

Trends in tropical forest loss and the social value of emission reductions

Received: 9 October 2022

Accepted: 14 June 2023

Published online: 13 July 2023

 Check for updates

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Reducing global forest losses is essential to mitigate climate change and its associated social costs. Multiple market and non-market factors can enhance or reduce forest loss. Here, to understand the role of non-market factors (for example, policies, climate anomalies or conflicts), we can compare observed trends to a reference (expected) scenario that excludes non-market factors. We define an expected scenario by simulating land-use decisions solely driven by market prices, productivities and presumably plausible decision-making. The land-use allocation model considers economic profits and uncertainties as incentives for forest conversion. We compare reference forest losses in Brazil, the Democratic Republic of Congo and Indonesia (2000–2019) with observed forest losses and assign differences from non-market factors. Our results suggest that non-market factors temporarily lead to lower-than-expected forest losses summing to 11.1 million hectares, but also to phases with higher-than-expected forest losses of 11.3 million hectares. Phases with lower-than-expected forest losses occurred earlier than those with higher-than-expected forest losses. The damages avoided by delaying emissions that would otherwise have occurred represent a social value of US\$61.6 billion (as of the year 2000). This result shows the economic importance of forest conservation efforts in the tropics, even if reduced forest loss might be temporary and reverse over time.

There is broad scientific consensus that halting forest loss is required to tackle the dual global crises of climate change and biodiversity loss^{1,2}. Notwithstanding their provision of multiple services, the contribution of forests in removing CO₂ from the atmosphere and storing it in a long-term carbon sink carries a particularly high social (economic) value³, and scientific research has produced increasingly sophisticated methods to assess this value⁴. In the global effort to reach net zero by 2050, combatting forest loss remains a feature of governmental and

private decarbonization initiatives, for example, the Race to Zero Campaign^{5,6} and the UNFCCC-REDD+ mechanism^{7,8} (Reducing Emissions from Deforestation and Forest Degradation and the Role of Conservation, Sustainable Management of Forests and Enhancement of Forest Carbon Stocks in Developing Countries). Analysing and assessing trends in forest losses is therefore of global social relevance, while identifying factors underlying these trends is a precondition to control the drivers of forest losses.

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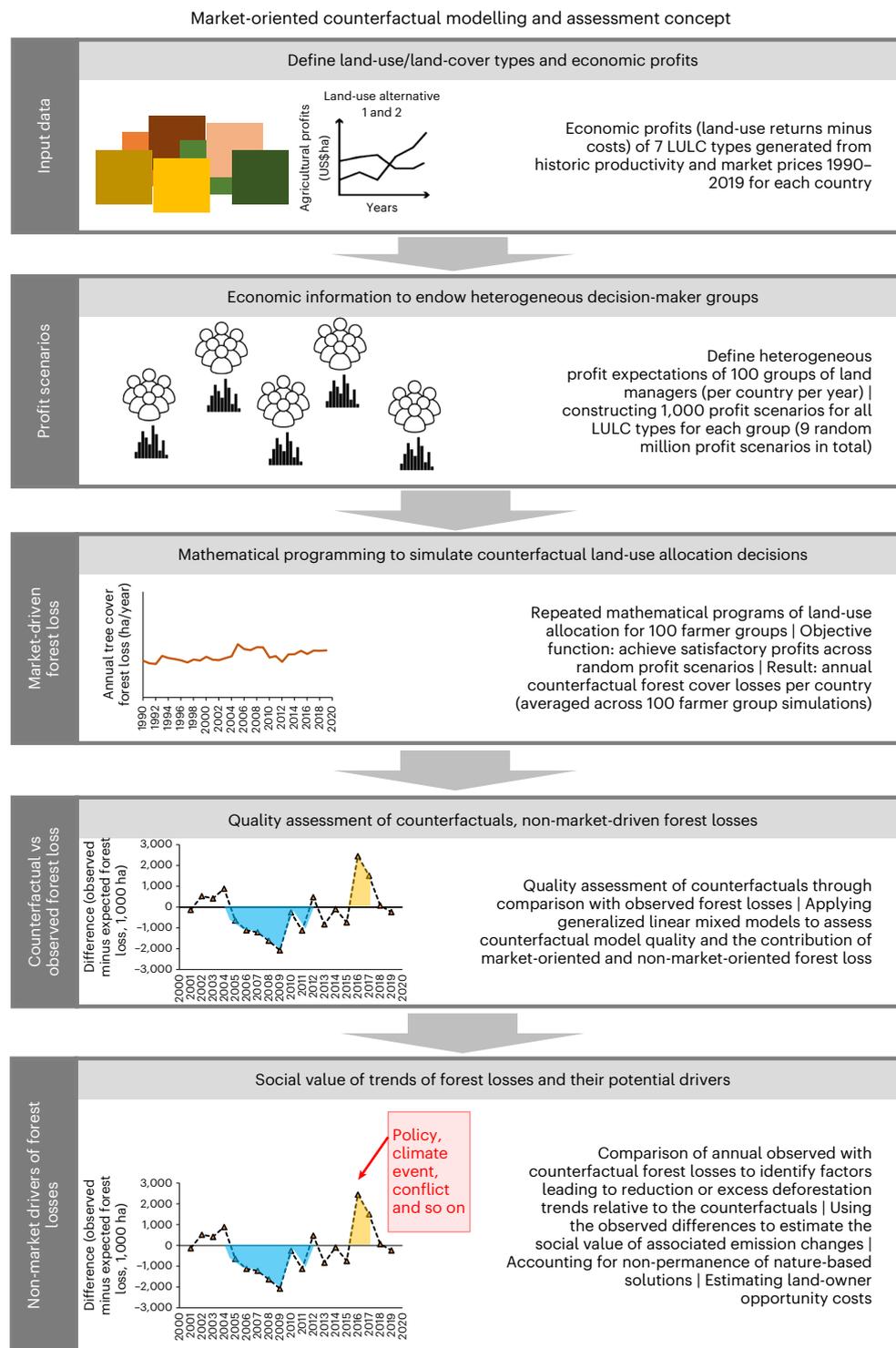


Fig. 1 | Model concept. Illustration of the market-oriented counterfactual modelling and assessment approach.

The effectiveness of policies and private financial incentives to reduce forest losses (for example, the REDD+ initiatives⁹ or payments for ecosystem services¹⁰) remains highly debated¹¹. Tracing back the impacts of domestic policies and other influential factors on forest loss is challenging¹². Commonly cited country-scale factors associated with trends in forest loss include market-based factors, such as demand for agricultural commodities¹³ or minerals¹⁴; governance-related factors (for example, command-and-control policies¹⁵, the rollout of land

titles for communities¹⁶ or pre-election promises¹⁷); factors associated with social conflicts and crises (for example, armed conflicts¹⁸ or COVID-19¹⁹); and climate anomalies, such as El Niño²⁰.

