranging from 30.1 (2000) to 44.1 US\$ per Mg CO₂ emission (2019) (in 2015 US\$ per tonne of CO₂, suggested by United States Government 2016), following the calculations reported in Knoke et al. (2023). This assessment is based on below-baseline deforestation rates from 2001 to 2009, since observed deforestation closely paralleled the counterfactual baseline from 2010 until the end of the study period.

The social value of the climate benefits associated with such reduced CO₂ emissions was estimated at \$5.7 billion (assuming the achieved emission reductions are permanent, Fig. 4b) or \$3.1 billion (assuming a risk of 1% p.a. of losing the achieved emission reductions after 2022). The foregone agricultural benefits incurred by conserving tropical forests to achieve the climate benefits were estimated at \$1.4 billion. Based on these evaluations, we obtain a rough benefit-cost ratio of 2.2.

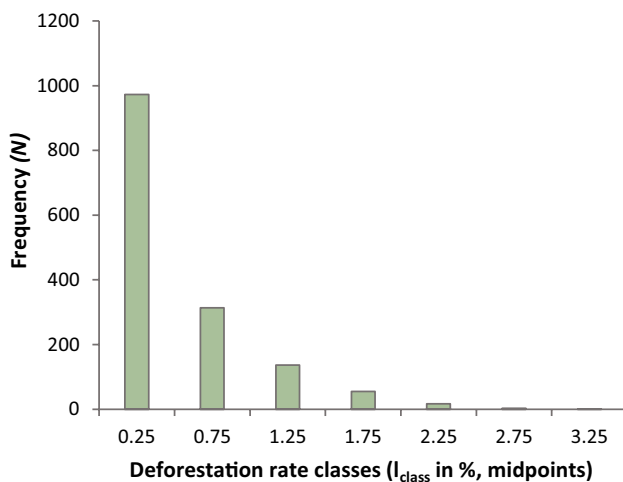
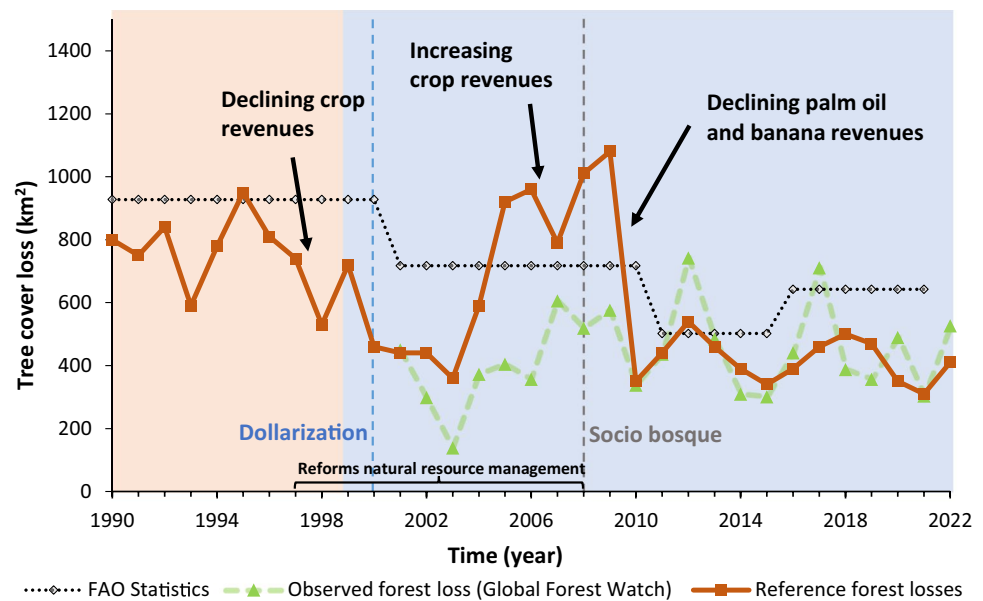


Fig. 2 Frequency distribution of simulated deforestation rates by l_{class} . l_{class} is the midpoint of the loss class, shown on the x-axis. The power law behind the distribution of the deforestation rates is described by a trendline with the following coefficients: $N = 2090.1 \exp(-2.288 l_{class})$. N is the frequency of the deforestation rates per loss class

