MASTER THESIS

To obtain the academic degree Master of Science (M.Sc.)

UNDERSTANDING THE RELATIONSHIP OF AGRICULTURAL INTENSIFICATION AND DEFORESTATION IN THE WORLD'S TROPICAL DRY FORESTS

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TDF	tropical dry forest
FL	forest loss
ΔY	yield change
nonStap	production share of non-staple crops
export	production share of export
suit	agro-ecological suitability
access	accessibility
PA	proportion of protected areas
IPL	Indigenous/community managed land
special	susceptible regarding specialization trap
popdens	change in rural population density
DAG	directed acyclic graph
GPS	generalized propensity score
MCMC	Markov Chain Monte Carlo
LOO-ELPD	leave-one-out expected log predictive density
SE	standard error

Abstract

Does the intensification of agriculture spare land for nature and thus slow down deforestation, or rather trigger counteracting rebound effects that motivate cropland expansion and accelerate forest loss? Prevailing complexity in land systems makes it impossible to arrive at an explicit answer to this controversy. Yet, given the tremendous, often irreversible, social and ecological tradeoffs of land use change, it is crucial to identify critical factors that condition whether intensification leads towards an expanded or contracted agricultural footprint – particularly in the weakly protected tropical dry forests already now experiencing high and rising pressure from agricultural frontiers. Drawing upon theories and empirical evidence, I built a causal model comprising different pathways of how intensification relates to deforestation under diverse social-ecological contexts. To estimate the effect of country-level yield growth on forest loss between 2000 and 2020 and investigate the established mechanisms, I applied a Bayesian multilevel modeling framework exploring both global trends and continent-specific variations. I found that in tropical dry forests, a 100% increase in yield was associated with a 3.8% increase in forest loss. Hence, higher yields have reinforced rather than reduced forest loss, but contextual factors diversify the outcome: While economic incentives of globally integrated, commercialized commodity agriculture can trigger strong rebound effects, constraints on land availability and accessibility facilitate land sparing in the concerned areas. Likewise, Indigenous or community land management fosters land sparing, especially in South America where land formalization is comparably advanced. Governance and global trade position have not shown clear effects. Given prevailing trends of global agriculture, among them the growing importance of agribusinesses and global markets, my findings have crucial implications on future land-use and conservation strategies – most importantly challenging oversimplified land system representations and highlighting the need for contextual and place-specific solutions.

Keywords

land systems, rebound effect, land sparing, Bayesian modeling, commodity frontier, Indigenous people, specialization trap

1. Introduction

Global demand for land-based products is and will continue to grow[1]. While the provision of food, fiber, and fuel is essential to human societies, land use is also a major driver of global environmental change[2,3], and especially the expansion of modern farming systems into natural ecosystems involves tremendous social and ecological trade-offs – which are no less critical to human societies. In the last 50 years, agricultural frontiers have shifted from temperate regions to the tropical forests[1,4,5], where they cause massive carbon emissions and pose a severe threat to local livelihoods, their unique biodiversity, and key ecosystem services[6,7]. How human societies use, manage and interact with land is thus a key driver of many sustainability challenges and identifying effective land-use interventions constitutes a priority for research and policy[3,8,9]. Yet, while such interventions are crucial for better balancing land-use trade-offs, they also constitute a potential lynchpin for sustainability. And despite the centrality of sustainability debates, land use interventions are still often based on incomplete understanding, partial framings, or misconceptions[10].

Intensification of agricultural production constitutes such critical intervention. Considering multiple and growing demands on productive lands[11], intensifying agriculture is often seen as path for sustainability[12], to lessen competition for productive land, to reconcile agricultural production and environmental conservation, and finally prevent forest loss[13–15]. Yet, the dynamics and outcomes of intensification remain insufficiently understood, and there is heated debate about whether productivity-increases slow down or amplify deforestation[12,14,16]. On one hand, the so-called Borlaug hypothesis of land sparing postulates that intensification, by fulfilling a given demand for land-based products with a smaller land base, releases land for other uses including conservation. On the other hand, an alternative hypothesis builds on the "rebound effect" or "Jevons' paradox"[17,18] describing how intensification increases agricultural profits, thus encouraging further expansion[12,19,20].

Understanding which of these hypotheses better explains the relationship of agricultural intensification and deforestation is critical, because cursory understanding does not only translate into a higher risk of misdirected governance schemes, failure of conservation action, and missed opportunities[21] but is also likely to backfire by triggering more forest loss with devastating outcomes for biodiversity and climate. Since the prevalence of complexity in land systems makes it difficult to arrive at an explicit answer to this controversy, it is crucial to identify factors that condition on the outcome of intensification and understand how different social-ecological contexts make places more or less susceptible to unintended spillovers. So far, two main shortcomings in research have prevented systemic understanding on how intensification relates to deforestation.

First, research on forest dynamics has generally lacked a systematic focus on causal analysis[7,22,23] and surprisingly little effort has gone into tracing, identifying and estimating causal pathways of intensification spillovers. Although scholars have pointed towards potential impact of different factors (see Conceptual Background), these variables have not been combined in a systemic and causal analysis yet. This impedes the development of a stronger evidence base to inform policy decisions. Second, research on intensification spillovers has often lacked an appropriate scale. While local case studies[24–38] have generated insights that are not readily transferable to other places[39], aggregate global scale studies have contributed to an overarching perspective[15,16,39–44] but hide that net land savings at the planetary level may co-exist with forest loss at the local level[15,20,45]. This is crucial, because land sparing findings at the global scale do not only indicate avoided expansion into natural ecosystems but can equally stem from cropland abandonment in ecologically less sensitive regions which would be less desirable from a conservation point of view[13,45].

These considerations demonstrate the need for broad-scale studies on causal mechanisms in those ecoregions that face the most active agricultural frontiers while not disregarding patterns that manifest at finer spatial scales. In my study, I address these research challenges for the world's dramatically under-researched tropical dry forest (TDF)[46–48] to better explore, whether yield-enhancing intensification does benefit conservation of native biomes in the ecologically most sensitive ecosystems, or not. TDF harbor exceptionally high biodiversity[49] and provide livelihoods for approximately one quarter of the global population[50] but have been mostly overlooked by science und politics[48,49] and remain weakly protected[47,51]. This is worrisome given TDF regions currently face high and rising human pressure, especially from drastically expanding agricultural frontiers. The knowledge gaps outlined above are barriers to more effective policy design preventing further exploitation of these sensitive social-ecological systems.

While previous works have explored intensification spillovers mainly against the backdrop of single factors, resulting in considerable shortcomings regarding systemic understanding and transferability of insights in space, I make progress in adopting a more holistic perspective. My objective is thus to identify shaping factors that condition whether agricultural intensification in TDF leads towards an expanded (rebound effect) or contracted (land sparing) agricultural footprint. Therefore, I combine the understanding of causal mechanisms through which intensification relates to deforestation, with statistical investigation of the causal effects resulting from these mechanisms. More specifically, I select variables informed by theories and case studies, and build a causal model linking these variables together to answer:

i. Has agricultural intensification slowed down or accelerated deforestation in the world's tropical dry forests?
ii. What factors condition on the direction of the intensification-deforestation relationship?
iii. How do these mechanisms vary across continents?

As a novelty in the field of land system science, I apply a Bayesian multilevel modeling framework to investigate causal mechanisms in land systems by estimating their corresponding average global effects as well as continent-specific variations.

2. Conceptual Background

Research on deforestation and agricultural intensification as land-use intervention is situated in the field of land systems science, thus being concerned with understanding the causes and impacts of land-system changes, as well as assisting in projecting changes and their consequences in the near-term future[52,53]. Analyzing land use through the lens of land systems emphasizes systemic aspects including feedback mechanisms, path dependency and complexity translating into rapid use transitions, ecological regime shifts, and distant impacts[53–55].

2.1. Complexity of land systems

Land systems constitute complex, adaptive social-ecological systems[56] shaped by interactions between (a) the different actors and demands that act upon land, (b) the technologies, institutions, and cultural practices through which societies shape land use[12], and (c) feedbacks between land use and environmental dynamics[9].

Historically, land changes have mostly been attributed to single-factor, local-scale causes, such as shifting cultivation or local population growth[57]. However, with ongoing globalization and increasing interconnectedness of (geographically distant) social-ecological systems, land-use change pathways – and their respective scientific handling – have gained complexity on multiple scales. Consequently, causal chains behind the land-change outcome of interest have grown in length. This is taken up by the framework of proximate causes and underlying drivers of environmental change[57]. It differentiates between proximate causes as human activities or immediate actions at the local level that directly impact land systems, and underlying driving forces as fundamental processes, such as human population dynamics or agricultural policies that underpin the proximate causes, and potentially operate on distant or higher spatial levels[57].

Today, both tropical deforestation and land use interventions, such as agricultural intensification, are determined by different combinations of various proximate causes and underlying driving forces in varying geographical contexts including economic, technological, cultural and political factors and influences by geopolitical interests and governance[57,58]. Understanding and governing land systems with such high complexity is challenging because drivers operate both directly and indirectly through dynamic interactions and feedbacks[23]. Complexity also implies that some seemingly rational interventions such as intensifying agriculture can trigger counteracting, undesired effects[10]. This has brought up the need for a systemic perspective and made the notion of land-use spillovers a research frontier in recent years[12]. Land-use spillovers describe the process by which "land-use changes or direct interventions in land use (e.g. policy, program, new technologies) in one place have impacts on land use in another place"[12].

