Agricultural intensification, Indigenous stewardship and land sparing in tropical dry forests[1]

Marie Pratzer [1,2], Álvaro Fernández-Llamazares [3], Patrick Meyfroidt [4,5], Tobias Krueger[1,2], Matthias Baumann [1], Stephen T. Garnett [6], Tobias Kuemmerle [1,2]

1 Geography Department, Humboldt-Universität zu Berlin, Berlin, Germany.
2 Integrative Research Institute for Transformations of Human-Environment Systems (IRI THESys), Humboldt-Universität zu Berlin, Berlin, Germany.
3 Helsinki Institute of Sustainability Science (HELSUS), Faculty of Biological and Environmental Sciences, University of Helsinki, Helsinki, Finland.
4 Earth and Life Institute, UCLouvain, Louvain-la-Neuve, Belgium.
5 F.R.S.-FNRS, Brussels, Belgium.
6 Research Institute for the Environment and Livelihoods, Charles Darwin University, Casuarina, Northern Territory, Australia.

Corresponding author:

Marie Pratzer, Geography Department, Humboldt-Universität zu Berlin, Berlin, Germany & Integrative Research Institute for Transformations of Human-Environment Systems (IRI THESys), Humboldt-Universität zu Berlin, Berlin, Germany (marie.pratzer@hu-berlin.de)

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Abstract

Agricultural intensification, an increase in per-area productivity, may spare forests otherwise lost to agricultural expansion. Yet which conditions enable such sparing or whether intensification amplifies deforestation through rebound effects remains hotly debated. Using a multilevel Bayesian regression framework, we analyse the effects of agricultural intensification on deforestation in the world's understudied and threatened tropical dry forests. We find that, overall, intensification has not lowered deforestation in tropical dry forests, particularly in countries where commodity crop production dominates—a situation typical for many areas where agriculture is expanding. However, country-level intensification reduced deforestation in areas where Indigenous land stewardship is widespread. More appropriately acknowledging the critical role of Indigenous peoples in preventing rebound effects, either on their lands or on the wider surrounding area, as well as recognizing and enforcing their rights, could thus translate into major opportunities for agricultural intensification to deliver positive outcomes for people and nature.

MAIN

Agricultural expansion into natural ecosystems is widely recognized as a major driver of the deeply intertwined climate and biodiversity crises[1,2,3]. Environmental impacts are particularly strong where modern agriculture expands into tropical and subtropical forests[4,5], often additionally eroding the livelihoods and cultures of millions of forest-dependent peoples[6,7]. Yet, global demand for agricultural products continues to grow[7,8,9], and agricultural expansion in the tropics and subtropics continues unabated[5,10]. Identifying land-use pathways that avoid the stark and often irreversible social–ecological impacts of converting natural ecosystems to agriculture has therefore become a central research issue in sustainability science[11,12].

Agricultural intensification may spare land[13] and hence could serve as a mechanism to lessen expansion pressure on the world's remaining forests[14], but how intensification influences deforestation remains insufficiently understood and, as a result, hotly debated[13,15,16]. On one hand, the 'land sparing' hypothesis postulates that intensification releases land for other uses, including for conservation purposes, as intensification increases production output on a given piece of land. As a result, deforestation is expected to decline where such a sparing effect materializes. On the other hand, the 'rebound effect' hypothesis postulates that intensification increases profitability, which then incentivizes further expansion of agriculture into forests[13,14,17]. Many factors have been shown to determine whether land sparing or a rebound effect dominates in a given context, including crop types, the response of prices to demand, the degree of market integration of regions where intensification takes place, the type of intensification, constraints on production factors (that is, labour, capital, land), the time horizon considered (that is, short- versus long-term effects) or governance and policy incentives for or against agricultural expansion[13,16,18].

However, two major gaps in the literature have so far prevented a more general, systemic understanding of how intensification relates to deforestation. First, most existing work has focused on either the very local or the global scales, neither of which correspond well with scales relevant to broad-scale policy decisions. Insights from local case studies are often very context-specific and cannot easily be transferred to other social–ecological systems[19,20]. In contrast, aggregate global scale studies typically characterize net forest change in larger regions, and are thus unable to account for the fact that net land savings at a broad scale can co-exist with major forest loss at regional to local levels[15,21]. Recognizing this is crucial because identifying a land sparing effect at an aggregate scale does not necessarily indicate that expansion into natural forests has been avoided, because agricultural expansion in some places[19] can be coincident with agricultural abandonment and reforestation[15] or an increase in plantation forestry[10], in other places. Such outcomes are less desirable from a conservation point of view than halting reductions of natural forest cover[21,22]. A focus on intermediate scales across biomes of high conservation interest could provide useful middle ground between exploring patterns in units large enough to internalize some of the spillover effects, while not erasing regional dynamics entirely and thus still capturing gross changes[18].

Second, although intensification outcomes can be expected, and have been shown, to differ between social–ecological settings[18,23,24], two contexts especially relevant for conservation have so far been inadequately characterized in empirical studies across regions. First, global market integration potentially increases the possibility of rebound effects[25,26]. Most contemporary agricultural expansion frontiers are driven by agribusiness corporations, producing commodities for international markets[27,28,29]. For a given region, this undermines the fundamental assumption of the land sparing hypothesis (that is, an inelastic demand for agricultural products, and thus declining expansion pressure once this demand is met[30]). Second, the roles and perspectives of Indigenous peoples have largely been neglected in previous research on the topic, although they manage or have tenure rights over at least 28% of the world's terrestrial surface[31]. This is a major shortcoming, given that the principles and values underpinning Indigenous land stewardship and governance are often strikingly different from the neoclassical economic framing of human decision-making that is assumed by the land sparing hypothesis[32,33,34]. The institutional arrangements, governance approaches and management systems of Indigenous peoples have been shown to slow down forest loss and degradation substantially[35,36], but their moderating effect on the relationship between agricultural intensification and deforestation remains unstudied.

Understanding how intensification relates to deforestation across these social–ecological contexts is critical because misdirected or ineffective policies that support intensification risk translation into deforestation, biodiversity loss and carbon emissions[37]. Addressing this research challenge is particularly relevant for the world's under-researched, yet important, tropical dry forests (TDF)[38,39,40]. TDF harbour exceptional biodiversity and sustain the livelihoods of hundreds of millions of people, but have often been overlooked in science and policy circles[39,40,41]. This is even more worrisome given that many TDF remain weakly protected and currently face high and rising human pressure[40]. Many expanding agricultural frontiers and global hotspots of deforestation are found in TDF[42,43,44]. Hence, both the stakes and the potential opportunities associated with intensification are high. Against this background, we aimed to explore how different social–ecological conditions affect the relationships of intensification and forest loss in the world's TDF. Specifically, we asked:

1. Does the degree of market orientation of agriculture influence the relationship between agricultural intensification and deforestation?
2. Does the presence of Indigenous lands influence that same relationship between intensification and deforestation?
3. How does the association of deforestation and intensification vary across continents?

We applied a Bayesian multilevel regression framework to investigate the causal link between agricultural intensification, measured as country-level yield change, and deforestation, measured as percentage forest loss within 3-km grid cells, for the period 2000 to 2020 (Fig. 1). We used this framework to explore how intensification outcomes on deforestation are influenced by (1) the degree of market orientation of agriculture, proxied using the country-level production share of non-staple crops, and (2) the presence of land managed or owned by Indigenous peoples. We furthermore controlled for local demand changes through rural population density, for fine-scale variations in agricultural suitability and for remoteness of forest areas. For a detailed description of our modelling strategy, input data and variables used, we refer to Methods and Supplementary Notes 1 and 6.

RESULTS AND DISCUSSION

Higher yields fail to spare land in TDF

Our models revealed that agricultural intensification between 2000 and 2020 was generally associated with increasing, not decreasing, forest loss in the world's TDF. Globally, a doubling in yield (that is, a 100% increase) was associated with an average increase in forest loss of 3.8%

(Table 1). These findings support the view that the most common pattern for tropical or low- to middle-income countries achieving growth in agricultural productivity has been to expand their agricultural footprint[18,23,45]. We caution that, as we focus on forest loss in TDF regions only, we cannot examine whether the locally identified rebound effects were accompanied by land sparing beyond our study area, for example, the extent to which it has been facilitated through global trade[46]. However, even if there was a net increase in land sparing globally, there would still be an increase in deforestation in the forests of the very threatened tropics and subtropics, thus representing an environmentally costly process of displacing forest loss[15].