Discussion

The comparison of observed deforestation with our simulated market-forces-only baseline shows a substantial conservation of Ecuadorian natural forests of a size of 2872 km² between 2001 and 2009. According to our model, if

Fig. 3 Observed and reference forest cover losses. Observed forest losses refer to tree cover losses (Global Forest Watch 2024). Forest losses from the Food and Agriculture Organization of the United Nations (FAO Statistics 2022) are compared and were used for calibration (1990–1999) in the absence of remotely sensed data. Light orange shadow represents the calibration period and light blue represents the assessed period. Dashed lines mean the beginning of dollarization (blue) and Socio Bosque program (grey)



deforestation decisions had been purely market-driven in this period, this forest cover would have been cleared. This is a remarkable result, considering that this period followed one of Ecuador's major crises in the late 1990s, during which the economy contracted and inflation surged by approximately 60% (Jokisch and Pribilsky 2002). Food prices in Ecuador increased substantially from 2000 to 2008 (Gilbert 2010), stimulating demand for agricultural land (Harding et al. 2021). During this period, our counterfactual simulations predicted accelerating deforestation in response to profit expectations alone, but this expectation was largely unrealized.

One interpretation might hold that the natural resource management reforms pursued by many Ecuadorian cantons between 1997 and 2008, potentially supported by higher currency stability as a consequence of the "dollarization" in 2000, may have been more effective than previously thought (Kauffman and Terry 2016).

Conversely, however, some evidence suggests that the dollarization of the national currency at a controversial rate of 25,000 *suces* per dollar likely exacerbated already-high emigration rates, which ultimately led to approximately 4% of the population leaving Ecuador (Acosta et al. 2014). The period 2000–2004 was particularly difficult for the agricultural sector, as the shuttering of various financial institutions in the years leading up to dollarization created a credit crunch (Chuncho Juca et al. 2021). Thus, an alternative explanation might be that the unexpectedly low deforestation rate between 2001 and 2009 was less the result of intentional policy choices or natural resource management reforms than it was a byproduct of inter-connected social, financial, and demographic crises contributing to farm abandonment, rural

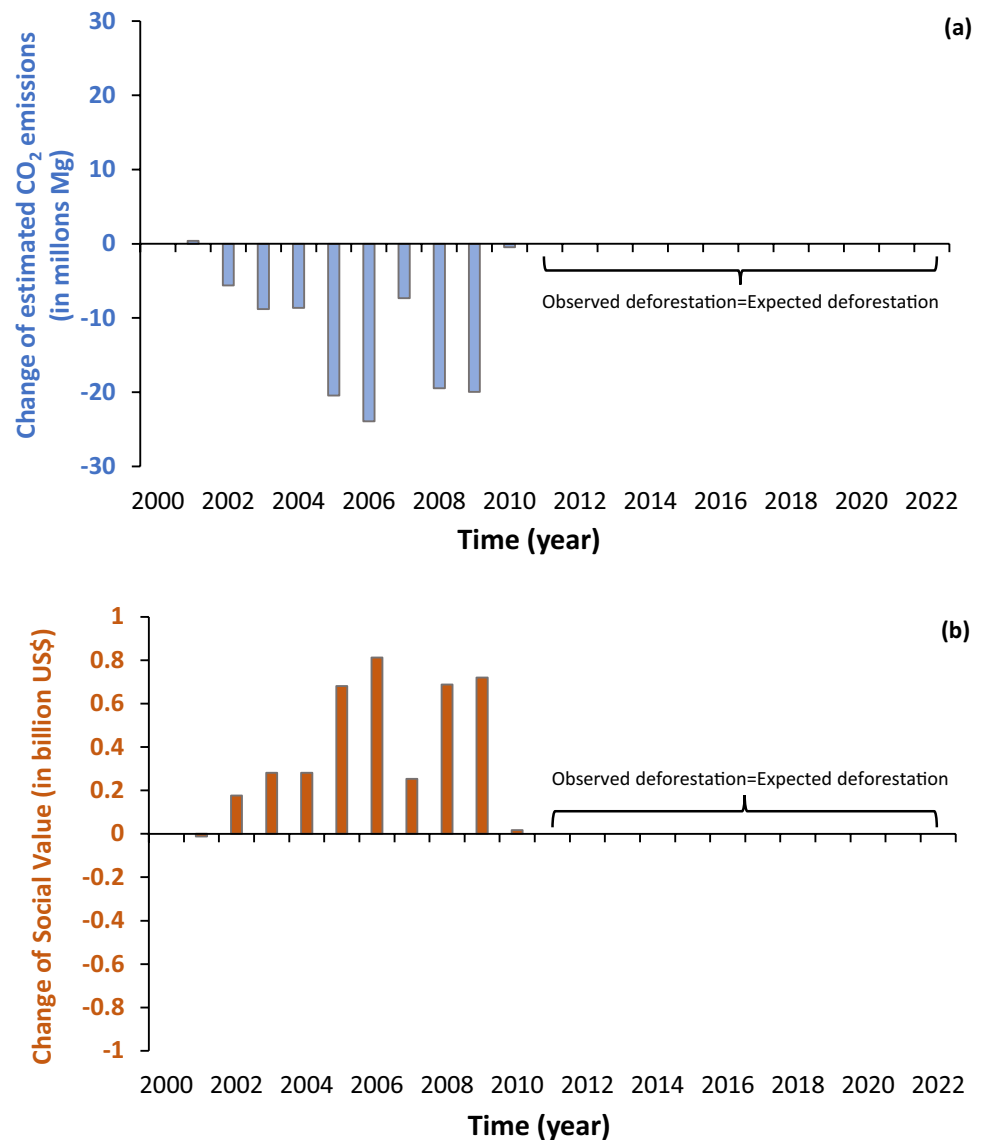
outmigration, and constraints on the labour resources needed to carry out deforestation.