To associate trends in forest losses with specific factors, counterfactuals are needed to show what losses would have occurred under a reference scenario that excludes these factors²¹. Reference scenarios are critically important to identify and demonstrate the additionality of achieved emission reductions²². Avoiding forest losses represents

BOX 1

Definition and use of the social cost of carbon

Emission of CO₂ has a warming effect that is approximately permanent and constant over time⁶⁶. This emission is valued as the present value of all future marginal damages resulting from this permanent temperature increase starting with the year of the emission⁶⁷. This value is known as the SCC⁴⁶. Similarly, a permanent reduction of CO₂ is valued at the SCC, that is, as the present value of an infinite stream of avoided marginal damages. A temporary emission reduction of CO₂ by reducing forest losses is valued as the present value of a stream of avoided marginal damages over the duration of the avoided forest loss trend. The value of a temporary emission reduction is always positive because it temporarily avoids damages. This implies that immediate mitigation has high priority⁶⁸. We consider the time-value of reduced or enhanced emissions resulting from changes in forest losses by using discount factors, which we apply to convert all benefits and costs to their present value (Methods equation (5)). The discount factors reflect issues such as income inequality aversion, positive growth in the economy and uncertainty about future growth. In principle, the discount factor could also reflect learning processes and technological change.

a nature-based solution (as an initiative to achieve societal goals by working with nature²³) to combat climate change. Additionality means that observed emission reductions would not have occurred under business-as-usual conditions²⁴. In the absence of government intervention, market forces can either exacerbate or mitigate trends in forest loss. Mitigation would happen when land managers become increasingly satisfied with the economic outcome of their current land-use allocation and stop clearing forest, or when decreasing commodity prices lead them to reduce agricultural expansion²⁵. Both trends would cause non-additional emission reductions. So far, counterfactual studies have mostly been constructed from empirical forest loss data by applying quasi-experimental statistical models (Supplementary Table 1). However, these approaches usually focus on a specific policy instrument, the effects of which are difficult to isolate empirically.

In light of this, our study presents a new simulation approach to derive counterfactual forest loss trajectories that are generalizable beyond the context of a specific policy instrument. We separate market-driven from non-market-driven forest losses: the former offer a counterfactual reference scenario, while the latter represent residual forest losses not driven by economic expectations. Our novel approach combines economic land-use allocation modelling, satisficing decision rules under the influence of future uncertainty and heterogeneous decision-makers borrowed from agent-based modelling²⁶ (see Supplementary Table 1 for land-use modelling alternatives). Thus, our model assumes that (1) forest loss is largely driven by agricultural land transformation processes²⁷, (2) land-use decision-makers probably seek satisficing ('good-enough') rather than maximal outcomes when accounting for uncertainty²⁸ and (3) social processes underlying land-use allocation are driven by heterogeneous individual intentions²⁹.

Our simulated counterfactual land-use allocation decisions build on market data and agricultural productivities from 1990–2019. We simulate a total of 9 million random profit scenarios of heterogeneous farmer groups (Fig. 1) to derive expected forest losses for three large contributors to global forest loss: Brazil, the Democratic Republic (DR) of Congo and Indonesia³⁰ (Supplementary Fig. 3). This economic

model accounts for the private incentives to convert forest to different land-use types (profits and uncertainties) and thus provides market-oriented counterfactuals (Fig. 1).

We address three main questions:

1. When do observed forest losses diverge considerably from those simulated by our economic model for the three selected countries?
2. What factors are likely to affect observed forest losses at the country scale and potentially explain reduced and excess forest losses compared with the market-based counterfactual forest loss?
3. What is the social economic value of avoided climate damages from reduced forest emissions?

The difference between our market-driven counterfactual model and the empirical forest loss data allows us to identify periods when forest loss is attributable to market forces (good alignment between our counterfactual and the empirical forest loss data), as well as periods where the forest cover change is likely attributable to additional non-market forces. While our counterfactual model does not offer clear attribution of single drivers and is not intended to evaluate the effectiveness of specific conservation policies, it can offer insights into which broad country-scale factors shape changes in the levels of forest losses based on temporal congruence¹⁷. These factors include armed conflicts, pre-election promises made by politicians, government changes, severe ENSO climate pressures (2015–2016) and command-and-control policies intended to reduce forest losses (Methods and Supplementary Methods 3).

One contribution of our innovative counterfactual approach is in estimating the social economic value associated with avoided deforestation, which is important for communicating the economic value of reducing forest losses. In climate economics, avoided climate damages through temporary cooling effects³¹—for example, by retaining instead of clearing carbon-rich forest—generate social economic value⁴. A useful concept for assessing this value is the social cost of carbon (SCC) (Box 1). Up to now, a frequently disregarded aspect of such valuations is the potential non-permanence of the achieved emission reductions^{4,31}, which we consider here. We use this approach to estimate the social value of emission reductions achieved by avoiding tropical forest losses.

Market-driven counterfactual forest losses

Our counterfactual land-use allocation model (Fig. 1) identifies the forest losses that would probably have resulted from market-driven decisions in Brazil, DR Congo and Indonesia—that is, without the influence of policies to reduce deforestation and without other non-market drivers of forest losses.

The highest counterfactual deforestation rates (forest loss relative to total forest area) are predicted for Indonesia and the lowest for DR Congo (Fig. 2a). The average (and median) deforestation rates differ more widely among the three countries in the period 1990–1994 than in 2015–2019. Additionally, the range of simulated deforestation rates tends to decrease over time for Brazil and Indonesia (Supplementary Methods 7). The distribution of these rates follows a power-law relationship (Fig. 2b), which can also be observed in empirical analyses (for example, for deforestation patch sizes in ref. 32).

To assess the quality of the predicted counterfactual forest cover losses, we conducted a series of statistical analyses and cross-study comparisons. Two independent counterfactual forest loss trajectories reveal similar results (Supplementary Fig. 1). The market-driven counterfactual forest losses show good agreement with observed forest losses. In a statistical comparison considering all three countries, market-driven forest losses predicted by our counterfactual model explain 59% of the variation of observed forest losses (Supplementary Fig. 2a). Controlling for periods coinciding with non-market factors (here, command-and-control policies, climate anomalies, armed