2.2. The land sparing-rebound effect-controversy

The above-mentioned controversy on land sparing vs. rebound effect is hence dealing with possible spillovers of agricultural intensification. The land sparing argument is premised on the Borlaug hypothesis which assumes that intensification of agriculture (i.e., increasing output per unit of land) spares land for natural ecosystems[12,14,26]. It seems evident when expressed in physical terms: Since globally, food demand is highly inelastic[59], increasing output per area is a necessary condition for reducing forest loss by avoiding agricultural area expansion. Yet, this simple reasoning conceals fundamental assumptions: On one hand, it equates inelastic global food demand with fixed global demand for agricultural products. On the other hand, it presumes that food production will increase as long as the initial fixed demand is not entirely met and remain constant thereafter[60]. Both does not sufficiently reflect reality. With the greater part of agricultural production being sold on markets, land management decisions are for most agricultural actors dependent on economic forces and ultimately reflect investment decisions made by farmers[60]. Pirard and Belna therefore suggest a reformulation of the Borlaug rationale from an economic view: an increase in yields leads to a decrease in agricultural commodity prices due to excess supply over demand, and finally causes supply adjustment through smaller growth in cultivated areas[60]. However, such framing reveals that an equally possible outcome of an increase in yields could be an increase in profitability. This ambivalence is taken up by the rebound effect, referring to the paradoxical situation where an increase in the productivity of one factor (here cropland) does not result in reduced utilization. Its reasoning draws upon the drive to increase profits inherent in capitalist modes of production which leads producers try to both reduce costs by reducing inputs (i.e., improving efficiency) and increase revenues by expanding[18,61]. Hence, in land systems, the rebound effect describes a type of spillover where adoption of intensifying, yield-rising practices increases profitability, and thereby stimulates land-use expansion[19,23,26]. The empirical observation of such “backfires”[62] questions the validity of deterministic and often simplifying grand theories of land systems science such as the theory behind Borlaug hypothesis of land sparing.

Previous literature on the controversy is ambiguous and has shown that there is no simple relationship between intensification and cropland expansion. Aggregate global scale studies by Burney et al. and Stevenson et al. suggest that historically, the Green Revolution has resulted in relative land sparing reducing the rate of agricultural expansion compared to the counterfactual scenario without intensification, although net agricultural area still increased[40,41]. Global studies analyzing more recent time periods found no empirical evidence for the Borlaug hypothesis either. Villoria demonstrated that in most countries of the world, productivity growth is either uncorrelated or positively associated with cropland expansion[63]. Rudel et al. observed that the most common pattern for countries achieving yield gains was to expand their agricultural footprint[43]. Ewers et al. detected a small land sparing trend for staple crops, which however disappeared through a significant increase in the production of non-staple crops that counterbalance the positive effects[39]. And most recently, Rodríguez García et al. showed that apart for staple crops, over the long run, intensification is unlikely to result in actual land sparing for nature[44]. Even where intensification does spare land, the amount saved is often disputed, given the complexity of interacting effects through globalized markets, labor migration and the difficulty of simulating a counterfactual scenario without intensification[20].

2.3. Contextuality of intensification spillovers

Given complexity of land systems, understanding the link between agricultural intensification and deforestation requires viewing it within a larger context. So far, empirical studies at global or regional scale have pointed to a range of potential influences. On that basis, the following portfolio of explanatory approaches first covers economic considerations from micro to macro level of agricultural production, then goes beyond a neoclassical theoretical standpoint to account for the diversity of actors involved, and finally builds upon concepts from ecological economics to include structural patterns of global trade.

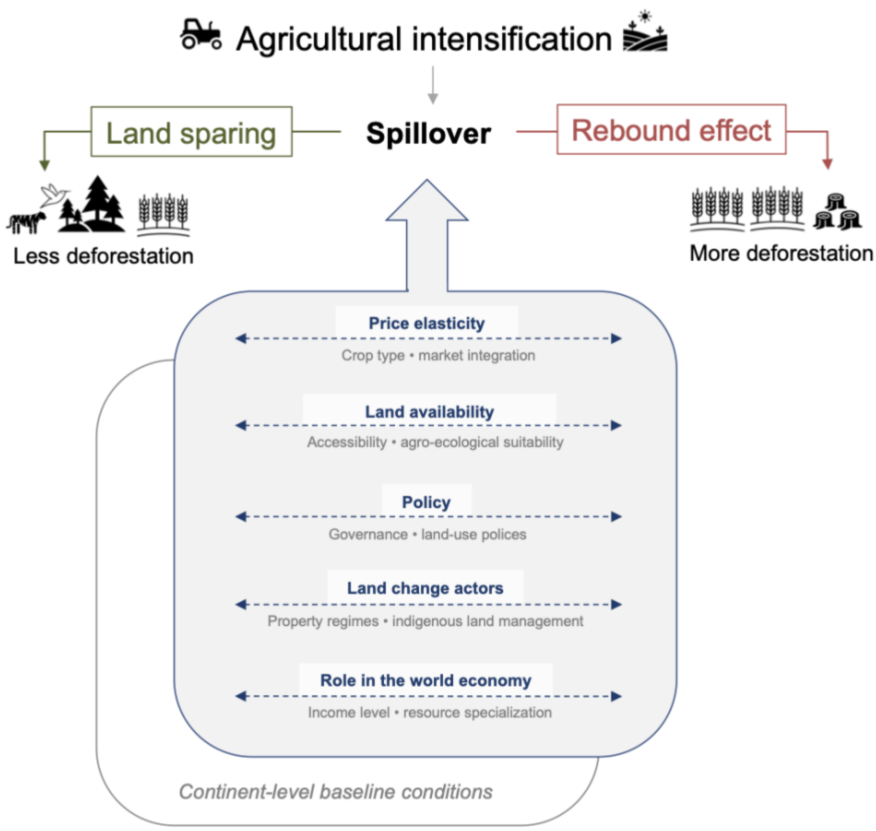

Figure 1: Conceptual framework. *The relationship of agricultural intensification and deforestation is shaped by a variety of contextual factors including environmental conditions as well as socioeconomic and structural patterns.*

According to Hertel et al., all relevant information about market outcomes of intensification is embodied in one parameter, the price elasticity of excess demand[16]. It indicates to what extent price changes translate into changes in the quantity demanded and provides insights into farmers' potential to increase revenues through improved productivity. Low price elasticity of demand (i.e., decrease in production costs does not lead to an increase in demand) is expected to make land sparing more likely. This is particularly the case for staple crops, and when markets are closed[12,16,19]: When farmers produce staple crops for their own consumption and do not have access to agricultural markets, price elasticity is low, meaning demand remains stable and intensification enables them to reach their needs with less lands[16]. In contrast, in the case of non-staple crops – or commodities/"cash-crops" – produced for rapidly expanding global markets, prices are insensitive to increases in production so that efficiency gains likely increase profitability, thus stimulating cropland expansion[42]. Statistical approaches by Ewers et al. and Rodríguez García et al. have found evidence that the intensification of staple crops especially in low-income countries results in land sparing. Inversely, they observe that intensification of non-staple crops is associated with a rebound effect[39,44]. Similarly, Hertel et al. used a global simulation framework and their findings included that the degree of market integration is a main determinant for potential land sparing[16]. In a range of empirical case studies, authors have revealed how the intensification of cash crops produced for global markets, so-called "commodity booms", have stimulated massive forest loss. This has been observed for soybean in Brazil and Bolivia[24,25,31], bananas in Ecuador[32], cocoa beans in Côte d'Ivoire[33] and palm oil in Indonesia and Malaysia[34]. In the opposite case, agricultural intensification of crops consumed locally relieved pressure from forests, especially in the less productive uplands, as observed for rice in the Philippines[35], in Indonesia[36], and rice and maize in Vietnam[37].

Price elasticity, as economic theory-based all-embracing parameter for the intensification controversy, only works under the preconditions of perfect markets[60]. When acknowledging the circumstances of imperfect markets, which are closer to the reality on the ground, several factors are likely to moderate demand impact, most of all, land supply. From this regard, land sparing seems more likely to occur, when there are biophysical and institutional restrictions on cropland expansion[12,19,64]. Case studies on intensification of domestically consumed crops support the hypothesis that land sparing is more likely under conditions of agricultural suitability and accessibility constraints. Under these circumstances, productivity enhancing technologies in the lowlands led to abandonment of low productive, e.g. slash-and-burn, cultivation on steep slopes in uplands[35–37]. In another study dealing with land constraints in the form of land zoning in Costa Rica, Fagan et al. observed how the rate of clearance of mature forests halved after the government zoned forests as off-limits for agricultural expansion[38]. In line with these findings, Meyfroidt et al. compared six published case studies of rapid commodity crop expansion and concluded that scarcity of suitable forestland, constrained by agroecological and accessibility conditions, and land use policies, was associated with a lower share of forest conversion[26]. Finally, Rudel et al. investigated paired country-level changes in yields and cropland for ten major crops and detected land sparing only in countries with strong land use policies incentivizing conservation set-asides[43].

Empirical studies have thus provided evidence on the significance of strong governance to enforce land use policies. However, Ceddia et al. have shown that it is not generally the level of governance but primarily specific aspects and types of governance that determine whether intensification is likely to promote land sparing[27]. By distinguishing between conventional and environmental dimensions of governance, they found that only strong performance in the latter led to a contracted footprint. Contrarily, in countries with high quality of conventional governance (i.e., low corruption, high rule of law, high voice, and accountability), agricultural intensification led to a rebound effect, presumably because conventional aspects of governance are associated with conditions necessary for the establishment of a market-oriented society, rather than environmental protection per se. Thus, under strong conventional governance, economic activity including agriculture tends to expand and, in the absence of effective environmental protection measures, leads to environmental degradation.