In January 2007, a new government promising to support conservation came to power (Acosta et al. 2014). Its initiatives included, *inter alia*, the recognition of the rights of nature (Martínez 2021), conservation incentives like the Socio Bosque program, and compensation programs for reduced oil exploration and exploitation (Moreano Venegas and Bayón, 2021). Insofar as the 2008 constitution presented a groundbreaking legal framework, its implementation has faced persistent challenges from powerful business interests and weak law enforcement (Kauffman and Martin 2017). Thus, the effectiveness of Ecuador's post-2008 environmental policy portfolio is generally viewed as inconsistent.

The Socio Bosque program was launched in 2008 with the aim of conserving forests and native grasslands and improving the livelihoods of rural populations (de Koning et al. 2011). Even though the compensation paid to beneficiaries typically falls short of the estimated land opportunity cost, from 2008 to 2017, the Socio Bosque program placed 16,700 km² of forest, mangroves, and *páramo* under protection—more than any other program in the country (Ministerio del Ambiente de Ecuador 2019). For comparison, the National Park System (*Sistema Nacional de Areas Protegidas*, SNAP) included just 6320 km² in the same period, while an additional 3800 km² were classified under the Protective Forests and Vegetation (*Bosques y Vegetación Protectores*, BVP) category (Ministerio del Ambiente de Ecuador 2019). Thus, the Socio Bosque program was expected to strongly decrease deforestation.

Our analysis is at least initially consistent with that expectation. Due to increasing crop revenues, our

Fig. 4 Social values of deforestation in a given year (2000–2009). **a** Estimated changes in $\text{CO}_{2\text{eq}}$ emissions from observed minus counterfactual forest losses. **b** Associated impact on the social value



counterfactual market-forces-only baseline predicts much higher deforestation levels than are observed from 2003 to 2008, a period of expanding natural resource management reform (Fig. 3). The divergence between expected and observed deforestation is especially prominent from 2008 to 2010, the first 2 years of the Socio Bosque program, with Ecuador losing 1000 km^2 less natural forest than expected. However, one can argue that this deforestation trend also appears to be partly influenced by the collapse of palm oil prices during 2008 and 2009, which brought serious problems to small producers in Ecuador (Potter 2011).

Unfortunately, this reduction in deforestation does not persist: observed and expected deforestation reconverge in 2010 and generally remain in agreement until the end of the study period, apart from two notable deforestation spikes in 2012 and 2017. This post-2010 reconvergence is

driven mainly by a sharp decrease in the level of expected deforestation due to declining palm oil and banana revenues, rather than a sustained increase in observed deforestation (Fig. 3). Falling palm oil prices at this time placed significant economic pressure on small producers (Potter 2011; Castellanos-Navarrete et al. 2021), making the prospect of clearing forest for oil palm plantations substantially less attractive (Vijay et al. 2016) and reducing the simulated deforestation rate.

