nature sustainability

Article

https://doi.org/10.1038/s41893-023-01175-9

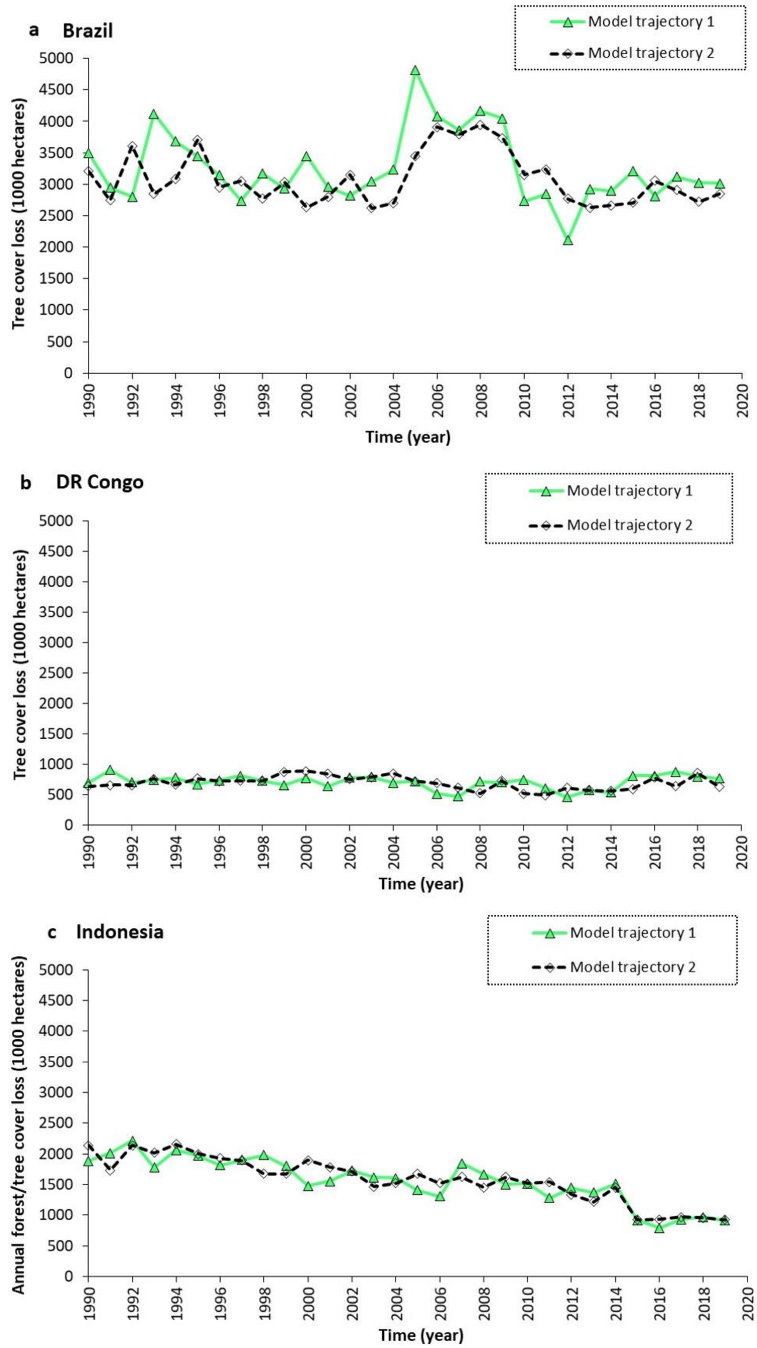
Trends in tropical forest loss and the social value of emission reductions