Above-outlined mechanisms related to price elasticity, land availability and policies are linked to a neoclassical economic perspective not distinguishing between different types of ownership and cultivation. Such view, implicitly considering all farmers rational economic agents that respond primarily to market incentives, often fails to identify the complexity of farmers' operational decision-making[65]. De facto, different pathways of agricultural spillover effects have often been traced back to the cultural context and actors involved[37,45,66]. A broad distinction can be made between smallholders (i.e., small, family farms operating with limited capital, and labor-intensive techniques) and large-scale actors (i.e., large, privately-owned farms, government parastatals or agro-industrial operations, often engaged in capitalintensive agriculture)[26]. Based on household survey data from the Philippines, Coxhead et al. assume that smallholders tend to emphasize different objectives by generally seeking food self-sufficiency and risk avoidance more than large farmers[29]. Meyfroidt et al. determined that expansion behaviors of small-scale and large-scale actors differ due to different constraints and opportunities associated with farm size[26]. Within their case study comparison, they observed that smallholders tend to use their already-cleared agricultural lands to develop commodity crops while large companies preferentially converted forests especially in regions with loose legal frameworks and limited recognition of customary rights on forestlands. Gutiérrez-Vélez et al. further noticed that although palm oil smallholder accounted for most cropland expansion in Peru, they mostly spread into degraded pastures and secondary forests, while large palm oil companies preferentially converted state-owned forests[30]. It is thus hypothesized that largescale high-yielding agriculture expands into state-owned primary forests rather than already cleared lands, to minimize transaction costs and avoid negotiations on land under patchy, uncertain or disputed tenure[26,30]. Furthermore, Kaimowitz and Smith found that in Brazil, cash-related restrictions prevented smallholders from using certain technological innovations that were adopted by large commercial farmers and finally associated with large-scale deforestation[24]. Eventually, there is ambiguity about the impact of Indigenous or local community land management at curbing deforestation. While BenYishay et al. have not identified any effect of formalizing land rights to Indigenous communities in the Brazilian Amazon[67], Baragwanatha and Bayi conducted a statistical analysis in the same study area, and found that granting property rights significantly reduces the levels of deforestation inside indigenous territories[68]. The authors argue that indigenous traditional land use, based on collective ownership, fulfills the necessary requirements for successful common-property resource management. In line with this, Pacheco and Meyer found that tenure by specifically indigenous communities reduced deforestation more effectively than any other property regime[69].

So far, I have demonstrated that the intensification-deforestation relationship is potentially shaped by a diversity of local contextual factors including target market, crop type, constraints on land supply, policy environment and actor-related characteristics of land use. Beyond that, land systems, and particularly intensification outcomes, are affected by structural patterns inherent in global economy. Since they manifest themselves in the relationship of trade and environment, different schools of thoughts from economy can be applied for studying the subject. Leveson-Gower recognizes three different approaches: neoclassical economics, environmental economics, and ecological economics[70]. The former's rationale is based on Ricardo's law of comparative advantage, meaning that every country will benefit from trade as long as the cost ratios differ between countries in the absence of it. As a follow, trade is assumed to generate welfare increases for all participants, and environmental policies are regarded as potentially harmful[71]. Although the second approach, environmental economics, generally agrees in terms of the positive relationship of trade and environment, it postulates that raising environmental standards would encourage sustainable development, instead of jeopardizing trade[72]. The third school, ecological economics, questions the ability of the trade system itself to promote ecological sustainability. Based on empirical observations of the relationship of trade, economic growth and welfare, ecological economists challenge the comparative advantage, and instead argue that trade leads to absolute advantage for some and absolute disadvantage for others[72]. The latter perspective is the one I am going to adopt, to reason why trade facilitates structural asymmetries. Linking this narrative to the concept of social-ecological traps, can contribute to understand cross-country difference in vulnerability to rebound effects.

Many authors describe how international trade taking place in an unequal playing field can lead to environmental cost-shifting from high-income to low-income countries[73–75]. They refer to the externalization of environmentally damaging withdrawal and production activities from the "core" of the global economic system to its "periphery"[76–78]. Muradian and Martinez-Alier further specify that low- and middle-income countries' positions in global supply chains and their respective role in the world economy might generate a "specialization trap"[72]: When the economic activity is specialized on natural resource-intensive, non-processed products, attempts to increase earnings by increasing supply are under current economic conditions often not successful in generating revenues or promoting innovative development[72,79]. Instead, since raw-material production tends to experience relatively weaker productivity growth than manufacturing, countries are prone to face deterioration in the terms of trade and a downward pressure on prices, especially when standards are low and institutions weak[80]. Under this trap-like scenario of absent economic development and price depression, intensification is unlikely to result in land sparing. The phenomenon here named "specialization trap" can be related to the discussion about "Dutch disease"[81]: It describes how positive trade shocks, i.e. rapid inflows of foreign exchange e.g., through natural resource booms push up the value of local exchange rates. In turn, production of non-boom exports and activities is discouraged, because they potentially compete with the lower-priced, imported goods[81]. As a consequence, non-boom exports and activities lose market share, profits and growth opportunities. When the "Dutch disease" occurs in extractive economies which are specialized in natural resources, non-extractive economic activities are discouraged, thus triggering ongoing resource exploitation instead of economic development. These symptoms are often referred to as "natural resource curse" constituting the negative link between resource abundance and growth[82]. Bahar and Santos provided empirical evidence on such "curse" by presenting how resource "windfalls", resulting in sharply increasing resource exports, directly determine economic activities: countries with large exports of natural resources exhibit high levels of non-resource export concentration[83]. Since this correlation is particularly pervasive in developing countries, the findings support the theory of the "specialization trap". Another study underlining the existence of such trap, draws upon the "premature de-industrialization". Here, Rodrik documented a recent de-industrialization trend in developing countries that is occurring at much lower levels of income compared to the experience of advanced, post-industrial economies[84]. While employment deindustrialization in Western countries was primarily triggered by technological progress, the observed "premature de-industrialization" in developing countries traces back to globalization and trade: As they opened up to trade, their manufacturing sectors were hit by a shock when exposed to the declining relative price trends originating from advanced economies. The consequence here described as "imported de-industrialization" coincides with the "specialization trap": Manufacturing tends to experience relatively stronger productivity growth than production, thus producing countries keep being stuck in a position as resource-intensive, primary commodity suppliers with continuously deteriorating terms of trade. If this trend is accompanied by a resource boom that discourages any non-boom economic activity ("Dutch disease"), economies can hardly escape this trap-like situation.

Summing up, all these concepts provide explanations and support the theory that under prevailing global trade conditions, enhancing resource extraction in economically less developed countries increases resource dependence instead of promoting innovation or sustainability. Intensification might thereby play a crucial role in two possible ways: On one hand, it might function as a stabilizing system feature. Boonstra and De Boer, who conceptualized social-ecological traps as processes producing both environmental degradation and poverty, named strong path dependency as one of the main preconditions for the ‘‘structural persistence’’ of these traps[85]. Based on this, it should be scrutinized whether intensification might function as self-reinforcing mechanism that results in path dependency and lock-ins for land systems of “specialization-trapped” countries. On the other hand, intensification could also work as a “sliding reinforcer”[86]. Costanza introduced this term to describe actions that initially yield positive outcomes but start to produce progressively more negative outcomes, or small interventions that have a beneficial effect, while larger interventions of the same kind have a negative effect. This view emphasizes the argued trade-offs of intensification induced commodity booms.

All these considerations reveal that the outcome of intensifying interventions is shaped by a variety of contextual factors, often reflecting system behavior including feedback mechanisms, path dependency, and diverse interactions across multiple scales. Despite this complexity, contextual generalizations of causal mechanisms can help identifying critical conditions under which intensification triggers undesired rebound effects. For my analysis, the above-presented conceptual framing (Figure 1) serves as groundwork for a systemic perspective on causal pathways of intensification spillovers in the world’s TDF.

3. Materials and methods

To understand how intensification relates to deforestation in TDF, I combined the identification of causal mechanisms of intensification spillovers, with statistical investigation of the causal effects resulting from these mechanisms (Figure 2). Drawing on the previous chapter, I developed a conceptual framework to identify the causal pathways provoking different effects in land systems, before translating the established narratives into an explicit causal model and quantifying their effects by making use of a Bayesian multilevel analysis.

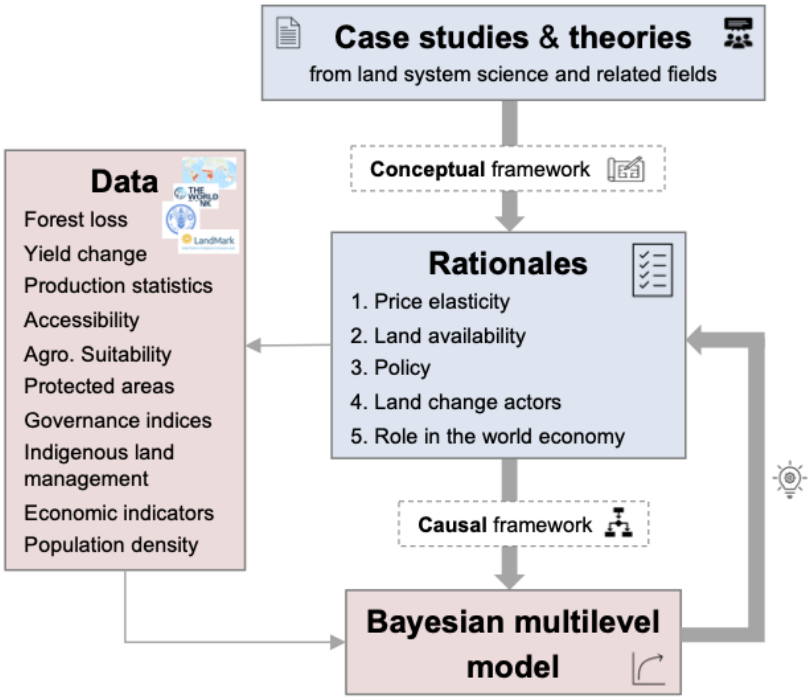

***Figure 2: Analytical approach**. Drawing on theoretical and empirical knowledge, I derived testable rationales and translated them into a causal model. Informed by the established causal pathways, I compiled a multilevel dataset entailing environmental variables as well as social-ecological parameters and economic indicators. Finally, I quantified their corresponding effects by making use of a Bayesian multilevel model.*

3.1. Study region

To define my study region, I followed previous work on TDF globally[51,87,88] and used an inclusive TDF definition[89]. In detail, I focused an all forests and woodlands falling into two biomes according to the updated version of Olson, et al. categorization[90,91]: (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 (Figure 3a), covering about 20% of the global terrestrial surface[51]. All of these ecosystems harbor large numbers of endemic species[46,92], are major carbon storages, and provide important ecosystem services including their positive impact on climate, nutrient and water cycles[93]. Moreover, TDFs are culturally rich and have maintained livelihoods to human populations for millennia[94].