Thus, while the Socio Bosque program likely plays an important role in shaping forest cover in Ecuador, national-scale deforestation trends are unavoidably shaped by a confluence of factors whose interacting effects are difficult to disentangle. Our method only enables the identification of aggregate effects which must be critically analyzed alongside supporting evidence concerning to social, economic, and policy developments. The launch of the Socio Bosque

program, for instance, coincided with the early stages of an important economic turnaround in Ecuador (The World Bank 2023), facilitated in part by a second oil boom (Cueva and Díaz 2022), as well as with a series of biofuel initiatives that increased the extent of palm oil plantations across a number of Latin American countries (Furumo and Aide 2017). Dynamics of this nature tend to increase the level of deforestation that would be expected in a market-forces-only scenario.

What about the anomalous spikes in observed deforestation that occurred in 2012 and 2017? The first of these spikes roughly coincides with the establishment of two new large-scale hydroelectric projects, the Coca Codo Sinclair Dam and the Sopladora Hydroelectric Power Plant, in 2010 and 2011, respectively (Vallejo et al. 2019). The construction of such megastructures typically exacerbates deforestation both directly (i.e. forest displaced by dams, reservoirs, roads, and transmission lines) and indirectly by stimulating activities associated with deforestation while increasing accessibility to remote forest areas (Marques Da Silva et al. 2018). Preliminary evidence suggests that Ecuador is unlikely to present a major exception to these well-documented patterns (Finer and Jenkins 2012; Vallejo et al. 2019; Llerena-Montoya et al. 2021).

The 2017 spike, in turn, coincides with the completion of both hydroelectric projects, widespread mortality in Amazon forests associated with a particularly strong El Niño event in 2015–2016 (Berenguer et al. 2021), and a legislative effort to loosen regulations regarding mining concessions in protected forests in particular (Roy et al. 2018). This deregulation effort directly contributed to a fourfold increase in the area subject to mining exploration (Vandegrift et al. 2018). The land category most affected by this regulatory change (*Bosques y Vegetación Protectores*, BVP) was first codified in the 1980s, and thus was in place for the entirety of our calibration period.

Other relevant factors implemented by the Ecuadorian government during the study period that may have influenced deforestation trends include:

Water funds Three funds aiming to protect watersheds through integrated water management, FONAG, FONAPA, and FORAGUA, were inaugurated in 2000, 2008, and 2009, respectively. These projects coincided with the period of canton-level natural resource management reform (Kauffman and Terry 2016). As of 2019, they incorporated 4614 km² of natural forests and private, communal, or acquired lands designated for restoration (Earth Innovation Institute 2019).

Command and control policies The most significant command-and-control anti-deforestation initiative in recent decades was probably the expansion of national park area under

the National System of Protected Areas (Utreras et al. 2017). Over the course of study period, 33 protected areas were established, covering 8560 km², with most protected areas located in the Amazon region (Ministerio del Ambiente, Agua y Transición Ecológica 2021).

Land tenure Our study period also encompassed the implementation of two land tenure policies. First, the Land Plan (2009–2013) aimed to foster cooperative approach to land management. Second, the Land Adjudication and Mass Legalization Project (2014–2018) focused on acquiring, redistributing, and legalizing state, private, and vacant properties, with a particular emphasis on agricultural productivity (potentially exacerbating deforestation, see Tanner and Ratzke 2022).

Overall, our results show that even temporarily effective forest conservation has high social value in terms of avoiding climate-driven damages. The additional forest conservation achieved between 2001 and 2010, worth approximately \$3.1 billion, easily outweighs the estimated land opportunity cost of \$1.4 billion associated with conservation. The economic benefits of the additional carbon storage alone thus suggest a benefit-to-cost ratio of 2.1. Crucially, the social value of tropical forest is substantially higher than its carbon storage value (e.g. Franklin and Pindyck 2018).