In the format provided by the authors and unedited

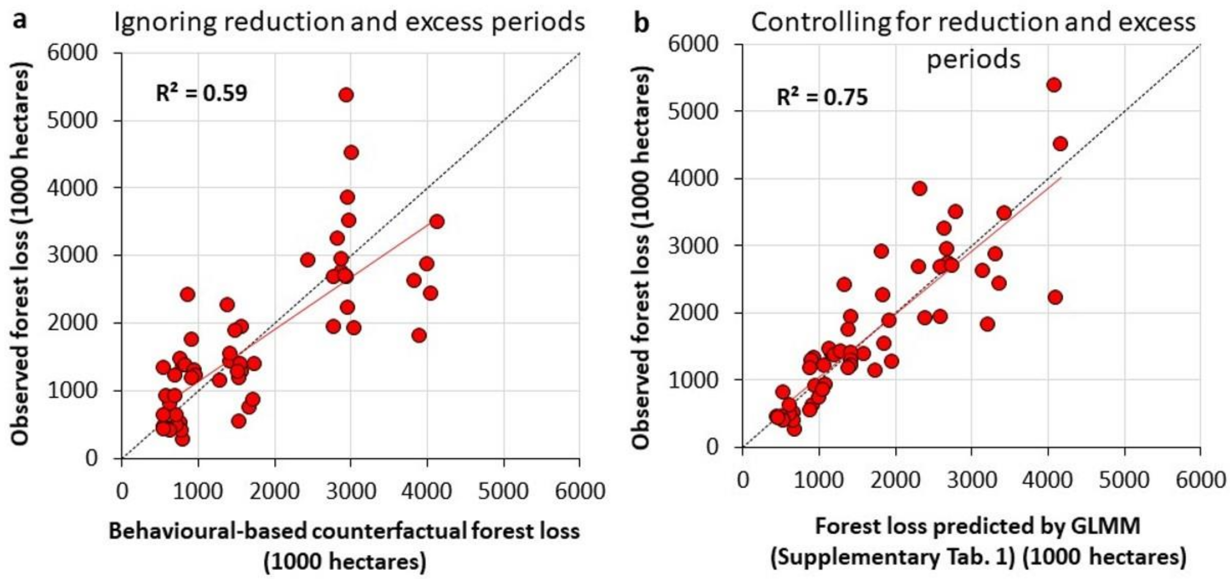
Supplementary Information

Table of content

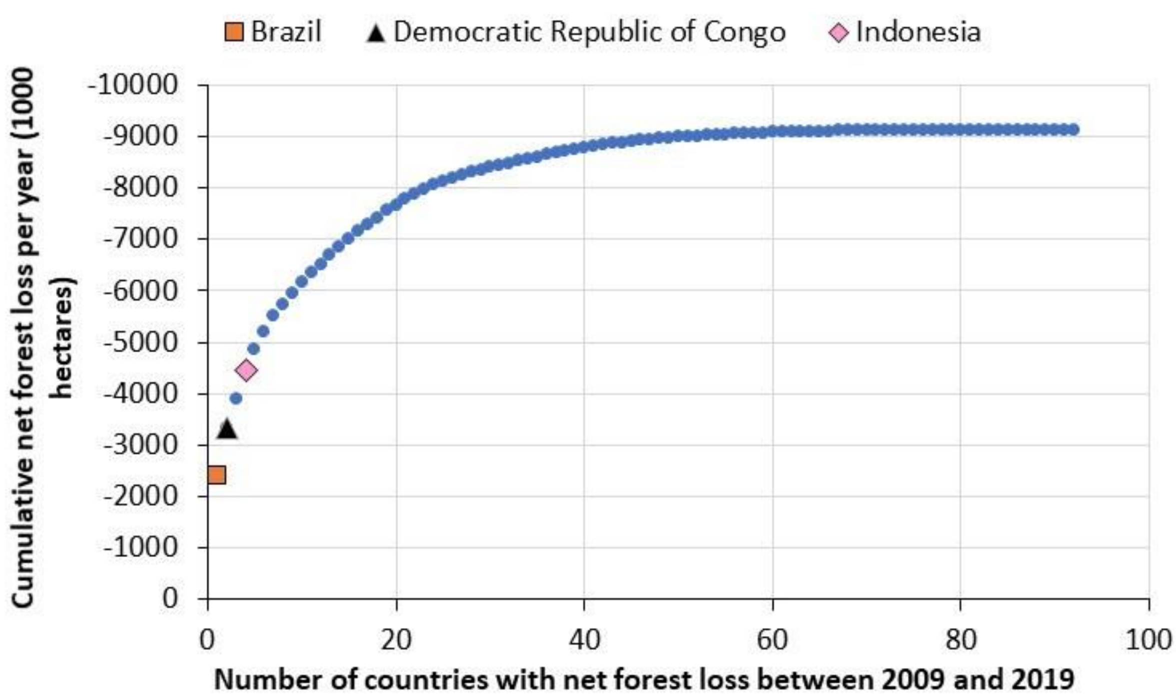
Supplementary Figures



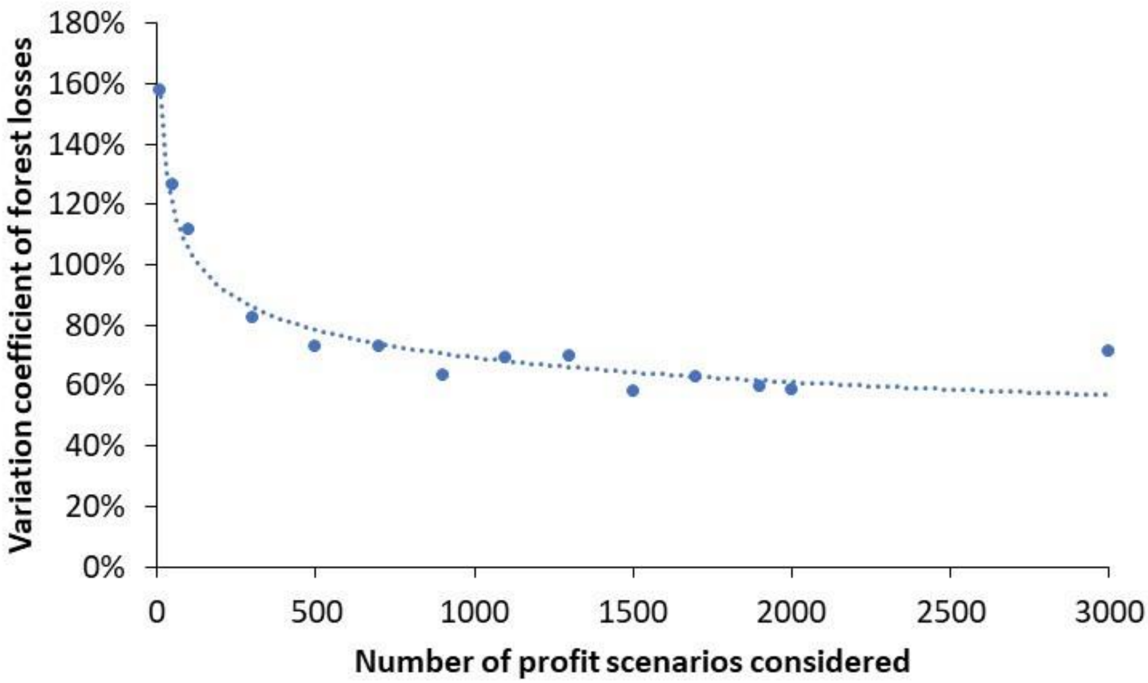
Supplementary Figure 1. Comparison of two model trajectories for reference forest losses, parameterized with two alternative sets of 4.5 million random profits. **a.** Brazil. **b.** DR Congo**. c.** Indonesia



Supplementary Figure 2. Observed versus behavioural-based counterfactual forest losses. **a.** Without accounting for the influence of non-market factors (coinciding with reduction and excess phases) **b.** Predictions made using a Generalized Linear Mixed Model accounting for periods influenced by non-market factors, the model is summarized in Supplementary Table 1.



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



Supplementary Figure 4. Variability of predicted counterfactual forest losses depending on the number of considered profit scenarios per simulated group of land managers.

Supplementary Tables

Supplementary Table 1. Different methods to model forest losses and land-use/land-cover changes

Method	Model examples	Strengths	Weaknesses	Remark
Quasi-experimental econometric (statistical) models	Synthetic control[2], difference in difference (change in change) methods[3] or machine learning[4] used to assess REDD+ projects; regression discontinuity methods[5] to evaluate impact of moratorium on forest concessions	Can control for a large number of covariates[6]; uses real-world empirical data	The validity of reference scenarios is often difficult to evaluate[7], because they build on observed deforestation levels and may thus be influenced by the policies to be analysed (policy non-invariance, Lucas critique)[8]	A very common and accepted method to assess political interventions and programs, see, e.g. ref.[9]
Economic optimization-based models, e.g. equilibrium models simulating market supply and demand in different sectors	Income[10], profit[11], or utility[12] maximization models; dynamic stochastic general equilibrium models[13]; equilibrium models used for environmental impact assessment[14–16]	Often well-grounded in micro-economic optimization techniques[8]	Often high level of abstraction and aggregation[17]; ignore heterogeneity of decision makers, exclude the impact of uncertainty on land-use decisions; e.g., maximization principle unrealistic to apply for many land managers, because of prevailing uncertainties[18]	Optimization often underlies integrated climate assessment models[15,19,20]
Agent-based models considering autonomous individual decision-makers	Abacra model, a stylized agent-based model to study intensification of cattle ranching and deforestation[21]; ALUAM-AB, where actors with heterogenous traits seek maximum land rents[22]	Cover heterogeneity of decision makers[23,24]	Ad hoc models, often less theory-based[25], which may have “black-box” character[26]	Can consider actor diversity[22]

Supplementary Table 2. Statistical model on average annual changes of forest cover losses (area in 1000 hectares) in reduction and excess periods assessed against levels of forest loss in market-oriented periods, using counterfactual averages of model trajectory 1 and 2 (Supplementary Fig. 1)**.** Average annual reductions (-) and excesses (+) shown by coefficients of a Generalized Linear Mixed Model (country as subject variable and year as repeated measures variable).