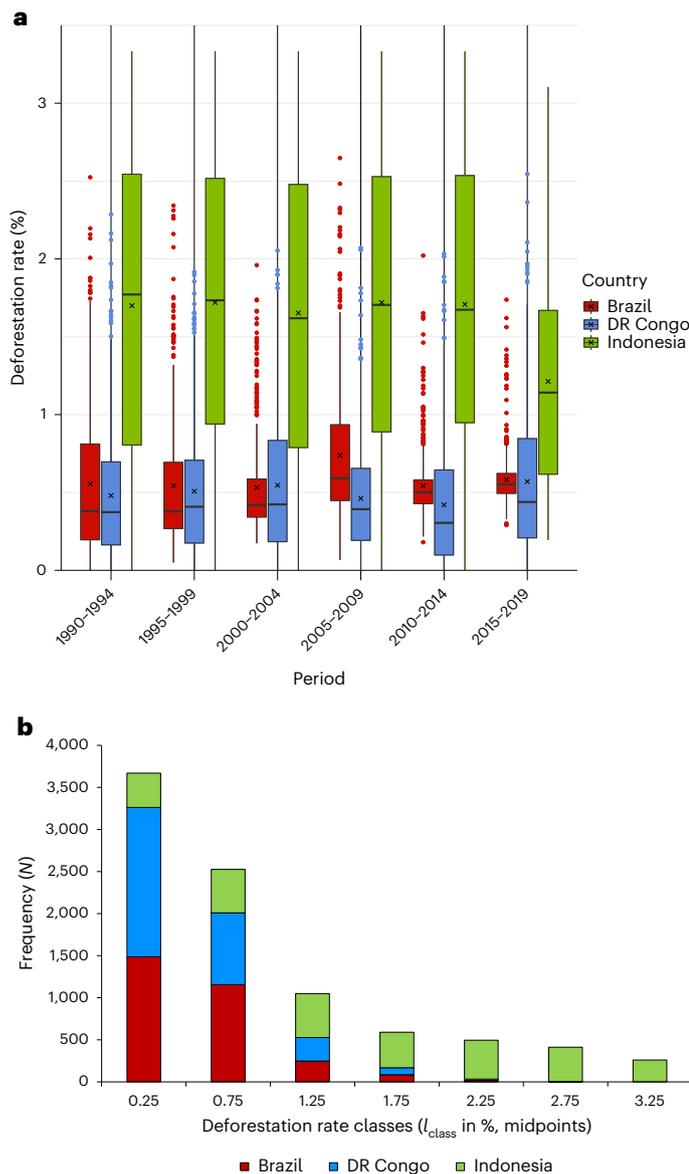


Fig. 2 | Counterfactual deforestation rates. **a**, Boxplots (consisting of $n = 9,000$ simulated deforestation rates, each single estimate obtained from a mathematical programme considering 1,000 economic profit scenarios; details of the simulations can be found in Supplementary Methods 1) of deforestation rates. The x-axis shows the start and end year of each 5 yr period. Solid vertical lines, median; crosses (x), arithmetic mean; lower and upper hinges, 25th and 75th percentiles; whiskers extend from the upper/lower hinge to the largest/smallest value no further from the hinge than 1.5 times the interquartile range. Data beyond the whiskers are 'outliers' and are plotted individually. **b**, The frequency distribution of the counterfactual deforestation rates follows a power-law relationship: $N = 3,936 \times 10^{-0.88 \times l_{class}}$. l_{class} is the forest loss class.

conflicts and pre-election promises), statistical model predictions explain 75% of the variation in observed forest losses (Supplementary Table 2 and Fig. 2b). The time series of counterfactual forest losses (Supplementary Fig. 1) respond to periods with declining crop prices by predicting smaller forest losses, for example, when soybean prices decreased in Brazil from 2005 onwards (Fig. 3a) and palm oil prices fell in Indonesia from 2010 onwards (Fig. 3c).

Non-market-driven forest losses

A general comparison suggests lower-than-expected forest losses (arising from non-market factors) of 11.1 million hectares overall

(6.7 million hectares in Brazil, zero hectares in DR Congo and 4.4 million hectares in Indonesia) in two phases of deforestation reduction coinciding with command-and-control policies. This amounts to 11% of the reference forest losses between 2000–2019 in the three countries (Table 1). In contrast, in periods of higher-than-expected forest losses (coinciding with pre-election promises, armed conflicts or climate phenomena), forest losses exceed the counterfactual levels by a total of 11.3 million hectares (Table 1), fully offsetting the aggregate forest loss reduction periods across the three countries. The estimated emissions from the observed forest cover losses are 0.20 gigatonnes CO₂ higher than the expected emissions (equivalent to a 0.4% increase relative to the emissions from expected forest losses).

Reduced and excess forest loss

For Brazil, deviations of the observed from counterfactual forest losses indicate one reduction period (coinciding with command-and-control policies) and one excess period of forest loss (coinciding with climate anomalies) (Fig. 3a). Mainly lower-than-expected forest cover losses are identified from 2004 to 2012 in a reduction phase of forest loss (Fig. 4a). From 2012 onwards, the modelled forest losses mimic the dynamics of observed forest losses well, suggesting a period of mainly market-oriented land-use decisions. The year 2016 marks a deforestation spike and a pronounced excess phase of deforestation with additional forest losses (Fig. 4a). In sum, a net saving of forest area of 3.4 million hectares remains (or 7.3 million hectares ignoring the extensive wildfire forest losses in 2016 and 2017), when subtracting excess forest losses from achieved reductions of forest losses (6%, or 12% without wildfire losses, of the 2000–2019 reference level of forest losses).

For DR Congo, we obtain an overestimation of forest losses from 2001 to 2005 compared with observed forest losses, but a good alignment with FAO-reported forest losses used for calibration (in the absence of remotely sensed information from 1990–1999) (Fig. 3b). However, our model does not mirror the observed forest losses from 2012 onwards. The identified deviations mark an excess phase of deforestation (Fig. 4b), suggesting higher-than-expected forest losses (Table 1) (coinciding with armed conflicts). The excess forest loss reaches 3.8 million hectares, some 29% of the reference level of forest losses (2000–2019).

In Indonesia, we identify both reduction (coinciding with command-and-control policies) and excess periods of forest losses (coinciding with pre-election promises). In the reduction period, observed forest losses sharply decrease in the period 2000–2005 (Fig. 4c). From 2006 to 2010, we again obtain a good agreement between observed and reference forest losses, pointing to a market-oriented period. Observed forest losses tend to exceed modelled forest losses from 2011 onwards, leading to an excess phase of forest loss (Fig. 4c). The net effect of reduction and excess phases is a less-than-expected forest loss of 0.12 million hectares, which is 0.5% of the reference level of forest losses (2000–2019). Excluding the wildfire forest losses in Indonesia in 2016 leads to a net reduction of forest losses by 0.86 million hectares (3% of the reference level of forest losses).

The social value of avoided emissions

The trend changes in forest losses for Brazil (2004–2012) and Indonesia (2000–2005) (Fig. 4d,f) have probably caused climate cooling effects, achieved by a reduction of CO₂ emissions (see ref. 4,31 for confirming such effects) coinciding with command-and-control policies. Such cooling effects are partly offset by later climate warming effects through increased emissions in Indonesia, coinciding with pre-election promises. The estimated cumulative avoided or increased CO₂ emissions from 2000–2019, which we used for our social valuation approach (Methods equation (5) and Supplementary Methods 4), range between +2.757 avoided (Brazil, enhanced carbon storage) and –1.573 additional gigatonnes CO₂ (DR Congo, reduced carbon storage) (Fig. 4 and Table 2). For our social value calculation, we use conservative SCC^{33,34}

