ENVIRONMENTAL STUDIES

Unsustainable development pathways caused by tropical deforestation

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Global sustainability strategies require assessing whether countries' development trajectories are sustainable over time. However, sustainability assessments are limited because losses of natural capital and its ecosystem services through deforestation have not been comprehensively incorporated into national accounts. We update the national accounts of 80 nations that underwent tropical deforestation from 2000 to 2012 and evaluate their development trajectories using weak and strong sustainability criteria. Weak sustainability requires that countries do not decrease their aggregate capital over time. We adopt a strong sustainability criterion that countries do not decrease the value of their forest ecosystem services with respect to the year 2000. We identify several groups of countries: countries, such as Sri Lanka, Bangladesh, and India, that present sustainable development trajectories under both weak and strong sustainability criteria; countries, such as Brazil, Peru, and Indonesia, that present weak sustainable development but fail the strong sustainability criterion as a result of rapid losses of ecosystem services; countries, such as Madagascar, Laos, and Papua New Guinea, that present unsustainable development pathways as a result of deforestation; and countries, such as Democratic Republic of Congo and Sierra Leone, in which deforestation aggravates already unsustainable pathways. Our results reveal a large number of countries where tropical deforestation is both damaging to nature and not compensated by development in other sectors, thus compromising the well-being of their future generations.

INTRODUCTION

The world has observed marked gains in economic activity and output in the last 20 years, but these have come at a high cost in terms of equitability (1) and sustainability—our capacity to pass to future generations the assets necessary for their future well-being. With increasing population and consumption per capita, sustainability is one of the main challenges of our time (2). This is reflected in the post-2015 development agenda in Rio+20 where the Sustainable Development Goals emerged as the successors of the Millennium Development Goals (3).

However, measuring sustainability is challenging. Gross domestic product (GDP) is now widely recognized as a metric that cannot comprehensively capture the wealth of countries (4). Instead, stock approaches that can measure variations in manufactured capital, knowledge and human capital, and natural capital (ecosystems) are necessary (5, 6). This is achieved through the evaluation of adjusted net savings (ANSs) over time. ANSs are obtained from national net savings after adding education expenditure and deducting energy, mineral, and forest depletion and damages from CO_2 and particulate emissions (6). Measuring variations in these stocks via ANSs is crucial because for countries to follow sustainable development pathways, it is at least necessary that the aggregate of these capital forms does not decline over time (7, 8). Two main criteria for sustainability have been proposed: weak and strong sustainability. Under a weak sustainability criterion, exchanges between different forms of capital are possible, and the development trajectory of a country is deemed sustainable as long as the aggregate capital is nondecreasing. In contrast, the strong sustainability criterion requires individually nondecreasing natural capital stocks. The strong sustainability criterion builds on the idea that the natural capital and the benefits and flows of ecosystem services (the benefits and flows provided by nature to humans; ESs) that it

provides cannot be substituted by other forms of capital, such as manufactured capital and knowledge and human capital (9). Here, we adopt a strong sustainability criterion based on maintaining the total economic value of tropical forest ESs in each country that is at least as high as the level of the year 2000.

To measure sustainability, the World Bank has led efforts in adjusting the ANSs in the accounts of the wealth of nations by incorporating traditional environmental indicators such as CO_2 emissions, timber extraction, and a fraction of the value of nontimber forest products (6). These indicators attempt to capture part of the losses due to the degradation in natural capital. However, a comprehensive incorporation of the losses of natural capital has not been undertaken because of technical difficulties, the main one being that most of the benefits and flows provided by ecosystems are not traded in markets (10). Further difficulties involve distinguishing between the ESs that are already indirectly included in national accounts through the support of economic activities (for example, a mangrove may support fisheries that produce fish that are sold in the market) versus supporting activities not captured by markets (for example, a mangrove supplies fish for subsistence consumption not registered by markets) and by the need to calculate the net loss of ESs versus the gains due to other forms of capital that may or may not be captured by markets and national accounts [for example, the replacement of forests by industrial agriculture (captured by the market) versus subsistence agriculture (not captured by the market) (10)].

However, marked developments in ES valuation techniques, fuelled by the Millennium Ecosystems Assessment report (11) and The Economics of Ecosystems and Biodiversity (TEEB) project (12), have stimulated a rapid increase in the number of studies quantifying the economic value of ESs (13). As a result, comprehensive databases of the economic value of ESs for multiple locations (for example, the TEEB database) are now available. This makes the time ripe to comprehensively assess whether nations are following sustainable development pathways. For instance, using the TEEB data set, the Inclusive Wealth Report has started to account for the depreciation of the natural capital via lost

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ESs in national accounts (14). These estimates have so far been produced by assuming that the total value of the ES provided is a sum that depends only on the area occupied by the ecosystem. Although these estimates are a starting point, they have limitations that result from not considering the spatial heterogeneity of ES values. The presence of beneficiaries, their level of use of ES, the scarcity of the ES provided, and the spatial configuration and size of the ecosystem are key determinants of ES values (15). The availability of high-resolution deforestation satellite data (16), the TEEB data set that allows the construction of spatially explicit meta-analytic models of ES values, and the development of global agricultural field size maps (17), combined with data sets to account for the spatial heterogeneity of ESs, offer a unique opportunity to comprehensively assess whether tropical countries are following sustainable development pathways.