	Predictors		**Lower 95% confidence limit**	**Upper 95% confidence limit**
	Factors/covariate	**Coefficients** [in 1000 ha.]		
	Constant	-102.669	-992.221	786.883
Effects of factors	Reduction Brazil < 2008; R^{Bra1}	-953.067	-1117.951	-788.183
	Reduction Brazil >= 2008; R^{Bra2}	-861.694	-1107.570	-615.819
	Reduction Indonesia; R^{Ind}	-711.347	-954.955	-467.738
	Excess deforestation Brazil; E^{Bra}	+1676.742	+1676.059	+1677.425
	Excess deforestation Congo; E^{Con}	+810.004	+808.024	+811.984
	Excess deforestation Indonesia; E^{Ind}	+458.791	+457.537	+460.045
	Period of market-oriented land-use (reference category)	0	0	0
	Counterfactual forest area losses; (L^{ref})	+0.969	+0.968	+0.970

Supplementary Table 3. 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.[27]
Arable land (C)	Soybean, maize, sugarcane	374	385	389	385	374	355	16	ref.[28]
Permanent crops (H)	Coffee	46	70	93	118	140	164	10	ref.[29]
Perm. meadows & pastures – Cultivated & natural (P)	Meat, milk	96	125	153	180	205	230	4	ref.[30,31]
Deforestation (Df)	Meat, milk	96	125	153	180	205	230	Calibrated (Suppl. Tab. 5); ref.[27,32]	
Naturally regenerating forest (N)	Timber	30	44	58	71	83	95	Calibrated (Suppl. Tab. 5); ref.[32]	

Supplementary Table 4. 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, $E(R_{...\ p})$, 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	111	142	172	201	228	253	40	ref.[33]
Arable land (C)	Cassava, maize, sugarcane	291	351	399	434	456	466	16	ref.[34,35,28]
Permanent crops (H)	Plantains, bananas, palm oil	290	340	379	408	425	432	10	ref.[36,37,38]
Perm. meadows & pastures – Cultivated (P)	Meat, milk	187	193	199	205	210	215	4	ref.[30,31]
Deforestation (Df)	Meat, milk	187	193	199	205	210	215	Calibrated (Suppl. Tab. 5); ref.[30,31]	
Naturally regenerating forest (N)	Timber	65	73	80	87	94	100	Calibrated (Suppl. Tab. 5); ref.[32]	

Supplementary Table 5. 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.[27]
Arable land (C)	Maize, rice, sugarcane	442	485	525	564	600	669	6	ref.[28]
Permanent crops (H)	Palm oil	1254	1286	1290	1265	1212	1130	21	ref.[36]
Perm. meadows & pastures – Cultivated (P)	Meat, milk	121	140	159	176	193	224	28	ref.[30,31]
Deforestation (Df)	Meat, milk	121	140	159	176	193	224	Calibrated (Suppl. Tab. 5); ref.[30,31]	
Naturally regenerating forest (N)	Timber	113	116	118	120	122	124	Calibrated (Suppl. Tab. 5); ref.[32]	

Supplementary Table 6. Calibration. First two periods (1990-1994; 1995-1999) were used to calibrate the model by varying u, l and the variation coefficient, vc, the latter for the profits from deforestation areas and natural forest. Aim was to achieve an acceptable fit of reported and simulated forest losses (assessed by the authors). u and l define the upper and lower limits, which include the random profits, $R_{\ldots\ p}$, with $E(R_{\ldots}) - l \cdot sd \leq R_{\ldots\ p} \leq E(R_{\ldots}) + u \cdot sd$. sd is the standard deviation of the profit and $(C+H)^{max}$ is the upper limit for the target proportion of total cropland area (land proportion covered by annual crops, C, and permanent crops, H)

Country	**Upper limit**	**Lower limit**	**Variation coefficient** vc in %		**Maximum proportion** in % 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 7. Emission factors. Information derived from median natural forest losses (period 2000-2005) and associated emissions as published in ref.[39].

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

Supplementary Table 8. Comparison of modelled carbon emissions with results of 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.[40]
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 9. Social cost of CO_2 (SCC_t) suggested by the United States Government (in 2015 US$ per tonne of CO_2)[41]. 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.

	Social costs of CO_2 in US$ per tonne
Year	3 % discount rate
1990	*24.7*
1995	*27.3*
2000	*30.1*
2005	*33.3*
2010	35.0
2015	40.7
2020	45.0

Supplementary Table 10. Opportunity costs land managers face when avoiding forest losses and shares of replacement land-use/land-cover types (LULC), obtained from counterfactual model. In DR Congo no opportunity costs occur, as no forest loss is avoided.

Country	**Land cover shares of LULC types in % per one hectare of converted natural forest**				**Opportunity costs [US$ per hectare per year] considering the years 2000 to 2019 (agricultural net-benefits minus natural forest net-benefits)**
	Planted forest (S)	Arable land (C) and Permanent crops (H)	Perm. meadows & pastures – Cultivated (P)	Where agricultural establishment failed; estimated based on ref.[32] and authors' experience	
Brazil	6	9	50	35	55-69
DR Congo	n.a.				
Indonesia	7	34	31	28	212-231

Supplementary Methods

1 Land-use allocation modelling

Building on findings from ref.[42] we provide that the loss of forests is strongly associated with agricultural land-use reallocation processes. Our land-use model thus obtains a land manager perspective to model market-oriented forest losses, which we call “reference forest losses” or “counterfactual forest losses” or “market-oriented forest losses”. The reference scenarios provide plausible trajectories under the absence of country-scale non-market-oriented 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. Weighing changes of CO_2 emissions associated with these deviations in reduction and excess periods of deforestation with the avoided/additional social cost of carbon (SCC_t) per unit CO_2 emissions provides us with useful starting points to estimate the social value of the emission changes associated with the trends of forest losses. Note that we define avoided SCC_t as economic benefit increasing the social value of forest[43], while enhanced SCC_t are economic cost, decreasing the social value of the forest trend.

We adopted land-use/land-cover (LULC) data for Brazil, Democratic Republic (DR) of Congo, and Indonesia from FAO Statistics[1]. Observed forest losses from Global Forest Watch refer to reductions of tree cover in the case of remotely sensed data[44]. We used FAO-reported forest losses (1990-1999) for calibration of our model only, which refer to area reductions in the LULC class “naturally regenerating forest”, which is predominantly composed of trees established by natural regeneration[45]. We did not account for forest regrowth and thus use gross forest losses for our analysis.

Our model follows recommendations by ref.[22,46] to incorporate new and more refined forms of heterogeneous decision-making and prospect theory into land-use allocation modelling, which we seek to achieve by modelling satisficing behaviour. Satisficing behaviour has first been defined by Simon[47] as: “… problem solving and decision making that sets an aspiration level, searches until an alternative is found that is satisfactory by the aspiration level criterion, and selects that alternative” (p. 168). The mathematical implementation of this decision behaviour is described later. Our model is based on subjective expectations of land managers which 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 land manager expectations. In our country-level estimation of forest losses we considered it as important to account for such land manager (or actor) heterogeneity[22] by including stochastic profit expectations.

The starting point to develop a land-manager-based expectation-driven and market-oriented land-use model was previous robust optimization models (e.g. ref.[31,48–60]). Ref.[31] has been the main underlying study. The previous optimizations adopted non-stochastic approaches, where differences between most desirable and actually achievable values concerning land manager objectives were used to express the dissatisfaction of land managers with their current and any future land allocation. Land managers 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 managers agree about desirable objective values and which outcomes they can achieve from current land-use allocations. Such an assumption is not realistic, as the expectations of land managers are heterogenous; excluding any stochasticity excludes the opportunity to simulate the annual fluctuations which are so characteristic for the really observed deforestation (see Fig. 3 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 land-use allocation decisions. We thus specified random decision-maker assumptions about the best possible and current profits that can be obtained from a given land-use allocation.