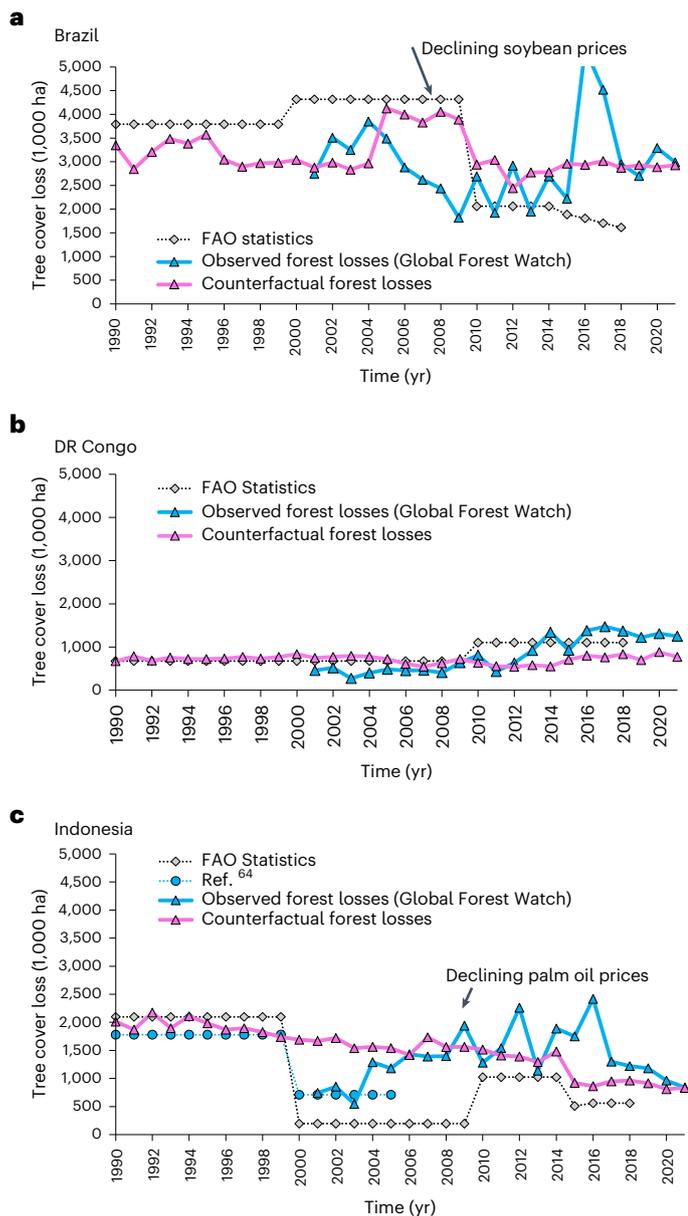


Fig. 3 | Observed and reference forest cover losses for the three selected countries. **a**, Brazil. **b**, DR Congo. **c**, Indonesia (see Methods and Supplementary Methods 1 for methodological details). Observed forest losses refer to tree cover losses obtained from Global Forest Watch. Forest losses from FAO Statistics are shown for comparison and were used for calibration (1990–1999) in the absence of remotely sensed data.

growing from US\$30.1 (2000) to US\$44.1 per tonne CO₂ emission (2019) (2015 US\$; see Supplementary Table 9). We exclude the emissions from natural wildfires occurring in association with climate anomalies in Brazil and Indonesia (2016–2017), which are probably mainly natural phenomena.

Benefits (reductions of emissions) and costs (increases of emissions) impact the social value of the trends of forest losses in the three countries. The social value of changes to forest losses from non-market forces considers the benefits of emission reductions and the costs of emissions measured from the perspective of 2000 (Fig. 4d–f). Yet the timing of these benefits and costs matters because their associated damages are discounted as in the case of the SCC⁴. We use a constant discount rate to convert all costs and benefits to their present value in 2019 (Methods, equations (3) and (5)). Our method penalizes temporary

warming (increased damages) and values temporary cooling³¹ (avoided damages). For example, CO₂ not emitted into the atmosphere by reducing forest losses in 2000 avoids social costs of damages over 20 yr, even when released into the atmosphere in 2019.

This social value of the non-market emission effects (Methods equation (5)) is then +US\$133.8 and +US\$36.7 billion in Brazil and Indonesia, respectively (see Table 2), but emission trends in DR Congo contribute negatively to the social value with –US\$71.3 billion, if we consider the CO₂ emission changes as permanent from 2020 onwards.

Accounting for possible non-permanence of emission changes after 2019 by assuming a 1% likelihood per year that the climate beneficial (Brazil and Indonesia) or adverse effect (DR Congo) reverses (see Methods, equation (5)) alters the value of the emission reduction, depending on how much CO₂ emissions are cumulatively avoided or added by the trend changes until 2019 (Table 2). The reduction of the social value is stronger in Brazil (–46%), where higher avoided CO₂ emissions have accumulated, than in Indonesia (–29%). However, the remaining climate benefits are still strongest in Brazil (social value of emission reduction accounting for non-permanence +US\$72.1 billion).

Reducing forest losses comes with a cost for land managers who forgo land-use benefits otherwise obtained from expanding agricultural land or timber plantations at the cost of tropical forest. We calculate the accumulated value of the forgone profits to land managers as present values in 2019 (Methods, equation (8)), which we also use as reference year for the social value calculation. These costs are moderate and much lower than the social value of the emission reductions achieved in Brazil (estimated land-opportunity costs of –US\$20.7 billion). Land-opportunity costs are higher in Indonesia than in Brazil, but still lower than the social value of the emissions reduced there (Table 2).

Discussion

Our study presents a new counterfactual land-use allocation model driven by assumptions of satisficing behaviour, heterogeneous farmer expectations and stochastic uncertainty, which can simulate market-oriented decision-making. It provides a suitable business-as-usual baseline to assess the social value of reducing forest losses, where forest conservation generates social value by avoiding emissions. We argue that modelling market-driven forest losses and separating them from non-market-driven losses provides a way to understand the net effect of broad policy interventions and other non-market factors that simultaneously influence forest cover. This approach complements quasi-experimental statistical approaches, which are agnostic to the factors determining the baseline scenario. Additionally, our counterfactuals enable the application of a cutting-edge method⁴ for quantifying the social (economic) value of changes to emissions from forest losses.

The counterfactual model reflects how landowners will likely respond to changing market forces, capturing very different conditions and deforestation rates ranging from an average of 0.50% (DR Congo, with cassava as the most profitable crop) to 0.58% (Brazil, with soybeans as the most profitable crop) to 1.61% per year (Indonesia, with palm oil as the most profitable crop). Thus, we expect that our approach can be extended to support studies in countries beyond the three considered here.

The assumption of satisficing behaviour supports realistic model outcomes: alternative assumptions would yield different counterfactual predictions. For example, giving more weight to maximizing decision rules would increase simulated reference levels of forest loss to higher than observed forest losses³⁵, whereas our model is able to capture empirically observed variations in forest cover losses across time with relatively little (and exclusively publicly available) input data. Further research could extend our model to include other drivers beyond heterogeneous expected future market prices and agricultural productivities. Finally, it is important to stress that our approach does not provide causal impact estimates and exact figures

Table 1 | Periods of change in trends of forest losses according to literature and differences from our market-driven counterfactual simulations

Factor #	Documented periods with domestic policies or other impacts on the level of forest loss				Forest cover losses (in million hectares) and emissions (gigatonnes CO ₂) (in brackets)		
	Source and reason	Country	Period (yr)	Type of forest loss phase	(1) Observed forest losses	(2) Market-driven (counterfactual) forest losses	(1)–(2) Residual: non-market-driven forest losses
1	Ref. ⁵¹ - Command-and-control: agreements with meat companies and soy moratorium	Brazil	2004–2012	Reduction	24.630 (9.31)	31.285 (11.83)	–6.655 (–2.52)
2	Ref. ²⁰ - Climate phenomenon El Niño	Brazil	2015–2017	Excess	12.120 (4.58)	8.909 (3.37)	+3.211 (+1.21)
3	Ref. ¹⁸ - Armed conflicts	DR Congo	2012–2019	Excess	9.260 (3.84)	5.467 (2.27)	+3.793 (+1.57)
4	Ref. ⁶⁴ - Command-and-control: consistent permitting rules and export taxes	Indonesia	2000–2005	Reduction	5.314 (2.93)	9.724 (5.35)	–4.410 (–2.43)
5	Ref. ¹⁷ - Public spending (additional harvesting allowances) before elections	Indonesia	2010–2019	Excess	15.980 (8.80)	11.697 (6.44)	+4.283 (+2.36)
Sum					67.304 (29.46)	67.082 (29.26)	+0.222 (+0.20)