Limitations and strengths

Assessing the reliability of our results means evaluating the plausibility of our simulated baseline scenario, the accuracy of observed deforestation data, and assumptions about the future status of newly harvested forest parcels. Because the baseline scenario is designed to capture something that is empirically unobservable—what would have happened under different circumstances—it is difficult to conclusively validate using traditional means, such as experimental controls. Instead, we demonstrate plausibility mainly by showing that the model is able to capture deforestation trends effectively by the model implementation under distinct social conditions and deforestation scales (Fig. 5). Although asserting that deforestation in the calibration period was shaped by market forces alone would be a step too far, the overall correlation between observed and simulated deforestation is rather high. The response of deforestation simulations to changes in crop prices (particularly banana and palm oil) is not only facially plausible but also accord well with past empirical work (Taheripour et al. 2019; Gaveau et al. 2022).

Regarding the data used to capture observed deforestation, there was a technical change in the accuracy of the forest loss estimates from Global Forest Watch after 2015 (Weisse and Potapov 2021). However, we do not identify a systematic shift of observed deforestation levels when

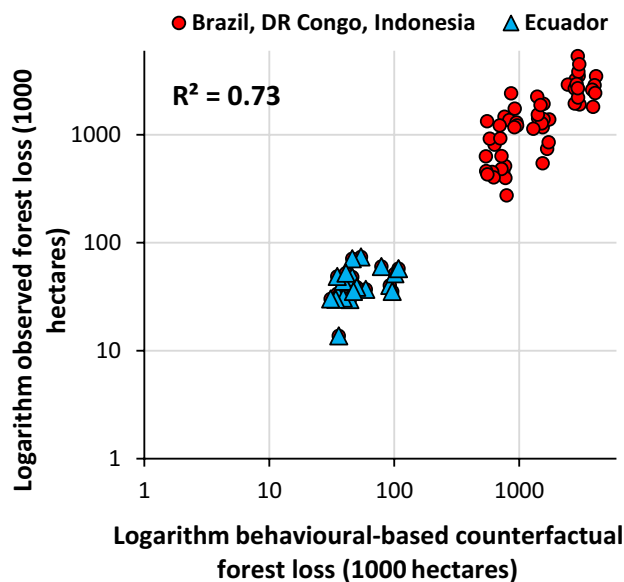


Fig. 5 Behaviour of our counterfactual model implemented in countries under different social and political conditions, and thus deforestation scales (data for Brazil, DR Congo, and Indonesia from Knoke et al. 2023)

comparing the periods 2010–2014 and 2015–2022 that could systematically bias our results (Fig. 3). We note that we used forest loss data specifically, which includes canopy removals that are not necessarily permanent and which might be expected to regenerate. Empirically, however, most recent deforestation in Ecuador is for agriculture, which is rarely followed by a land-use change back to forest (Feng et al. 2022). In sum, we expect that our market-oriented reference scenario is plausible and that the observed deforestation levels are valid (because excluding non-market factors rather too high than too low).

Conclusions

Using counterfactual land-use modelling, we estimate the aggregate effect of non-market factors like policy reform and conservation initiatives on national-scale deforestation trajectories in Ecuador. During a study period that encompassed large political, economic, and social change—including the ratification of a constitution granting rights to nature and the introduction of the largest payments for ecosystem services program in Ecuador’s history—we identify substantial reductions in deforestation relative to a market-forces-only counterfactual. This suppressed deforestation appears to have spared some 2872 km² of forest—an area roughly equivalent to the Ecuadorian provinces of Santa Elena or Carchi—between 2000 and 2010. Depending on assumptions about the permanence of emissions reductions, this

corresponds to a delayed or avoided social cost of carbon in the range of \$3.1–\$5.7 billion, easily outweighing the value of foregone agricultural production.

While our method only allows for the estimation of aggregate trends and not causal attributions to specific events or policy initiatives, it is plausible that policies such as the Socio Bosque program, which placed more surface area under protection than any other program in Ecuador, likely contributed to decreasing deforestation at least temporarily, even relative to a dynamic baseline. Moving forward, efforts to develop and refine mechanisms that reward land managers for their role in sustaining the high social value that tropical natural forests contribute to global society need further support. In conjunction with efforts to quantify the social value of the ecosystem services provided by tropical forests, research and policy should continue to develop strategies to foster the integration of local stakeholders into tropical land-use policy and decision-making.

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Declarations

Conflict of interest The authors declare no competing interests.

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