The land-use allocation model builds on the following mathematical logic: The desired long-term proportion of natural forest (defined as tree cover of natural forests, not being planted[61]) in land manager group i, N_{Ti}, is part of a target LULC portfolio of a single land manager group who seek minimize their dissatisfaction (the difference between (i) anticipated best possible and (ii) realized profit) with the profits expected from the desired land composition. This target LULC portfolio is estimated using mathematical programming[31]. Each land manager group strives to reduce their dissatisfaction by rearranging the land-use allocation over a planning period of 30 years towards the desired land-use portfolio, which usually involves the loss of natural forest to expand agricultural

LULC types. To capture the variability in profit expectations among individual land managers in each group, we drew 1000 random profit expectations (referred to as profit scenarios, each consisting of a random profit vector for seven LULC types) for each land-use alternative and each land manager group in a Monte Carlo simulation. These heterogeneous expectations are accounted for in the objective function of the mathematical programming approach by minimizing the maximum dissatisfaction among all land managers (land managers represented by profit scenarios) within one group (see below). We subsequently averaged the achieved reference areas of forest loss L_i across the land manager groups, thus accounting for within and between group heterogeneity in the simulation approach.

We used in total $n = 100$ land manager groups considered per country and per year, with the average forest loss p.a. in a given country and year being $L_{c,t} = (1 \div 100) \cdot \sum_i L_i$ (for simplicity we omit the subscripts c, t for the random forest losses L_i. To assess the stability of the results we carried out two separate simulation rounds for each country, with $n = 50$ repetitions each (results shown in Supplementary Fig. 1). As this averaging approach largely ignores collaboration of land managers at a local scale, one could classify our method as a „wisdom of the crowds" approach[62]. The forest loss simulated for the land manager group i in a given year is:

$$L_i = A \cdot (N - N_{Ti}) \cdot k \qquad \text{(Eq. S1)}$$

L_i	Area of natural forest lost p.a. [hectare] for land manager group i
A	Total land area of a country [hectare]
N_{Ti}	Desired future proportion of natural forest after T years; $0 \le N_{Ti} \le 1$
N	Current proportion of natural forest; $0 \le N \le 1$
k	Factor accounting for the planning horizon, $k = 1 \div T$
T	Planning horizon (assumed with 30 years); $T = 30$

We used no more than 100 Monte-Carlo repetitions to simulate land manager group decisions to retain a certain degree of year-to-year fluctuation across the averaged forest losses L, as we also observed fluctuations in the remotely sensed forest losses (see Fig. 3, main text).

Individual land manager dissatisfaction in a specific random profit scenario p is D_p, measured by the difference between the per land manager expectation assumed highest possible profit (revenues minus costs) given by R_p^* of a certain scenario and what land managers assume to actually achieve with a given LULC composition, R_p.

$$D_p = \frac{R_p^* - R_p}{R_p^* - R_{p*}} \cdot 100 \qquad \text{(Eq. S2)}$$

$$R_p = N_{Ti}R_{Np} + Df_{Ti}R_{Dp} + P_{Ti}R_{Pp} + C_{Ti}R_{Cp} + H_{Ti}R_{Hp} + S_{Ti}R_{Sp} + O_{Ti}R_{Op} \qquad \text{(Eq. S3)}$$

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

D_p	Land managers' dissatisfaction in profit-scenario p
R_P^*	Highest individually assumed profit [US$ per hectare] (accounts for maximum possible proportion of croplands) in profit scenario p
R_{p*}	Lowest individually assumed profit [US$ per hectare]
R_p	Actual profits land managers expect for a specific future LULC composition, with N_{Ti} ... O_{Ti} being the future proportions of different LULC types and R_{Np} ... R_{Op} being their random profits in scenario p
$N_{Ti}R_{Np}$	Future proportion of *natural forest* times profits of natural forest in profit scenario p; $0 \leq N_{Ti} \leq N$
$Df_{Ti}R_{Dp}$	Future proportion of *deforestation* areas (forest conversion to agriculture) times profits of deforestation in profit scenario p; $0 \leq Df_{Ti} \leq N_{Ti}$
$P_{Ti}R_{Pp}$	Future proportion of *pasture* times profits of pasture in profit scenario p
$C_{Ti}R_{Cp}$	Future proportion of *cropland* (annual crops) times profits of cropland in profit scenario p
$H_{Ti}R_{Hp}$	Future proportion of *permanent crops* times profits of permanent crops in profit scenario p
$S_{Ti}R_{Sp}$	Future proportion of *forest plantations* times profits of forest plantations in profit scenario p
$O_{Ti}R_{Op}$	Future proportion of *other land* times profits of other land (profits assumed for other land are zero)

Individual profit scenarios are defined by empirical data for different LULC types and assumptions about their variation. The profits were assumed to occur in intervals ranging around average profits derived from FAO Statistics for various periods[1] (Supplementary Tabs. 2-4). Random profits were simulated using Eq. S4.

$$R_{\dots\, p} = E(R_{\dots}) + u \cdot sd - r_{\#} \cdot (u + l) \cdot sd \qquad \text{(Eq. S4)}$$

$R_{\dots\, p}$	Random profits of a specific LULC type under profit scenario p in a given period
$E(R_{\dots})$	Mathematical expectation value of profit [US$ per hectare]
u	Multiplier to obtain upper interval limit; $0 \leq u \leq 1$
sd	Standard deviation of profits
$r_{\#}$	Uniformly distributed random number; $0 \leq r_{\#} \leq 1$
l	Multiplier to obtain lower interval limit; $2 \leq l \leq 3$

The multipliers u and l were selected during a calibration process and differed between Brazil/Indonesia and DR Congo (Supplementary Tab. 6). The first two periods (1990-1994 and 1995-1999) were used to calibrate the model by varying u, l and the variation coefficient of the expected profits for specific LULC types, vc. Calibration of vc was done only to obtain the variability of profits from deforestation areas and natural forest, because here the information about a plausible variation of land manager expectations was very scarce. For the other LULC types vc was derived empirically (Supplementary Methods 5). The aim of our calibration was to achieve an acceptable fit of reported and simulated natural forest losses in the periods 1990-1994 and 1995-1999 (acceptability assessed by the authors). u and l define the upper and lower limits which included the random profits.