Counterfactual simulations are shown in Fig. 4. We excluded the model calibration phase (1990–1999) from this table (see Supplementary Methods 1).

for specific forest loss reduction policies, instead providing net deviations from a market-only reference scenario. In other studies, highly advanced integrated assessment models are used in prospective studies³⁶ or sophisticated quasi-experimental models for ex-post analyses³⁷. Instead, we present a counterfactual modelling and broad assessment approach as a parsimonious and less data-demanding complement to these techniques while still providing generalizable patterns of likely country-scale drivers of forest losses and a robust estimation of the order of magnitude of the social value of avoided forest losses.

In Brazil, the counterfactual forest cover trajectory identified reduced forest losses at a plausible order of magnitude for 2004–2009, a period that corresponds to the implementation of the ‘Action Plan for the Prevention and Control of Deforestation in the Legal Amazon’ (PPCDAm). For example, ref. 38 found a deforestation reduction of 73,000 km² (emission reduction of 2.7 gigatonnes CO₂), which is similar to our estimated forest loss reduction for the same period (67,000 km², emission reduction of 3.1 gigatonnes CO₂).

Developments in DR Congo from 2012 onwards illustrate how disruptions in social cohesion and local governance structures (here represented by armed conflicts¹⁸) can trigger deviations from the expected market-only forest loss trajectory. Displaced populations and forced migrations indicate serious disturbances to local communities and governance, probably eroding land users’ confidence about their ability to exploit future benefits of avoided deforestation. Moving forward, the disturbance of social systems by global or national crises could become an even more important driver of forest loss.

Indonesia is a country characterized by high land-opportunity costs, which are the enemy of any forest conservation³⁹. Trends in forest losses show a climate cooling effect (smaller than in Brazil) from forest loss reductions in 2000–2005, with some social value even after accounting for possible non-permanence of the reduction effect. Our retrospective analysis identifies pre-election promises as important drivers of excess forest losses¹⁷, with peaks in 2015–2016 associated with elevated wildfire frequency⁴⁰. We suggest that several factors may have been underlying the excess deforestation in Indonesia from 2010 onwards. For example, spillover effects were associated with the Indonesian palm oil moratorium leading to increased deforestation⁴¹. Additionally, this period was influenced by the REDD+ agreement

and a moratorium concerning peatland and primary forests between Indonesia and Norway. While the moratorium was assessed as being cost-effective⁴², it has probably contributed only marginally to aggregate reductions of CO₂ emissions over the period 2011–2018. It will be important to analyse and assess future forest loss trends, for example, regarding the new ‘Omnibus law’ in Indonesia issued in 2020 to support more work opportunities and attract foreign and domestic investments by relaxing regulatory requirements for businesses⁴³.

Our approach accounts for the non-permanence of the cumulative emission reductions achieved by changing forest loss trends. It avoids overestimating the value of forest protection initiatives and offers a transparent and credible means of estimating the social value associated with avoiding forest loss⁴. Similarly, while past scholarship has been criticized for overstating reference trajectories⁹, our counterfactual approach provides reference estimates that are independent from (often very high) historical forest losses. Overstating the value of nature-based solutions risks discrediting this crucial set of climate mitigation and adaptation strategies⁴⁴, which often effectively bundle social and ecological co-benefits.

Here we calculate a social value of past trends of forest losses worth US\$61.6 billion even when accounting for the non-permanence of achieved emission reductions. This value climbs to US\$92.2 billion if conflict-linked deforestation spikes in DR Congo are ignored. The social value of these avoided emissions alone outweighs the forgone private agricultural net benefits imposed by forest conservation, and carbon storage is just one part of the total social value provided by tropical forest³. For Brazil, we calculate that the social value of avoided emissions (US\$72.2 billion) is 3.5 times the private agricultural land-opportunity costs. This result supports the findings of a recent global study⁴⁵ that found benefit–cost ratios of general global climate policies ranging between 1.5 and 3.9. Our result is even more remarkable, as we used SCC to assess past trends of forest losses at the lower end of recently published SCC⁴⁶.

The economic valuation of the benefits and costs associated with the services of nature comes with criticism⁴⁷. However, our study highlights that reducing forest losses, even when faced with the risk of non-permanence³¹, may generate real economic benefits, which humans cannot afford to ignore. Provided that credible methods to assess their potential are used, one can value how such solutions may

