Supplementary Information

for

Economic benefits of reduced deforestation are offset by excess deforestation – a counterfactual simulation

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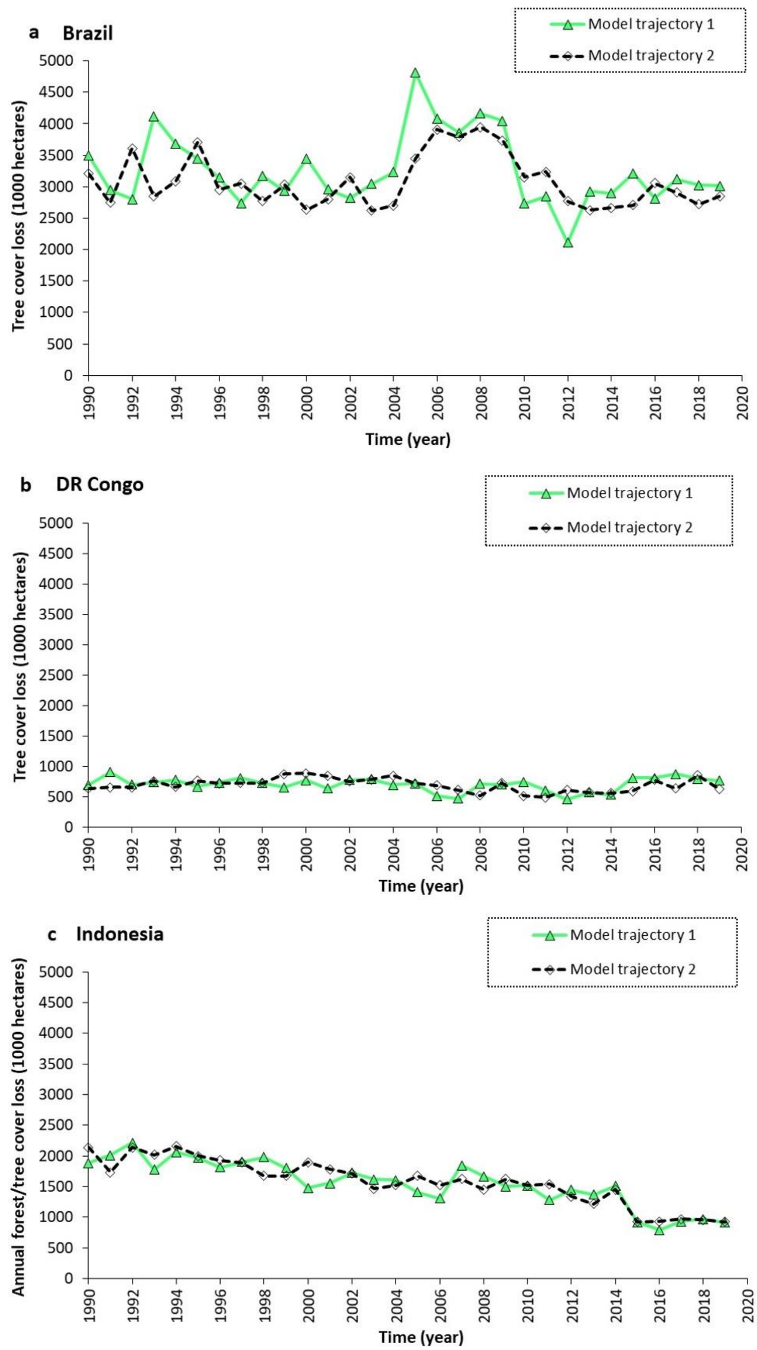
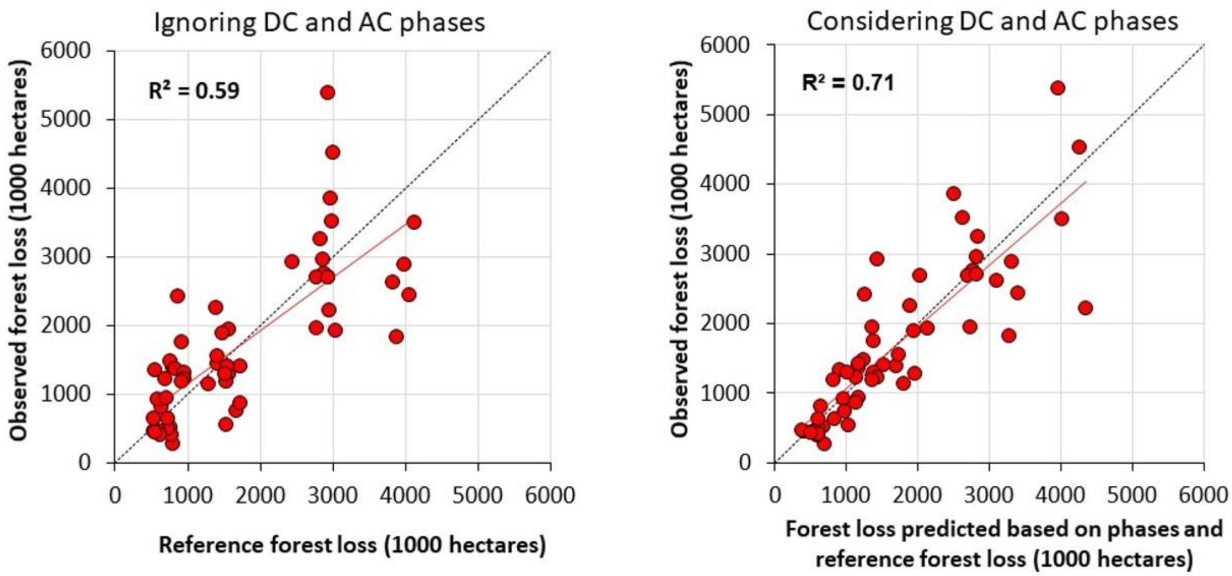
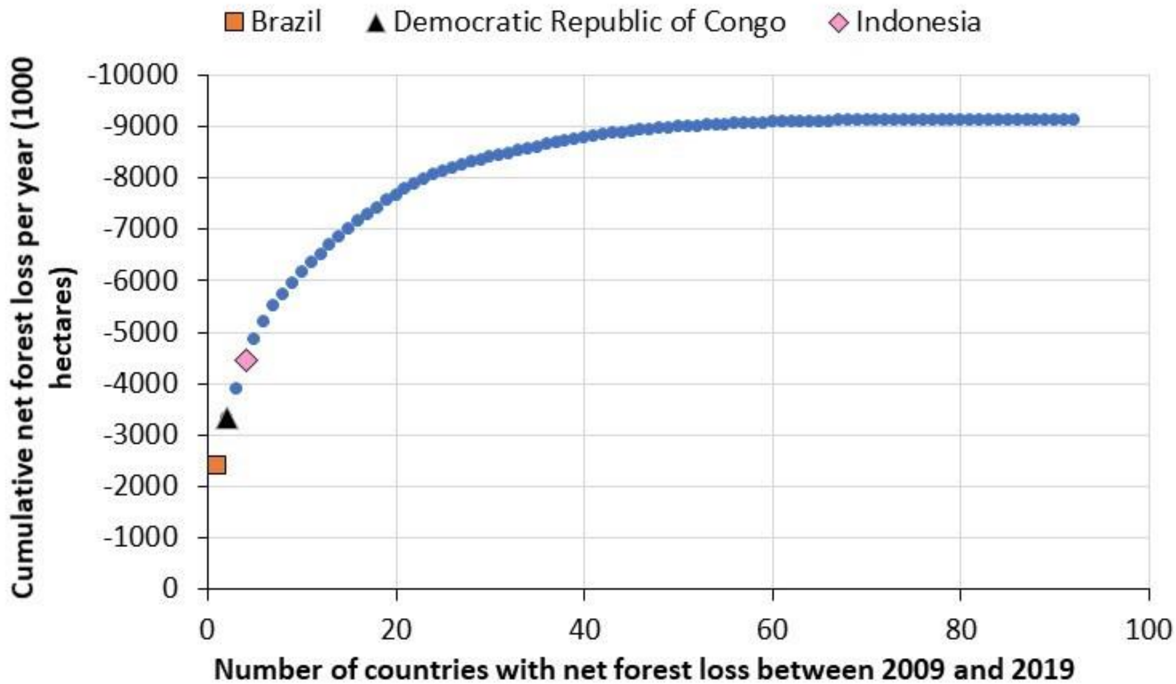
Supplementary Figures