We used 1000 Monte-Carlo profit scenarios to obtain random values for $R_{\dots\ p}$, resulting in 1000 different $R_{\dots\ p}$ row vectors (consisting of a series of seven profits, one for each LULC type) for a specific LULC composition computed as an area weighted average. The number of 1000 Monte-Carlo profit-scenarios was chosen since the variability of the obtained reference forest losses did not further decrease beyond this number of scenarios (Supplementary Fig. 4). Our reference forest loss simulations thus consisted of $i = 1 \text{ to } 100$ Monte-Carlo iterations for different land manager group land-use decisions, each iteration using a 1000-by-7 matrix of random profit coefficients (Eq. S5) (for the seven land-use types considered, see Supplementary Tables 3-5). We used Frontline System's Analytic Solver V2020 and the function "PsiOptParam" to consider the 50 matrices (which we run 2 times, see Supplementary Fig. 1) with randomly differing profit coefficients, for each of which one linear program was built and solved.

$$\begin{matrix} R_{N1} & R_{Df1} & R_{P1} & R_{C1} & R_{H1} & R_{S1} & R_{O1} \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ R_{N1000} & R_{Df1000} & R_{P1000} & R_{C1000} & R_{H1000} & R_{S1000} & R_{O1000} \end{matrix} \qquad \text{(Eq. S5)}$$

In each group i, land managers were assumed to rearrange their current land allocation long-term to improve the actually achievable profits, thus reducing the difference, D_p, between assumed best possible (R_p^*) and achievable profits (R_p) gradually and with this their dissatisfaction. In sum, we mimicked land managers' land reallocation processes by seeking a long-term LULC composition to minimize the maximum dissatisfaction, $\min \delta_i = \max\{D_p\}$ (see ref.[63] for a similar approach applied to simulate general group decision-making processes), across all profit scenarios.

$$\min \delta_i \quad \text{(Eq. S6)}$$

with $\delta_i = max\{D_p\}$

$$\delta_i \geq \frac{R_p^* - R_p}{R_p^* - R_{p*}} \cdot 100 \qquad \forall p \quad \text{(Eq. S7)}$$

We simulated the annual forest loss L_i for each Monte-Carlo iteration in a dynamic way, using 5-year periods, while considering temporal changes of average profits according to Supplementary Tables 3-5 and different start LULC compositions (after undergoing land reallocation processes in the previous period) at the beginning of each period. The average LULC composition at the end of each period was based on five repetitions (each single repetition later represented one of the five years of a 5-year period) and provided the start LULC composition for the subsequent period. The periods $z = 0 \text{ to } 5$ refer to 1990-1994; 1995-1999; 2000-2004; 2005-2009; 2010-2014; 2015-2019. We also modelled counterfactuals for 2020 and 2021 to explore any possible influences of the COVID-19 pandemic[64] (but this was only a side aspect, described in Supplementary Methods 3).

To implement the model, we used the following area constraints:

$$O_{Ti} \geq O_{2019+z\cdot 5} \quad \text{(Eq. S8)}$$

$$S_{Ti} = S_{2019+z\cdot 5} \quad \text{(Eq. S9)}$$

$$C_{Ti} + H_{Ti} \leq (C_{2019} + H_{2019}) + z \cdot 5 \cdot \frac{(C+H)^{max} - (C_{1990} + H_{1990})}{T} \quad \text{(Eq. S10)}$$

$$N = N_{Ti} + Df_{Ti} \quad \text{(Eq. S11)}$$

$O_{2019+z\cdot 5}$	Minimum proportion of category “other land” during the land manager planning process (assumed to grow at a rate derived from previous ten years)
z	Number of periods considered; $z = 0 \text{ to } 5$ covering periods 1990-1994 to 2015-2019
$S_{2019+z\cdot 5}$	Area trajectory of forest plantations during the land manager 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 Tab. 6)
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 average forest losses randomly to a corresponding year within the five-year period. Figure 2a (main text) provides an overview over the resulting variation of the Monte-Carlo simulated deforestation rates for all countries.

Deforestation rates were defined as:

$$d_i = \frac{(N_{Ti} - N) \cdot k}{N} \cdot 100 \qquad \text{(Eq. S12)}$$

2 Observed forest losses

Reported or observed forest losses were taken either from FAO Statistics[1] or from Global Forest Watch[44]. Solid remote sensing data underlie Global Forest Watch forest losses[65], which rely on a method developed by ref.[66].

3 Factors influencing the levels of forest losses

Owing to our focus on the country scale we searched for country-level underlying factors[67], which may have caused deviation from market-driven reference levels of forest losses. We based our selection on evidence published in refereed papers and considered temporal coincidence of the documented factors with the observed deforestation changes as a selection criterion[68]. Our counterfactual deforestation levels (=reference) were influenced only by market price signals[69], productivity[70], associated profit expectations[71] (treated as a random variable) and the behavioural assumption of satisficing[18]. Based on the specific timing mentioned in the considered refereed publications we identified domestic 1) “command-and-control policies”, 2) “climate anomalies”, 3) “armed conflicts” and 4) “public spending/pre-election promises” as country-scale policies or factors with a proven strong influence on the level of deforestation (see also Methods, main text).

However, we had to exclude other factors. For example, we could not show temporal coincidence of factors such as “mining”[72], the “rollout of community land titles”[73], or the “changes of exchange rates”[74] with changes of deforestation levels. In addition, a REDD+ agreement concerning peatland and primary forests between Indonesia and Norway, which ref.[5] have assessed for the period 2011-2018, also showed no coincidence with changes of forest losses. Large part of the period of the agreement was overlapping with pre-election promises. In addition, many local (household-level) factors influencing deforestation were not assessed in our country-scale approach, including off-farm income[56], labour availability[75], access to capital[10], education[76], or size of the household[77].

Another factor one may have expected to be influential, for example in Brazil, is the COVID-19 pandemic, which however, could not be identified as a strong factor to increase deforestation, but comparison with our counterfactual reveals an increase of forest losses by 4030 km^2 for Brazil in 2020. Another study[64] estimated a size of excess deforestation of 4851 km^2 worldwide and attributed this to the influence of COVID-19. COVID-19 could potentially disturb governance structures and weaken law enforcement to achieve forest conservation[64]. Similarly, we could neither identify additional conservation success, nor much enhanced deforestation after the government change in 2019 in Brazil. We conclude that Brazil's deforestation has rebounded to the same levels as before the establishment of the PPCDAm in 2004.

4 The social value of emission changes associated with trends of forest losses

4.1 Emission factors

Emissions factors, EF_c, quantify the CO_2 releases into the atmosphere per hectare of forest lost[78]. 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. 7). These emission factors account for the loss of aboveground forest biomass and the corresponding carbon stocks[39].

The estimated changes of emission levels E_t in a specific country c were:

$$E_t = (L^{obs} - L^{ref}) \cdot EF_c \quad \text{(Eq. S13)}$$

L^{obs} and L^{ref} are the observed and reference (counterfactual) forest losses. 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 possibly 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[40] (Supplementary Tab. 8), 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. 8), which is probably a consequence of excluding the degradation effects in our study. We can thus assume that we have adopted conservative emission data.

4.2 Changes of social value associated with changes of emissions

The annual changes of social value Δv_t in a given country shown in Figure 4def (main text) were computed as follows:

$$\Delta v_t = E_t \cdot SCC_t \quad \text{(Eq. S14)}$$

For an aggregation of the annual changes see Eq. 5, main text. The SCC_t we used, are shown in Supplementary Tab. 9. For estimating the social value of the changes of emissions from reduced or enhanced forest losses we started with $SCC_{t=2000} = 30.1$ US$ per tonne CO_2. Assuming the SCC_t to grow by 0.0202 p.a. (derived from data in ref.[79]) implies a damage caused by one tonne CO_2 in the year 2000 of $D_{t=2000} = 0.28677$ US$.