Our model results explicitly demonstrate the variability of intensification outcomes. By predicting the effect of yield change on the precision of forest loss (see Methods), we show that higher yield increases are associated with lower precision—and thus higher dispersion—of forest loss outcomes (Table 1). This suggests that heterogenous social–ecological conditions diversify the forest loss outcome of yield change. Moreover, our results support the expectation that the divergent outcomes of agricultural intensification (that is, a land sparing effect versus a rebound effect) are likely to be context dependent. Specifically, with stronger intensification, contextual factors are more important for shaping the overall outcome, thus highlighting the need to improve understanding of how different social–ecological settings foster or inhibit these outcomes[18,24,47]. A corollary to this is that policies that lead to a desired outcome in one social–ecological context can be ineffective or detrimental in others[37].

Commodity agriculture reinforces the rebound effect

A central finding from our work is that the rebound effect was stronger for situations where agricultural production is predominantly for commodity markets, as evidenced through the positive interaction effect of our measure of market orientation (that is, share of non-staple crops, correlated with the share of exported production) on the intensification–deforestation relationship (Fig. 3 and Table 1). The role of market integration in strengthening the rebound effect confirms model simulations[26], and is also in line with previous findings on the influence of crop type on the magnitude of rebound effects, such as land sparing being more likely for staple crops versus non-staple crops18, or land sparing effects of staple crops being counteracted by the effect of expanding non-staple crops[45].

Our results add to a growing body of evidence that land sparing is more likely to materialize when agricultural demand is inelastic to price[13,17,26], in other words, when decreasing prices that can derive from increasing productivity and efficiency gains do not lead to an additional demand for a commodity. Such price inelasticity is typical for staple crops for direct human consumption, or in closed markets where crops are mostly sold locally, so that surplus production reached through higher yields renders agriculture unprofitable on marginal lands[26]. In contrast, prices of commodities produced for global markets are often insensitive to local or regional increases in production and demand is relatively elastic, so that efficiency gains from intensification are likely to translate into more profitable agriculture. Because agricultural expansion is particularly responsive to commodity prices[14], high profitability of cultivation acts as an incentive to expand the crop frontier, thereby stimulating a rebound effect.

Taken together, these results highlight that the form of intensification strongly mediates its impact on forest cover. In particular, the intensification of commodity crops produced for rapidly expanding global markets, so-called ‘commodity booms’, risks stimulating major forest loss through rebound effects[48,49]. Such commodity booms drive much contemporary cropland expansion into tropical forests and other natural areas[27,28,50], where staple production in closed local markets is increasingly supplemented and replaced by non-staple production for distant or globalized markets[27,50,51], as even the remotest areas can rapidly be integrated into global supply chains[52,53]. Our estimates of yield change, outranking the traditionally strong effect of rural population on forest loss in all continents (Table 1), suggest that contemporary deforestation frontiers are better explained by distant demand from urban areas and other domestic markets, and international markets, than by local demand[28,51]. Clearly, this finding poses a major challenge to leveraging land sparing under current trends in global agriculture and highlights the importance of considering market dynamics when designing policy interventions aimed at fostering sustainable outcomes from intensification.

Among continents, the finding that market-oriented agriculture reinforced a rebound effect was strongest for Asia. This probably reflects the growing importance of agricultural commodities often destined for export, such as palm oil, rubber, tea, pepper and coffee[50], yet especially also the role of rice, which is increasingly exported to international markets[54]. Although much of the marketed rice is wet rice, contributing relatively little to deforestation directly, rice intensification could have major indirect effects at the scale of countries. For example, rice intensification can promote the expansion of other crops that are more likely to promote deforestation by freeing up labour, capital or land45. Interestingly, testing our models with rice classified as a staple crop, we found a trend reversal (Extended Data Fig. 2), supporting the role of rice intensification as an indirect driver of forest loss.

As in Asia, we found market-oriented agriculture to reinforce a rebound effect for South America (Fig. 3). This is not surprising, given the recent wave of expansion of export-oriented agribusiness that has triggered rampant deforestation, including in the Cerrado[55], the Gran Chaco[51] and the Chiquitano Forest[56]. These market-oriented, highly capitalized actors, often operating with little direct government intervention[51], are likely to re-invest revenues from agriculture to increase profitability and thus to lead to persistent or increasing deforestation pressure without policy interventions[43,57]. Thus, our findings do not support the notion that agribusiness agriculture facilitates land sparing because of higher land-use efficiency[58], generally, and particularly not for South American TDF (Fig. 4).

In contrast, in Africa, where smallholders producing for themselves or local markets dominate[59,60] (Fig. 4), farmers are likely to be much less responsive to changes in global commodity markets, explaining why we found that the effect of market orientation on the intensification–deforestation relationship was small. In line with our results, African deforestation frontiers are largely associated with smallholder agriculture[43,60,61]. However, Africa is now attracting increasing interest from agribusiness investors[53], increasing domestic demand for commodity crops[43] and expanding export-oriented farming of crops such as soy and oil palm in sub-Saharan Africa[43] or maize in Madagascar[62]. These expanding African frontiers have similarities, and sometimes connections, to early South American frontiers63. This signals increasing pressure on African dry forests and savannas[43,50], especially as our results suggest that this pressure is likely to be reinforced by rebound effects, in line with prior work[26].

Land sparing effects are more likely in Indigenous lands

Intensification of agriculture at the country level was more likely to be associated with lower forest loss in areas owned and/or managed by Indigenous peoples (Table 1). This finding can be explained by two underlying mechanisms. First, lower forest loss in lands under Indigenous stewardship can indicate land sparing as a direct effect of agricultural intensification on Indigenous lands. Such a conclusion is plausible as Indigenous land uses are generally based on collective ownership and conditions that, having coevolved with the local ecologies, often translate into sustainable use of common-pool resources[32]. Further, agricultural production in Indigenous land systems is often small-scale, subsistence-oriented and based on traditional agroecological practices[64,65], making these systems less prone to the drive to increase profitability, and thus be subject to rebound effects from agricultural intensification. Smallholders might refrain from intensification due to increased labour intensity and/or ecological concerns[66,67]. However, it is important to highlight that intensification has frequently occurred in smallholder communities, including in Indigenous communities[68,69,70].

Second, lower forest loss in areas where Indigenous stewardship is widespread can indicate forest conservation amid intensification outside mapped Indigenous lands (yet within the same country, the scale at which our intensification measure was calculated). This outcome can either be interpreted as forests spared by intensification outside Indigenous lands (that is, a spillover effect), or as forests conserved inside Indigenous lands alongside intensification and rebound effects outside these lands. Such positive effects of Indigenous land-based stewardship on nature conservation and ecosystem service provisioning has recently been identified by several scientific studies[31,32,36], in addition to Indigenous scholars and knowledge holders who have long provided rich contextual evidence of the innumerable ecological values of their territories[71,72,73]. Indeed, forests on lands owned or managed by Indigenous peoples often form the very foundation of livelihoods and cultural identities[6,74]. Indigenous land-based stewardship is often compatible with, and frequently actively supports, forest conservation and restoration, and this recognition has spawned innovative ways to design multi-functional reserves, policy instruments and management programmes[31].

We stress that, while both explanations highlight the potential importance of Indigenous peoples in enabling land sparing and conserving forests, our data do not allow us to distinguish clearly between the two explanations. More fine-scale data on intensification, which to our knowledge are not available across the extent of all TDF we assess here, would be needed to quantify whether the positive net effect of intensification on forests in Indigenous lands results from intensification on Indigenous agricultural areas themselves, or from interactions between intensification in the wider landscape and land sparing on Indigenous lands. While future, field-based efforts to measure agricultural intensification on and in the areas surrounding mapped Indigenous lands will be valuable, we stress that this would require a long-term study, as yield change data are required to disentangle the mechanisms behind the positive net effect of Indigenous peoples' presence on reducing forest loss we find here. Such data cannot be gathered retrospectively for regions that have undergone forest loss. Finally, and more generally, it is important to note that, by capturing relative land sparing, we here only refer to reducing forest loss, not halting or reversing it.