Assessing sustainable development pathways is especially important in the case of tropical nations. They harbor a spatial confluence of endemism and high species richness contained in tropical forests with rapid economic development that exerts high tropical deforestation rates (16). Rapid tropical deforestation leads to a radical exchange between natural capital and other forms of capital with implications that are poorly understood. This poses fundamental sustainability questions: Under a weak sustainability criterion, is natural capital depreciation (using the economic value of tropical forest ES losses as surrogate) compensated by gains in other forms of capital in tropical nations? Which tropical nations are following unsustainable development pathways under weak and strong sustainability (where strong sustainability is defined as maintaining the economic value of tropical forest ESs at least as high as the level in the year 2000) criteria?

We combined high-resolution deforestation satellite data on forest loss (16) with (i) spatially explicit meta-analytic models of ES values in tropical forests, (ii) agricultural field size maps to proxy the distribution of subsistence activities not captured by markets, and (iii) the World Bank time series of ANSs from 2000 to 2012 (18) to assess whether 80 nations were following sustainable trajectories after deducting the net losses of ESs resulting from tropical deforestation from 2000 to 2012. We first adopted a weak sustainability criterion as benchmark and later evaluated the loss of ES value since the year 2000 to assess our adopted strong sustainability criterion. We apply a weak sustainability criterion to identify countries that are clearly on unsustainable development pathways (that are not even weakly sustainable). Among countries with development trajectories that pass the weak sustainability criterion, we assess strong sustainability on the basis of loss of ESs from tropical forests, thus identifying countries that are clearly on sustainable development paths (that is, strongly sustainable in terms of forest ES). This finding leaves a set of countries that pass the weak but not the strong sustainability test where more information is required about the distribution of ES losses and development gains to assess sustainability. We considered uncertainty in the analyses by performing bootstrapping in the ES meta-analytic models, considering different types of field sizes associated with subsistence agriculture and ES losses not captured by markets and different scenarios for a range of time horizons (T = 50 and 100 years) and discount rates (δ = 1, 4, and 10%) (see Materials and Methods).

RESULTS

The resulting average meta-analytic model using the TEEB data set was composed of three component models (see Materials and Methods). This model indicated that large ES values in tropical forests were pos-

itively associated with high average temperature and the area of the forest providing the service and were negatively associated with the year of publication of the study and bird species richness. Revealed and stated preference valuation methods produced lower ES value estimates than cost-based methods, and provision and regulating ESs had higher values than cultural ESs (Table 1). ES values were predicted to be high in India, followed by Southeast Asia and the Congo Basin (Fig. 1; with uncertainty ranges provided in figs. S1 and S2).

Among the 80 countries analyzed, 16 presented negative ANSs on average before the ES correction was performed and over the time period considered. Here, we report results using a time horizon of 100 years (the results for 50 years follow in parallel and are available in table S1). Under a weak sustainability criterion, when ES losses are included into national accounts, aggregate ANSs became negative in 22, 26, and 30 countries using discount rates of 10, 4, and 1%, respectively, over the 100-year time horizon. If the upper tail of uncertainty on ES values is considered, the number of countries with negative ANSs would be 25, 30, and 34, respectively (table S1). We observed a variety of trajectories among countries that could be classified as follows: (i) countries, such as China, Bhutan, Bangladesh, India, and Thailand, that displayed large and positive aggregate ANSs that remained positive even after deducting the net lost value of ESs (Fig. 2 and table S2); (ii) countries, such as Brazil and Indonesia, that incurred very large losses of ESs, which failed the strong sustainability criterion, and presented weak sustainable development pathways that were not robust to model uncertainty in the value of ESs, the choice of discount rate, and time

Table 1. Average linear mixed-effects model resulting from the meta-analysis of studies from the TEEB data set. The model is composed of the three top models ranked within two small sample size–corrected Akaike information criterion (AICc) units of the model with respect to the lowest AICc model (δ). Bold font indicates significance at the 5% level. Valuation methods (VMs) are compared against cost-based methods, and ES types are compared against cultural services. AP, average precipitation; AT, average temperature; SA, service area; YP, year of publication; BR, bird species richness.