With more than 60% of the population in countries with TFD engaged in agriculture[95], human activities have caused major transformations in these ecosystems. Especially in the last decades, many TDFs have experienced high and rising pressure from land-use change and overexploitation[47,96,97]. While in some regions, forests have been substantially reduced by historical deforestation, such as India[98] and Indochina[99] (Figure 3e), many regions have only recently turned into global deforestation hotspots, such as Madagascar[100] (Figure 3d), and the South American Chaco, Chiquitano[97,101] (Figure 3b) and Cerrado[102] (Figure 3c). Finally, there are regions currently undergoing an activation of deforestation frontiers, such as the African Miombo[103,104] (Figure 3f).

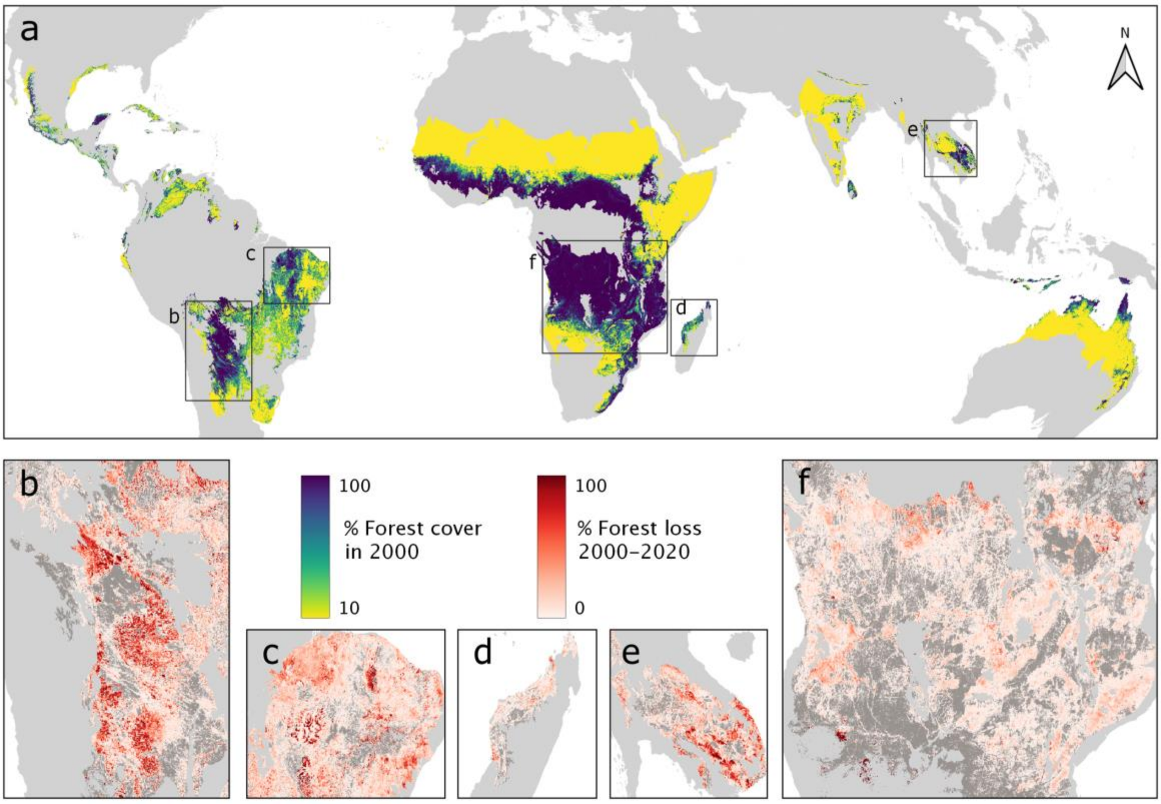

Figure 3: Global tropical dry forest regions and deforestation hotspots. *A large proportion of global terrestrial surface is covered by TDF, distributed through South and Central America, Africa, Southeast Asia, and Australia (a). Rising human pressure has triggered considerable forest loss in the last two decades, especially in the deforestation hotspots in the South American Gran Chaco & Chiquitano (b), Cerrado & Caatinga (c), African Miombo and Mopane woodlands (f), Madagascar (d) and Indochina tropical dry forests (e). Data on forest cover and loss from Global Forest Watch[96].*

Although it is widely agreed that TDF are under considerable threat[50,51,105], and despite their high ecological, cultural, and provisioning value, TDF have been largely overlooked when it comes to research effort, government policies and public awareness[49,51], and remain weakly protected[47,99]. Due to strong social-ecological differences among TDF regions in terms of land-use history and dominant land-use practices[106], governance schemes have often failed when designed as "one-size-fits-all" panaceas. Therefore, it is crucial to account for the diversity of agricultural actors and production systems[50,106] or contextual land-use conditions[95,107], to adequately integrate underlying and distal drivers[19,23,108], and to take into account system dynamics such as feedbacks, path-dependency and multiple interactions[10].

3.2. Rationales of intensification outcomes

Based on the theoretical and empirical context of my study mapped in a conceptual framework, I derived five testable rationales. They establish causal pathways around potentially influential factors shaping the relationship of agricultural intensification and deforestation.

1. Price elasticity. High price elasticity of excess demand is hypothesized to increase the risk of a local rebound effect. This depends mainly on crop type and market integration. For staple crops mostly consumed domestically, intensification enables reaching the needs with less lands while demand remains stable because surplus production has no outlets. Thus, low price elasticity makes agricultural intensification relieve pressure on forests. Inversely, in the case of non-staple crops produced for rapidly expanding global markets, efficiency gains are likely going to increase profitability and logically act as an incentive to expand the crop frontier.

2. Land availability. Strong biophysical or institutional restrictions on land are expected to promote land sparing because, under productivity increases, scarcity of productive, accessible, or legally available land can encourage the abandonment of cultivation on less suitable or poorly accessible land.

3. Policy. Protective land use policies prevent the expansion of agriculture into forest, usually relying on high governance quality. Yet, while strong environmental governance has shown to facilitate land sparing, conventional aspects of governance mostly incentivize the establishment of operational markets. Under such conditions, economic activity – including agriculture – tends to expand thus likely resulting in a higher risk of rebound effect.

4. Land change actors. Differences in motivation, constraints and cultural background of land actors translate into different modes of agricultural management thus affecting the outcome of intensification. Indigenous or local community managed lands – presumed less subjected to the drive to increase profits – are hypothesized be less prone to rebound effects than privatized lands. Further, state-owned forested land seems to face a higher risk of deforestation because large scale actors have shown to avoid negotiations on land under patchy or uncertain tenure to reduce transaction costs.

5. Resource specialization. Structural patterns inherent in prevailing global trade conditions are hypothesized to affect intensification spillovers as manifestation of the “specialization trap”: Accordingly, enhancing primary sector productivity in economies specialized in natural resource extraction is likely going to foster resource dependence instead of promoting innovation or sustainability, especially when their positions in global supply chains and their respective role in the world economy makes them exposed to price trends originating from more advanced economies (“pre-mature deindustrialization”). Since intensification might function as a reinforcing element under this scenario, natural resource specialization combined with a low economic development stage is argued to increase the risk of rebound effect.

3.3. Data sources and processing

To operationalize my rationales and the underlying research questions, I assembled a multilevel dataset of 154,979 observations containing both country-level variables and pixel-scaled information at a 3km-grid over the timespan of 2001-2020 which constitutes one timestep encompassing 20 years. My dataset comprised all pixels that are at least 10% covered by tropical dry forest in the year 2000 according to Global Forest Watch[96], and was further reduced by systematically sampling every third grid cell in x- and y-direction to minimize effects of spatial autocorrelation. Although land sparing and rebound effects cannot only occur within the region that experiences intensification but also remotely[12], I disregarded potential displacement to other countries and focused on spillovers within country borders.

Since in the tropics, the largest share of new cropland areas comes at the expense of forests[60,109,110], I addressed my research questions using forest loss as proxy for cropland expansion. So far, many studies have investigated cropland expansion by deploying data on harvested area for a specified sample of crops[39,41,43,44] but such approach – although needed to investigate crop-specific responses – can neither account for interchanges among plants, nor can it capture spillovers between livestock and cropping systems. In contrast, my approach covered deforestation regardless of crop type, thus capturing land use change dynamics that do not manifest in crop-specific harvested area changes. The proportional forest loss variable (*FL*) comprised accumulated forest loss from 2001-2020 as percentage of forest cover in 2000 for each grid cell, which I derived from data on forest change from Global Forest Watch[96] and aggregated to my target resolution of $3x3km^2$ grid cell (Table 1).