The influence of Indigenous land stewardship on deforestation varied among continents. The dampening effect of Indigenous influence on forest loss and the magnitude of the rebound effect was particularly strong for South America, but was still evident in Africa and Asia. In South America, we found a trend reversal, with land sparing as the most probable outcome of intensification on lands owned or managed by Indigenous peoples, yet the opposite for other lands (Fig. 3 and Table 1). Importantly, we stress that the 'sparing effect' we identify refers to the maintenance of forest cover, but does not imply that these forests are, or should be, uninhabited or unused. On the contrary, we recognize that this reduction in forest loss is most often due to the leadership and agency of Indigenous communities in keeping these forests free from industrial development pressures[75,76]. The stronger effect we reveal for South America might be attributable to the relatively higher tenure security of many Indigenous peoples there, with land titling programmes being generally more formalized and enforced than in large swathes of Africa and Asia[77,78]. Although Indigenous peoples in South America also suffer from land tenure insecurity and encroachment[79], they generally have a stronger ability to engage in land-use planning and decision-making, when compared with other regions in the Global South[78]. Tenure insecurity and overlapping tenure affects land management decisions and tends to undermine any conservation impacts that might be associated with Indigenous land stewardship[32,80]. Furthermore, in many places, and particularly large parts of Africa and Southeast Asia, multiple layers of settlement and colonization have made definitions of Indigeneity contentious and difficult to apply[31]. Consequently, there are local communities that share many characteristics with Indigenous peoples (for example, long histories of place-based living, semi-subsistence economies, distinct cultural practices), but do not meet the definition of Indigenous peoples that was applied in the dataset we used for our analysis (see Methods and Supplementary Note 5). We believe it is valuable to maintain a consistent definition of Indigenous peoples across studies, but highlight that we may miss some effects associated with other local communities.

Overall, our results highlight the key role of Indigenous communities as land stewards. However, and despite their importance, Indigenous peoples' perspectives and views are so far only marginally considered in scientific and policy debates about intensification, land sparing or conservation strategies. In fact, the overall framing of the debate around the land sparing effect versus rebound effect does not tally with Indigenous ways of knowing and relating with their lands81. Instead, in much of this literature, spared lands are commonly understood as 'wilderness' areas where human interventions should be at least minimized[13]—a conceptualization that fails to recognize the crucial material and non-material needs these lands fulfil to Indigenous communities, and overlooks the crucial stewardship contributions of Indigenous peoples[82].

Predicting potential future forest loss associated with extrapolating yield increases based on our modelling results illustrates how rebound effects could translate into alarming deforestation, particularly in some frontier hotspot regions (Fig. 5). While this prediction represents a hypothetical simulation and is by no means a forecast into the future, such a visualization highlights the heterogeneity of potential intensification outcomes, diversified by varying social–ecological conditions. At least 21% of the world's TDF are owned or managed by Indigenous peoples (Fig. 4). This provides numerous opportunities for delivering more positive outcomes of agriculture for both people and nature, as we highlight with our modelling results, but urgently requires Indigenous peoples' perspectives and management approaches to be considered more deeply in the design and implementation of sustainable land-use strategies.

Implications for leveraging sustainable land use

Given current trends and the anticipated strong growth of demand for agricultural products, the world still seems far from 'peak cropland'[14]. Agriculture continues to expand rapidly, particularly into natural areas in the Global South, where it leads to stark environmental and social trade-offs[5]. Given that much of the world's remaining lands that could be used for agriculture are found in the world's TDF and savannas[83], land-use pressure on these ecosystems will probably continue to rise. These regions already harbour many global deforestation hotspots, particularly in South America and Asia, and new ones are emerging rapidly, particularly in Africa[44]. Forward-looking sustainability planning is urgently needed for these regions.

Much hope is placed on sustainable agricultural intensification to lessen pressure on the remaining tropical and subtropical forests[9]. In assessing past forest loss and yield changes in the world's TDF, we here provide a cautionary note to such expectations. Increasing productivity and land-use efficiency by itself are unlikely to lower deforestation pressure, particularly where market-oriented agribusinesses dominate—a situation emblematic for many expanding commodity frontiers in the Global South. As such, intensification is likely to lead to more, not less, deforestation through rebound effects, and additional policy measures such as land-use zoning, land protection, or supply-chain mechanisms are needed to halt forest loss[84,85]. Importantly though, we find agricultural intensification, measured at the country level, is much more likely to be associated with lower local forest loss where Indigenous land stewardship is widespread, adding to the many well-documented local-to-global benefits of Indigenous land-based stewardship[72,73,76]. Ensuring the participation of Indigenous peoples in policy and planning for their lands, as well as recognizing their inherent rights on their traditional territories, can thus provide major opportunities for leveraging sustainable intensification.

Furthermore, our results have relevance for the long-lasting scientific debate on whether land sparing or land sharing strategies are the best means to minimize the trade-offs between agricultural production and biodiversity conservation. Land sparing seeks to use less land by intensifying agricultural production, resulting in a spatial segregation of production and conservation areas. In contrast, land sharing assumes that production and conservation goals can be achieved on the same lands, particularly if production takes place in biodiversity-friendly ways[86]. Given that we found widespread rebound effects in the world's TDF, our study corroborates views that intensification by itself is unlikely to spare land for nature without additional policy interventions at multiple levels and scales[58,84]. More generally, our work highlights how scientific and policy debates too often seek universal, silver-bullet solutions that are unlikely to meet complex social–ecological challenges, such as ensuring sustainable land use[37]. Considering the diverse social–ecological contexts that are found locally, and therefore a diversity of solutions, is urgent if pathways to sustainable land use are to be identified. In the context of the land sparing debate, ignoring social–ecological context risks overestimating the potential for market mechanisms to promote sustainability, and does not do justice to the leadership and agency of Indigenous peoples in curbing deforestation on their territories.

METHODS

TDF

To define our study region, we followed previous work on TDF globally[44,87,88] and used an inclusive TDF definition. Specifically, we focused on all forests and woodlands falling into two biomes according to the updated version of Olson et al.'s categorization[89,90]: (1) tropical and subtropical dry broad-leaved forests; and (2) tropical and subtropical grasslands, savannas and shrublands. Accordingly, TDF regions are distributed through South and Central America, Africa, Southeast Asia and Australia, covering about 20% of the global terrestrial surface[87]. All these ecosystems harbour large numbers of endemic species[38,91], are major carbon stores and provide important ecosystem services92. Moreover, TDFs are culturally rich and have been inhabited for millennia[93], causing widespread transformations in these ecosystems94. While in some TDF regions, forests have been substantially reduced by historical deforestation, such as in India[95] and Indochina[96], many regions, such as Madagascar[62] and the South American Chaco, Chiquitano[56,97] and Cerrado[42], have only recently turned into global deforestation hotspots. There are also many regions where deforestation frontiers are currently activated, such as the African Miombo[43,59,63].

Data sources and processing

To analyse the causal link between agricultural intensification and deforestation in the world's TDF, we assembled a multilevel dataset for the period 2001 to 2020, consisting of country-level variables and pixel-level information at a 3 × 3 km2 grid. Specifically, we included all grid cells that had at least 10% TDF cover in the year 2000 according to the Global Forest Watch dataset[10]. Although forest data derived from satellite images entail some weaknesses in the forest–grassland transition areas where tree cover is on the margin of the remote sensing definition of forest, these data still have an overall accuracy of more than 80%, which is further increased through aggregating onto a coarser grid. We systematically sampled every third grid cell in x- and y-direction to minimize effects of spatial autocorrelation, resulting in a total of 154,979 cells that we retained. Because, in the tropics, most new cropland comes at the expense of forests[30,98], we used forest loss as our dependent variable. The Global Forest Watch captures all forest loss, but in TDF regions, most forest loss is either due to agricultural expansion or management (for example, shifting cultivation)[99]. This is particularly true for forest loss associated with fire, which has historically been an intrinsic part of the ecology of many TDF regions but, in many parts of the world today, often signals clearance for agriculture[39] or, to a lesser extent, shifting cultivation[100] (see Supplementary Note 4 and Supplementary Fig. 2). We did not separate different forms of agriculture, which would be challenging empirically due to lack of fine-scale data, as well as conceptually due to links between different forms of agriculture. For example, cattle ranching is a main proximate cause of deforestation in South America[50,101], yet often connected to cropland expansion[102] and indirectly driven by cropping expanding over pasture areas[103,104]. Consequently, we used proportional forest loss as our measure of agricultural expansion, calculated as the accumulated forest loss from 2001 to 2020 as percentage of forest cover in 2000 per 3-km cell. A sensitivity analysis based on a differently scaled forest change measure (that is, absolute forest loss as the dependent variable and initial forest cover as an independent variable) led to qualitatively identical results, suggesting robustness of our analytical setup and findings (see Supplementary Note 3 and Supplementary Table 1). Importantly, by measuring forest loss instead of forest area, our analyses addressed relative land sparing[13], that is, the rate of agricultural expansion compared with a counterfactual scenario without intensification, and did not directly indicate absolute cropland contraction.