|	Value	SE	z value	P value
Intercept	4.17	0.75	5.46	<10⁻¹⁶
VM: Revealed preference	−1.21	0.53	2.24	0.03
VM: Stated preference	−1.39	0.78	1.75	0.08
AP	−0.36	0.33	1.11	0.27
AT	0.57	0.16	3.47	<10⁻³
SA	0.55	0.17	3.25	<10⁻³
YP	−1.17	0.22	5.33	<10⁻³
ES: Provisioning	0.37	0.49	0.74	0.46
ES: Regulating	0.36	0.58	0.61	0.54
BR	−0.31	0.33	0.95	0.34
Model components	AICc	δ	Weight	
VM + AP + AT + SA + YP + ES	293.49	0	0.4	
VM + AT + SA + YP + ES + BR	293.89	0.4	0.33	
VM + AP + AT + SA + YP +ES + BR	294.25	0.76	0.27	
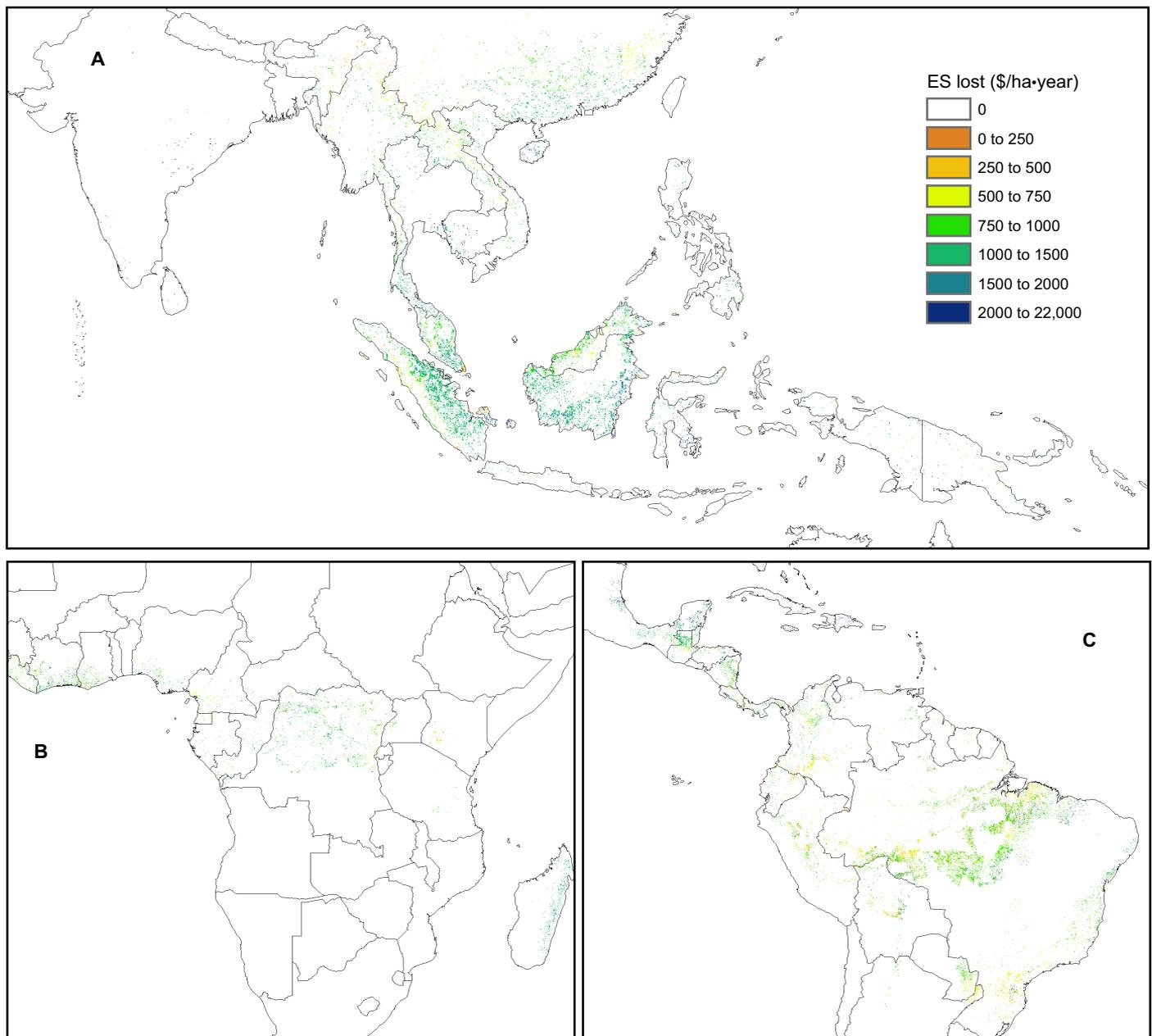
Fig. 1. ESs lost from deforestation. Map of tropical deforestation in 2010–2012, overlaid with economic values of ESs from median predictions of the final average meta-analytical model.

horizon (Fig. 2 and table S1); and (iii) countries displaying unsustainable development pathways under both weak and strong sustainability criteria as a result of deforestation, although this category of countries varied depending on the discount rate used. For example, Liberia, Papua New Guinea, Laos, Central African Republic, and Bolivia displayed negative ANSs with discount rates as high as 10%. For a discount rate of 4%, countries such as Madagascar, Nicaragua, and Belize also had negative ANSs, and finally, for a discount rate of 1%, Cambodia, Guatemala, Paraguay, and Colombia additionally registered negative ANSs (Fig. 2 and table S1). (iv) Last, countries can be classified as those, such as the Democratic Republic of Congo, Congo, Sierra Leone, and Gabon, where deforestation further aggravated already unsustainable pathways (Fig. 2 and table S1).

Small field sizes were spatially associated with deforestation in low-income countries, such as Liberia, Papua New Guinea, Belize, Nicaragua, and Madagascar. However, in most cases, correcting for the agricultural rents gained did not counteract the losses of ESs due to agricultural replacement except for Sierra Leone, Kenya, and Haiti (fig. S3). Our sustainability analysis results were not sensitive to the choice of field size. Using a wide uncertainty range spanning from assuming that only small field sizes corresponded to subsistence agriculture to assuming that all types of field sizes behind deforestation corresponded to subsistence agriculture, the analysis of the sustainability of development trajectories did not change for all countries except Ivory Coast and Nicaragua (fig. S4).