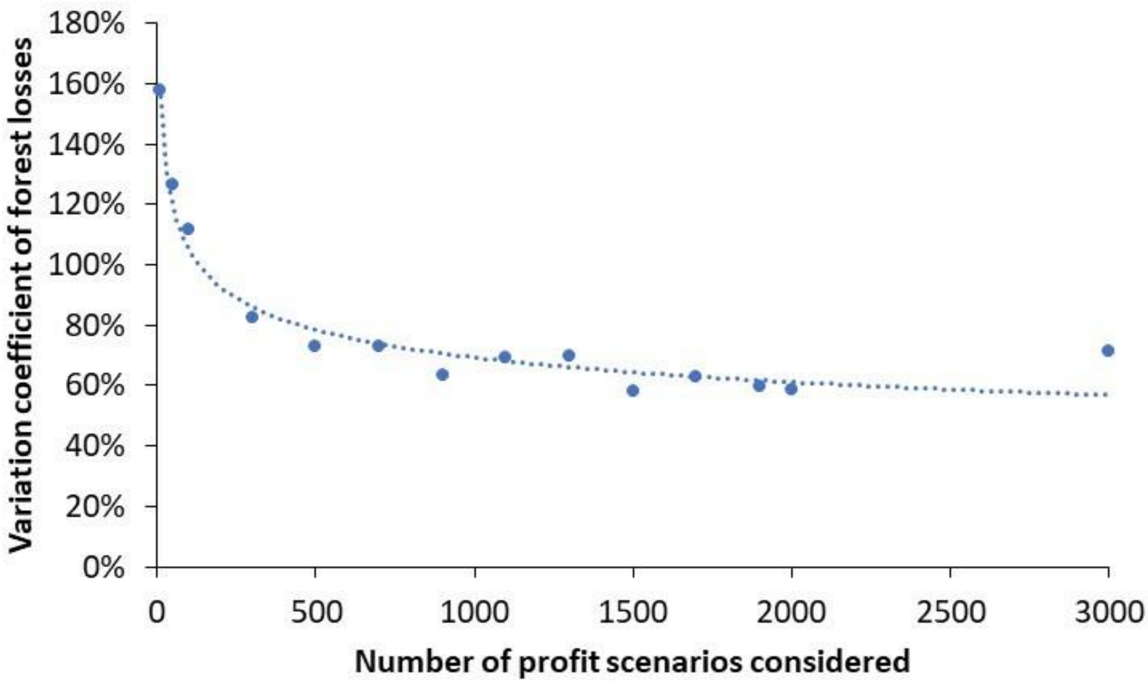
Supplementary Figure 1. Comparison of two model trajectories for reference forest losses, both parameterized with alternative sets of 4.5 million random profits.



