Global deforestation rates deviate from a profit-oriented baseline

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Abstract: Despite decades of global efforts to conserve natural forests, deforestation continues to surpass international conservation targets[1–3], highlighting the need for efficiently measuring the success of conservation actions. This is challenging because it remains unclear how deforestation would have changed without policy efforts to reduce it[4–6]. Here, we model an alternative past for 28 countries in which land managers make unconstrained deforestation decisions, solely based on heterogeneous agricultural profit expectations. We show that observed deforestation patterns differ from this counterfactual in the world's deforestation hotspots. Relative to the counterfactual, deforestation was reduced in Latin America (-18%) and Asia (-8%), but increased in Africa (+6%), suggesting an overall reduction of past global deforestation rates. While only a few countries with effective forest conservation policies have achieved substantial deforestation reductions [7–9], other countries, such as Malaysia, Madagascar, and Paraguay, exceeded the profit-oriented counterfactual due to drivers unrelated to agricultural profits. These results demonstrate that forest protection against profit-oriented deforestation is possible at a global scale. Consistent counterfactual deforestation baselines, such as those generated by our simulation approach, are essential for robust and reliable assessments of forest conservation achievements[10–12] and provide a stronger foundation for future forest policy.

Global rates of deforestation remain persistently high[1], yet the effectiveness of global efforts to reduce deforestation, defined as the purposeful and permanent conversion of forests to other land uses[13], remains unclear[2,10,11,14]. This is most problematic, since halting and reversing deforestation is a central objective of key international agreements, including the Aichi Targets[15], the New York Forest Declaration[16], Sustainable Development Goal 15[17], and the Glasgow Leaders' Declaration[16]. A wide range of national and international policies, such as the 'Action Plan for the Prevention and Control of Deforestation in the Legal Amazon'[7], the UN framework 'Reducing Emissions from Deforestation and Forest Degradation'[18] (REDD+), and the EU Deforestation-Free Supply Chains Regulation[19], have been implemented to address this issue. However, the net effects of these initiatives on global deforestation rates have rarely been convincingly quantified.

Continued deforestation, however, does not necessarily imply the complete failure of forest protection efforts. To investigate whether conservation policy has been effective, one needs to know what would have happened in the absence of any efforts to combat deforestation, i.e. under a plausible business-as-usual scenario[4]. In other words, the impact of policy change can only be identified against a consistent *counterfactual baseline* that disregards any forest protection efforts. A realistic baseline scenario is important, not only to assess forest protection measures, but also for demonstrating additionality in carbon accounting[20], biodiversity conservation[21], and realistic target setting[1].

Agriculture dominates as the driver of tropical tree cover losses by far[13]. Assuming that land managers behave as if they maximise agricultural benefits from land-use changes (approximated by profits) under 'business-as-usual' is therefore plausible[2,13,22–25]. To build realistic counterfactual baseline trajectories on this premise in turn allows the testing of our study's underlying hypothesis: '*The rate of deforestation would have been higher than the observed real-world deforestation if land managers had made unconstrained, purely agricultural profit-*

76 *oriented land-use decisions*'. Such a counterfactual deforestation trajectory can increase faster
77 than the real-world observation, indicating an effective deforestation reduction policy, as, for
78 example, shown by Roopsind et al.[26].

79 Current baseline-setting approaches for commercial carbon-offset projects have been critically
80 discussed[10,11,27] for using *ex-ante* methods that extrapolate deforestation trends from before the
81 start date of a project or a policy. This is problematic because it implicitly assumes that defor-
82 estation pressures are constant, whereas they often change over time[28,29]. An improved alterna-
83 tive includes *ex-post* data to build the baseline. For example, difference-in-difference[5] and syn-
84 thetic control approaches[30] use the development of deforestation in a control area outside the
85 policy area as a baseline. Assuming parallel deforestation trends in the control and policy areas,
86 the control areas serve as a proxy for what would have occurred without the protection policy,
87 thus incorporating ex-post shifts in deforestation pressure. These observational methods en-
88 counter two difficulties in practice, however. First, they require baseline areas without policy
89 as a control, which are subject to the same deforestation pressures and trends. Such controls are
90 often not available, for example, when other confounding factors impact the policy and/or the
91 control area[5]. In addition, when policies are nationwide, one would need whole countries with
92 exactly the same deforestation pressures[26], but without the policy impact, although deforesta-
93 tion often differs greatly across countries[31]. The second difficulty is that policy and baseline
94 areas may not be independent. Landowners may shift deforestation to regions with weaker pol-
95 icy enforcement[25], including the control areas.

96 To address these limitations, we combine a theoretical model with empirical observations. We
97 model land managers' incentives to deforest explicitly based on land-use profits, their uncer-
98 tainty, and land-use changes of non-forest lands. Existing agricultural land will likely be aban-
99 doned and replaced by new deforestation when it degrades. To predict counterfactual deforesta-
100 tion rates, we develop a theory-consistent land-change simulation method introduced by Knoke

et al.[6]. This is an alternative to complement the existing observational[32] and regional- or country-level baseline construction methods[5,26,33]. To obtain an unbiased reference, we simulate policy-invariant[34] counterfactual baselines as hypothetical deforestation trajectories under regret-minimising land manager behaviour[34–36], which can be a highly effective decision-making strategy under uncertainty[37]. Our model simulates how different groups of land managers would reallocate their land through deforestation decisions to enhance their annual profit across numerous future profit expectation scenarios (drawing on a total of 32.2 million Monte-Carlo simulated profit scenarios).