As a measure of intensification, we used country-level yield change over the period 2000–2019 (see Supplementary Note 1 for a detailed description). We retrieved yield and production statistics from the FAOSTAT database, the only long-term, global scale, cross-country dataset available. Using yield growth as a measure of intensification implies a simplified representation of land-use intensity because it does not distinguish among the practices behind increased output per land unit (technological improvements, higher inputs per land unit or higher frequency of land use)[105,106], and thus does not consider potential impacts on biodiversity and ecosystem properties[107]. Some authors have suggested consideration of technological progress in agriculture using total factor productivity (that is, the efficiency of the overall mix of production factors due to improved technologies, farmers' skills and knowledge)[18,108]. Yet, due to our study design based on using forest loss as the dependent variable, we could only capture cropland expansion but no reduction, so that output per unit of land (that is, yield) was a more appropriate measure. As our yield data have a country-level resolution, we here explicitly focus on intensification–deforestation links within country borders. We note that land sparing and rebound effects can theoretically also occur across country boundaries13, but we want to capture dynamics in TDF explicitly, and thus disregarded potential displacements to other regions. Applying such a resolution provides a sensible middle ground to explore broad patterns across different regions by internalizing some of the local spillover effects, while remaining close to gross changes in our biome of interest.

To represent the degree of market orientation of a country's agricultural sector, we calculated country-level mean shares of non-staple crop production and shares of exports for 2000 to 2019 based on FAOSTAT data[109]. Both variables were highly correlated, but the mean shares of non-staple crop production resulted in better models, and we therefore chose it to capture market orientation. Non-staple (or commodity) crops are primarily grown to be sold on international markets, including many crops related to deforestation risk such as soybean, sugar cane, cocoa, coffee, tea, rubber, palm oil or cotton[43,110]. Because of the growing importance of rice as a commodity and export crop, we also included rice in the list of non-staples[54].To capture the presence of Indigenous land stewardship in our grid cells, we used a recent dataset compiled by (ref. 31) to yield a binary variable (that is, presence/absence of Indigenous lands). We adopted the definition of Indigenous peoples from (ref. 31) as those who identify as having "descended from populations which inhabited a country before the time of conquest or colonization [and] who retain at least some or all of their own social, economic, cultural and political institutions"[31]. While this dataset represents the most comprehensive assessment of lands where Indigenous peoples have customary ownership, management or governance arrangements in place, regardless of legal recognition, it still underestimates Indigenous lands in some countries or does not cover certain regions where local communities do not self-identify as Indigenous (for example, several southern African countries) or do not adhere to the applied working definitions of Indigenous peoples for other reasons (many Pacific island nations; see Supplementary Note 5). We therefore caution that absences in our data do not necessarily imply an absence of Indigenous peoples or their lands[31].

As control variables potentially affecting the yield change–deforestation relationship, we included accessibility as travel time to the nearest city of population >50,000[111], agroecological suitability[112] and change in rural population density from 2000 to 2020, calculated in a 9 km2 buffer around the given grid cell based on the Gridded Population of the World data[113]. All data processing was carried out in R[114].

The temporal design of our study constitutes one timestep encompassing 20 years (2001–2020) and thus relies on temporally aggregating both forest loss and yield change (see Supplementary Note 2 where we explain and discuss the implications of such approach). While the use of aggregated information entails the risk of missing dynamics occurring at finer scales, it also provides the opportunity to internalize confounding effects such as short-term time lags.

Further, we performed robustness checks on the temporal study design that supported the assumed constancy of modelled effects (Extended Data Fig. 3 and Supplementary Note 2).

Modelling framework

Drawing valid causal inference on the basis of complex, heterogeneous social–ecological data requires adjusting for possible observation bias[115,116]. In contrast to controlled experiments, estimates based on observation data are typically biased by confounders, which are variables associated with both intervention and outcome[117]. Checking our data for imbalances with respect to measurable potential confounders (population density change, accessibility and agroecological suitability) across the range of yield change revealed dissimilar exposure regarding accessibility and agroecological suitability. To adjust for this imbalance, we weighted data points based on the generalized propensity score for continuous treatment by (ref. 118) using the R package WeightIt[119].

We applied a multilevel Bayesian regression framework to investigate the causal relation of agricultural intensification and deforestation in different social–ecological contexts (that is, lands dominated by agribusiness agriculture or Indigenous communities). Our varying-effects regression framework included continents as a level, thus allowing us to estimate the average global effect as well as continent-specific variations of this effect. As likelihood function for the outcome, we specified a zero-inflated beta distribution, as our response variable was continuously distributed between 0 and 1, as well as zero-inflated[120]. The resulting mixed model had two components. First, a Bernoulli distribution predicted the binary zero-forest-loss responses. To estimate this zero-inflation probability, we defined a linear model including accessibility as a predictor based on the expectation that remotely located, poorly accessible data points have a higher probability of the outcome of zero forest loss, independent of effects of intensification. The second, and major, part of our model consisted of a beta distribution for all non-zero responses in the open (0,1) interval. Here, we wanted to identify the effect of yield change in different social–ecological contexts on mean forest loss, so that we included those variables in a linear model predicting mean forest loss. Furthermore, we wanted to explore the heterogeneity of potential effects of yield change on forest loss, so that we also included yield change in a linear model predicting the precision of forest loss.

We specified the mixed varying-effects model as follows (see Supplementary Note 6 for information on the choice of priors):

$$FL_i \sim ZIBeta(p_i,\mu_i,\phi_i) \qquad (1)$$

$$\mathrm{logit}(p_i)=\alpha_p+\beta_A A_i \qquad (2)$$

$$\mathrm{logit}(\mu_i)=\alpha_{\mu,cont[i]}+\beta_{PD,cont[i]}PD_i+\Delta Y_i\times(\beta_{\Delta Y\mu,cont[i]}+\beta_{NSt,cont[i]}NSt_i+\beta_{S,cont[i]}S_i+\beta_{IPL,cont[i]}IPL_i) \qquad (3)$$

$$\log(\phi_i)=\alpha_\phi+\beta_{\Delta Y\phi}\Delta Y_i \qquad (4)$$

where FL_i indicates proportional forest loss predicted for every data point i by the zero-inflated beta model ZIBeta, p_i the zero-inflation probability, predicted by accessibility A_i, μ_i mean forest loss, predicted in a multilevel model by population density PD_i, and yield change ΔY_i in interaction with share of non-staple crops production NSt_i, agricultural suitability S_i and Indigenous land management IPL_i with continent-level varying effects and ϕ_i forest loss dispersion, predicted by yield change ΔY_i.

We sampled 4,000 realizations of the posterior distribution using Markov chain Monte Carlo with four sampling chains running for 2,000 iterations and a warm-up period of 1,000 iterations each. Convergence was verified using the Rhat statistic and examination of trace plots. We evaluated model fit based on posterior predictive checks, that is, predicting new hypothetical data sampled from the posterior predictive distribution and comparing it to a random draw of observed data (see Extended Data Fig. 4). Further, we determined out-of-sample predictive accuracy using leave-one-out expected log predictive density using the R package loo[121]. We performed all modelling through the brms package120 in R114 as an interface to the Bayesian inference engine Stan[122].

Once our models were specified, we projected yield-change-related forest loss another timestep of 20 years into the future (that is, 2021–2040) under a future scenario that is based on extrapolating the yield change patterns from 2011 to 2020. Assuming rural population density to stay constant, and leaving all other conditions unchanged, we calculated the mean posterior estimate as well as the posterior standard error comprising both parameter uncertainty and predictive uncertainty, and mapped the outcome spatially. While this scenario is hypothetical and explorative by nature, and not meant to reproduce realistic trajectories, it is useful to identify the potential of future forest loss associated with rebound effects of intensification.