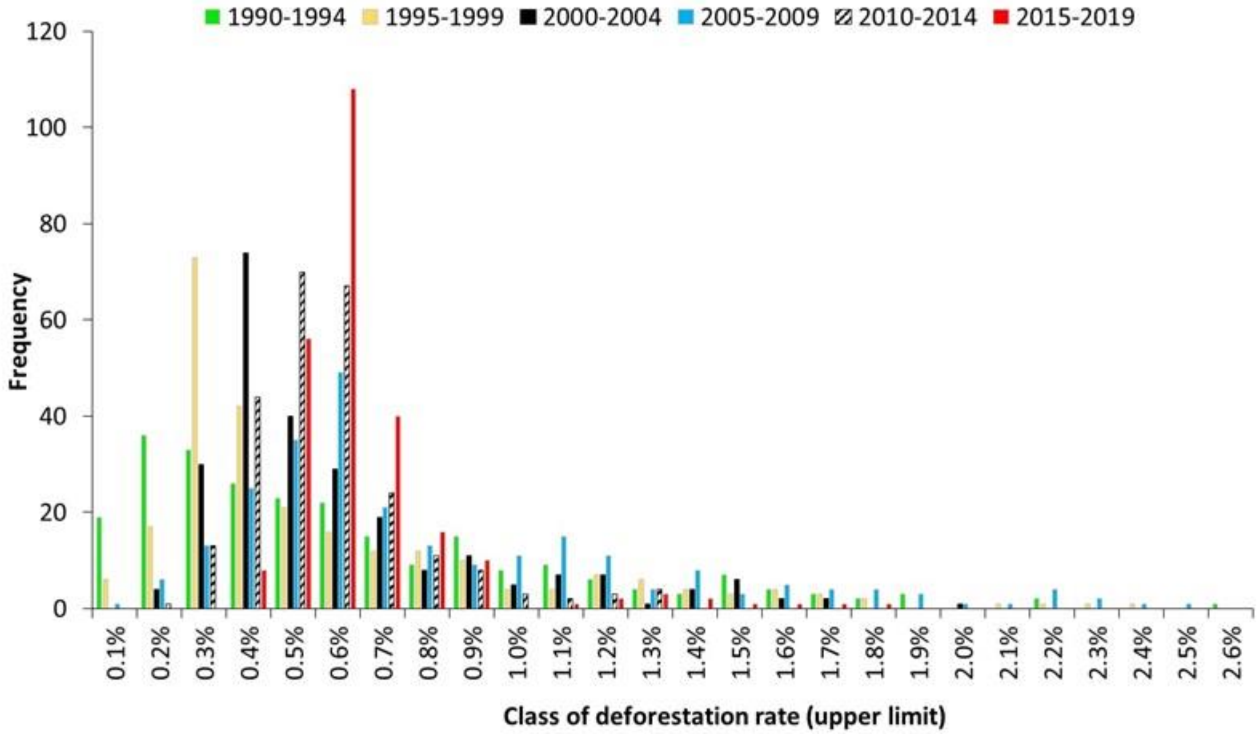
Supplementary Figure 2. Observed versus reference forest losses.



Supplementary Figure 3. Cumulative forest losses per year for all countries with net forest losses reported in FAO Statistics[1].



Supplementary Figure 4. Variability of natural forest losses depending on the number of considered profit scenarios per simulated farmer group.



Supplementary Figure 5. Monte-Carlo simulated deforestation rates for the example of Brazil (Model trajectory 1). Simulated deforestation rates from N=1500 farmer groups, each represented by 1000 random profit scenarios, with 50 repeated simulation-optimizations for each of the considered 30 years (using 1.5 million random profit scenarios in total).

Supplementary Tables

Supplementary Table 1. Average changes of forest losses p.a. in DC and AC phases compared to profit-oriented phases, using averages of model trajectory 1 and 2**.** Average annual reductions and increases of forest losses shown by coefficients of a General Estimation Equation (country as subject variable and year as inner subject variable). The coefficients indicate the average difference of observed and counterfactual deforestation areas in thousand hectares p.a.

	Variable/intercept	**Coefficient (all coefficients with $p \leq 0.001$, except constant, with $p = 0.61$ and AC Conge with 0.033)** [average annual forest savings (-) or additional forest losses (+) in 1000 hectares]		
		Coefficient	**Lower 95% confidence limit**	**Upper 95% confidence limit**
Effects of AC- and DC-phases	Constant	-71.481	-346.202	+203.240
	DC Brazil	-444.012	-513.728	-374.083
	DC Indonesia	-518.999	-671.147	-366.850
	AC Brazil	+1344.295	+1304.507	+1384.083
	AC Congo	+472.694	+39.284	+906.103
	AC Indonesia	+574.675	+381.561	+767.788
	Profit-oriented land-use (reference level)	0	0	
	Reference forest losses	+0.958	+0.862	+1.053

Supplementary Table 2. Profit data used for Brazil. LULC: Land-use/land-cover type, periods 0-5: 1990-1994, …, 2015-2019; vc=variation coefficient.