Although the ANSs trajectories over time for most of the countries did not indicate any apparent trends, there were important exceptions
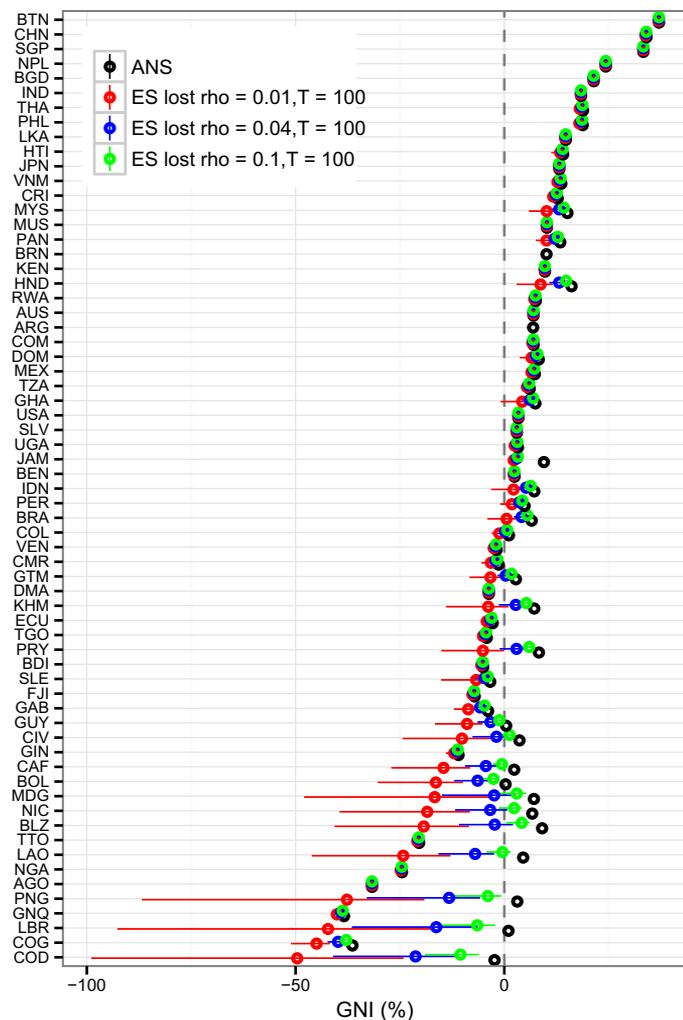
Fig. 2. Average ANSs in countries presenting tropical forests from 2002 to 2012 after deducting losses of ESs due to tropical deforestation. Bars indicate 2.5th and 97.5th percentiles from 1000 bootstrapped simulations. rho, discount rate; T, time horizon; GNI, gross national income.

(figs. S5 to S11). For example, Indonesia displayed an unsustainable trajectory from ES losses due to deforestation from 2002 to 2008 but recovered to a weak sustainable pathway from 2008 onward (fig. S10). However, other countries, such as Cambodia, Central African Republic, Dominican Republic, and Guatemala, had sustainable trajectories with positive ANSs turning unsustainable with negative ANSs trajectories (fig. S6 to S9).

In general, the final corrected ANSs trajectories were the result both of trends in the ANSs before ES correction (for example, due to the growth in other forms of capital) and of the level of deforestation and ES losses over time. Different patterns could be distinguished. Countries such as Brazil, Cambodia, Guatemala, Honduras, and Nicaragua presented ES losses that varied substantially over time, for example, with greater ES losses in the early 2000s than later time periods, responding to a reduction in deforestation rates (figs. S5, S6, and S9 and table S1). In contrast, in countries such as Cameroon, Colombia, Costa Rica, Ecuador, Thailand, and Mexico, the correction due to ES losses was small across time, not influencing the trends in aggregate ANSs in other forms of capital (table S1).

The countries presenting the largest absolute losses in the values of ESs from deforestation were Brazil, Indonesia, Malaysia, Democratic Republic of Congo, and Colombia (Fig. 1 and table S3). On a per capita basis, the largest losses of ESs occurred in Belize, Nicaragua, Malaysia, and Laos (table S3). As a result of these large losses of ESs with respect to their initial value in the year 2000, we could identify countries that presented weak sustainable development pathways but that did not pass the strong sustainability criterion. Examples of these countries are Malaysia, Honduras, Tanzania, Indonesia, and Brazil (Fig. 2 and table S3). In contrast, countries such as Bangladesh, Bhutan, India, Singapore, and Sri Lanka presented sustainable development trajectories both under weak and strong sustainability criteria because of both positive ANSs and very low losses of ESs (Fig. 2 and table S3).

DISCUSSION

These results demonstrate that a considerable number of countries follow unsustainable development pathways as a result of tropical deforestation, even under a less strict weak sustainability criterion. The loss of ESs appears to reinforce already unsustainable pathways chiefly in Central African countries, pointing toward a downward spiral of impoverishment through natural capital destruction that is not converted to other forms of capital (for example, education and manufactured capital), thus compromising the well-being of their future generations.