Our primary contribution is an analysis of how observed deforestation has changed from 2001 to 2023 in tropical and subtropical countries, when assessed against novel, counterfactual deforestation trajectories driven by agricultural profits. We derived gross deforestation from tree cover losses[38] by subtracting estimated temporary losses (see Methods). Our simulated baselines explicitly model uncertainty over future land management profits[6,39]. To capture nationwide changes of deforestation, we adopted a broad, country-level baseline approach for 28 countries, which together represent 87% of global gross deforestation (Supplementary Fig. 1). The land-change model used historical agricultural profits and initial land-use/land cover data from FAOSTAT[40] for the simulations. Deforestation data from a period presumably without forest conservation policy impact was used for its calibration. The represented land managers were unconstrained by forest protection policies in our simulations. Using this novel approach, we go beyond Knoke et al.[6], who analysed only a few exemplar countries. We provide the first analysis of deforestation changes against consistent profit-oriented baselines on continental and global scales. The results are relevant for a realistic assessment of the net effect of deforestation reduction policies, additionality assessments, political target-setting and monitoring deforestation reduction progress.

Results

Between 2001 and 2023, observed deforestation across the 28 countries included in our study increased by 49.4 ± 1.3 (SE, standard error) million hectares, relative to the 2001 deforestation level (blue dashed line in Fig. 1, see also Supplementary Tab. 1). In contrast, our profit-oriented baseline estimation deforested area increased by 68.6 ± 0.8 million hectares. This is 39% higher than the observed deforestation increases over the same period, suggesting a deforestation reduction of -19.2 ± 1.2 million hectares attributable to forest protection policies.

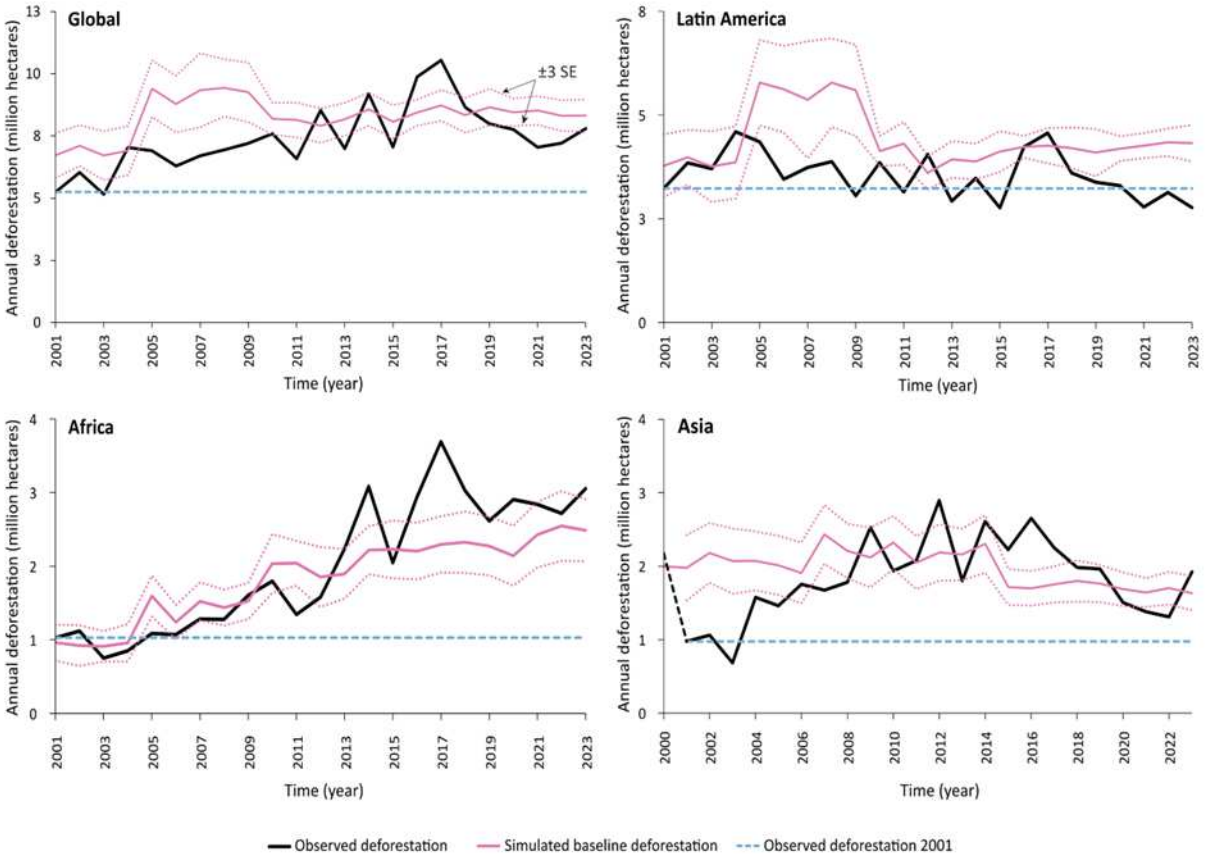

Figure 1. Global and continental simulated baseline deforestation compared with observed deforestation rates between 2001 and 2023. Observed deforestation derived from Global Forest Watch[38] tree cover losses (black lines), with adjustments (see Methods). Pink dashed lines indicate ± 3 SE of the simulated baseline deforestation, derived from 50 land-change optimisations informed by random profits from Monte-Carlo simulations, reflecting the considered variation in deforestation decisions due to heterogeneous expectations of land managers. In Asia, we calibrated the Indonesian baseline with reliable observed deforestation data from 1997 to 2000 based on Hansen et al.[8]. The Asian observed deforestation rate in the year 2000 was reconstructed assuming that the deforestation rate in Asian countries other than Indonesia was the same as in the year 2001 (black dashed line). The blue dashed lines indicate the 2001 level of observed deforestation.