LULC	**Crops/goods used for parameterization**	**Expected profits,** $E(R_{....})$, **from fitted trend lines** [US$ per hectare per year] in period z						vc [%]	**Further input information** (e.g. costs) adopted from
		0	1	2	3	4	5		
Other land (O)	-	-	-	-	-	-	-	-	-
Planted forest (S)	Timber	98	119	138	157	174	191	40	ref.[2]
Arable land (C)	Soybean, maize, sugarcane	374	385	389	385	374	355	16	ref.[3]
Permanent crops (H)	Coffee	46	70	93	118	140	164	10	ref.[4]
Perm. meadows & pastures – Cultivated & natural (P)	Meat, milk	96	125	153	180	205	230	4	ref.[5,6]
Deforestation (Df)	Meat, milk	96	125	153	180	205	230	Calibrated (Suppl. Tab. 5); ref.[2,7]	
Naturally regenerating forest (N)	Timber	30	44	58	71	83	95	Calibrated (Suppl. Tab. 5); ref.[7]	

Supplementary Table 3. Profit data used for DR Congo. LULC: Land-use/land-cover type, periods 0-5: 1990-1994, …, 2015-2019; vc=variation coefficient.

LULC	Crops/goods used for parameterization	Expected profits, $E(R_{\dots p})$, from fitted trend lines [US$ per hectare per year] in period z						vc [%]	Further input information (e.g. costs) adopted from
		0	1	2	3	4	5		
Other land (O)	-	-	-	-	-	-	-	-	-
Planted forest (S)	Timber	111	142	172	201	228	253	40	ref.[8]
Arable land (C)	Cassava, maize, sugarcane	291	351	399	434	456	466	16	ref.[9,10,3]
Permanent crops (H)	Plantains, bananas, palm oil	290	340	379	408	425	432	10	ref.[11,12,13]
Perm. meadows & pastures – Cultivated (P)	Meat, milk	187	193	199	205	210	215	4	ref.[5,6]
Deforestation (Df)	Meat, milk	187	193	199	205	210	215	Calibrated (Suppl. Tab. 5); ref.[5,6]	
Naturally regenerating forest (N)	Timber	65	73	80	87	94	100	Calibrated (Suppl. Tab. 5); ref.[7]	

Supplementary Table 4. Profit data used for Indonesia. LULC: Land-use/land-cover type, periods 0-5: 1990-1994, …, 2015-2019; vc=variation coefficient.

LULC	**Crops/goods used for parameterization**	**Expected profits, $E(R_{\ldots p})$, from fitted trend lines** [US$ per hectare per year] in period z						$\boldsymbol{vc}$ [%]	**Further input information** (e.g. costs) adopted from
		0	1	2	3	4	5		
Other land (O)	-	-	-	-	-	-	-	-	-
Planted forest (S)	Timber	226	236	246	255	264	272	59	ref.[2]
Arable land (C)	Maize, rice, sugarcane	442	485	525	564	600	669	6	ref.[3]
Permanent crops (H)	Palm oil	1254	1286	1290	1265	1212	1130	21	ref.[11]
Perm. meadows & pastures – Cultivated (P)	Meat, milk	121	140	159	176	193	224	28	ref.[5,6]
Deforestation (Df)	Meat, milk	121	140	159	176	193	224	Calibrated (Suppl. Tab. 5); ref.[5,6]	
Naturally regenerating forest (N)	Timber	113	116	118	120	122	124	Calibrated (Suppl. Tab. 5); ref.[7]	

Supplementary Table 5. Calibration. First two periods (1990-1994; 1995-1999) were used to calibrate the model by varying u, l and the variation coefficient, vc, for the profits from deforestation areas and natural forest. Aim was to achieve an acceptable fit of reported and simulated natural forest losses (assessed by the authors). u and l define the upper and lower limits which include the random profits, $R_{\dots\, p}$, with $E(R_{\dots}) - l \cdot sd \leq R_{\dots\, p} \leq E(R_{\dots}) + u \cdot sd$.