DATA AVAILABILITY

Datasets used in this analysis are publicly available. Forest cover and loss data are available at https://data.globalforestwatch.org/; agricultural production statistics are available at https://www.fao.org/faostat/en/#data; population density data are available at https://sedac.ciesin.columbia.edu/data/set/gpw-v4-population-density-rev11; accessibility data are available at https://figshare.com/articles/dataset/Travel_time_to_cities_and_ports_in_the_year_2015/7638134; agricultural suitability data are available at https://www.gaez.iiasa.ac.at/. Indigenous peoples' lands data were derived from the spatial layer created in https://doi.org/10.1038/s41893-018-0100-6, but restrictions apply to the availability of these data. However, data are available from the corresponding author S.T.G. of the original paper upon reasonable request.

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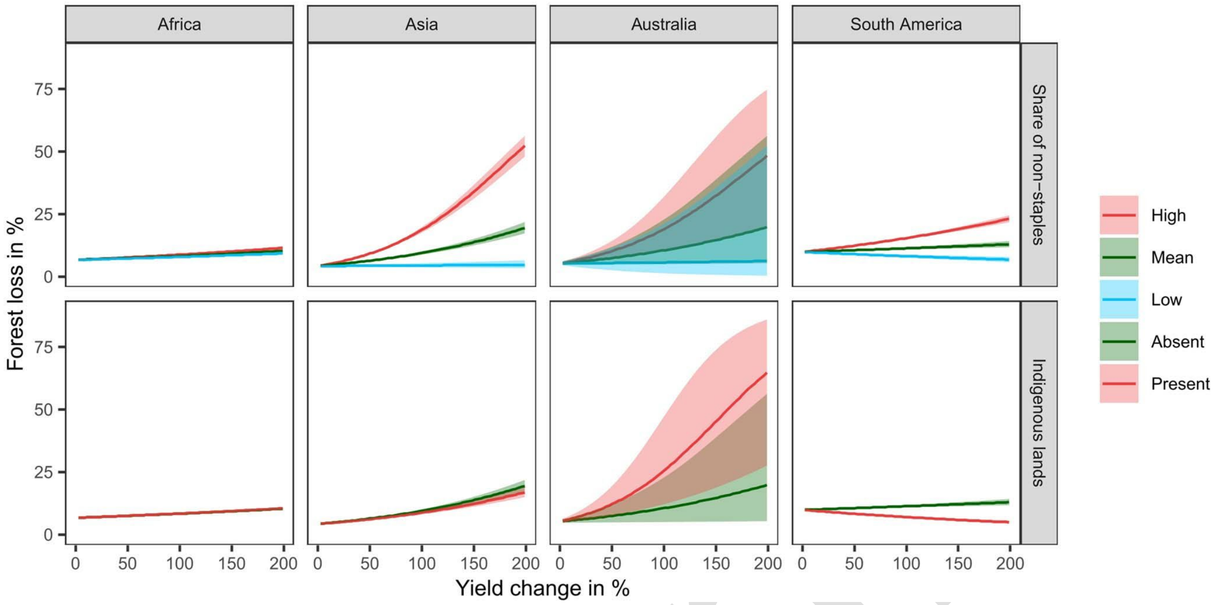
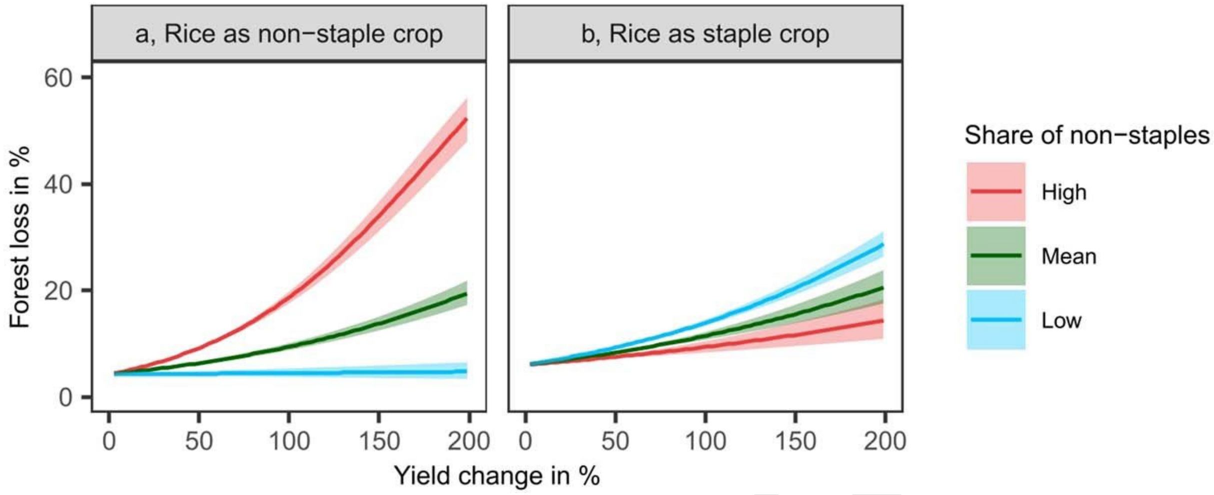
EXTENDED DATA FIG. 1: CONDITIONAL EFFECTS OF MARKET ORIENTATION AND INDIGENOUS LAND STEWARDSHIP ACROSS CONTINENTS.



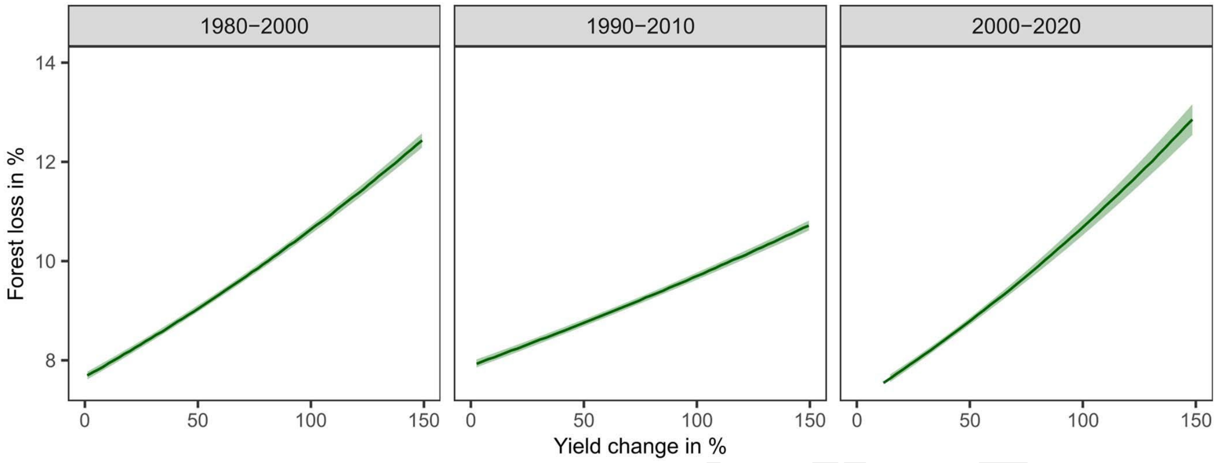
Curves show the mean effect and shadows the 95% credible interval of the posterior distribution when all model predictors, besides the one of interest, are set to their mean value or reference category. Green curves represent the average continent-level effect of yield change on forest loss on lands without Indigenous land stewardship. Red and blue curves show how the relationships between yield change and forest loss is affected by high (1 standard deviation above mean) or low (1 standard deviation below mean) values of market orientation, or presence of Indigenous lands.

EXTENDED DATA FIG. 2: HIGH INFLUENCE OF RICE CLASSIFICATION ON MODELLED EFFECT OF SHARE OF NON-STAPLE CROPS (APPROXIMATING MARKET ORIENTATION) IN ASIA.