Intensification has been defined in different ways, often adding to confusion in discussing its impacts on land use[20]. I used yield increase as a measure of intensification representing the productivity of land measured by higher output per land unit. I retrieved key variables on yield and production statistics from the FAOSTAT database[111]. Despite limitations associated with this archive, it remains the only long-term, cross-country dataset for exploring such empirical question. Given the importance of understanding intensification outcomes, working with imperfect data seems warranted[43]. I operationalized agricultural intensification as country-level aggregated yield change (ΔY) over the period of 2000-2019 (Table 1). The applied procedure accounted for potential time lags, crop group specific differences in weights and anomalies in country-level trajectories (Appendix A).

To investigate the varying impact of intensification of different crop types, I further stratified overall yield change into yield change of staple crops versus yield change of commodities/non-staple crops. Staple crops are defined as the world's energetically most important food sources constituting paddy rice, maize, wheat, sugar beet, barley, potatoes, cassava, sorghum, sweet potatoes, groundnuts, millet, onions, oats, coconuts, sunflower seeds, fresh vegetables, bananas, plantains, and yams. The remaining non-staple crops are primarily grown to be sold on international markets, fed to animals, or have industrial applications, constituting among others palm oil, soybean, rapeseed, sugar cane, fruits, cocoa, coffee, tea, tobacco, rubber, and cotton.

The presented approach relying on temporally aggregating both forest loss and yield change bears the risk to inadequately represent finer temporal dynamics and especially neglect the chronology of events. If both aggregated yield change and forest loss were attributable to short periods of only few years, and the forest loss event occurred earlier in time than the one causing yield change, my data structure would not allow accounting for this order, and thus risk to wrongly identify given forest loss as a follow of yield change. Yet, such potentially misleading chronology could be ruled out after having inspected country-level yield trajectories revealing that only four countries experienced significant stagnation and peak in yield change while the large majority displayed relatively steady yield increases over the entire study period (Appendix A). Furthermore, alternative approaches such as time series analyses including lags, or difference-in-difference-models based on constructing a timing of intervention and respective pre- and post-treatment trends were carefully considered but have not proven advantageous due to several pre-assumptions and simplifications that I evaluated as more severe than the ones linked to temporal aggregation. Finally, to maximize robustness I performed checks to test whether different assumptions regarding time lags of intensification spillovers affected my results. Therefore, I 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 (2000-2019).

To quantitively represent the hypothesized conditioning factors on the relationship of intensification and deforestation, I derived the following variables (listed in Table 1):

Price elasticity in rationale 1 is argued to be determined by crop type and market integration. Therefore, I calculated country-level mean share of non-staple crop production (*nonStap*) in the time period 2000-2019 from FAOSTAT database applying the same classification as noted above[111]. Similarly, I calculated production share of export (*export*) as country-level mean share of total agricultural export value from agricultural gross production value between 2000 and 2019. Agricultural re-exports resulting in export-share values >1 are dealt with by bounding all values to a maximum of 1.

To describe agroecological suitability (*suit*) as first element of physical land availability described in rationale 2, I derived data from the Global Agro-Ecological Zones dataset from FAO and IIASA[112] mapping summed, standardized agroclimatic potential for low-input, rainfed agriculture of the main crops and commodity crops globally (wheat, soy, maize and rice, cassava, banana, cocoa, coffee, tea, sugarcane, oil palm). To represent the second element, accessibility (*access*), I obtained grid-level information on travel time to the nearest city of population > 50,000 in 2015[113]. I reaggregated data on both agroecological suitability and accessibility to the study grid-cell resolution of 3 km. As third element affecting land availability, I received country-level proportion of terrestrial protected areas of total land area from the World Database on Protected Areas (WDPA)[114].

With respect to the varying effect of different governance aspects argued in rationale 3, I covered conventional dimensions of governance, combining three indicators developed by the World Bank (*WGI*), related to voice and accountability, rule of law, and control of corruption[115]. To capture the environmental dimensions of governance, I relied on the Environmental Performance Index (*EPI*) developed by the Yale Centre for Environmental Law and Policy which incorporates indicators over policy categories related to the effect of environmental degradation on ecosystems vitality[116].

Table 1: Model variables and datasets used.

Variable	*Description*	*Scale*	*Source*
Deforestation/outcome			
Proportional forest loss (*FL*)	accumulated FL from 2000-2020 as percentage of forest cover in 2000 (F_{2000}): $$FL = \frac{\sum_t FL_t}{F_{2000}}\ with\ t = \{2001; \dots; 2020\}$$	3km	96
Intensification/treatment			
Yield change (*ΔY*) a) overall mean b) mean of staple crops c) mean of non-staple crops	temporally aggregated ΔY on country-level calculated in a three-step procedure: 1. yearly crop group yield change $\Delta Y_{t,c}$ compared to the mean of the two previous years 2. yearly yield change ΔY_t as mean of $\Delta Y_{t,c}$ weighted by harvested area in 2000 (HA_c) 3. study-level yield change ΔY as product of ΔY_t from 2000-2019	country	111
Shaping factors/effect modifiers			
Rationale 1			
Production share of export (*export*)	Mean % of agriculture export value in agriculture gross production value (2000-2019)	country	111
Production share of non-staple crops (*nonStap*)	Mean % of non-staple production in agriculture production (2000-2019)	country	111
Rationale 2			
Agroecological suitability (*suit*)	Summed, standardized agroclimatic potential for low input, rainfed agriculture	3km	112
Accessibility (*access*)	Travel time to the nearest city of 50,000	3km	113
Proportion of protected areas (*PA*)	Proportion of terrestrial protected areas (% of total land area)	country	114
Rationale 3			
Conventional governance (*WGI*)	Combined governance quality indicators developed by the World Bank	country	115
Environmental governance (*EPI*)	Environmental performance index	country	116
Rationale 4			
Indigenous/community managed lands (*IPL*)	Indigenous land management (binary)	3km	117
Rationale 5			
Susceptible regarding specialization trap (*special*)	Combination of: - mean primary sector, value added 2000-2019 > 15 % of GDP - World bank income group = low/lower middle	country	118,119
Control variable for demand			
Change in rural population density (*popdens*)	Change in population density 2000-2020 in a buffer (moving window approach) around the grid cell	3km	120

To examine the impact of different land actors following rationale 4, I constructed the presence of Indigenous or community managed lands (*IPL*) as a binary variable on grid-level based on the spatial dataset created by the authorship team of Garnett et al.[117]. The use of data on IPL always includes a socio-political notion that requires acknowledging that these boundaries describe prevailing power structures, while few of them are entirely undisputed and often in a state of permanent flux which makes them difficult to map[117]. Nonetheless, progressively identifying and considering IPL is essential to comply with the large global importance they hold for conservation[117].

Finally, regarding rationale 5 addressing the specialization trap, I described countries' specialization in primary sector and their respective position in supply chains by obtaining GDP share of agriculture, forestry, and fishing in terms of added value from the World Bank as mean from 2000-2019[118]. Combined with the income group classification from the World Bank[119], I constructed a binary variable indicating whether a country is especially susceptible to the dynamics of the specialization trap (*special*) which is true if both its primary sector constitutes more than 15% of national GDP and it is categorized as low-, or lower-middle income economy.

Besides the above noted variables associated with my rationales, I controlled for changes in demand by including change in rural population density (*popdens*) in the study period, based on the assumption that rural population is most dependent on domestic agriculture[110]. Therefore, I derived grid level population density data for 2000 and 2020 from the Gridded Population of the World (GPW) data product from Socioeconomic Data and Applications Center (SEDAC)[120], calculated mean population density in a 9km^2-buffer around the given grid cell with a moving window approach for both timesteps and computed the percentage change.

All data operations and manipulations were carried out in the statistical programming environment R[121] with many applications of the R package tidyverse[122].

3.4. Establishing causality

With the objective of linking the established rationales to their corresponding effects, and making these mechanisms statistically analyzable, I applied the perspective of causal inference. Generally, such approach describes the statistical process of concluding that an observed association is due to causation, not mere correlation[123]. When built upon observational data, as in my case, it relies on the premise that those can be viewed as a conditionally randomized experiment[124]. However, many social-ecological processes including land-use change take place in settings where random interventions hardly occur and unobservable variables may lead to bias[123,125]. Thus, drawing valid causal inferences on the basis of social-ecological observational data is not a mechanistic procedure but requires acknowledging that it involves adjusting steps based on domain knowledge, and implies very strong assumptions[126]. In order to facilitate awareness of implied assumptions in my model, I made use of directed acyclic graphs (DAGs)[127]. These graphical causal diagrams are a powerful tool for transparently communicating assumptions, theories and causal claims made in the context of social-ecological modeling.