144 A closer temporal analysis revealed that most deforestation reduction occurred between 2005
145 and 2011, except for Asia, where it occurred between 2001 and 2005 (Fig. 1). The global trend
146 was dominated by Latin America, where absolute deforestation rates and their reductions were
147 highest. In Asia, the decline is largely attributable to reductions in Indonesian deforestation. In
148 contrast, from 2012 onward, the aggregated observed and simulated baseline deforestation rates
149 matched, indicating no substantial reduction from 2012 to 2019, and thus no predicted net effect
150 of anti-deforestation policies. However, in the more recent years of 2020 to 2022, observed
151 deforestation rates once again fell below the simulated baseline.

152 The relationship between the simulated baseline (when used as a predictor) and the observed
153 deforestation was best described by a quadratic model (R^2 = 0.86, rmse = ± 152 kha, Fig. 2A).
154 A comparison of observed and simulated deforestation indicates substantial deforestation re-
155 ductions up to 30% for countries with large deforestation rates (shown by the difference be-
156 tween the grey dashed and dark cyan line in Fig. 2A). Alternative models, such as logarithmic
157 ones (of the type $\widehat{D} = a + b \cdot lnL$), performed worse ($R^2$ = 0.61, rmse = ± 272 kha). Under
158 smaller average annual deforestation rates (below 0.48 million hectares), observed deforesta-
159 tion was 30% to 50% higher than suggested by the counterfactual profit-oriented baseline, po-
160 tentially because of factors such as subsistence requirements (Africa) or election promises
161 (Asia), which favour increases in deforestation (more reasons why observed can exceed profit-
162 oriented deforestation are discussed in Supplementary Text 2). Consistent with this observation,
163 Fig. 2B shows that the relative deforestation rates tend to be smaller on average than their sim-
164 ulated profit-oriented counterfactuals in countries with large natural forest areas.

165

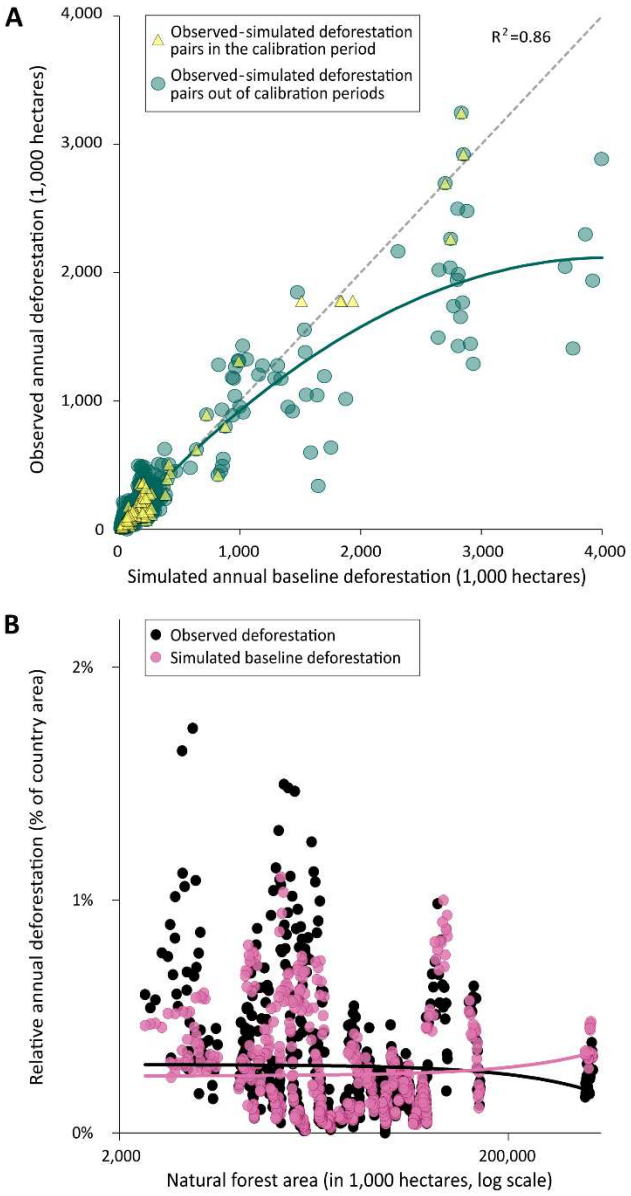

Figure 2. Outcomes of the counterfactual baseline deforestation model. A. Comparison of annual observed and simulated baseline deforestation rates, building on 644 pairs of observed and simulated deforestation, representing 28 countries over a period of 23 years (161 observed-simulated deforestation pairs used for calibration, 483 simulated deforestation rates out of the calibration period). When $\widehat{D}$ is the statistical estimate of the observed deforestation rate using the simulated baseline deforestation L as a predictor variable, the function $\widehat{D} = 15.598 + 1.036 \cdot L - 0.0001277 \cdot L^2$ describes the relationship between both deforestation variables (R^2=0.86). Country- or year-specific predictions with this function require accounting for random intercepts (Supplementary Tab. 3). The yellow triangles show which data we used for calibration (25% of the available data). For high deforestation rates, the simulated baseline tends to predict substantially higher profit-oriented deforestation than observed deforestation, which can be attributed to successful deforestation reduction policies. Consequently, more data points lie below the 1:1 line (grey dashed) than above for such cases. **B.** Observed and simulated relative annual deforestation showed deforestation reduction mainly in countries with large natural forest areas.