Country	**Upper limit**	**Lower limit**	**Variation coefficient** vc in %		**Maximum proportion** in % (2049) (proportion 2019 in parentheses)
	u	l	**Deforestation**	**Forest**	$(C + H)^{max}$
Brazil	1	2	50	30	9.5 (7.8)
DR Congo	0	3	50	30	8.3 (5.9)
Indonesia	1	2	50	50	34.0 (27.3)

Supplementary Table 6. Emission factors. Information derived from median natural forest losses (period 2000-2005) and associated emissions as published in ref.[14].

Country	Forest loss	Emissions from deforestation	Emission factor
	[1000 hectares yr^{-1}]	[Tg C yr^{-1}]	[Mg C $hectare^{-1}$]
Brazil	3292	340	103
DR Congo	203	23	113
Indonesia	701	105	150

Supplementary Table 7. Comparison of modelled carbon emissions with results of recently quantified live biomass carbon stock changes.

	Average annual carbon emissions 2000-2019 [Tg C yr^{-1}]		
	Resulting from observed forest losses in our study	Resulting from reference forest losses in our study	Emission data from biomass stock changes published in ref.[15]
Brazil	306.6	334.5	483.5
DR Congo	86.8	77.8	30.8
Indonesia	211.2	204.2	154.4
Sum	**604.6**	**616.5**	**668.7**

Supplementary Table 8. Social cost of CO_2 (in 2015 US$ per Mg of CO_2)[16]. Converted from 2007- to 2015-US$ by price deflator values shown in Table 1.1.9, U.S. Bureau of Economic Analysis' (BEA) NIPA, using a factor of 1.1301. Grey numbers included to compute a growth function to extrapolate SCC to years before 2010, see Supplementary Methods 3.2.

	Social costs of CO_2 in US$ per Mg
Year	3 % discount rate
2010	35.0
2015	40.7
2020	47.5
2025	52.0
2030	56.5
2035	62.2
2040	67.8
2045	72.3
2050	78.0

Supplementary Methods

1 Land-use allocation modelling

Building on findings from ref.[17] we provide that deforestation is strongly associated with agricultural land-use reallocation processes. Our land-use model thus obtained a farmer perspective to model profit-oriented forest losses, which we call “reference forest losses”. The reference scenarios provide plausible trajectories under the absence of external influences, such as specific domestic policy interventions, extreme climate events or armed conflicts. Such reference series allows for the study of deviations between observed and expected (counterfactual) forest losses. Valuing these deviations in acceleration (AC) and deceleration (DC) of deforestation provides us with useful starting points to estimate the social costs of carbon (SCC) tropical nations may save by establishing effective forest preservation policies, but also with estimates of possible additional SCC associated with external influences, such as climate anomalies.

We adopted land-use/land-cover (LULC) data for Brazil, Democratic Republic (DR) of Congo, and Indonesia from FAO Statistics[1]. Forest losses refer to reductions of tree cover in the case of remotely sensed data[18]. We used FAO-reported forest losses (1990-2000) for calibration of our model, which refer to area reductions in the LULC class “naturally regenerating forest”, which is predominantly composed of trees established by natural regeneration[19]. We did not account for forest regrowth and thus use gross forest losses for our analysis.

Our model follows recommendations by ref.[20,21] to incorporate more refined forms of heterogeneous decision-making and prospect theory into land-use allocation modelling. The subjective expectations of farmers will vary, for example depending on individual risk-attitudes, but also across different regions. Productivity and market conditions are commonly different from region to region, and also have an influence on farmer expectations. In our country-level estimation of forest losses we considered it as important to account for such farmer (or actor) heterogeneity[21] by including stochastic profit expectations.