We found a spatial correspondence between the high value of ESs and deforestation in some countries, such as Indonesia, Papua New Guinea, and Madagascar, where a large proportion of the population rely on forests to complement their income or to provide suitable living conditions (Fig. 1) (19). At the outset, some countries are capable of maintaining weak sustainable development pathways despite large levels of ES losses (for example, Brazil and Indonesia) (figs. S5 and S10), whereas others are not (for example, Madagascar and Liberia) (fig. S11 and table S2). These differences could be explained by the relatively small role of agriculture and forestry in national economic output in countries such as Indonesia and Brazil (contributing 14 and 5.5% of their GDP, respectively); that is, net investment in other sectors such as manufacturing and services are dominant and growing in these countries and drive the aggregated ANSs upward, keeping the ANSs positive despite the losses of natural capital and ESs from tropical deforestation. In contrast, other countries without the capacity to offset the loss of natural capital by economic activities other than agriculture, such as Madagascar (28% of GDP from agriculture), Liberia (63% of GDP from agriculture), and Democratic Republic of Congo (44% of GDP from agriculture), are more vulnerable to impoverishment through deforestation and thus tend to follow unsustainable pathways.

Although our results under the weak sustainability criterion offer robust indication of unsustainable development in countries such as Madagascar and Liberia, following a weak sustainable development trajectory is not sufficient to indicate that countries such as Brazil and Indonesia follow sustainable pathways. On the one hand, the weak sustainable development trajectories for countries such as Brazil and Indonesia are not robust to uncertainty (a switch from positive to negative ANSs) in the predictions of the value of ESs, discount rate, and time horizon chosen. On the other hand, these countries experience rapid reductions of the values of their ESs, which is not compatible with the adopted strong sustainability criterion. In reality, the extent to which megadiverse tropical forests are substitutable by manufactured and human capital is uncertain, making the weak sustainability criterion less strict. Tropical forests provide biodiversity and cultural, ecological, and

intrinsic values that cannot be readily monetized and that are not included in our analysis. In addition, forests play important roles in climate change–related feedbacks, the resilience of ecosystems, and social equity within and between generations, making their substitutability with other forms of capital questionable. Given this severe uncertainty, a strong sustainability criterion is useful to complement the weak sustainability analysis. Under this criterion, countries such as Brazil, Peru, and Indonesia, for instance, present very rapid losses of ESs that point toward unsustainable development pathways.

Our analysis presents several limitations. For instance, we did not consider the impact of trade between countries as a possible masking factor; that is, countries that appear to follow strong sustainable pathways may be outsourcing the loss of natural capital to other countries. For instance, Vietnam exerts strong deforestation pressures through timber imports from Cambodia and Laos (20) that are not reflected in Vietnam's accounts. Similar masking may occur with India, China, and Singapore that are strong net importers of raw materials (21). In addition, not being able to capture the ethnographic reality of each country and the complexity of socioecological systems is one of the main limitations of our analysis, which is a limitation of any study reliant on aggregate data. In reality, modifying socioecological systems heavily reliant on ESs into other systems based on other forms of capital through, for instance, large logging and agricultural concessions to agribusinesses is bound to generate winners and losers that cannot be observed at the aggregate national account levels; that is, higher inequality may be masked by the observed sustainable development trajectories as a result of contributions by other economic activities. These limitations call for on-the-ground studies to correlate national aggregated trajectories with ethnographic studies evaluating the social equity dimensions of deforestation.

A further limitation is the small number of available ES valuation studies that prevented us from developing individual meta-analytical models for each type of ESs. Ideally, for example, we would perform ES meta-analysis for only water-related services to account for the hydrogeological characteristics of each catchment and other custom meta-analyses for other specific ESs and their unique ecological and biophysical characteristics. We also assumed that small field sizes were a good proxy of subsistence agriculture. This is plausible to the extent that field sizes appear correlated with overall levels of agricultural development, income, and mechanization (17, 22–24). This is nonetheless an assumption that entails high uncertainty because the relationship between field size and subsistence would vary according to the agrarian practices in each country. We addressed this uncertainty by performing a broad uncertainty analysis. This analysis showed that even when considering that any field size could correspond to subsistence agriculture, our results were not affected by the correction of rent gains from subsistence agriculture and ES losses (fig. S4). In addition, we adopted a conservative approach that is likely to lead to an overestimation of the economic benefits of subsistence agriculture. For instance, we did not consider that farmers may have been displaced from other locations so that there is no net gain in agricultural rents; we included high-value crops (for example, oil palm and coffee) that are not likely to be used primarily for subsistence and did not consider that farmers may not be able to maintain yields in the long term because of tropical soil loss and degradation. Similarly, our results are conservative because we considered all areas where field sizes are present as agricultural lands replacing forests. In reality, a proportion of tropical agriculture is not economically viable and would have not replaced forests without government subsidies, tax and trade regimes, and industrialization incentives that encourage wasteful resource-depleting logging (25).