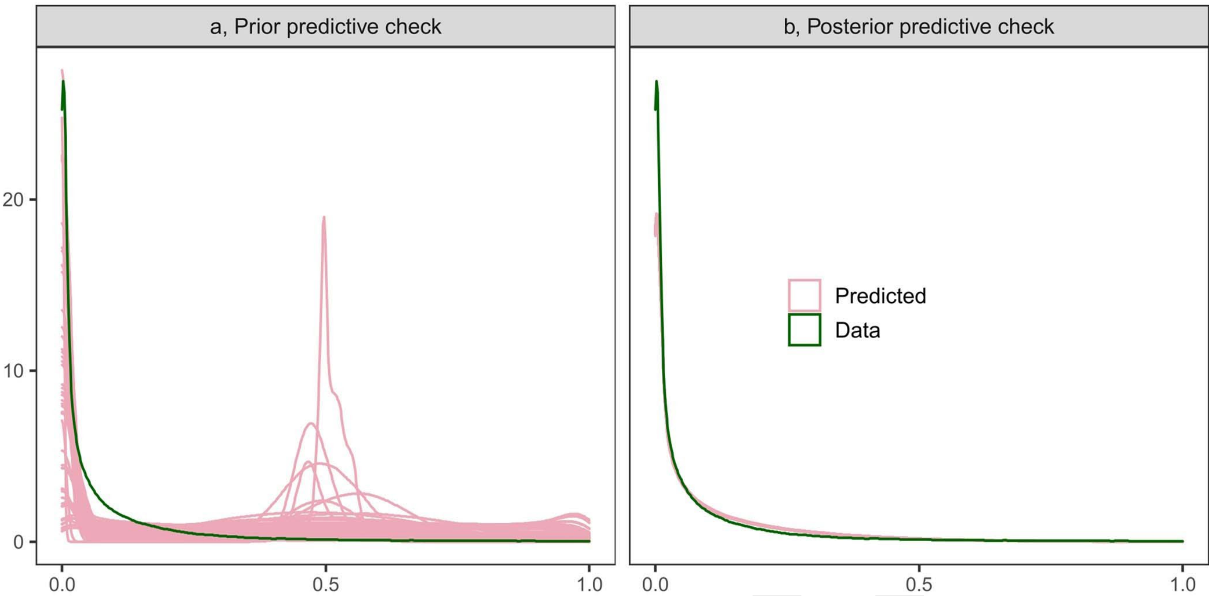
a, With rice classified as non-staple crop, interaction effect of share of non-staples reinforces positive relationship of yield change and forest loss in Asia. **b**, With rice classified as staple crop, share of non-staples has a dampening effect on the positive relationship of yield change and forest loss in Asia.

EXTENDED DATA FIG. 3: MODELLED EFFECT OF YIELD CHANGE FROM EARLIER TIME PERIODS ON FOREST LOSS IN THE STUDY PERIOD.



The modelled effect of yield change on past time periods showed the same trend and was of comparable magnitude as the effect of yield change in the study period, thus strengthening the assumption that the temporal design of our analysis did not miss significant time lag effects of intensification on deforestation.

EXTENDED DATA FIG. 4: PREDICTIVE CHECKS.



a–**b**, Comparing observations to a sample of 100 **a**, prior model predictions generated according to our final prior specifications, and **b**, posterior model predictions based on priors and data, provided insights about the plausibility of model assumptions and the reliability of model results.

SUPPLEMENTARY INFORMATION

Supplementary Notes

Supplementary Note 1: Intensification measure

We operationalized agricultural intensification as country-level yield change, calculated in a three-step procedure. First, annual yield changes of different crop groups were calculated separately compared to the mean of the two previous years. To measure the outcome of intensification, the period of interest was shifted one year ahead (2000-2019) compared to forest loss (2001-2020). The smoothing step of referring change to the two preceding years instead of one was applied to mitigate the impact of inconsistencies that can likely occur in the FAO database, e.g., through countries irregularly reporting production statistics.

$$\Delta Y_{t,c} = \frac{Y_{t,c}}{(Y_{t-1,c} + Y_{t-2,c})/2} \; with\; c = \{cereals; \ldots ; treenuts\}\; and\; t = \{2000; \ldots ; 2019\}$$

Second, annual yield change at country level was compiled by averaging the crop groupspecific yield changes weighted by the respective proportion of harvested area in 2000 (HAc). This procedure allowed to aggregate yield changes of different crop categories in one number without risking biases due to variations in harvest weight among different crop groups.

$$\Delta Y_t = \frac{\sum_c(\Delta Y_{t,c} * HA_c)}{\sum_c(HA_c)}$$

The resulting yield trajectories revealed that most countries experienced relatively steady yield dynamics over the entire study period, thus justifying our summation of yield over time without neglecting crucial patterns. Accordingly, as a last step, we aggregated study-level country yield change as the product of annual yield change from 2001-2019.

$$\Delta Y = \prod_t \Delta Y_t$$

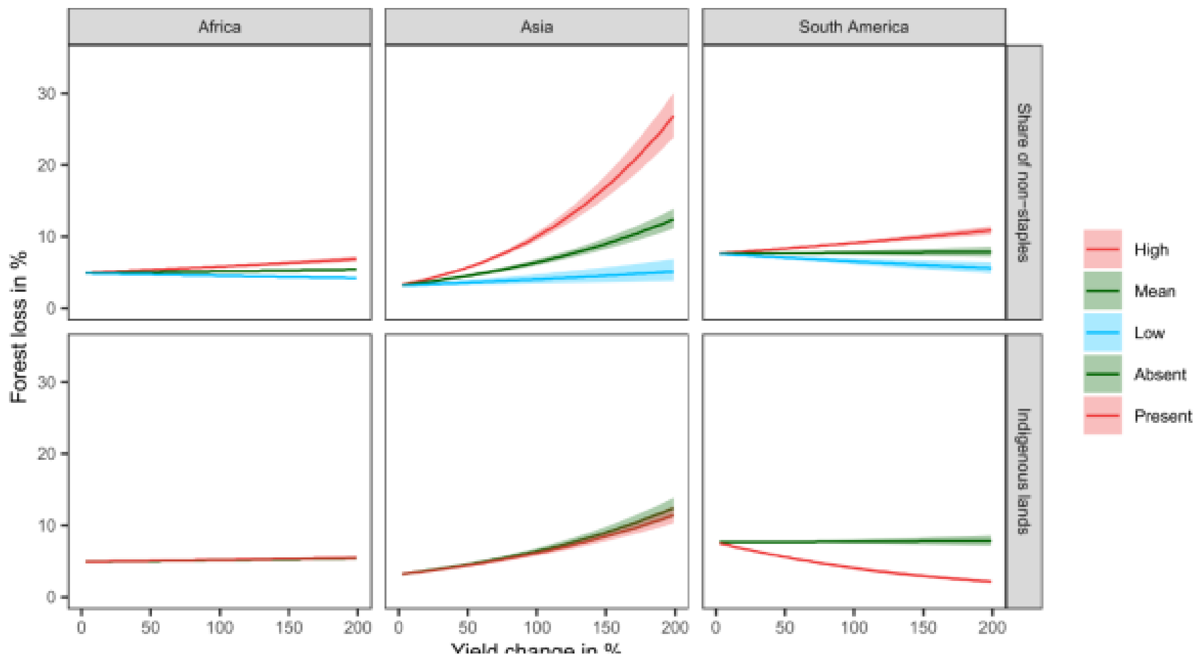
In most countries, yield increases were of moderate or high magnitude while some countries experienced an overall decline in yield.

Supplementary Note 2: Robustness checks of temporal aggregation

The presented approach relying on temporally aggregating both forest loss and yield change provides the opportunity to internalize confounding effects such as short-term time lags, but simultaneously bears the risk of neglecting the chronology of events. If both aggregated yield change and forest loss were attributable to short periods of only a few years, and the forest loss event occurred earlier in time than the one causing yield change, our data structure would not allow accounting for this order, and thus risk wrongly identifying the given forest loss as following yield change. However, such potentially misleading chronology could be ruled out after inspecting the country-level yield trajectories, which revealed that the large majority of countries experienced relatively steady yield dynamics. To maximize robustness, we checked whether different assumptions regarding time lags of intensification spillovers affected the results. To this end, we calculated yield change in the periods 1981-2020 and 1991-2010 to check whether conditioning present forest loss on earlier yield change time spans would yield essentially different results compared to the analysis based on the original yield change variable in the study period (2000-2020). The resulting model estimates demonstrated that conditioning present forest loss on past yield change generated similar relationships (Extended Data Fig. 3). This strengthens our assumption that the temporal study design did not miss significant time lag effects of intensification on deforestation.