Across all country-annual comparisons between observed and baseline deforestation, 57% of the observed deforestation rates fell within ± 3 SE of the simulated country-level baseline deforestation (Supplementary Figs. 2-4), showing similar observed and simulated deforestation rates. Considering the uncertainty inherent in our baseline simulations, we regard the remaining 43% of comparisons as substantial or 'robust' deforestation differences. For this robust subset of observations, the net effect corresponds to a –10% reduction in observed deforestation relative to the simulated profit-oriented baseline, attributable to forest conservation policies in a few countries (explanation in Supplementary Text 2). This net reduction equals -19.3 ± 1.3 million hectares.

Among the robust differences between observed and simulated baseline annual deforestation, total deforestation reductions, i.e., deforestation below the simulated baseline, sum up to -35.2 ± 0.8 million hectares, while increases in deforestation rates total +16.0 ± 0.6 million hectares (see Fig. 3 for their spatial distribution). For comparison, all deforestation decreases (not only the robust ones) sum to -41.5 ± 0.8, and all increases to +22.3 ± 0.6 million hectares.

At the continental level, the robust deforestation differences provide a heterogeneous pattern. Latin America showed a substantial deforestation reduction corresponding to -18.3 ± 0.8 million hectares or a net effect of -18.0% (see Fig. 1, Supplementary Text 1, and Supplementary Tab. 2). In Africa, the observed deforestation was 2.6 ± 0.4 million hectares or 6% greater than the simulated baseline deforestation, suggesting higher than profit-oriented deforestation. In Asia, our simulations showed a robust deforestation reduction by -3.6 ± 0.6 million hectares, corresponding to 8% of their baseline rates.

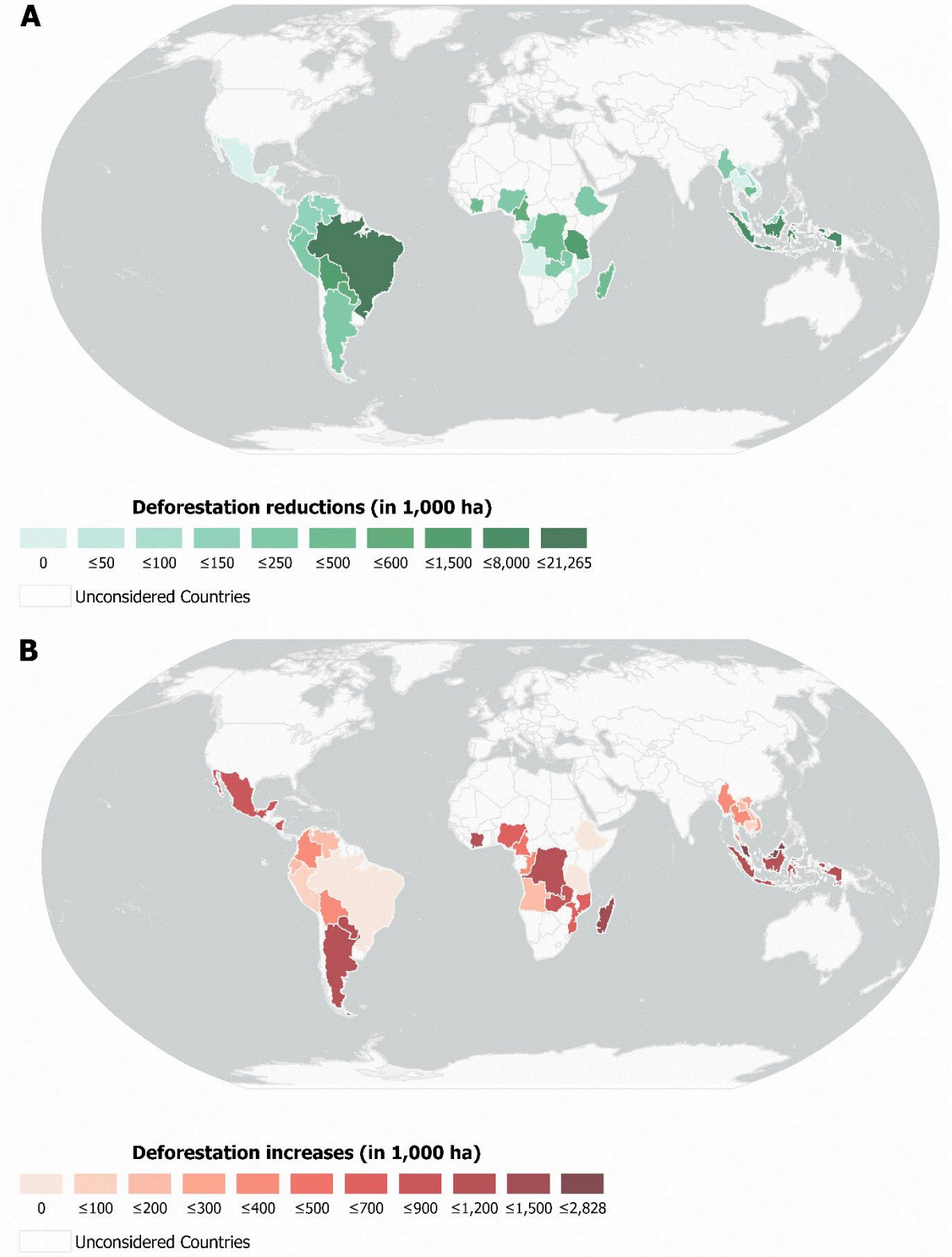

Figure 3. Global reductions (A) or increases (B) of deforestation compared with the simulated counterfactual baseline (only robust differences considered) for the 28 countries investigated in tropical and subtropical regions. The legend refers to (A) classes of reduction in deforestation in thousands of hectares in a specific country (we accumulated differences between observed and baseline deforestation, when observed deforestation was below the baseline) or (B) classes of increase in deforestation in a specific country (here we accumulated differences when observed deforestation was above the baseline). The darker the colour, the larger the decrease or increase.