Despite the unavoidable limitations of our estimates, our analysis was sufficiently robust to identify a large number of vulnerable countries

that urgently need alternative development strategies that foster diversification of investments and economic activities other than agricultural development based on tropical forest conversion. These strategies should also include initiatives to reduce corruption and improve the transparency of how returns from deforestation obtained from government agencies are reinvested in other forms of capital. Corruption may involve allocation of agricultural and logging concessions at the expense of tropical forests that provide critical contributions to ESs for local communities. It may also allow overharvesting timber beyond concessions and illegal logging (26). Under a corrupt system, the concession fees may be underpriced and received for private gain by officials instead of being reinvested for education or infrastructure development. For instance, a reduction of perceived corruption has been linked to decreased deforestation rates (27). Other potential measures toward correcting unsustainable development pathways caused by deforestation would be revision of the prices of key cash crops, such as palm oil, soybean, and rubber; enhancement of certification schemes; and education of consumers in importing countries to recover part of the loss of ESs (28). This could help mitigate the problem of agricultural production being underpriced in tropical countries (29).

Our results provide global evidence that tropical deforestation causes unsustainable development trajectories in multiple countries once the losses of ESs are incorporated into national accounts. Measures to correct these unsustainable trajectories are imperative so that these countries can realize their potential development opportunities without compromising the well-being of their future generations.

MATERIALS AND METHODS
Mapping ES values in tropical forests
Challenges in mapping the value of ESs
ES valuation studies are necessary to update national accounts; however, they are sparse, and only a few locations have been covered. Benefit transfer methods are thus needed to be able to generate wide-coverage maps. However, benefit transfer, which extrapolates the value from one location to another, is challenging. The type of method used for valuation, beneficiaries of the service, scarcity of the service, time period, and environmental and socioeconomic context variables specific to each location can influence the value estimated (30). Geographic information systems (GISs) and regression metamodels that explicitly account for these factors can mitigate these problems (31). The implicit assumption of these methods is that the statistical relationship between value and context variables holds to other locations when values are scaled up. Checking that the data set used to represent the meta-analytic model is representative of the area for which the model predictions will be scaled up can further be used to provide confidence that scaling up value predictions is reliable (table S1) (32).
Data collection
Taking into consideration the challenges of ES value transfer methods, we developed a spatial meta-analytic model of ES to project ES values onto tropical forests globally. We considered all types of ESs classified by TEEB (13) but conservatively excluded supporting services to avoid double counting (33). The meta-analytic model was constructed using ES valuation studies in tropical forests from the TEEB data set, excluding those studies that used benefit transfer methods. This meta-analysis is an update from a previous meta-analysis (34). The main changes are that we adopted information theory for model selection, increased the temporal match between the explanatory variables and the studies in the TEEB data set, and used models without variance structures to

facilitate bootstrapping. The location of each study was extracted using a GIS. Only site-specific studies were included, and all studies with a global or national scope were excluded (34). All values were expressed in international dollars of 2012 per hectare per year using the area of forest providing ES and discount rates reported in the studies selected. Studies reporting net present values but not reporting discount rates or time horizons were excluded. The dependent variable was logged to bound value predictions to positive numbers. The final sample size was $n = 78$ observations (table S4 contains the final data set).

Variables

To account for study methodological biases, spatial heterogeneity, and the potential shortcomings of benefit transfer in wealth accounting (31), three groups of variables were used in the models: (i) methodological variables describing the type of valuation method, the type of ESs, whether studies were peer-reviewed or not, and year of publication (accounting for temporal biases); (ii) context variables including average temperature and precipitation (to capture the influence of climate on ecosystem function) (35), accessibility (to account for how easy it is for beneficiaries to benefit from ESs) (36), population density (to account for density of potential beneficiaries of ESs) (37), elevation (35), geographically based GDP (38), area of the forest (to account for the scarcity of the ESs, where missing values were entered as zero in the TEEB), protected area status (39), species richness of birds (40) [to account for relationships between species richness and ecosystem function level (41), species richness of amphibians, small mammals, and vascular plants were also considered], and carbon content (as a proxy for secondary and primary forests) (42); and (iii) country-level variables for which no spatially explicit data were available and a random intercept for each country was used instead. This random intercept was intended to control for sources of nonindependence, corruption, and sociopolitical and institutional factors. Variables that varied temporally and for which maps were available for multiple years (population density and geographically based GDP) were chosen to match their temporal observations to the year that the studies were conducted. Whereas most of the variables chosen are based on theoretical grounds to directly capture factors that may influence ES values, some variables did not have available maps, and proxy variables were used instead. Among these, the climatic and biodiversity variables are a proxy for ecosystem functioning, altitude is another proxy of accessibility, and carbon content is a proxy for the type of forest.

Statistical analyses

The statistical model had the form

$$V_i = \alpha + \sum_1^J \beta_{Cj} X_{Cji} + \sum_1^K \beta_{Sk} X_{Ski} + c_m + \varepsilon_i$$

where

$$c_m \sim N(0, \sigma_1^2); \ \varepsilon_i \sim N(0, \sigma^2)$$

where V_i represents the logarithmic transformation of the ES value estimate i measured in U.S. dollar per hectare and per year, α is the intercept, β_C and β_S are the coefficients for the J context variables (X_{Cji}) and K methodological variables (X_{Ski}), c_m is the random intercept for country m that is assumed to follow a normal distribution with mean 0 and variance σ_1^2, and ε is the error term.