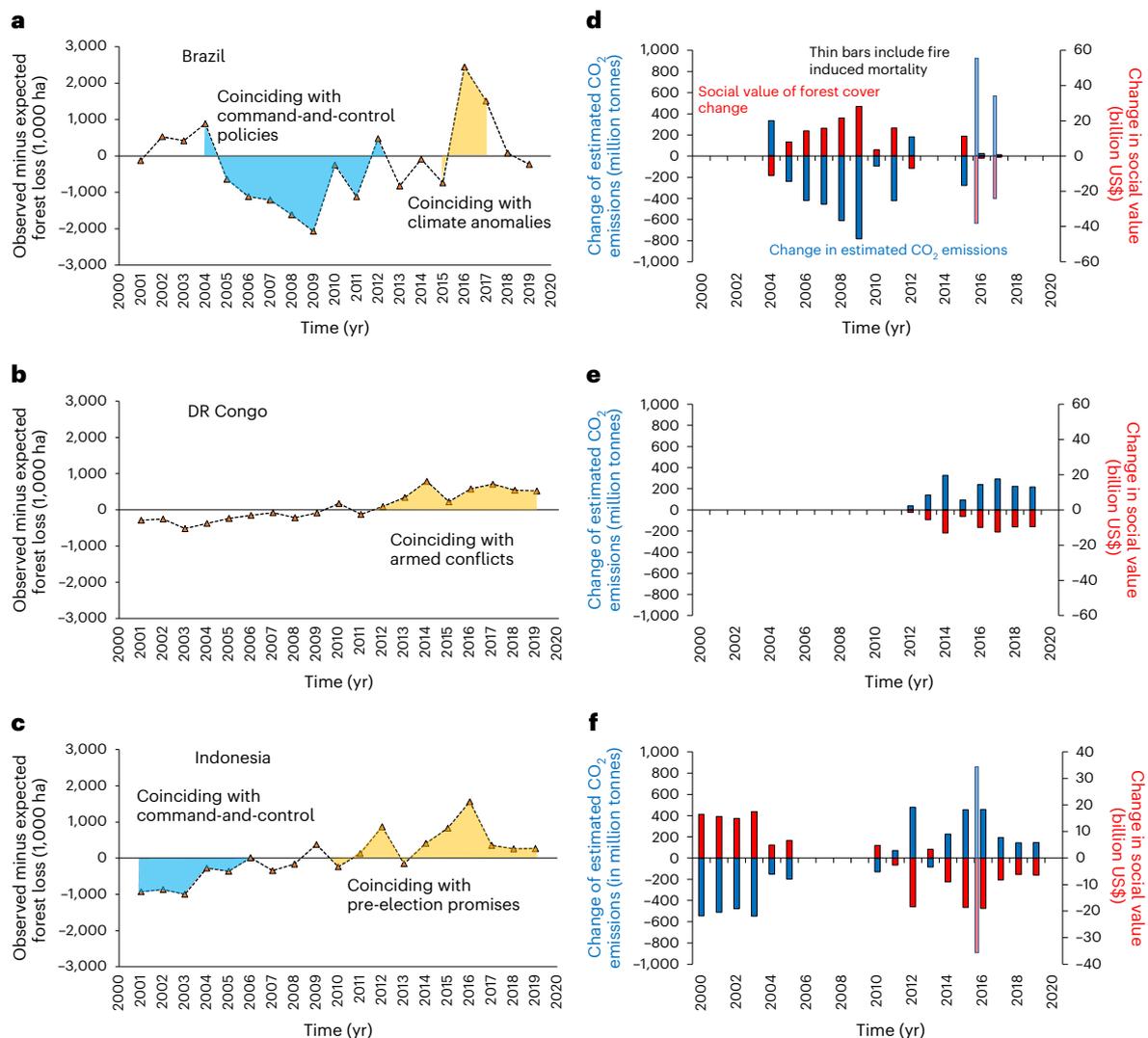


Fig. 4 | Differences in observed and counterfactual forest losses and related changes in CO₂ emissions. a–c, Differences between observed and counterfactual forest losses in documented reduction and excess periods of forest loss for Brazil (a), DR Congo (b) and Indonesia (c) (Table 1). **d–f**, The

corresponding estimated changes in CO₂ emissions together with the associated impact on their social value in a given year. The thin bars in 2015 and 2016 for Indonesia and Brazil, respectively, include emissions by wildfire, which we however excluded from the calculation of the social value of emission reductions.

effectively complement efforts to reduce human greenhouse gas emissions elsewhere³¹. We argue that valuing avoided emissions from forest losses is important because the magnitude of their social value vastly outweighs imperfections in assessment methods. Doing so may help to identify leverage points for sustainable development, for example reducing perverse incentive structures that redirect capital to projects that generate net social and environmental harm^{48,49}.

Among the limitations of our counterfactuals is a lack of spatial detail in modelled forest losses; no local inference is possible with this first version of our model. Other limitations include the problem that several influences may overlap. For example, another study has shown that mining has been responsible for 9% of the forest losses in the Brazilian Amazon from 2005–2015¹⁴. However, possible mining-related excess forest losses were probably compensated by simultaneous command-and-control policies at the country scale. We limited the factors included in our counterfactual model to market price signals, productivities and the associated profit expectations of farmers, but other factors can also be influential (for example, the effects of changing discount rates⁵⁰ or movements of exchange rates⁵¹). We suggest that such effects have partially been encapsulated by market price signals⁵².

Additionally, non-monetary factors, such as access to labour⁵³, as well as cultural values⁵⁴ can influence the level of forest loss. Our counterfactual model can be advanced to integrate such factors by including multiple objectives to be satisfied³⁵.

We conclude that generating suitable reference scenarios is pivotal for analysing forest loss trends, as one cannot intersubjectively assess what one cannot measure²¹. Our approach enables the identification not only of trends but also of possible drivers. Illustrating trends and estimating their social value can be an important communication strategy. Our estimates of the social value of inducing changes to expected forest loss rates are moderate but encouraging, particularly for Brazil's case, providing a proof-of-concept that past deforestation reductions were of substantial social value, even if they were short-lived. This underlines both the feasibility and the urgency of integrating the economic dimensions of forest losses into decision-making⁵⁵ and welfare-accounting systems⁵⁶ to harness the momentum of the Glasgow Leaders' Declaration on Forests and Land Use.

Achieving larger and more enduring reductions in forest losses is among society's greatest challenges. Here we show that efforts to protect forests can also be economically rewarding. Future initiatives

Table 2 | Social value of emission trends under various assumptions and land-opportunity costs for land managers

Country	Cumulatively avoided (+) or additional (-) emissions 2000–2019 (gigatonnes CO ₂) (in brackets when considering emissions from wildfires)	Social value of the CO ₂ emission trend changes (billion US\$)		Private opportunity costs of avoided forest losses (billion US\$) (Methods)
		Assuming permanence of emission changes after 2019	Assuming a likelihood of 1% per year (after 2019) that the saving/loss effect is reversed (Methods)	
Brazil	+2.757 (+1.310)	+133.8	+72.1	-20.7
DR Congo	-1.573	-71.3	-36.6	n.a.
Indonesia	+0.471 (+0.070)	+36.7	+26.1	-24.4

Land-opportunity costs for land managers refer to economic net benefits land managers forgo with forest conservation. For DR Congo, land-opportunity costs do not apply, as forest losses have not been reduced there. n.a., not applicable.

could address the causes rather than the symptoms⁵⁷ of forest loss, including the demand side for agricultural commodities¹³, and influence the social identity⁵⁸ of land managers rather than considering their actual behaviour as a mistake to be corrected.

Methods

Counterfactual deforestation model

The common maximization paradigm in land-use models implies that land managers would always seek, for example, the maximum productivity, service provisioning, net present value, utility or profit. Such analyses commonly assume just one future condition or average alternative scenario outcomes (sometimes using probabilities as weights). However, the uncertain real world does not allow application of the maximization assumption for many land managers because the one land-use allocation that achieves a maximum outcome across all possible future scenarios would not be available. Moreover, maximizing the average of all possible scenarios might be acceptable for rich land managers but not for those needing acceptable land-use income each year. We thus started with the premise that satisficing behaviour is a more reasonable and consistent assumption for land-use decisions²⁸, given that multiple futures are possible and that decision-makers have imperfect information on the likelihood of occurrence of these futures. Uncertainty includes market price and productivity fluctuations, as well as potential crop losses by natural hazards and sudden political changes. Land managers consider multiple possible profits for the future in our model. In our approach, satisficing means that land managers gradually improve their current land-use profits by seeking a compromise land-use allocation that promises ‘sufficient’ outcome levels for all states of the world they assume are possible. To achieve this, individual land managers would consider two types of information: (1) profits they expect under current land-use allocation and (2) the best achievable profits they expect under a changed land allocation (for multiple possible future profit scenarios). Our suggested model (see Fig. 1 for workflow) captures the potential for improvement by the difference between (2) and (1), which shows the degree of land manager dissatisfaction with current profits. Groups of farmers then reallocated land between land-use/land-cover (LULC) types, seeking to reduce the maximum difference between (2) and (1) across multiple (randomly simulated) future profits they expect. However, in contrast to a previous model¹⁵, we used a large range of stochastic profit scenarios to acknowledge that individual expectations are heterogeneous⁵⁹. This implies that not all farmers would contribute equally to LULC changes, but mainly those who see the largest potential for improving their profits (that is, those who experience the largest dissatisfaction with

current profits). While we clustered individual land managers into groups (to represent potential regional heterogeneity), we assumed that such groups would arrange their land-use allocation in a way that minimizes their maximum dissatisfaction across multiple future profit expectations over time, taking their heterogeneous profit expectations into account. The simulated market-driven counterfactual forest loss predicts the expected annual reduction of the area cover of the LULC type ‘natural forest’ (Supplementary Methods 1, equation (1)). For a mathematical description of our counterfactual deforestation model, see Supplementary Methods 1.