Despite the reductions in Asia, however, persistently steep declines in the Asian forest areas are notable, indicating the highest relative deforestation rates among all countries analysed (Supplementary Fig. 5). Supplementary Figure 2 shows the critical role of fires in most Latin American countries, which may affect up to 2.5 million hectares of forest in extreme years. These mostly unintended fires are difficult to control, so it becomes even more important to reduce purposeful and permanent forest conversion to other land uses (i.e., deforestation). The simulated baseline deforestation trajectories for all 28 countries are shown in Supplementary Figures 2-4.

Discussion

Our study offers novel counterfactual deforestation baselines using a comprehensive method for identifying and understanding past changes to deforestation. Our approach constructs an alternative version of the past, a reference trajectory independent of observed deforestation, which serves as a counterfactual[41] for evaluating policy outcomes[5]. The changes we identified at the global level translated to a net 10% reduction in deforestation compared to the simulated baseline. This supports our hypothesis that deforestation would have been higher under purely profit-oriented deforestation decisions and in the absence of anti-deforestation policies.

A comparison of observed deforestation in countries representing 87% of the world's deforestation with a robust simulated counterfactual is unique. Our main finding, a net deforestation reduction effect, clearly underlines that successful forest protection against profit-oriented deforestation is possible. The identified changes over time and the differences between countries perfectly assist in evaluating broad country policies and conditions (see Supplementary Text 2). We consider even modest global achievements and examples from countries outperforming others in deforestation reductions as valuable, both practically and psychologically. In contrast, persistent narratives of policy failure risk reinforcing eco-anxiety, especially among younger generations, who may continue to become increasingly disillusioned[42].

Our study underlines the necessity and challenge of constructing and interpreting solid deforestation baselines as an essential precondition for analysing policy impacts. While comparable studies are rare, alternative observational methods to assess past deforestation reductions exist[5]. Due to their regional[43] or country-level character[26] conclusions from most available studies concerning global deforestation are difficult. Nevertheless, the recent observational analysis by Wuepper et al.[32] equally identified a global policy-dependent reduction of forest losses, showing that the annual probability of tree cover loss decreases if public forest protection policies are present in a country. Although both studies used completely different methods, their results support each other. Achieving similar results with different methodologies corroborates that global policies have likely reduced deforestation rates.

We attribute the deforestation reductions identified in our study primarily to established forest protection policies, particularly in Brazil, Indonesia, and Tanzania (described in more detail in Supplementary Text 2). However, we consider that other factors might have contributed to the identified differences between observed and simulated baseline deforestation. A common reason for non-policy-induced historical deforestation decline is falling agricultural commodity prices[44], which is explicitly accounted for in our land-change model. However, under successful deforestation reduction policies, food scarcity might increase and producer prices raise[43], so that profit-oriented baseline deforestation might be modelled at higher levels than without these price increases. However, the observed deforestation will also respond to such price increases[25] in the country's regions with weaker policies. We thus consider it unlikely that such endogeneity effects have led to overstated deforestation reductions. For example, an earlier study[43] showed a policy-related deforestation reduction for the Brazilian Amazon alone (covering about 60% of Brazil's territory) of 7.3 million hectares from 2004 to 2008 (-56%), using an observational model. Our study confirms a deforestation reduction by 5.9 ± 1.1 million hectares (or -32%) for the total territory of Brazil and the same period. This comparison does not signal

overstating the baseline by our method. Our estimation at the country level includes likely deforestation increases in Brazilian regions with weaker policies, reducing the net forest conservation effect. The observed difference between the two methods may thus be plausible. Similarly, some economists postulate that decreases in deforestation can be predicted mainly based on changes in a country's exchange rate[45], rather than by policy change. Exchange rates influence agricultural commodity prices[46], which are signals for some land managers to expand or reduce their production. Our land-use optimisation model incorporates such market signals, along with considering the impact of land-use composition, the area development of non-forest land and expected uncertainties. Finally, declining deforestation in the absence of policy interventions underlies some phases of the theoretically expected forest transition. This theory predicts that forest cover losses will automatically reduce as forests become scarcer[47], when countries become more developed. We modelled forest cover changes and updated the land-use/land-cover composition every five years[48] to account for such effects. Overall, while multiple interacting drivers shape deforestation trends, we cannot identify factors other than implemented policies (discussed in Supplementary Text 2) that better explain the deforestation reduction against our simulated baseline.

We conclude that assessing the effects of policies on deforestation requires comparing observed trends with a consistent counterfactual, one that shows the "what if?" outcomes without such policies in place[4]. Our study contributes to this principle by developing a means of generating comprehensive, consistent, and profit-oriented baselines. These help to identify and assess changes to global deforestation that cannot be explained by changes in profits for agricultural outputs, the primary economic incentive to clear natural forests.