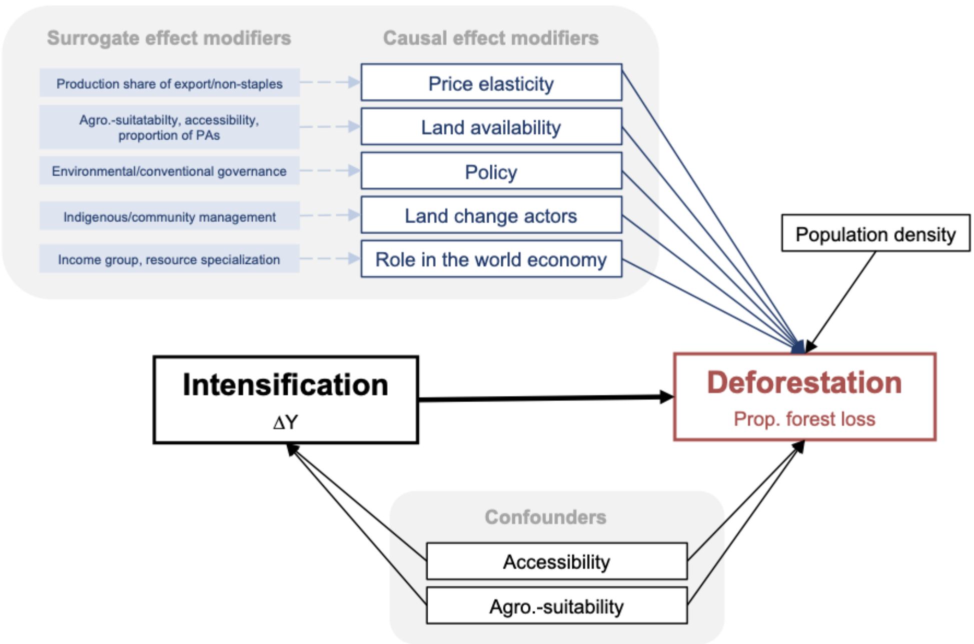

Figure 4: Directed acyclic graph (DAG)*. Arrows connecting the variables represent causal assumptions about correlations derived from case studies and theory.*

The DAG in Figure 4 visually represents the causal assumptions I have made to infer causal effects of agricultural intensification on deforestation. The arrows in the graph display association between the nodes (variables) and can be used to guide model building. Applying the framework of causal inference, I conceptualized intensification as treatment and deforestation as outcome. My rationales on shaping contextual factors enter the model as effect modifiers, meaning that they potentially alter the magnitude or direction of the average causal effect of treatment (intensification) on the outcome (deforestation)[124]. Generally, a distinction can be made between causal effect modifiers and surrogate ones. While the former is assumed to actually play a causal role, the latter refers to variables that are either correlated with unidentified variables, or proxies for not quantifiable causal effect modifiers[124]. Hence, I assume an association between the listed surrogate effect modifiers and causal effect modifiers, thus substituting the latter with the former. Furthermore, population density appears as yield-change unrelated yet potentially important determinant for forest loss.

In order to consistently identify and quantify causal effects, the condition of exchangeability must be met which is fulfilled in the case of randomized assignment of treatment[124]. Yet, in observational contexts, where fully randomized experimental setups do not exist, estimates can be biased by confounders, variables associated with both treatment and outcome[124]. In my analysis, accessibility and agro-ecological suitability are likely to affect both intensification and deforestation. The resulting open backdoor path between treatment and outcome creates an unobserved additional source of association, thus leading to confounding bias and requiring balancing adjustment[123,125]. An approach that has gained widespread popularity for balancing dissimilar treatment exposure with respect to baseline covariates is the propensity score proposed by Rosenbaum and Rubin[128]. It is defined as the probability of treatment, given the observed covariates. Propensity score methods first estimate propensity scores for each observation and then use the scores to statistically balance treatment groups and thereby remove the association between covariates and treatment[129,130]. Rosenbaum and Rubin[128] developed the propensity score for balancing binary treatment, but literature has extended these methods to the cases of continuous treatments using the generalized propensity score (GPS) defined by Hirano and Imbens[131] (Appendix B). I applied this procedure to statistically balance across the range of yield change and adjust for dissimilar exposure regarding accessibility and agro-ecological suitability, thus removing the association between the covariates (accessibility, agro-ecological suitability) and treatment (intensification). I used the R package WeighIt[132] to calculate propensity score weights as well as checking the resulting balance in my data.

3.5. Bayesian multilevel modeling

I applied a Bayesian multilevel modeling framework to statistically investigate causal mechanisms of variables representing the established rationales by estimating their corresponding average global effects as well as continent-specific variations.

Multilevel models offer great flexibility for modeling statistical phenomena that occur on different levels[133]. This is achieved by fitting models that include both constant and varying effects. Such varying-effects strategy is especially useful when handling complex dependency structures in the data[133], such as continents' different baseline conditions regarding history, drivers and actors of land use change, and the resulting variation in the intensification-deforestation patterns. By specifying a multilevel/varying-effects model with continents as model levels, I can account for the fact that observations from the same continent are not independent. I enable the model to both capture and explore variance among continents while still acknowledging the similarities of global land system dynamics in global TDF. By partitioning the total variance into variation due to the groups and to the individual, I gain insights about the generalizability of the findings[134]. Apart from these contextual benefits, multilevel models offer natural solutions to some sampling issues: Since they can adaptively pool information among parameters, they usually achieve better estimates and are superior in negotiating the trade-off between underfitting and overfitting[134]. Especially when there are imbalances in sampling of some clusters, multilevel models automatically cope with differing uncertainty across these clusters which prevents over-sampled clusters from inappropriately dominating inference[134].

I chose the Bayesian approach because it involves two advantageous features beyond classical statistics that respond well to the challenges associated with analyzing causal effects in complex, structured data. First, uncertainty can propagate throughout the modeling process so that predictions for future outcomes account for both uncertainty in the model parameters and predictive uncertainty, and second, a priori knowledge can be incorporated in data analysis via prior distributions[135] (Appendix C).

In my study, the process of Bayesian analysis involved four major steps, beginning with setting up a probability model for all the entities at hand and specifying prior distributions (1), then drawing from the posterior distributions using Markov Chain Monte Carlo (MCMC) for different model specifications (2), evaluating how well the models fit the data and revise the models by optimizing predictor selection (3), and finally drawing from the posterior (predictive) distributions in order to analyze how predictors affect the outcome (4).

In the first step, I defined the probability model that takes the form of a likelihood distribution for the outcome conditional on prior distributions for the unknowns. Since the response variable forest loss (*FL*) is continuously distributed between 0 and 1 with an inflation at the outcome zero, a zero-inflated Beta distribution is appropriate to match these observed data features to model assumptions. Hence, I specified a mixed model to predict FL based on a zero-inflated Beta distribution that characterizes bounded quantities in the closed [0,1[interval, and has two components: a beta distribution for responses in the closed]0,1[interval (Appendix D), and a Bernoulli distribution for the binary {0} responses.

In mathematical form, I specified the following mixed varying-effects model, after having transformed predictors following recommendations in Gelman, Hill and Vehtari 2020[135] (Appendix E).

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

$$\boldsymbol{logit(p_i) = \alpha_p + \beta_{acc} access_i} \tag{II}$$

$$\begin{aligned}\boldsymbol{logit(\mu_i)} = {} & \boldsymbol{\alpha_{\mu,cont[i]} + \beta_{PD,cont[i]} popdens_i + \Delta Y_i} \\ & * \big(\boldsymbol{\beta_{\Delta Y\mu,cont[i]} + \beta_{exp,cont[i]} export_{[i]} + \beta_{nSt,cont[i]} nonStap_{[i]}} \\ & + \boldsymbol{\beta_{suit,cont[i]} suit_{[i]} + \beta_{PA,cont[i]} PA_{[i]} + \beta_{WGI,cont[i]} WGI_{[i]}} \\ & + \boldsymbol{\beta_{EPI,cont[i]} EPI_{[i]} + \beta_{IPL,cont[i]} IPL_{[i]}} \\ & + \boldsymbol{\beta_{spec,cont[i]} special_{[i]}}\big)\end{aligned} \tag{III}$$

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

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

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

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

$$\beta_{acc} \sim Normal(0, 0.1) \tag{VIII}$$

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

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

I defined the use of 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 p_i for zero-responses predicted by the Bernoulli distribution (line I). As μ_i and p_i must be (0, 1), I 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, I used a log link function to ensure that ϕ_i is positive (line IV). To estimate p_i, I defined a linear model with a global intercept α_p and slope β_{acc} for accessibility ($access$) (line II). Including accessibility as effect parameter in the formula was 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. To estimate the mean magnitude of forest loss (μ_i), I specified a multilevel model (line III). Here, μ_i is predicted by population density ($popdens$), and yield change (ΔY) in interaction with the shaping factors production share of export ($export$), production share of non-staple crops ($nonStap$), agro-ecological suitability ($suit$), proportion of terrestrial protected areas (PA), conventional governance (WGI), environmental governance (EPI), Indigenous land management (IPL), and susceptibility regarding the specialization trap ($special$). All parameter coefficients were modeled to vary across continents, thus exploring global average patterns as well as variance among continents, and providing insights about generalizability. I defined a linear model to approximate ϕ_i with a global intercept α_ϕ and slope $\beta_{\Delta Y \phi}$ for ΔY(line IV). The argumentation of predicting the dispersion of FL_{prop} by ΔY assumes that intensification potentially facilitates both land sparing and rebound effects, thus increasing the dispersion of the observed response in forest loss.

Finally, I chose prior distributions for the unknown parameter coefficients (lines V-X). I optimized prior settings in an iterative process of performing prior predictive checks i.e., predicting the data only based on the chosen priors (Appendix F), and subsequently adjusting those prior distributions based on information obtained from sampling diagnostics and predictive checks. In this way, I derived informed priors that are on one hand regulatory enough to facilitate model convergence, and on the other hand result in plausible predictive simulations while not restricting the outcome distribution in a biasing way and predetermine model results (Appendix F). Consequentially, priors for α_p , and β_{acc} were chosen as normally distributed centered on 0 resulting in regularizing Gaussian priors in 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 ($\alpha_{\mu,cont[i]}$) 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 phi values <1 in the outcome scale after log-transformation which prevents U-shaped beta distributions. Varying effect parameters ($\beta_{...,cont[i]}$) were assigned a weakly informative Gaussian prior centered on 0. Both the distribution of varying intercepts and slopes had an *Exp(10)*-distributed prior standard deviation ($\sigma_\alpha, \sigma_\beta$), thus restricting the range of possible values to positive ones. Internally, the covariance i.e., correlation between varying intercepts and slopes was modeled by a multivariate normal distribution with an uninformative correlation prior of $LKJcorr(2)$ representing flat covariance assumptions[134].