Observed forest losses

Observed forest losses were taken from Global Forest Watch⁶⁰, defined as ‘... the complete removal of tree cover canopy at the Landsat pixel scale’. Data from FAO Statistics⁶¹ refer to annual area reductions of the LULC class ‘naturally regenerating forest’ (Supplementary Methods 1). Forest losses included both deforestation (permanent loss of forest) and temporary forest losses (for example, due to natural forest fires) partly followed by forest regrowth. We excluded extensive forest losses due to natural fires in Brazil and Indonesia (2016 and 2017), which are probably temporary, from the assessment of the social value of the forest loss trends. Solid remote sensing data underlie Global Forest Watch forest losses, which rely on a method developed in ref. 62. We compared observed and counterfactual forest losses to identify deviations from reference trajectories of forest losses, these deviations being manifested as periods of reduction or excess of deforestation. The FAO-reported data show that Brazil, DR Congo and Indonesia account for 43% of the average global net forest losses over the period 2009–2019 (Supplementary Fig. 3, based on ref. 61).

Model assessment

The influence of the reduction and excess periods of forest losses affected by non-market factors on the level of forest loss (L^{obs}) was statistically analysed using a generalized linear mixed model to evaluate the quality of the counterfactual model. Countries were defined as subjects and the year of the observation as the repeated measure variable. We evaluated the portion of the variation of the observed forest losses (L^{obs}) that can be explained by the estimates L^{obs} , using the counterfactual forest losses L^{ref} , and the reduction and excess phases as predictors (Supplementary Fig. 2).

$$L^{obs} = a + b \times R^{Bra1} + c \times R^{Bra2} + d \times R^{Ind} + e \times EX^{Bra} + f \times EX^{Con} + g \times EX^{Ind} + h \times L^{ref} \quad (1)$$

Bra1 is Brazil reduction period 1, Bra2 is Brazil reduction period 2, Ind is Indonesia, Bra is Brazil, Con is DR Congo and ref is counterfactual forest loss. Reduction (R) and excess periods (EX) were contrasted against a reference level of 0 (\approx phase of market-oriented forest loss).

Equation (1) considers market-oriented counterfactual forest losses by variable L^{ref} , but also controls for the impact of periods influenced by non-market factors. One would expect that, given unbiased counterfactual (reference) forest losses, the coefficient h of the variable L^{ref} would obtain a value close to one. In fact, we obtained $h = +0.969$ (see Supplementary Table 1).

Country-level influences on the level of forest loss

We used ref. 63, which structured the drivers of forest loss into proximate causes and underlying driving forces, as an orientation to identify potential country-scale factors driving forest loss. The underlying forces mentioned in ref. 63 included economic factors (which our counterfactuals covered using production values computed as prices \times productivities), institutional and policy influences, remote factors, but also behavioural factors (which our counterfactuals considered by assuming satisficing decision-making). Examples of the proximate causes

included agricultural expansion, wood extraction and infrastructure extension. Social events (such as revolution) and biophysical drivers (for example, climate events) were classified as between the underlying and proximate levels.

While our counterfactual model included already important underlying drivers (agricultural productivities, market prices and consistent satisficing decision behaviour), we also searched for country-scale factors as possible causes for deviations of observed from counterfactual forest losses. These factors represented institutional and policy factors (for example, command-and-control policies and pre-election promises), social events (for example, conflicts) and extreme climate events (for example, biophysical drivers). On the basis of literature searches, we qualitatively tested whether such factors, for which reliable evidence had been published, temporarily coincided with deviations from the counterfactuals. Concerning factors supporting a reduction in forest losses, these selection criteria were met for command-and-control policies associated with the PPCDAm, launched in 2004 by Brazil's government. These policies included land planning, establishing and expanding protected areas, remote sensing-based monitoring and control, environmental licences, fines for illegal deforestation and on-the-ground enforcement of the law¹⁵. Domestic political interventions to reduce forest losses, such as agreements with meat companies and a soy moratorium, were also established⁵¹. The moratorium banned trading, financing or purchasing of soybeans produced on land parcels previously covered by rainforest. As an approximate end of the period under command-and-control policies, the Brazilian Forest Code was established in 2012¹⁵, which weakened the initially ambitious deforestation reduction aims. In the case of Indonesia, command-and-control policies were associated with Forestry Act No. 41 in 1999 (which we considered for 2000–2005 following ref. 64), according to which everybody had to protect the environment and forests⁶⁵. This legal act also supported more stringent forest clearing permission rules enforced by the government and consistently applied fiscal measures, such as export taxes (limiting the attractiveness of exporting palm oil), implemented after a change in the government⁶⁴. On factors potentially leading to excess forest losses, we suggest social disturbances by armed conflicts in DR Congo as a possible cause of higher-than-expected deforestation from 2012 onwards. A strong increase in conflicts has been documented from 2009 onwards in DR Congo (from below 1,000 to almost 3,500 cases per year)¹⁸. Main conflict types were battles, violence against civilians and riots or protests. For Indonesia, we suggest perverse political incentives (pre-election promotion of agricultural development and additional harvesting concessions) as regional-level factors driving excess forest losses from 2010 onwards. The number of direct elections was shown to be significantly positively correlated with the level of forest loss¹⁷. Finally, we traced back extreme peaks of forest losses (mainly in Brazil, but also in Indonesia) to the extreme climate events of 2016. Local and other factors potentially influencing the level of forest loss but not included in our approach are discussed in Supplementary Methods 3.

Social value and opportunity costs

Our counterfactual forest loss trajectories facilitated quantifying the social value of avoiding CO₂ emissions, here based on our real-world example of reducing forest losses. Our assessment method was guided by a newly developed method⁴ to value nature-based emission reductions starting with the social costs of carbon (SCC_t), which aggregate the costs of damages caused by one additional unit of CO₂ emitted today from a societal perspective over an unlimited period.

$$SCC_t = \sum_t^{\infty} (1+r)^{-t} \times D_t \quad (2)$$

D_t is the temperature-dependent marginal damage (in US\$) caused by the emission of one unit CO₂ emitted in one specific year, which increases at a constant rate per year in our study, and r is the constant

discount rate ($r = 0.03$ in our case³³). SCC_t data were taken from ref. 33 and D_t grew at 0.0202 per annum (derived from data in ref. 34).