Our results provide a sound platform for in-depth policy impact analyses in individual countries, which is complementary to quasi-experimental identification strategies to attribute

changes in deforestation to national forest protection policies[5]. Countries such as Brazil, Indonesia, or Tanzania show a substantial reduction in deforestation, and that is an important starting point to assess the policies and structural changes that these countries have put in place to curb deforestation. Not only did these countries strengthen their sustainable supply chains, but they also developed political will and law enforcement, particularly in Brazil[49]. For that country, our counterfactual allowed revealing impressive past deforestation reductions[50]. The counterfactual baselines can be revised using extended profit data beyond the agricultural profits used here, whilst alternative decision behaviour other than minimising the maximum regret criterion applied with our study can also be explored. In addition, for the carbon emissions saved by the identified deforestation reductions, we can establish additionality. This can then be used to assess the social value of associated forest protection policies[20].

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Methods

Observed deforestation *D*

We derived observed deforestation from tree cover losses reported by Global Forest Watch[38], a widely recognised and peer-reviewed global monitoring platform. Tree cover loss is defined as a 'stand-replacing disturbance', or more specifically, as '… the complete removal of tree cover canopy at the Landsat pixel scale'[51]. The quality of this information is high, as it has been extensively validated across diverse ecological regions[52]. In our study, we defined 'deforestation' as the permanent conversion of natural forest to any other land use[13]. Consequently, we subtracted the tree cover losses assigned to managed forest areas by Global Forest Watch (forestry or logging). Forestry means that in forests reaching the harvesting age, the dominating canopy cover is replaced by a young forest, which does not represent deforestation according to our definition[53]. Tree cover losses can also include losses by unintended fires, while the forest may often recover in the burnt areas[54]. Some intended fires in limited areas to clear forests for agriculture may accidentally expand far into the natural forest[55]. Unintended fire events reported by Tyukavina et al.[56] were subtracted from tree cover losses in our study. As background information, we display the annual forest area affected by fires in Supplementary Figures 2-4. Compared to net deforestation, which is often reported by forest resource assessments[57], we analysed gross deforestation, so we did not account for compensations by expanding forests elsewhere. This is because we focused on the dynamics and incentives of clearing land, and we conjecture that reforestation follows different dynamics and incentives.

Selected countries, land-use/land-cover types, and their profits

We pre-selected 26 countries based on data from FAOSTAT, sorted by descending deforestation as compiled in the study by Knoke et al.[6]. These countries together accounted for approximately 90% of the documented net deforestation, referring to changes of the FAO category 'naturally regenerating forests'. To ensure data reliability and consistency, five African countries were subsequently excluded due to irregularities and data gaps: Sudan, Chad, Somalia, Namibia, and Botswana. We replaced these countries with seven alternative countries from Africa and Asia for which more consistent data were available. The final selection included 28 countries (Fig.3 and Supplementary Tab. 1), which collectively represented 87% of the global gross deforestation of natural forests from 2001 to 2023 derived from Global Forest Watch data (Supplementary Fig. 1). This coverage ensures a comprehensive and geographically diverse representation of global deforestation dynamics while maintaining a high standard of data quality for model calibration and analysis. To derive the land-use profits per country, we used the initial land-use/land-cover types for the main agricultural products during the calibration period (from FAOSTAT[40], see Supplementary Coefficients). We also set constraints to control the expansion of 'other land', 'planted forests', 'arable land' and 'permanent crops'. Beyond these four mentioned land-use/land-cover types, we considered 'permanent meadows', 'new deforestation', and 'natural forest'. Profits from agriculture were derived from economic production (output) values published by FAOSTAT (in 2014-2016 US$), reduced by direct production costs (for labour and other inputs), per hectare of the corresponding land-use type[6]. The profits were fit with a trend line to obtain profit averages for seven considered subperiods (1990-1994, 1995-1999, …, 2015-2019, 2020-2023). The trend lines' root mean square errors were divided by the mean predicted profit to obtain the profits' coefficient of variation (vc). We used the vc

to construct lower and upper bounds of profit intervals. From these intervals (see Supplementary Coefficients), we randomly drew land-use profits that informed our land allocation optimisations, which we simulated for land manager groups.

Changes in deforestation and comparisons

We used D for the observed, L for the simulated baseline, and H_{2001} for the year 2001 observed (historical) deforestation rates per year.

The derived changes Δ in deforestation rates over time are, when considered against the observed deforestation in 2001:

Observed deforestation $$\Delta_{D-H} = \sum_{t=2001}^{2023} (D - H_{2001})_t \quad (1)$$

Simulated baseline deforestation $$\Delta_{L-H} = \sum_{t=2001}^{2023} (L - H_{2001})_t \quad (2)$$

The net changes Δ in observed deforestation rates against the simulated baseline deforestation were, when aggregated over time:

$$\Delta_{D-L} = \sum_{t=2001}^{2023} (D - L)_t \quad (3)$$

Δ_{D-L} was also computed separately for only decreases $(D - L) < 0$ or only increases $(D - L) > 0$.

Simulating profit-oriented baseline deforestation *L*

A cornerstone of our study is a set of 28 modelled profit-oriented baseline deforestation trajectories at the country level (Supplementary Figs. 2-4), obtained with a novel uncertainty-sensitive land-change model, which can simulate land allocation decisions by land manager groups[6]. The modelled managers seek satisfactory land-use profits over a range of expected future profit scenarios. Each such profit scenario consists of a set of random profits for seven land-use/land-cover types per country. Among the seven profits, there is a maximum (or reference point) with which the modelled land managers can compare the area-weighted profit expected from a given

land-use/land-cover composition. With their land allocation decisions, the land managers seek to minimise the largest distance between the maximum profit and the area-weighted profit for a given land-use/land-cover composition across multiple profit scenarios. Note that there is no single land-use/land-cover composition which can maximise the expected profit over all scenarios. We call the land managers' decision-making 'satisficing'[58], which is consistent with analyses of real farmer decisions[59]. Our land-change model is the current endpoint of a series of land-change models, which have been developed from 2011 to 2025, see refs.[39,48,60–62] for examples. As the full model is comprehensively described in two previous papers[6,39], here we provide a conceptual overview of the modelling strategy in a 'nutshell'.