We fitted first a linear model containing only the main effects of the variables. The model was checked for multicollinearity using variance inflation factors and heteroscedasticity by inspecting plots of the residuals versus fitted values and versus each of the explanatory variables. Because of collinearity and the small number of observations per ES type, ES types were reclassified into three main groups: cultural, provisioning, and regulating. A similar type of valuation method was reclassified as follows: cost-based, stated preference, and revealed preference methods. These reclassifications corrected the problems of multicollinearity. Nonindependence was dealt with using a random intercept by country in a linear mixed-effects model (34). To evaluate spatial autocorrelation, we constructed semivariogram plots of model residuals and compared the model with only country as a random intercept with models that also included the average distance from each observation to all observations as a random slope (as a proxy for spatial independence) (43). These models were compared using the AIC, and we did not find evidence of spatial autocorrelation problems. No problems of heteroscedasticity and nonnormality were observed.

We considered an information theoretic approach to account for multiple competing explanations of the data through proposing multiple models (44). Models were proposed using the R package MuMIn (45) based on a mixed-effects model fitted using maximum likelihood with the package lme4 (46). The initial model contained all the main effects of the explanatory variables considered and with country as a random effect. A total of 256 models were proposed and ranked using AICc for small sample size. Models within two AICc units of the model with the lowest AICc score were deemed to present high support (44) and used to construct the final average model. The models presenting high support were evaluated further for homoscedasticity and assumptions of normality of errors, showing conformity with model assumptions.

Correcting for rents from agriculture not captured by national accounts

Deforestation leads to the loss of natural capital that may be replaced by other forms of capital, for example, in the form of agricultural activities. Whereas these activities may engage with markets and be captured by national accounts, subsistence agriculture will not be captured. Hence, an analysis attempting to correct national accounts would need to update the gains from subsistence agriculture (10) and deduct agricultural rents from ES losses. To attempt to approximate subsistence agriculture, we used a global map of qualitatively identified field sizes through experts and crowdsourcing into small, medium, and large field sizes according to the spatial patterns of the fields in high-resolution satellite images (17). This map has weaknesses and strengths. On the one hand, expert classification of patterns instead of areas may help avoid issues such as the differences in smallholder farm sizes in different agricultural systems; on the other hand, a classification based on actual areas would provide further information about the crops that may be cultivated. We initially assumed that the agricultural rents generated by deforestation that was spatially associated with small field sizes were not captured by national accounts; that is, these agricultural rents corresponded to subsistence agriculture. Because of the uncertainty associated with this assumption, it was later relaxed to consider the full range of field size combinations under different scenarios: (i) only small field sizes correspond to subsistence agriculture; (ii) small and medium field sizes correspond to subsistence agriculture; and (iii) small, medium, large, and deforested areas without identified field sizes correspond to subsistence agriculture (fig. S4). We calculated the revenue from agriculture within the different scenarios for field sizes by compiling the distribution of the 10 crops with the highest production value and the 10 crops with the highest production area in the tropics (47), yielding a list of 18 crops to which we

added cattle production (*47*), which indirectly took into account pasture production. The list of crops is the following: banana, bean, cassava, cocoa, coconut, coffee, cotton, cowpea, groundnut, maize, millet, oil palm, rice, rubber, sorghum, soybean, sugarcane, and wheat.

Crop distribution maps were available only for the year 2000 (*48*); therefore, it was not possible to determine which crops replaced forests across all cells. Given this uncertainty, we estimated agricultural benefits by first replacing a converted forest with the crops already found in that cell, in proportion to their relative coverage in that cell in the year 2000. This approach attempted to approximate the current situation by taking into account agricultural activities within each cell and assumed the expansion of crops that are already known to be locally successful. For those cells for which no current crop information was available, we developed an algorithm to retrieve information from the closest cell with crop data. These two approaches are supported by the strong spatial autocorrelation that is prevalent in agricultural land use dynamics (*49*). Transport costs were estimated using travel times to the nearest city (*36*), driver wages, and fuel prices in each country (*50*). Labor costs were also considered using standard person-hours needed for crop development in tropical countries from multiple sources (*51*–*56*) and agricultural sector salaries (*50*). Because of the lack of global maps on capital inputs for agricultural production in the tropics, these costs could not be included.

The net benefits from agriculture (NB) in each cell were then calculated as

$$NB_i = \sum_{u=1}^{U} \frac{a_{ui}}{\sum_{u=1}^{U} a_{ui}} (y_{ui} p_u - c_u)$$

where U represents the total number of agricultural activities occurring in map cell i, a_{ui} is the proportion of agricultural activity occurring in the cell i, y_{ui} is the yield of crop u in i that was obtained from global agricultural yield maps for specific crops (*48*), and p_u is the annual national farm gate price of the crop per quantity produced obtained from FAOSTAT (*57*) averaged between years 2000 and 2009 to avoid price fluctuations. In those cases where a country did not present price values for specific crops, regional average prices were considered. c_u is the cost of production of crop u (transport and labor costs). In the case of cattle, the average carcass efficiency per country was estimated (*57*) and multiplied by the proportion of pasture (*58*) and the density of cattle in the cell (*59*). All economic values were expressed in 2012 international dollars.