The basic equation derived in ref. 4 to assess the social value V of avoided CO₂ emissions under the premise of permanence of the emission reduction and climate effects after T (T is when our consideration ends) is as follows:

$$V = \sum_{t=0}^{T=19} (1+r)^{-t} \times E_t \times SCC_t = \sum_{t=0}^{\infty} (1+r)^{-t} \times S_t \times D_t \quad (3)$$

E_t is either an annual reduction of CO₂ emissions relative to the counterfactual, contributing positively to the social value of the trend of forest loss, or an increase, contributing negatively to the social value (Supplementary Methods 4.1). S_t is the stock of the accumulated avoided (positive S_t) or additional emissions (negative S_t), which we assumed to become constant from T onwards.

$$S_t = \sum_0^t E_t \quad (4)$$

To account for the possibility of a reversion of the carbon stocks to their initial values (=non-permanence), we assumed a likelihood of reversion of 1% per annum from T onwards. This assumption was implemented by using an adjusted social value V^* to account for possible non-permanence. V^* uses the year 2019 as reference year for the present value.

$$V^* = \sum_{t=0}^{T=19} (1+r)^{19-t} \times S_t \times D_t + \sum_{t=20}^{\infty} (1+r)^{-(t-19)} \times (1+\rho)^{-(t-19)} \times S_t \times D_t \quad (5)$$

ρ is the probability of reversion to the pre-assessment state per annum ($\rho = 0.01$ in our case). For the SCC_t and D_t , see Supplementary Table 9 and Supplementary Methods 4.2.

Our estimation of the land-opportunity costs (economic net benefits land managers forgo when refraining from forest clearing) caused by tropical forest conservation followed the same logic as our estimation of the social value of emission reductions. The land-opportunity costs represent the foregone net benefits for land managers when they decide to retain tropical forest instead of converting them to alternative LULC types. These costs were calculated by considering the expected relative contributions of different LULC types to the simulated forest losses (Supplementary Table 10). Due to changing market prices and productivities, we obtained specific opportunity costs for each period. The aggregated costs result from:

$$C = \sum_{t=0}^{\infty} (1+r)^{-t} \times S_t^{\Delta L} \times O_t \quad (6)$$

$S_t^{\Delta L}$ is the accumulated area of the avoided forest losses (enhancing $S_t^{\Delta L}$) or of the additional forest losses (reducing $S_t^{\Delta L}$), which we assumed to become constant from T onwards. O_t is the land-opportunity cost per hectare per year, growing at 0.007 per annum in Brazil and at 0.004 per annum in Indonesia after T (Supplementary Table 10).

$$S_t^{\Delta L} = \sum_0^t \Delta L_t \quad (7)$$

ΔL_t is the difference between observed and expected area of forest losses. To account for the possibility of a reversion, we also assumed a likelihood of reversion of 1% per annum here, from T onwards.

$$C^* = \sum_{t=0}^{T=19} (1+r)^{19-t} \times S_t^{\Delta L} \times O_t + \sum_{t=20}^{\infty} (1+r)^{-(t-19)} \times (1+\rho)^{-(t-19)} \times S_t^{\Delta L} \times O_t \quad (8)$$

C* are the land-opportunities accounting for non-permanence. As the discount rate to estimate opportunity costs, we used the same $r = 0.03$ used for assessing climate benefits.

Reporting summary

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

Data availability

Datasets used are published and cited scientific work. We used information on agricultural productivity and prices available from FAOSTAT at <https://www.fao.org/faostat/en/>. Data on observed forest loss were obtained from Global Forest Watch: Forest Monitoring, Land Use and Deforestation Trends available at <https://www.globalforestwatch.org/> and GDP data from <https://data.worldbank.org/indicator/NY.GDP.MKTP.KD?locations=BR>. Compiled data are documented in Zenodo at <https://doi.org/10.5281/zenodo.8016364>. Data used to create figures are available via figshare at <https://doi.org/10.6084/m9.figshare.23366501>.

Code availability

Spreadsheet versions of the optimization are available in Zenodo at <https://doi.org/10.5281/zenodo.8016364>.

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Acknowledgements

T.K. acknowledges support from Deutsche Forschungsgemeinschaft project KN586/19-1 (as part of the Research Unit 2730, RESPECT: 'Environmental changes in biodiversity hotspot ecosystems of South Ecuador: RESponse and feedback effECTs'). C.P. acknowledges support from Deutsche Forschungsgemeinschaft projects PA3162/1 and CRC990, project number 192626868. F.V. acknowledges financial support from the Grantham Research Institute on Climate Change and the Environment, at the London School of Economics and the ESRC Centre for Climate Change Economics and Policy (CCCEP) (ref. ES/R009708/1). F.V. and B.G. acknowledge financial support from the BIOADD NERC grant (ref. NE/X002292/1). We thank L. Bingham and P. Hahn for language editing of the paper and K. Bödeker for help with Fig. 2.

Author contributions

T.K. and C.P. developed the counterfactual model, carried out the simulations, drafted the first paper version and revised previous paper versions. N.H., B.G., F.V. and R.M.R.C. developed, discussed and revised the concept and text of the paper. B.G. and F.V. provided the methodological approach to estimate the social value of the identified trends of forest losses. All authors compiled, analysed and summarized relevant literature from their fields.

Competing interests

The authors declare no competing interests.

Additional information

Supplementary information The online version contains supplementary material available at <https://doi.org/10.1038/s41893-023-01175-9>.

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Peer review information *Nature Sustainability* thanks Cauê Carrilho, Adam Daigneault and the other, anonymous, reviewer(s) for their contribution to the peer review of this work.

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Data collection Monte Carlo simulations were carried out in Excel; spreadsheets versions and obtained data are available on zenodo: 10.5281/zenodo.8016364

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Recruitment	not applicable
Ethics oversight	not applicable

Note that full information on the approval of the study protocol must also be provided in the manuscript.

Field-specific reporting

Please select the one below that is the best fit for your research. If you are not sure, read the appropriate sections before making your selection.

Life sciences Behavioural & social sciences Ecological, evolutionary & environmental sciences

For a reference copy of the document with all sections, see [nature.com/documents/nr-reporting-summary-flat.pdf](https://www.nature.com/documents/nr-reporting-summary-flat.pdf)

Behavioural & social sciences study design

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

Study description	Quantitative data with purely mechanistic model based on published input coefficients, no experimental (behavioural) data collection involved
Research sample	We selected Brazil, Congo and Indonesia as countries as they represent large share of global forest loss
Sampling strategy	We used a Monte Carlo simulation to derive random distributions around a time series of agricultural production and prices
Data collection	Data was derived from databases given above
Timing	Time series were derived until 2019 as data on forest loss and agricultural productivity/prices were available until this date by the time of analysis from Autumn 2021 to Summer 2022
Data exclusions	no exclusions
Non-participation	no participants involved
Randomization	no randomization; we used a mechanistic approach where uncertainty is incorporated in the optimization approach via Monte Carlo Simulation and robust optimization approach

Reporting for specific materials, systems and methods

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

Materials & experimental systems

n/a	Involvement in the study
<input checked="" type="checkbox"/>	<input type="checkbox"/> Antibodies
<input checked="" type="checkbox"/>	<input type="checkbox"/> Eukaryotic cell lines
<input checked="" type="checkbox"/>	<input type="checkbox"/> Palaeontology and archaeology
<input checked="" type="checkbox"/>	<input type="checkbox"/> Animals and other organisms
<input checked="" type="checkbox"/>	<input type="checkbox"/> Clinical data
<input checked="" type="checkbox"/>	<input type="checkbox"/> Dual use research of concern

Methods

n/a	Involvement in the study
<input checked="" type="checkbox"/>	<input type="checkbox"/> ChIP-seq
<input checked="" type="checkbox"/>	<input type="checkbox"/> Flow cytometry
<input checked="" type="checkbox"/>	<input type="checkbox"/> MRI-based neuroimaging