The modelling consists of repeated optimisations of a desirable future land-use/land-cover composition based on various sets of randomly simulated profits. To consider feasibility, the land change model gradually modifies the given land-use/land-cover composition by converting natural forests to agricultural land use, aiming to improve anticipated profits under uncertainty. We fitted the model during a calibration period in which we assumed the absence of any forest conservation policy (more under Methods 'Calibration'). The model's output is a range of simulated baseline deforestation rates ($\tilde{L}_i$) in hectares per annum for each iteration i, which is a random variable, Monte-Carlo-simulated per country. A specific $\tilde{L}_i$ is one realisation out of 50 repeated optimisations in total, based on 1000 random profit scenarios, used to derive a randomly varying average deforestation rate per year per country, called $\tilde{L}$ (see Supplementary R code).

$$\tilde{L} = \frac{1}{50}\sum_{i=1}^{50} \tilde{L}_i \quad (4)$$

A single $\tilde{L}_i$ is based on the difference between the current natural forest proportion at any time throughout the considered period (f_n, n for natural forest) and its predicted future land-cover/land-use proportion after T years ($\tilde{f}_{nT}$), annualised by the factor $k = \frac{1}{30}$. With this factor

k, the model implies a planning horizon of 30 years, approximating one land manager generation[63]. The annual percentage decline $(f_n - \tilde{f}_{nT}) \cdot k$ of the natural forest is multiplied by the country's area (A) to obtain absolute deforestation rates in hectares.

$$\tilde{L}_i = A \cdot (f_n - \tilde{f}_{nT}) \cdot k \quad (5)$$

More specifically, $\tilde{f}_{nT}$ is a predicted random variable resulting from a portfolio optimisation using random profit scenarios for seven land-use/land-cover types to find their optimal future composition (i.e., the optimal land-use portfolio). The optimal land-use portfolio consists of the area proportions of the land-cover/land-use types. The optimisation assumes that land manager groups share their profit expectations with u denoting each profit scenario, to find an optimal compromise land allocation[64,65]. The model mimics how each simulated group allocates its land to minimise the land managers' maximum expected future regret (see Eq. 6), should the land managers realise post hoc that their land-use allocation has not been optimal.

$$\tilde{\delta}_i = max\{\widetilde{D}_u\} \quad (6)$$

$\tilde{\delta}_i$ is the maximum distance of iteration i among 1000 distances ($\widetilde{D}_u$) resulting from comparisons of the best expected profit ($\tilde{p}_u^*$) and the area-weighted expected profit from a given future land allocation ($\tilde{P}_u$) across all considered individual profit scenarios u. We tested the influence of the number of selected scenarios on the variability of the deforestation rate predictions and found only a small impact, with hardly any changes for more than 1000 scenarios[6]. To give lower weight to extreme profit draws and enhance comparability across the scenarios, we normalised the distances with respect to the best and worst profits within a profit scenario. As a result, all distances were members of an interval from zero to 100% (dividing by $\tilde{p}_u^* - \tilde{p}_{u*}$ with $\tilde{p}_{u*}$ being the worst expected profit within a profit scenario).

$$\widetilde{D}_u = \frac{\tilde{p}_u^* - \tilde{P}_u}{\tilde{p}_u^* - \tilde{p}_{u*}} \cdot 100 \quad (7)$$

$\tilde{P}_u$ was computed for each of $u = 1000$ profit scenarios and resulted from profit expectations ($\tilde{p}_{lu}$) for seven land-use/land-cover types (l) and their future land-cover proportions (f_{lT}).

$$\tilde{P}_u = \sum_{l \epsilon L} f_{lT}\, \tilde{p}_{lu} \quad (8)$$

To linearise our non-smooth objective function[66,67], we enforced that no individual $\widetilde{D}_u$ can exceed $\tilde{\delta}_i$.

$$\tilde{\delta}_i \geq \frac{\tilde{p}_u^* - \tilde{P}_u}{\tilde{p}_u^* - \tilde{p}_{u*}} \cdot 100 \;\; \forall u \quad (9)$$

In total, we used 32.2 million profit scenarios to parameterise the model for all deforestation baselines: 1000 individual profit scenarios per simulated land manager group, 50 group simulations per year, 23 years per country and 28 countries in total. To obtain such profit scenarios, random profits were chosen from an interval constructed around the average profit provided by a trendline (Supplementary Coefficients). Clearly, an assumption behind the model is that land managers have sufficient private property rights to choose such an optimisation plan on the land they manage, and that they all follow a strategy which can be approximated by minimax regret. After simulating annual deforestation rates for five subsequent years and allocating the outcomes randomly to the years, we updated the land-use/land-cover composition (as the simulated forest proportion impacts the deforestation rates) and the expected annual profits for each land-use/land-cover type before continuing the simulation-optimisation process. The average land-use/land-cover composition at the end of each five-year period was thus based on a five-year basis, as this provided robust results.