As a second step, I drew from the posterior distribution using MCMC sampling to explore model estimations. Four sampling chains ran for 2000 iterations with a warm-up period of 1000 iterations for each model, thereby yielding 4000 samples for each parameter coefficient. I ran several competing models with and without a multilevel structure and including different sets of highly correlated predictor variables (*export*, *nonStap*, *PA*, *WGI*, *EPI*). Further, I differentiated among the different categories of calculated *ΔY* (overall mean, within staple crops and within non-staple crops). Finally, I executed two additional model runs based on *ΔY* of earlier time periods to check robustness of my results, as described above.

In a third step, I evaluated model fit based on posterior predictive checks i.e., predicting new hypothetical data sampled from the posterior predictive distribution and comparing it to a random draw of observed data. For purposes of comparing predictor selections of competing models, I determined out-of-sample predictive accuracy using leave-one-out expected log predictive density (LOO-ELPD) as described by Vehtari et al. 2017[136]. In essence, the LOO-ELPD gives a relative measure of predictive performance when the model is confronted with new data. Using the R-package loo[137] to efficiently compute leave-one-out cross-validation including Pareto smoothed importance sampling, I compared estimates of predictive accuracy and their standard errors among models.

In the final step, I analyzed posterior distributions. I plotted conditional effects of the parameter coefficients of interest by setting all model predictors, besides the one of interest, to their mean value or reference category to demonstrate the effect for the average sample. For the binary predictors, I calculated and visualized contrasts between the two levels as a measure of evidence of the given effects. Eventually, I modeled *ΔY*-related forest loss for another time step of 20 years under a hypothetical future yield change scenario that is based on extrapolating past 10 years' yield change patterns. Disregarding change in rural population density, and leaving all other conditions unchanged, I calculated the mean posterior estimate as well as the posterior standard error comprising both parameter uncertainty and predictive uncertainty. I drew from the respective posterior predictive distribution and mapped the outcome spatially to explore deforestation threat of intensification spillovers in global TDF. I performed all modeling and estimation through the brms package[138] in R[121] as an interface to the Bayesian inference engine Stan[139].

4. Results

4.1. Predictive performance

For all model runs, sampling diagnostics (R-hat, effective sampling size) and trace plots related to MCMC sampling indicated high sampling efficiency, good mixing, stationarity, and convergence of the independent model chains, thus signaling reliability of the modeling process (Appendix G).

Table 2: Final model specifications*. Model comparison was based on the performance diagnostic LOO-ELPD providing information about predictive accuracy of competing models.*

Model part	***Baseline***	***Final model***
Predictor selection of ΔY effect modifiers	nonStap, export, suit, PA, EPI, WGI, IPL, special	nonStap, suit, IPL, special
Model structure	Varying effects, fixed effects	Varying effects

Model comparison based on LOO-ELPD revealed one best performing model including *access*, *popdens,* and *ΔY* in interaction with *suit*, *nonStap*, *IPL* and *special* as predictors (Table 2). The remaining *ΔY*-effect modifiers were not included in the final model because they added more complexity than explanatory power (*export*, *EPI, WGI*), or were estimated inconsistently across models (*PA*). Regarding model structure, models allowing continent-level varying effects clearly outperformed the ones without multilevel structure (Table 2).

The resulting final model was able to reproduce the observed data well, as demonstrated by posterior predictive checks (Appendix F). Finally, robustness checks confirmed constancy of the modeled effects (Appendix H): *ΔY* effects estimated by conditioning on earlier periods were consistent with modeled effects in the original study time, thus strengthening the assumption that the temporal design of my analysis does not miss significant time lag effects potentially undermining the results.

4.2. Posterior effect estimates

Deforestation was widespread in the world's TDF between 2000 and 2020, with an average of 8.1% proportional forest loss (hereafter: forest loss). By design, the specified mixed model comprised two parts to predict forest loss: first, a Bernoulli distribution for the binary zero forest loss responses, and second, a Beta model for the distribution of non-zero forest loss. Since both model parts had restricted outcome ranges, I used link functions to map the result of the linear model to the appropriate scales. In the following, all parameters are re-transformed to the probability scale, to make the results more intuitive to interpret (see Appendix I for untransformed values).

The first model component estimated a global mean zero-inflation probability of 0.086 (standard error (SE) 0.001). Travel time to nearest city (*access*) had a positive effect on the zero-inflation probability (mean 0.61; SE 0.002) (Figure 5a), translating into a negative effect on forest loss (Figure 5b). Effect of *access* on forest loss was not constant over the parameter space but most pronounced in the middle value range.

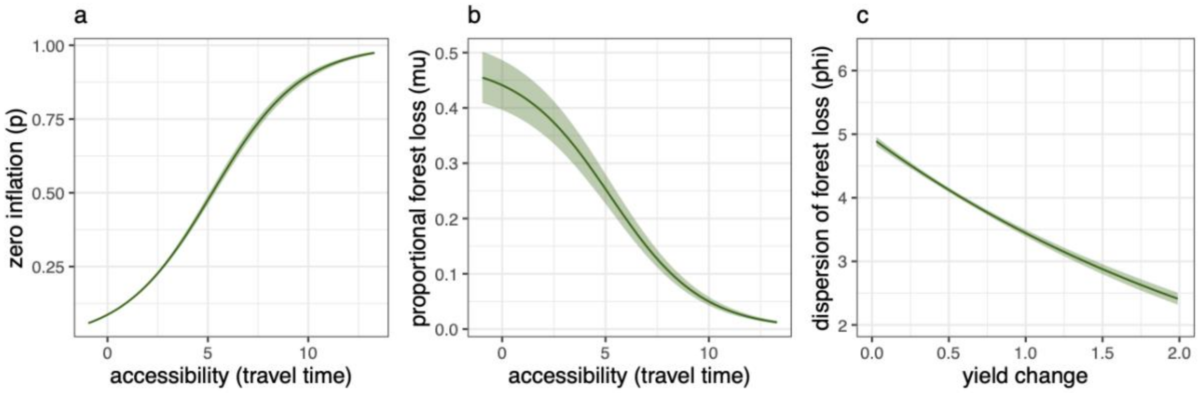

Figure 5: Conditional effects on probability of zero forest loss and forest loss dispersion*. Curves show the mean effect and the 95% credible interval of the posterior distribution for the average sample. Accessibility operationalized as travel time to nearest city > 50,000 is given in units of standard deviation.*

The second component of the model estimated *ΔY* effect on forest loss by the Beta parameters dispersion (phi) and mean magnitude (mu). *ΔY* had a negative effect on the dispersion (mean -0.51, SE 0.008) (Figure 5c) translating into a widening effect on the response of the Beta distribution. Hence, an increase in *ΔY* was associated with higher variation of responding forest loss.

Posterior *ΔY* effect on the mean magnitude of forest loss (hereafter: effect on forest loss) was positive. Globally on average, a 100% increase in yield was associated with a 3.8% increase in forest loss. The multilevel model structure enabled continent-level variations: While the effect was close to the global mean in South America, magnitude was higher in Asia and lower in Africa (Table 3). For Australia, *ΔY*-related continent-level parameter coefficients are not regarded in the further analysis, because they were associated with too high levels of uncertainty (Figure 6). The modeled global effect of rural population density change –

assumed to represent changes in agricultural demand – was not meaningful (Table 3). The only significant estimate is the posterior *popdens* effect for Africa (mean -0.014, SE 0.008).

Table 3: Global mean and continent level effect coefficients *with posterior mean as measure of central tendency, and standard error as measure of variability. Values for the global parameters are taken from the global model without varying effects, the remaining continent-level specifications are taken from the final (multilevel) model.*

Parameter coefficient	***Global***	***Continent-level deviation***		
		Africa	*Asia*	*South America*
popdens ($\beta_{PD,cont[i]}$)	-0.003; SE 0.004	-0.014; SE 0.008	-0.017; SE 0.023	0.001; SE 0.009
ΔY ($\beta_{\Delta Y\mu,cont[i]}$)	0.038; SE 0.013	0.017; SE 0.003	0.071; SE 0.052	0.033; SE 0.020
ΔY:nonStap ($\beta_{nSt,cont[i]}$)	0.43; SE 0.007	0.011; SE 0.093	-0.27; SE 0.098	0.22; SE 0.096
ΔY:suit ($\beta_{suit,cont[i]}$)	0.055; SE 0.004	0.013; SE 0.009	0.004; SE 0.097	0.26; SE 0.008
ΔY:IPL ($\beta_{IPL,cont[i]}$)	-0.054; SE 0.011	-0.009; SE 0.014	-0.12; SE 0.10	-0.54; SE 0.025
ΔY:special ($\beta_{spec,cont[i]}$)	0.14; SE 0.29	0.013; SE 0.049	-0.029; SE 0.060	-0.001; SE 0.065

Given the posterior distributions of the estimated *ΔY*-interaction terms, effect modifiers *nonStap*, *suit*, *IPL* and *special* considerably affected the relationship of *ΔY* and forest loss, yet with remarkable differences among continents (Figure 7). In both Africa and South America, share of non-staple crops had an amplifying effect on the positive correlation of *ΔY* and forest loss. Whereas the effect of *nonStap* was not significant in Africa (Table 3), it was of high and meaningful magnitude in South America, where low values of *nonStap* even reversed the positive effect of *ΔY* on forest loss. Hence, under conditions of low share of non-staple crop production, *ΔY* in South America was associated with decreasing forest loss. Inversely, high share of non-staple crop production amplified the effect of *ΔY* resulting in high levels of forest loss. Results were markedly different in Asia where *nonStap* had a reverse, negative interaction with *ΔY* regarding forest loss. Agro-ecological suitability had a reinforcing effect on the *ΔY*-forest loss correlation in all continents. Highest magnitude