5 Land-use/land-cover data and profits

LULC and profit data were adopted from FAO Statistics[1], see Supplementary Table 3-5. Gross profits were derived from gross production values (constant 2014-2016 US$), obtained by multiplying agricultural productivity (produced quantities) by the corresponding market price. Production values 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[27] times timber prices adopted from Global Forest Products model (planted forests)[80]. 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. 6). We assumed that upfront profits from clearing the natural forest were high enough to finance the new establishment of pasture.

6 Social value of avoided carbon emissions in relation to total social forest value per hectare

We used social value of CO_2 not emitted because of avoided forest losses, but this economic value is only part of the total social value of tropical forest. For example, ref.[81] used published social value estimates not only for carbon storage, but also for future timber and non-timber forest products, ecotourism, water resoucres, biodiversity and existence value for a hectare of tropical forest in the Brazilian Amazon. For their assessment, the authors of the cited study used a discount rate of 2.5% and constant 2017-US$. The result was a total of US$ 39,830 per hectare. In addition to their social value of carbon storage (US$ 22,000 per hectare in ref.[81]) the authors considered a value of US$ 1368 per hectare for timber products, US$ 200 per hectare for the non-timber forest products, US$ 216 per hectare for ecotourism, US$ 13,066 per hectare for the value of water resources, US$ 1344 per hectare for the value of biodiversity protection, and US$ 1636 per hectare for the existence value of tropical forest. This comparison underlines that we have considerably under-estimated the real social value of tropical forest in our study, by focussing only on the value of carbon storage.

7 Interpretation of convergence effects (Fig. 2 main text)

The empirically observed convergence of the level of forest losses across countries has been interpreted as a catch-up effect showing that forest conservation policies become effective across a range of countries[82]. Our counterfactual simulation showed also a tendency of converging deforestation rates, where average annual rates ranged from ~0.3% to ~1.8% in 1990-1994 and from ~0.4% to ~1.2% in 2015-2019 (Fig. 2, main text). In addition, the variability of the deforestation rates per period decreased in Brazil and Indonesia.

We cannot trace back this model behavior to any conservation policy, as we explicitely excluded such factors from the counterfactual model. We thus explain the observed dynamic by the behavioral assumptions we have made. By repeatedly minimizing the maximum dissatisfaction with the land-use composition across profit scenarios and land managers within one land manager group, the maximum dissatisfaction among land managers shrinks over time. This supports growing agreement about the “desirable” land-use decisions and thus the convergence of forest losses.

References

1. Food and Agriculture Organization of the United Nations. FAOSTAT. Available at https://www.fao.org/faostat/en/#home (2022).
2. West, T. A. P., Börner, J., Sills, E. O. & Kontoleon, A. Overstated carbon emission reductions from voluntary REDD+ projects in the Brazilian Amazon. *PNAS* **117,** 24188–24194; 10.1073/pnas.2004334117 (2020).
3. Assunção, J., McMillan, R., Murphy, J. & Souza-Rodrigues, E. Optimal Environmental Targeting in the Amazon Rainforest. *The Review of Economic Studies*; 10.1093/restud/rdac064 (2022).
4. Wunder, S., Schulz, D., Montoya-Zumaeta, J., Börner, J. & Frey, G. Modest forest and welfare impacts from current REDD+ initiatives; 10.21203/rs.3.rs-2429873/v1 (2023).
5. Groom, B., Palmer, C. & Sileci, L. Carbon emissions reductions from Indonesia's moratorium on forest concessions are cost-effective yet contribute little to Paris pledges. *PNAS* **119**; 10.1073/pnas.2102613119 (2022).
6. Athey, S. & Imbens, G. W. The State of Applied Econometrics: Causality and Policy Evaluation. *Journal of Economic Perspectives* **31,** 3–32; 10.1257/jep.31.2.3 (2017).
7. Magliocca, N. R., Dhungana, P. & Sink, C. D. Review of counterfactual land change modeling for causal inference in land system science. *J. Land Use Sci.* **18,** 1–24; 10.1080/1747423X.2023.2173325 (2023).
8. Moos, K. A. The Facts and the Values of the Lucas Critique. *Review of Political Economy* **31,** 1–25; 10.1080/09538259.2019.1586363 (2019).
9. Abadie, A. & Cattaneo, M. D. Econometric Methods for Program Evaluation. *Annu. Rev. Econ.* **10,** 465–503; 10.1146/annurev-economics-080217-053402 (2018).
10. Combes, J.-L., Delacote, P., Combes Motel, P. & Yogo, T. U. Public spending, credit and natural capital: Does access to capital foster deforestation? *Econ. Model.* **73,** 306–316; 10.1016/j.econmod.2018.04.006 (2018).
11. Kindermann, G. E., Obersteiner, M., Rametsteiner, E. & McCallum, I. Predicting the deforestation-trend under different carbon-prices. *Carbon Balance Manage* **1,** 15; 10.1186/1750-0680-1-15 (2006).
12. Piazza, A. & Roy, S. Deforestation and optimal management. *Journal of Economic Dynamics and Control* **53,** 15–27; 10.1016/j.jedc.2015.01.004 (2015).
13. Babatunde, K. A., Begum, R. A. & Said, F. F. Application of computable general equilibrium (CGE) to climate change mitigation policy: A systematic review.

Renewable and Sustainable Energy Reviews **78,** 61–71; 10.1016/j.rser.2017.04.064 (2017).

14. An, K., Zhang, S., Zhou, J. & Wang, C. How can computable general equilibrium models serve low-carbon policy? A systematic review. *Environ. Res. Lett.*; 10.1088/1748-9326/acbbe2 (2023).

15. Mosnier, A. *et al.* Modeling Impact of Development Trajectories and a Global Agreement on Reducing Emissions from Deforestation on Congo Basin Forests by 2030. *Environ. Resource Econ.* **57,** 505–525; 10.1007/s10640-012-9618-7 (2014).

16. Moore, F. C., Baldos, U., Hertel, T. & Diaz, D. New science of climate change impacts on agriculture implies higher social cost of carbon. *Nat Commun* **8,** 1–9; 10.1038/s41467-017-01792-x (2017).

17. Verburg, P. H. *et al.* Beyond land cover change: towards a new generation of land use models. *Current Opinion in Environmental Sustainability* **38,** 77–85; 10.1016/j.cosust.2019.05.002 (2019).

18. Findlater, K. M., Satterfield, T. & Kandlikar, M. Farmers' Risk-Based Decision Making Under Pervasive Uncertainty: Cognitive Thresholds and Hazy Hedging. *Risk analysis : an official publication of the Society for Risk Analysis* **39,** 1755–1770; 10.1111/risa.13290 (2019).

19. Overmars, K. P. *et al.* Estimating the opportunity costs of reducing carbon dioxide emissions via avoided deforestation, using integrated assessment modelling. *Land Use Policy* **41,** 45–60; 10.1016/j.landusepol.2014.04.015 (2014).