Dealing with uncertainty: Predictions, representativeness of ES values, and scenarios

The maps of ES values presented the highest uncertainty in the analysis. Uncertainty in the analyses was modeled following two approaches: bootstrapping in the modeling of ES maps and use of scenarios to account for different discount rates and time horizons.

The predictions from the ES meta-analytic models were carried out using the function bootMer (to perform bootstrapping of predictions) from the lme4 package (*60*). Bootstrapping consists of resampling the data set and refitting the models to assess how changes in the data affect the estimation of model parameters and model predictions. We performed 1000 bootstrapped iterations of model refitting for each of the models presenting the highest support according to AICc (that is, a total of 3000 refitted models because 3 models presented high support). Each refitted model was used to predict the average value of a regulating, cultural, and provisioning ES in a grid of 0.25° across the global extent of the tropical forest biome. Each type of ES was itself predicted under cost-based, stated preference and revealed preference valuation methods.

The predictions across the three valuation methods were averaged per cell. The contextual value for each predicted cell in the grid was extracted using a GIS. For variables such as year of publication and area of forest, the average values in the data set used to fit the models were used. The predicted layers per type of ES were aggregated for each cell considering five types of provisioning services, seven types of regulating services, and five types of cultural services from the TEEB data set, while excluding one provisioning service and one regulating service. This exclusion was done to represent carbon-related services (climate regulation) and raw materials (timber), because these ESs are already partially incorporated into ANSs by the World Bank through impacts of CO_2 emissions and timber extraction, respectively. Predictions for each cell were then aggregated across the three models presenting high support using the weight of each model (Table 1) to calculate weighted averages of values per cell in the map. As a result, a distribution ($n = 1000$) of ESs lost annually in each cell in the map was obtained. These uncertainty distributions were used to obtain median and 2.5th and 97.5th percentiles (figs. S2 and S3).

To assess how reliable the ES model was when scaling up values to the tropical biome, the representativeness of the fitted model to the rest of tropical forests was assessed by comparing the median and interquartile range of the explanatory variables for the locations for which observations were available with the ranges of those values in the tropical biome domain (*61*). The median of the observations used to construct the model was located within the interquartile range of the values in the tropical biome, showing reliability for scaling up to generate pantropical ES value maps (table S5) (*34*).

Because ESs are provided as flows through time, deforestation limits the flow through the future as a stream of benefits that needs to be discounted to obtain a net present value (*10*). To account for uncertainty in the discounting approach and time horizon used, we considered the following scenarios: discounting rates of 1, 4, and 10% and time horizons of 50 and 100 years, leading to six scenarios.

Combining ES losses with national accounts
We overlaid the uncertainty distributions of predicted ES losses after deducting agricultural rent gains by different agricultural field sizes with high-resolution deforestation maps for each year from 2000 to 2012 (*16*). For computational reasons, these maps, at an initial resolution of 1 s, were aggregated to a resolution of 30 s, yielding a proportion of deforestation per year and cell. These maps were multiplied by the predicted distribution of uncertainty of ES values while accounting for the area size of each cell. The resulting maps were later aggregated by country and year to produce maps of net present values of net ES losses per cell.

ANSs for each country between 2000 and 2012 (to match with the aggregate estimates of net ES losses) were obtained from the World Bank annual World Development Indicators reports (*62*). Because ANSs already include a correction for nontimber forest product ES that is provided by forests (10% of $27/ha·year) (*63*), we deducted this value to our estimated annual ES values before deducting them to the ANSs to avoid double counting. The loss of ESs expressed as net present values under the different scenarios aggregated over each year for each country was expressed as percentage of the gross national income in each country and year and finally deducted from the ANSs time series.

SUPPLEMENTARY MATERIALS

fig. S3. Log of annual losses of ESs in the countries analyzed.
fig. S4. Average ANSs in countries with tropical forests from 2002 to 2012 after deducting losses of ESs due to tropical deforestation, corresponding to no agricultural land and small, medium, and large field sizes.
fig. S5. ANSs for Brazil corrected due to losses of ESs through deforestation.
fig. S6. ANSs for Cambodia corrected due to losses of ESs through deforestation.
fig. S7. ANSs for Central African Republic corrected due to losses of ESs through deforestation.
fig. S8. ANSs for Dominican Republic corrected due to losses of ESs through deforestation.
fig. S9. ANSs for Guatemala corrected due to losses of ESs through deforestation.
fig. S10. ANSs for Indonesia corrected due to losses of ESs through deforestation.
fig. S11. ANSs for Madagascar corrected due to losses of ESs through deforestation.
table S1. Disaggregated annual results per country under time horizons of 50 (T50) and 100 years (T100) and discount rates (rho) of 1, 4, and 10%.
table S2. ANSs corrected due to losses of ESs through tropical deforestation after deducting agricultural rents by all sizes of agricultural fields.
table S3. Losses of ES economic values from 2000 to 2012 from tropical deforestation.
table S4. Data used to build the ES meta-analytic models.
table S5. Representativeness of the TEEB database of tropical forests for the variables used in the meta-analytic model.

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Unsustainable development pathways caused by tropical deforestation

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