The starting point to develop an individual-based expectation-driven and profit-oriented land-use model was previous robust optimization models (e.g. ref.[6,22–29]). Ref.[6] has been the main underlying study. The previous optimizations adopted non-stochastic approaches, where differences between most desirable and actually achievable values for farmer objectives where used to express the dissatisfaction of farmers with their current and any future land allocation. Farmers were assumed to reallocate land to LULC types with the aim to minimize this dissatisfaction. However, the previous non-stochastic approaches all assumed that different farmers agree about desirable objective values and what they can achieve from current land-use allocations. Such an assumption is not realistic and does also not allow to simulate the annual fluctuations which are so characteristic for the really observed deforestation (see Fig. 1 in main text). To improve the realism of the modelling, we thus relaxed the assumption of homogenous expectations and developed the current stochastic model version. The new model considers that in reality decision-makers' individual (and variable) expectations are important for their decisions. We thus specified random decision-maker assumptions about the best possible profits that can be obtained from a given land-use allocation.

To implement the model described in Methods M1 (main text) we used the following area constraints:

$$O_{Ti} \geq O_{2019+z\cdot 5} \quad \text{(Eq. S1)}$$

$$S_{Ti} = S_{2019+z\cdot 5} \quad \text{(Eq. S2)}$$

$$C_{Ti} + H_{Ti} \leq (C_{2019} + H_{2019}) + z \cdot 5 \cdot \frac{(C+H)^{max} - (C_{1990} + H_{1990})}{T} \quad \text{(Eq. S3)}$$

$$N = N_{Ti} + Df_{Ti} \quad \text{(Eq. S4)}$$

$O_{2019+z\cdot 5}$	Minimum proportion of category "other land" during the farmer planning process (assumed to grow at a rate derived from previous ten years)
z	Number of periods considered; $z = 0$ to 5 covering periods 1990-1994 to 2015-2019
$S_{2019+z\cdot 5}$	Area trajectory of forest plantations during the farmer planning process (assumed to grow at a rate derived from previous ten years)
$C_{Ti} + H_{Ti}$	Target proportion of total cropland area (land proportion covered by annual crops, C, and permanent crops, H)
$(C + H)^{max}$	Estimated maximum possible area proportion of arable land in 2049 (Supplementary Table 4)
N	Proportion of natural forest at the beginning of each period

For each period, we carried out five repetitions with constant initial LULC composition and identical average profits and allocated the resulting forest losses randomly to a corresponding year within the five-year period. Supplementary Figure 5 provides an overview over the resulting variation of the Monte-Carlo simulated deforestation rates for the example of Brazil.

Deforestation rates were defined as:

$$d_i = \frac{(N_{Ti} - N) \cdot k}{N} \cdot 100 \qquad \text{(Eq. S5)}$$

2 Observed forest losses

Reported or observed forest losses were taken either from FAO Statistics[1] or from Global Forest Watch[18]. Solid remote sensing data underlie Global Forest Watch forest losses[30], which rely on a method developed by ref.[31].

3 Social costs of carbon

The social costs of carbon (SCC) in a given year resulted from three variables, where observed or reference forest losses $\boldsymbol{L}$ have been described above.

$$SCC = L \cdot E \cdot C \qquad \text{(Eq. S6)}$$

SCC	Social costs of carbon in a given year [US$]
L	Area of natural forest lost in a given year [hectares]
E	Emission factor; amount of CO_2 emitted when losing one hectare of forest [Mg hectare^{-1}]
C	Social costs of carbon per Mg of CO_2 or equivalent emitted in a given year [US$ Mg^{-1}]

3.1 Emission factors

Emissions factors, E, quantify the CO_2 releases into the atmosphere per hectare of natural forest lost[32]. We used median published estimates for carbon emissions from deforestation and divided them by the estimated area of the associated natural forest losses to obtain emission factors (Supplementary Tab. 6). These emission factors account for the loss of aboveground forest biomass and the corresponding carbon stocks[14].