Supplementary Note 3: Sensitivity analysis of forest loss variable

In our model, we used grid-level proportional forest loss relative to the initial forest cover in 000 as the dependent variable. Measuring relative instead of absolute forest loss allowed us to compare across landscapes with varying baseline forest-cover densities, which is an important advantage in the diverse tropical dry forest ecosystems. However, this also implies that the forest loss effects directly depend on initial forest cover. To check whether our results are robust towards the measure of forest loss (i.e., relative vs. absolute forest loss), we performed a sensitivity analysis using absolute forest loss as the dependent variable and adding initial forest loss as an independent variable. The resulting model estimates supported the positive effect of yield change on forest loss between 2000 and 2020 globally, as well as at continent level. Further, the sensitivity analysis supported the effects of market orientation and Indigenous land stewardship on the intensification-deforestation relationship indicating a positive interaction effect of share of non-staple production and negative interaction effects of Indigenous land management. While the magnitude of the modelled parameter coefficients varied between the model runs based on the two different dependent variables, all results were thus qualitatively identical, both at the global level and continent level.



Supplementary Fig. 1: Conditional interaction effects of sensitivity analysis based on absolute forest loss as the dependent variable. Both market orientation (proxied by the share of non-staple crops) and Indigenous land stewardship (proxied by the presence of Indigenous Peoples) influence the relationship of yield change and forest loss markedly. Curves show the mean effect and 95% credible interval of the posterior distribution when all model predictors, besides the one of interest, are set to their mean value or reference category. Green curves represent the average continent-level effect of yield change on forest loss on lands without Indigenous land stewardship. Red and blue curves show how the relationships between yield change and forest loss are affected by high (1 SD above mean) or low (1 SD below mean) values of market orientation, or presence of Indigenous lands.

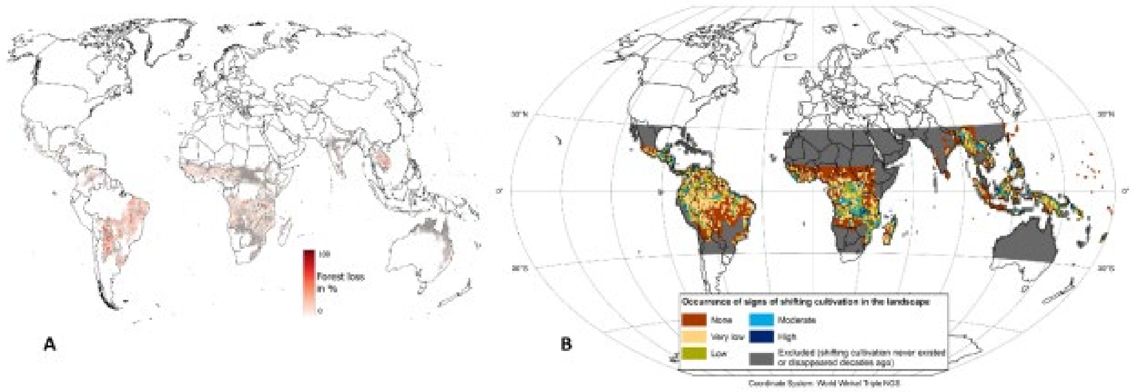
Supplementary Table 1: Regression results with absolute forest loss as the dependent variable. Global mean and continent-level model estimations for the effects of initial forest cover ($\boldsymbol{\beta}_{FC}$), yield change ($\beta_{\Delta Y\mu}$) and population density change (β_{PD}) on forest loss, and the effects of share of non-staple crops (β_{NSt}) and Indigenous Peoples' land management (β_{IPL}) on the relationship of yield change and forest loss. Posterior means and the standard error (SE) are shown. All parameters are re-transformed to the probability scale to make the results more intuitive to interpret (see Table 1 for untransformed values and model statistics).

Model coefficient	**Global results**	**Continent-level results** *Africa*	*Asia*	*Australia*	*South America*
FC (β_{FC})	0.025 SE 0.010	0.59; SE 0.015	0.34; SE 0.041	0.34; SE 0.06	1.03 SE 0.014
ΔY ($\beta_{\Delta Y_{\mu}}$)	0.015; SE 0.010	0.05; SE 0.009	0.75; SE 0.037	0.33; SE 0.26	0.20; SE 0.032
PD (β_{PD})	-0.003; SE 0.014	-0.02; SE 0.008	-0.17; SE 0.037	-0.02; SE 0.04	0.008; SE 0.009
ΔY:NSt (β_{NSt})	0.015; SE 0.007	0.13; SE 0.008	0.49; SE 0.056	0.23; SE 0.21	0.18; SE 0.015
ΔY:IPL (β_{IPL})	-0.025; SE 0.11	-0.009; SE 0.014	-0.049; SE 0.029	1.11; SE 0.29	-0.69; SE 0.023

<u>Supplementary Note 4: Shifting cultivation and fire as a management practice in TDF</u>

When utilizing remotely-sensed forest loss data, there is a risk of mischaracterizing Indigenous fire regimes that are part of management practices leading to temporary forest loss but not necessarily to environmental degradation[1]. For instance, in Australian savannas, where fire is a common annual feature intrinsic to savanna ecosystems, burning has become an important source of income for Indigenous communities. Since early dry season fire both produces less greenhouse gas than late dry season fire, and prevents the spread of late dry season fire, landowners are paid for the area not burnt in the late dry season compared to a baseline[2]. Although the arrangement has generated significant emission reductions[3], burnt areas might appear as forest loss in our data and thus distort regional model results. This might explain the rebound-reinforcing pattern we found for Indigenous land management in Australia (Fig. 5, Extended Data Fig. 1, Table 1).

However, globally, areas where recorded forest loss might be attributable to shifting cultivation are limited in number and extent. Visual interpretation of overlaying our forest loss data[4] with recent estimations of the global extent of shifting cultivation suggests that a very small amount of forest loss occurred in landscapes indicating moderate or high occurrence of shifting cultivation according to Heinimann et al.[5], with the exception of parts of Central and southeastern Africa (e.g., north of Zambia, south of the Democratic Republic of the Congo, Mozambique) (Supplementary Fig. 2). The very low occurrence of shifting cultivation within the majority of TDF regions points towards shifting cultivation being either a form of management practiced in landscapes dominated by land uses other than agriculture, or a residual form of cultivation in landscapes that have mostly been transformed to other management practices. These findings strengthen the assumption that derived forest loss caused by fire as a management practice integral to shifting cultivation does not bias our findings on a global level.



Supplementary Fig. 2: Comparison of a, utilized forest loss data from Hansen et al.[4] and b, recent estimations of landscapes showing signs of shifting cultivation from 30˚S and 30˚N by Heinimann et al.[5] suggests that those forest loss signals caused by fire as a management practice integral to shifting cultivation are limited in number and extent.

Supplementary Note 5: Definition of Indigeneity

The principles of Indigeneity adopted in this article align with those of the Article 1 of the International Labor Organization Indigenous and Tribal Peoples Convention 1989 (No. 169), which describes Indigenous Peoples as: "peoples in independent countries who are regarded as indigenous on account of their descent from the populations which inhabited the country, or a geographical region to which the country belongs, at the time of conquest or colonization or the stablishment of present state boundaries and who, irrespective of their legal status, retain some or all of their own social, economic, cultural and political institutions"[6]. This definition is itself broadly consistent with descriptions adopted by other international agencies and forums[7–9].

Yet, several studies note that the definitions of Indigeneity are often context-specific and vary within and across regions[10,11]. For example, in large parts of Africa and Southeast Asia, multiple layers of settlement and colonization have made definitions of Indigeneity particularly contentious and difficult to apply[12]. In many places, the historical movement of people across millennia renders a strict definition of "Indigenous" as first Peoples or non-settler difficult[13]. In others, certain Governments refuse to recognize certain ethnic groups as "Indigenous", given that Indigenous Peoples' rights are protected by international law[14]. The United Nations State of Indigenous Peoples, states that "the prevailing view today is that no formal universal definition of the term is necessary, given that a single definition will inevitably be either over- or underinclusive, making sense in some societies but not in others"[15].