20. Meiyappan, P., Dalton, M., O'Neill, B. C. & Jain, A. K. Spatial modeling of agricultural land use change at global scale. *Ecological Modelling* **291,** 152–174; 10.1016/j.ecolmodel.2014.07.027 (2014).

21. Müller-Hansen, F. *et al.* Can Intensification of Cattle Ranching Reduce Deforestation in the Amazon? Insights From an Agent-based Social-Ecological Model. *Ecol. Econ.* **159,** 198–211; 10.1016/j.ecolecon.2018.12.025 (2019).

22. Grêt-Regamey, A., Huber, S. H. & Huber, R. Actors' diversity and the resilience of social-ecological systems to global change. *Nat Sustain* **2,** 290–297; 10.1038/s41893-019-0236-z (2019).

23. Brown, C. *et al.* Agent-Based Modeling of Alternative Futures in the British Land Use System. *Earth's Future* **10**; 10.1029/2022EF002905 (2022).

24. Brown, C., Brown, K. & Rounsevell, M. A philosophical case for process-based modelling of land use change. *Model. Earth Syst. Environ.* **2**; 10.1007/s40808-016-0102-1 (2016).

25. Groeneveld, J. *et al.* Theoretical foundations of human decision-making in agent-based land use models – A review. *Environ. Model. Softw.* **87,** 39–48; 10.1016/j.envsoft.2016.10.008 (2017).

26. Napoletano, M. A Short Walk on the Wild Side: Agent-Based Models and their Implications for Macroeconomic Analysis. *Revue de l'OFCE* **157,** 257; 10.3917/reof.157.0257 (2018).

27. Knoke, T. *et al.* Afforestation or intense pasturing improve the ecological and economic value of abandoned tropical farmlands. *Nat. Commun.* **5,** 5612; 10.1038/ncomms6612 (2014).

28. Meade, B. *et al. Corn and Soybean Production Costs and Export Competitiveness in Argentina, Brazil, and the United States* (2016).

29. Global Coffee Report. The Cost of Coffee Cultivation. Available at https://www.gcrmag.com/the-cost-of-coffee-cultivation/ (2011).

30. Feltran-Barbieri, R. & Féres, J. G. Degraded pastures in Brazil: improving livestock production and forest restoration. *Royal Society open science* **8,** 201854; 10.1098/rsos.201854 (2021).

31. Knoke, T. *et al.* Accounting for multiple ecosystem services in a simulation of land-use decisions: Does it reduce tropical deforestation? *Glob. Chang. Biol.* **26,** 2403–2420; 10.1111/gcb.15003 (2020).

32. Knoke, T. *et al.* Can tropical farmers reconcile subsistence needs with forest conservation? *Front. Ecol. Environ.* **7,** 548–554; 10.1890/080131 (2009).

33. Forrester, D. I., Bauhus, J., Cowie, A. L. & Vanclay, J. K. Mixed-species plantations of Eucalyptus with nitrogen-fixing trees: A review. *Forest Ecology and Management* **233,** 211–230; 10.1016/j.foreco.2006.05.012 (2006).

34. Costa, C. & Delgado, C. *The Cassava Value Chain in Mozambique* (World Bank, Washington, DC, 2019).

35. Okyere, P. & Baidoo, J. Profitability of cassava production in the Ashanti region of Ghana. *APSTRACT* **14,** 66–69; 10.19041/APSTRACT/2020/1-2/8 (2020).

36. Chrisendo, D., Siregar, H. & Qaim, M. Oil palm and structural transformation of agriculture in Indonesia. *Agricultural Economics* **52,** 849–862; 10.1111/agec.12658 (2021).

37. Joel Taiwo Oluseye, O., Ayodeji Sunday, O. & Ayodeji Damilola, K. Profitability of Investment in Plantain Value Chain in Osun State, Nigeria. *EEB* **4,** 23; 10.11648/j.eeb.20190402.13 (2019).

38. Castro, L. M., Calvas, B. & Knoke, T. Ecuadorian banana farms should consider organic banana with low price risks in their land-use portfolios. *PLOS ONE* **10,** e0120384; 10.1371/journal.pone.0120384 (2015).

39. Harris, N. L. *et al.* Baseline map of carbon emissions from deforestation in tropical regions. *Science (New York, N.Y.)* **336,** 1573–1576; 10.1126/science.1217962 (2012).

40. Xu, L. *et al.* Changes in global terrestrial live biomass over the 21st century. *Sci. Adv.* **7**; 10.1126/sciadv.abe9829 (2021).

41. United States Government. Technical Support Document: Technical Update of the Social Cost of Carbon for Regulatory Impact Analysis Under Executive Order 12866. Available at https://www.epa.gov/sites/default/files/2016-12/documents/sc_co2_tsd_august_2016.pdf (2016).

42. Pendrill, F. *et al.* Disentangling the numbers behind agriculture-driven tropical deforestation. *Science (New York, N.Y.)* **377,** eabm9267; 10.1126/science.abm9267 (2022).

43. Groom, B. & Venmans, F. The Social Value of Offsets. *Nature,* forthcoming; 10.21203/rs.3.rs-1515075/v1 (2023).

44. Global Forest Watch. Forest Monitoring, Land Use & Deforestation Trends | Global Forest Watch. Available at https://www.globalforestwatch.org/ (2022).

45. Food and Agriculture Organization of the United Nations. *World programme for the census of agriculture 2020* (Food and Agriculture Organization of the United Nations, Rome, 2015-2018).

46. Meyfroidt, P. *et al.* Middle-range theories of land system change. *Glob. Environ. Change* **53,** 52–67; 10.1016/j.gloenvcha.2018.08.006 (2018).

47. Simon, H. Theories of Bounded Rationality. In *Decision and organization. A volume in honor of Jacob Marschak,* edited by C. B. McGuire (North-Holland Publ, Amsterdam, 1972), pp. 161–176.

48. Knoke, T. *et al.* Optimizing agricultural land-use portfolios with scarce data—A non-stochastic model. *Ecol. Econ.* **120,** 250–259; 10.1016/j.ecolecon.2015.10.021 (2015).

49. Paul, C., Weber, M. & Knoke, T. Agroforestry versus farm mosaic systems - Comparing land-use efficiency, economic returns and risks under climate change effects. *The Science of The Total Environment* **587-588,** 22–35; 10.1016/j.scitotenv.2017.02.037 (2017).

50. Knoke, T. *et al.* Compositional diversity of rehabilitated tropical lands supports multiple ecosystem services and buffers uncertainties. *Nat. Commun.* **7,** 11877; 10.1038/ncomms11877 (2016).

51. Gosling, E., Reith, E., Knoke, T. & Paul, C. A goal programming approach to evaluate agroforestry systems in Eastern Panama. *J. Environ. Manage.* **261,** 110248; 10.1016/j.jenvman.2020.110248 (2020).

52. Knoke, T. *et al.* Confronting sustainable intensification with uncertainty and extreme values on smallholder tropical farms. *Sust. Sci.*; 10.1007/s11625-022-01133-y (2022).

53. Rössert, S., Gosling, E., Gandorfer, M. & Knoke, T. Woodchips or potato chips? How enhancing soil carbon and reducing chemical inputs influence the allocation of cropland. *Agric. Syst.* **198,** 103372; 10.1016/j.agsy.2022.103372 (2022).