Our emission estimates are gross emissions which refer to gross area losses of tropical forest multiplied with emission factors, ignoring the new carbon accumulation through regrowth of secondary forest or forest/palm oil plantations. We also ignore carbon stocks accumulating in the other forest replacement systems (e.g., croplands or pastures). In addition, our approach excluded degradation of forests by unsustainable management practices, which leads to additional carbon emissions. Given these simplifications, we finally compared our data with alternative emission data resulting from recently published carbon stock changes[15] (Supplementary Tab. 7), where stock changes represent the net emissions. The alternative stock-change data showed in sum for all three countries even higher expected emissions than those we accounted for (see Supplementary Tab. 7). We can thus assume that we have adopted conservative emission data.

3.2 Social costs of carbon per Mg of CO_2 and economic growth

The SCC from damages associated with the emission of CO_2 today were taken from ref.[16] and converted to 2015-US$ (Supplementary Tab. 8). Damages accounted for in this reference include decreasing net agricultural productivity, risks for human health, increased natural disasters, disturbance of energy systems, more frequent conflicts, more environmental migration, and losses of ecosystem services values.

Interpolation and computing SCC of forest losses prior to 2010 (no SCC provided in ref.[16]) was achieved using growth factors, g.

$$g = \left(\frac{SCC_{2050}}{SCC_{2010}}\right)^{\left(\frac{1}{40}\right)} - 1 \quad \text{(Eq. S7)}$$

$$SCC_{yr} = SCC_{2015} \cdot (1+g)^{(yr-2015)} \quad \text{(Eq. S8)}$$

g was 1.0202 for a discount rate of 3%.

The average (absolute) economic growth (change of Gross Domestic Product) in constant 2015-US$ was used for comparison and obtained from ref.[33].

4 Land-use/land-cover data and profits

Land-use/land-cover and profit data were adopted from FAO Statistics[1], see Supplementary Table 2-4. Gross profits were derived from gross production values (constant 2014-2016 US$). These were divided by area harvested (crops) or area of LULC type (milk and meat). For forest LULC types we used timber volume harvested per hectare times price derived from export value (naturally regenerating forest) or we used calculated volumes from a forest growth model[2] times timber prices adopted from Global Forest

Products model (planted forests)[34]. For DR Congo we used data from neighbouring countries, when gross production values were not available. Variation coefficients, vc, were adopted to obtain standard deviations of profits, sd. The variation coefficient was built on the root mean square error of fitted trend lines, $vc = rmse/\bar{R} \cdot 100$. The LULC category "Deforestation" had the same coefficients as "Permanent meadows & pastures" but a different vc (Supplementary Tab. 5). We assumed that upfront profits from clearing the natural forest were high enough to finance the new establishment of pasture.

5 Social costs of carbon in relation to total social costs of forest loss

As per-hectare SCC we obtained for a Brazilian, Congolese or Indonesian tropical forest in 1990 economic values of US$ 9,327; 10,232 or 13,583 and US$ 16,996; 18,277 or 24,261 in 2019 (based on a discount rate of 3%). However, SCC are only part of the total social costs of forest losses. For example, ref.[35] used published social cost estimates not only for carbon emissions, but also for the loss of future timber and non-timber forest products, ecotourism, water resoucres, biodiversity and existence value for a hectare of tropical forest lost in the Brazilian Amazon. For the assessment, the study used a discount rate of 2.5% and constant 2017-US$. The result was a total of US$ 39,830 per hectare, when such tropical forest ecosystem would transition to a savannah. In addition to their SCC (US$ 22,000 per hectare in ref.[35]) the authors considered in their study a cost of US$ 1368 per hectare for the lost timber products, US$ 200 per hectare for the non-timber forest products, US$ 216 per hectare for lost ecotourism, US$ 13,066 per hectare for the value of lost water resources, US$ 1344 per hectare for the value of lost biodiversity protection, and US$ 1636 per hectare for the lost existence value of tropical forest. This comparison underlines that we have considerably under-estimated the real social costs of tropical forest loss; but even our conservative estimates for only the SCC already offset or exceed the economic growth in the considered countries.

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