Any definition of Indigeneity is particularly difficult to apply in the African context. With the backdrop of historical European colonialism, all ethnic groups in Africa could describe themselves as being "Indigenous" (as stated by ACHPR 2003[16]). In view of this, we here followed the recommendations made by the African Commission's Working Group of Experts on Indigenous Populations/Communities, under the African Commission on Human and People Rights (ACHPR). As such, we do recognize that all people in Africa can describe themselves as Indigenous, but note that our use of the term specifically refers to those groups who "identify themselves as indigenous and who experience particular forms of systematic discrimination, subordination and marginalization"[18]. All groups identified by the African Commission on Human and Peoples' Rights as being Indigenous (e.g., Amazigh, Baka, Khwe San, Maasai) were considered as such (see ACHPR 2006 for further details[18]), as well as those that have been identified as being Indigenous in landmark court rulings and litigation processes both nationally and internationally (e.g., Endorois, Ogiek, Ogoni[14,19]).

Supplementary Note 6: Specifying prior distributions

We used a zero-inflated Beta distribution to model proportional forest loss (FL_i) using a parameterization with mean μ_i and precision parameter ϕ_i for non-zero forest loss predicted by the Beta distribution, and probability pp_i for zero-responses predicted by a Bernoulli distribution (line I). As μ_i and p_i must be (0, 1), we used a logit link function to transform the results of the linear models for μ_i and p_i to the (0, 1) interval (line II, III). Similarly, we used a log link function to ensure that ϕ_i was positive (line IV). To estimate p_i, we defined a linear model with a global intercept α_p and slope β_A for accessibility (A) (line II). To estimate the mean magnitude of forest loss (μ_i), we specified a multilevel model (line III). Here, μ_i is predicted by population density (PD), and yield change (ΔY) in interaction with the shaping factors production share of non-staple crops (NSt), agro-ecological suitability (S), and Indigenous Peoples' land management (IPL). All coefficients were modeled to vary across continents, thus exploring global average patterns as well as variation among continents, providing insights about generalizability. We defined a linear model of ϕ_i with a global intercept $\alpha\phi$ and slope $\beta_{\Delta Y\phi}$ for ΔY(line IV).

$$FL_i \sim ZIBeta(p_i, \mu_i, \phi_i) \quad \text{(I)}$$

$$\boldsymbol{logit(p_i) = \alpha_p + \beta_A A_i} \quad \text{(II)}$$

$$\boldsymbol{logit(\mu_i) = \alpha_{\mu,cont[i]} + \beta_{PD,cont[i]} PD_i + \Delta Y_i * \left(\beta_{\Delta Y\mu,cont[i]} + \beta_{NSt,cont[i]} NSt_i + \beta_{S,cont[i]} S_i + \beta_{IPL,cont[i]} IPL_i\right)} \quad \text{(III)}$$

$$\boldsymbol{\log(\phi_i) = \alpha_\phi + \beta_{\Delta Y\phi} \Delta Y_i} \quad \text{(IV)}$$

$$\alpha_p \sim Normal(0,0.1) \quad \text{(V)}$$

$$\alpha_{\mu,cont[i]} \sim Normal(0, \sigma_\alpha) \quad \text{(VI)}$$

$$\alpha_\phi \sim logN(0,1) \quad \text{(VII)}$$

$$\beta_A \sim Normal(0,0.1) \quad \text{(VIII)}$$

$$\beta_{\dots,cont[i]} \sim Normal(0, \sigma_\beta) \quad \text{(IX)}$$

$$\sigma_\alpha, \sigma_\beta \sim Exp(10) \quad \text{(X)}$$

The prior distributions for the unknown coefficients (lines V-X) were optimized in an iterative process of prior predictive checks, i.e., predicting the data only based on the chosen priors, and subsequently adjusting those prior distributions to yield physically realistic predictions based on information obtained from sampling diagnostics and predictive checks. In this way, we derived weakly informed priors that were on one hand regularizing enough to facilitate model convergence, and on the other hand resulted in plausible predictive simulations while not restricting the outcome distribution in a biasing way (Extended Data Fig. 4). Consequentially, priors for α_p , and β_A were chosen as normally distributed centered on 0 resulting in regularizing Gaussian priors on the (0,1) interval once transformed to the outcome scale by the corresponding link function. For μ_i, each continent was given a unique intercept ($\alpha_{\mu,\text{cont}[i]}$) issued from a Gaussian distribution centered on 0, meaning that there might be different mean scores for each continent. The prior intercept for ϕ_i was defined by a log-normal distribution with mean 0 and standard deviation 1 which limits values to the positive response space, thus avoiding values <1 on the outcome scale after log-transformation which prevents U-shaped beta distributions. Varying effect parameters ($\beta_{\ldots,conti[i]}$) were assigned weakly informative Gaussian priors centered on 0. The distributions of varying intercepts and slopes had exponentially distributed prior standard deviations (σ_α, σ_β), thus restricting the range of possible values to positive ones. Internally, the covariance, i.e., correlation between varying intercepts and slopes was modelled by a multivariate normal distribution with an uninformative correlation prior of *LKJcorr(2)* representing flat covariance assumptions.

Supplementary Note 7: Untransformed model coefficients

All model parts of the zero-inflated beta model have restricted outcome ranges. Therefore, the model by design used (log-/logit-) link functions internally to map the result of the linear model o the appropriate outcome scales. In the main text, we retransformed all parameters to the probability scale, to make the results more intuitive to interpret. See Supplementary Table 2 for untransformed parameter values and regression statistics in internal model scale.

Supplementary Table 2: Model summary statistics. Parameters are summarized using mean (estimate) and standard error (SE) of the posterior distribution as well as central 95% credible intervals. Bulk and tail ESS are diagnostics of the sampling efficiency, estimating the effective sample size that the bulk and tail of the posterior distribution are informed by. Note that all numbers are given in model scale (untransformed logit/log scale).

Parameter	Estimate	SE	Credible interval	Bulk ESS	Tail ESS
Regression coefficients					
Intercept	-2.48	0.01	-2.47;-2.44	3686	2928
phi_Intercept	1.58	0.01	1.57;1.60	3710	3300
zi_intercept	-2.35	0.01	-2.37;-2.33	5131	2973
PD	-0.06	0.00	-07;-0.06	5437	2878
ΔY	0.44	0.01	0.41;0.46	3289	2941
ΔY:S	0.06	0.00	-0.05;0.06	5218	2992
ΔY:NSt	0.43	0.01	0.41;0.44	3779	3320
ΔY:IPL	-0.05	0.01	-0.08;-0.03	4749	2943
phi_ΔY	-0.43	0.01	-0.46;-0.41	3539	2878
zi_access	0.45	0.01	0.44;0.47	4993	3161
Continent-level effects					
sd(Intercept)	1.23	0.20	0.89;1.68	1946	2102
sd(PD)	0.14	0.07	0.07;0.32	1777	1869
sd(ΔY)	0.36	0.12	0.18;0.65	3452	2896
sd(ΔY:S)	0.33	0.09	0.19;0.54	3682	3437
sd(ΔY:NSt)	0.28	0.09	0.15;0.51	3580	2940
sd(ΔY:IPL)	0.48	0.12	0.30;0.75	4617	3584
cor(Intercept,PD)	0.18	0.34	-0.51;0.76	5029	2810
cor(Intercept,ΔY)	-0.40	0.20	-0.75;0.04	4243	2978
cor(PD,ΔY)	-0.11	0.29	-0.64;0.45	4235	3320
cor(Intercept,ΔY:S)	-0.28	0.21	-0.64;0.14	4083	2987
cor(PD,ΔY:S)	0.17	0.28	-0.39;0.68	3361	3072
cor(ΔY,ΔY:S)	0.31	0.26	-0.27;0.75	2543	2672
cor(Intercept,ΔY:NSt)	-0.15	0.23	-0.57;0.32	3904	2865
cor(PD,ΔY:NSt)	0.33	0.28	-0.27;0.81	3099	3183
cor(ΔY,ΔY:NSt)	-0.06	0.26	-0.55;0.44	4594	3213
cor(ΔY:S,ΔY:NSt)	0.35	0.28	-0.28;0.82	3821	3220
cor(Intercept,ΔY:IPL)	-0.03	0.20	-0.42;0.35	4405	3825
cor(PD,ΔY:IPL)	-0.05	0.25	-0.51;0.44	4332	2763
cor(ΔY,ΔY:IPL)	0.13	0.26	-0.40;0.61	2849	3085
cor(ΔY:S,ΔY:IPL)	0.40	0.22	-0.07;0.76	4331	3470
cor(ΔY:NSt,ΔY:IPL)	0.05	0.29	-0.52;0.56	3025	3228

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