54. Jarisch, I. *et al.* The influence of discounting ecosystem services in robust multi-objective optimization – An application to a forestry-avocado land-use portfolio. *For. Policy Econ.* **141,** 102761; 10.1016/j.forpol.2022.102761 (2022).

55. Reith, E., Gosling, E., Knoke, T. & Paul, C. Exploring trade-offs in agro-ecological landscapes: using a multi-objective land-use allocation model to support agroforestry research. *Basic and Applied Ecology*; 10.1016/j.baae.2022.08.002 (2022).

56. Knoke, T., Gosling, E. & Reith, E. Understanding and modelling the ambiguous impact of off-farm income on tropical deforestation. *J. Land Use Sci.* **17,** 658–676; 10.1080/1747423X.2022.2146220 (2022).

57. Uhde, B. *et al.* Bringing ecosystem services into forest planning – Can we optimize the composition of Chilean forests based on expert knowledge? *For. Ecol. Manage.* **404,** 126–140; 10.1016/j.foreco.2017.08.021 (2017).

58. Gosling, E., Knoke, T., Reith, E., Reyes Cáceres, A. & Paul, C. Which Socio-economic Conditions Drive the Selection of Agroforestry at the Forest Frontier? *Environmental Management* **67,** 1119–1136; 10.1007/s00267-021-01439-0 (2021).

59. Gosling, E. & Reith, E. Capturing Farmers' Knowledge: Testing the Analytic Hierarchy Process and a Ranking and Scoring Method. *Soc. Nat. Resour.* **33,** 700–708; 10.1080/08941920.2019.1681569 (2020).

60. Gosling, E., Reith, E., Knoke, T., Gerique, A. & Paul, C. Exploring farmer perceptions of agroforestry via multi-objective optimisation: a test application in Eastern Panama. *Agroforest. Syst.* **94,** 2003–2020; 10.1007/s10457-020-00519-0 (2020).

61. Keenan, R. J. *et al.* Dynamics of global forest area: Results from the FAO Global Forest Resources Assessment 2015. *Forest Ecology and Management* **352,** 9–20; 10.1016/j.foreco.2015.06.014 (2015).

62. Hamada, D., Nakayama, M. & Saiki, J. Wisdom of crowds and collective decision-making in a survival situation with complex information integration. *Cogn. Research* **5,** 48; 10.1186/s41235-020-00248-z (2020).

63. Zhang, B., Liang, H. & Zhang, G. Reaching a consensus with minimum adjustment in MAGDM with hesitant fuzzy linguistic term sets. *Information Fusion* **42,** 12–23; 10.1016/j.inffus.2017.08.006 (2018).

64. Brancalion, P. H. S. *et al.* Emerging threats linking tropical deforestation and the COVID-19 pandemic. *Perspectives in Ecology and Conservation* **18,** 243–246; 10.1016/j.pecon.2020.09.006 (2020).

65. Winkler, K., Fuchs, R., Rounsevell, M. & Herold, M. Global land use changes are four times greater than previously estimated. *Nat. Commun.* **12,** 2501; 10.1038/s41467-021-22702-2 (2021).

66. Hansen, M. C. *et al.* High-resolution global maps of 21st-century forest cover change. *Science* **342,** 850–853; 10.1126/science.1244693 (2013).

67. Geist, H. J. & Lambin, E. F. Proximate Causes and Underlying Driving Forces of Tropical Deforestation. *BioScience* **52,** 143; 10.1641/0006-3568(2002)052[0143:PCAUDF]2.0.CO;2 (2002).

68. Cisneros, E., Kis-Katos, K. & Nuryartono, N. Palm oil and the politics of deforestation in Indonesia. *J. Environ. Econ. Manag.* **108,** 102453; 10.1016/j.jeem.2021.102453 (2021).

69. Gaveau, D. L. A. *et al.* Slowing deforestation in Indonesia follows declining oil palm expansion and lower oil prices. *PLOS ONE* **17,** e0266178; 10.1371/journal.pone.0266178 (2022).

70. Ferreira Filho, Joaquim Bento De Souza & Hanusch, M. A Macroeconomic Perspective of Structural Deforestation in Brazil's Legal Amazon; 10.1596/1813-9450-10162 (2022).

71. Clough, Y. *et al.* Land-use choices follow profitability at the expense of ecological functions in Indonesian smallholder landscapes. *Nat Commun* **7,** 13137; 10.1038/ncomms13137 (2016).

72. Sonter, L. J. *et al.* Mining drives extensive deforestation in the Brazilian Amazon. *Nat Commun* **8,** 1013; 10.1038/s41467-017-00557-w (2017).

73. Kraus, S., Liu, J., Koch, N. & Fuss, S. No aggregate deforestation reductions from rollout of community land titles in Indonesia yet. *PNAS* **118**; 10.1073/pnas.2100741118 (2021).

74. Carvalho, W. D. *et al.* Deforestation control in the Brazilian Amazon: A conservation struggle being lost as agreements and regulations are subverted and bypassed. *Perspectives in Ecology and Conservation* **17,** 122–130; 10.1016/j.pecon.2019.06.002 (2019).

75. Vasco, C. *et al.* Off-Farm Employment, Forest Clearing and Natural Resource Use: Evidence from the Ecuadorian Amazon. *Sustainability* **12,** 4515; 10.3390/su12114515 (2020).

76. Caulfield, M. E. *et al.* Unpicking the Inter-relationships Between Off-Farm Livelihood Diversification, Household Characteristics, and Farm Management in the Rural Andes. *Front. Sustain. Food Syst.* **5,** 295; 10.3389/fsufs.2021.724492 (2021).

77. Mullan, K., Sills, E., Pattanayak, S. K. & Caviglia-Harris, J. Converting Forests to Farms: The Economic Benefits of Clearing Forests in Agricultural Settlements in the Amazon. *Environ. Resource Econ.* **71,** 427–455; 10.1007/s10640-017-0164-1 (2018).

78. Sy, V. de *et al.* Tropical deforestation drivers and associated carbon emission factors derived from remote sensing data. *Environ. Res. Lett.* **14,** 94022; 10.1088/1748-9326/ab3dc6 (2019).

79. United States Government. Technical Support Document: Social Cost of Carbon, Methane, and Nitrous Oxide Interim Estimates Under Executive Order 13990. Available at https://www.whitehouse.gov/wp-content/uploads/2021/02/TechnicalSupportDocument_SocialCostofCarbonMethaneNitrousOxide.pdf (2021).

80. Buongiorno, J. GFPM – Joseph Buongiorno. Available at https://buongiorno.russell.wisc.edu/gfpm/ (2022).

81. Franklin, S. L. & Pindyck, R. S. Tropical Forests, Tipping Points, and the Social Cost of Deforestation. *Ecol. Econ.* **153,** 161–171; 10.1016/j.ecolecon.2018.06.003 (2018).

82. Assa, B. S. K. The deforestation-income relationship: evidence of deforestation convergence across developing countries. *Environ. Dev. Econ.* **26,** 131–150; 10.1017/S1355770X2000039X (2021).