Calibration

We calibrated the baseline deforestation predictions to approach the observed deforestation from 2001 to 2004. We assumed that there were no strong influences of forest protection poli-

564 cies in these years. For the calibration, we utilised the fact that the land change model's predic-
565 tions of baseline deforestation rates are sensitive to the assumptions concerning the uncertainty
566 of the profits. The modelled land managers consider land-use/land-cover types with less uncer-
567 tain benefits as more desirable than land-use/land-cover types with more uncertainty. Conse-
568 quently, the model predicts lower deforestation if natural forest benefits become less variable,
569 because land managers consider it more rewarding to maintain natural forests with less uncer-
570 tain benefits. Vice versa, the model predicts higher deforestation if the benefits of deforestation
571 become less uncertain. Based on this underlying mechanism, the coefficient of variation of
572 profits from natural forest or deforestation was chosen to reproduce observed deforestation on
573 average (2001 to 2004, see Supplementary Fig. 7 for an example). For both land-use/land-cover
574 types, natural forest and deforestation, we lack solid information on the associated uncertainties,
575 i.e. the expected profit variation, so that the uncertainty of these land-use/land-cover types could
576 be derived from calibration.

577 We used the observed deforestation from 2001 to 2004 for calibration due to the availability of
578 reliable remote sensing data from 2001 onwards. Because we know that a policy change influ-
579 enced deforestation in Indonesia from 2000 to 2005, and as reliable remote sensing data was
580 available prior to 2000 for this country[8], we calibrated Indonesia's baseline with observed de-
581 forestation from 1997 to 2000.

582 The years 1990 to 2000 served as a burn-in period for most countries. The burn-in period en-
583 sures that the baseline considers profit-oriented deforestation also before 2001. Such a burn-in
584 period is meaningful to avoid model artefacts from too strong land-use re-allocation when the
585 model is used for the first time, as for example seen for Argentina, Bolivia, and Brazil (Supple-
586 mentary Figs. 2a,b,c). Such effects would have biased the simulated baseline when occurring
587 in the calibration period.

For some countries, we observed an abrupt increase in deforestation levels around the year 2010. The main reason for such a change in the observed deforestation rates is likely technical, as the algorithms and sensors to measure observed deforestation have improved from 2011 (and particularly from 2015) onwards[13,68]. This hardly affects countries with large-scale natural forest clearings, such as Brazil or Indonesia. However, the deforestation detection in some African and Southeast Asian countries is affected by these improvements[69]. For these countries, we conducted a second calibration using the years 2010 to 2015. The new settings for the coefficients of variation of the concerned countries are indicated in Supplementary Coefficients. In total, we used 25% of the observed deforestation data for the calibration, so that 75% of the predicted baseline deforestation data fell outside the calibration periods.

It was difficult to align the observed deforestation exactly with the simulated deforestation in the calibration periods. We thus calculated the average difference between the observed and simulated deforestation during the calibration periods and used this difference to correct the whole series of baseline predictions.

In addition, we calibrated the baseline deforestation results by choosing the upper and lower bounds that limit the range of the profits in the random simulations. The bounds were computed by adding or subtracting between 0.5 and 2.5 standard deviations to/from the average profit, depending on the best agreement of land change model predictions and observed deforestation in the calibration periods. All the coefficients we used are detailed in the Supplementary Coefficients file.

Estimation of the standard errors

To estimate the upper and lower error bounds of the baseline deforestation trajectories, we used the standard errors based on $n = 50$ repeated simulation-optimisation runs with alternative profit scenarios per country c and per year.

To obtain the standard errors $\mathrm{SE}(\Delta)$ of the aggregated deforestation differences between observed and baseline deforestation, we summed all covariances across the investigated countries for all pairs of countries $c1$ and $c2$.

$$SE(\Delta) = \sqrt{\sum_{c1 \in C} \sum_{c2 \in C} cov(\Delta_{c1}, \Delta_{c2})} \quad (10)$$

This equation implies that all covariances are represented twice and that $cov(\Delta_{c1}, \Delta_{c1}) := var(\Delta_{c1})$, if $c1 = c2$. With this formulation, we implicitly included the diagonal of the variance-covariance matrix. The consideration of the covariances increased the standard errors by about 6% compared to considering only the variances.

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Author contributions: TK and CP designed previous counterfactual model versions, and TK developed the current version, carried out the calibrations and simulations, wrote the first manuscript, and revised previous manuscript versions. JC reviewed and revised the country selection, and JC and LB compiled all profit information and checked it for consistency. LB programmed plausibility tests and translated the original optimisation model implemented into Frontline Systems Solvers into an R code. KP, MKindu, and MD created the world map, and KP and MKindu prepared the manuscript for submission. FV improved calibration, and NH, MH, DW, and FV provided economic and econometric advice on justifying and discussing the counterfactual modelling approach. MK improved the consistency of the deforestation language we used. JC, LB, KP, MKM, MD, JF, MK, AM, AR, CS, PB, DW, MH, FV, NH, and CP developed, discussed, and revised the concept and text of the paper. CP supported the overall analytical concept. All authors compiled, analysed, and summarised relevant literature from their fields.

Code availability: We provide a Supplementary R code which demonstrates the simulation of random annual deforestation rates for Brazil from 1990 to 1994. For the implemented land-change model, example spreadsheets are also available, which were published along with the study by Knoke et al.[6] (https://doi.org/10.5281/zenodo.8016364). These spreadsheets can be used with Frontline Analytic Solver Optimization plus Simulation® (V2022.5).

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- SupplementaryRcode.txt
- SupplementaryCoefficients.xlsx
- SupplementaryMaterial.docx