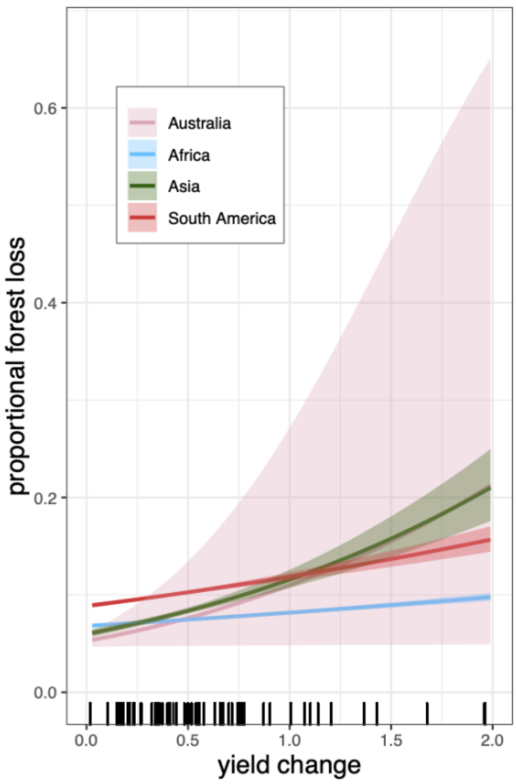

Figure 6: Continent-level conditional ΔY effect*. Curves show the mean effect and 95% credible interval of the posterior distribution for the average sample. Black marks along the x-axis visualize the distribution of ΔY values that the predictions were based on.*

was obtained in South America where high levels of suitability significantly intensified the effect of ΔY while low values practically offset any ΔY effect. In Africa, effect of *suit* was small but significant, and in Asia, magnitude of the posterior standard error exceeded the posterior mean effect indicating high uncertainty. The posterior effect of Indigenous/community land management depended on the continent. While the presence of IPL did not significantly affect ΔY effect in Africa and Asia, it reversed the effect of ΔY in South America. Here, the combination of yield increase and Indigenous/community land management was even associated with decreasing forest loss. Finally, countries' attribution as especially prone to the specialization trap did not affect the correlation of ΔY and forest loss.

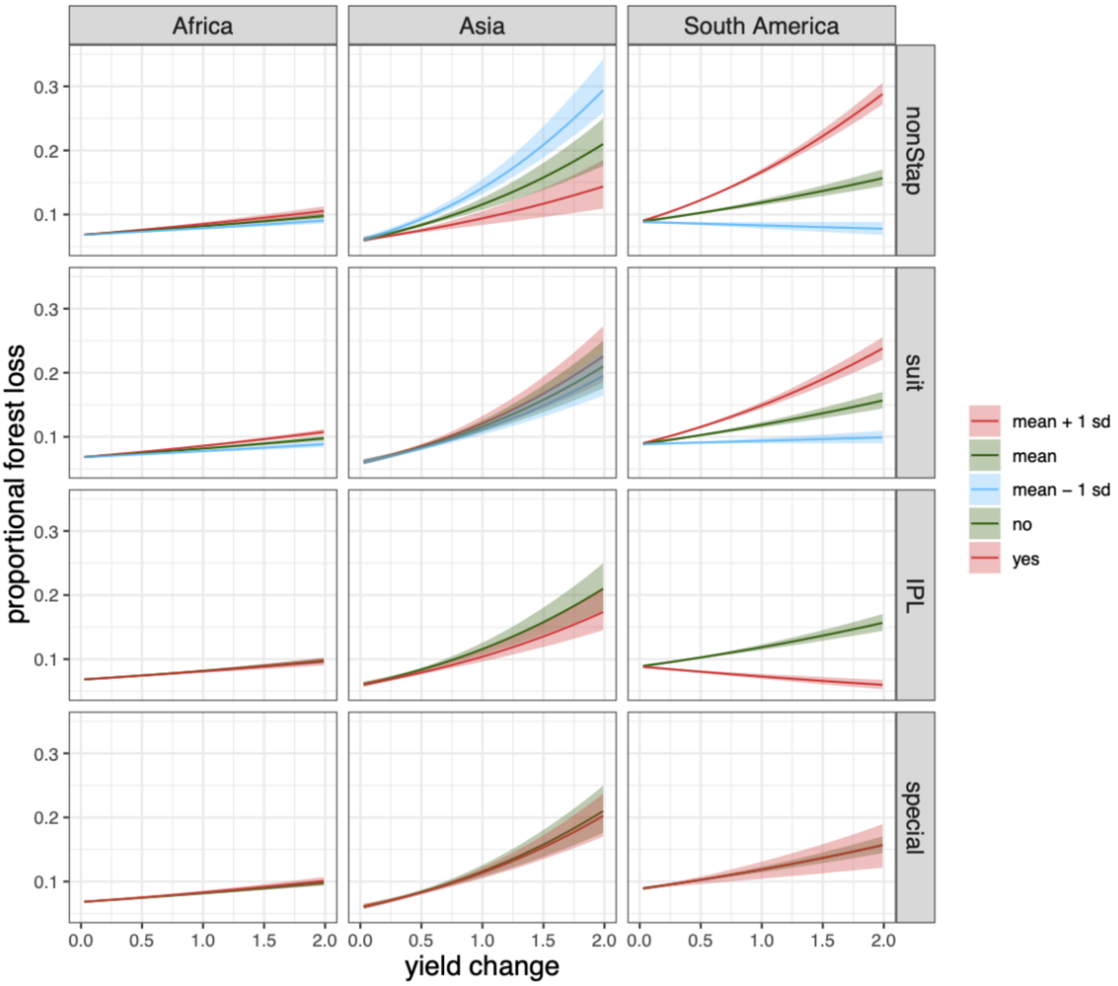

***Figure 7: Conditional effects of yield change interactions on continent level**. Curves show the mean effect and 95% credible interval of the posterior distribution for the average sample. Green curves are identical for every continent column.*

Stratifying the analysis for specific crop groups yielded similar results regarding ΔY-effect of staple crops: ΔY was positively correlated with forest loss but of smaller magnitude than the estimated effect of mean ΔY (mean 0.037; SE 0.01). Effect modifiers caused qualitatively similar outcomes (Appendix J). In contrast, *ΔY* effect estimates of non-staple crops were not significant (mean -0.012; SE 0.08). Still, some significant results were obtained regarding modifying effects of *IPL* and *special*. Posterior contrasts between *ΔY* effect with and without *IPL* indicated that Indigenous/community land management alleviated *ΔY* effect on forest loss in Asia and South America under every *ΔY* setting, and for non-staple crops in Africa (Figure 8).

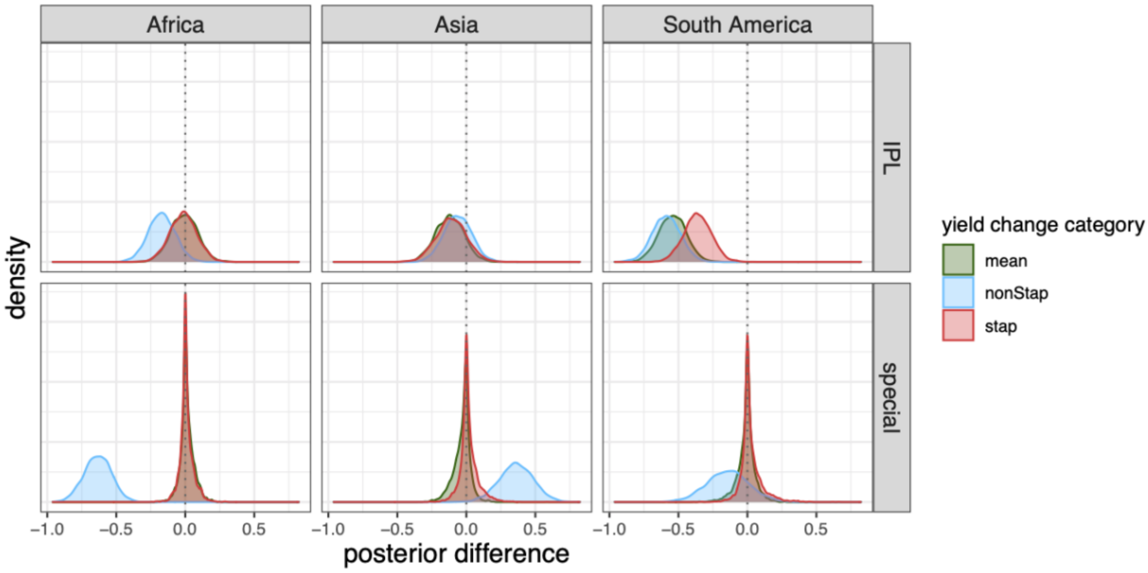

Figure 8: Posterior contrasts. *The curves visualize the posterior expected difference of the effects of IPL and special. Large parts of the distribution different from 0 indicate that the effect is meaningful.*

The estimated *ΔY*-effect difference regarding susceptibility to the specialization trap was not evident for mean and staple-crops but did suggest an impact when conditioning forest loss on non-staple crops' *ΔY*. While in Africa and South America, non-staple crops' *ΔY* effect on forest loss was estimated lower in countries classified as resource-specialized, *ΔY* effect was amplified in those Asian countries (Figure 8).

Finally, mapping model predictions of *ΔY*-associated forest loss for the next 20 years under extrapolated *ΔY* patterns revealed varying deforestation threat from intensification spillovers in global TDF (Figure 9). Although proportional forest loss predictions mainly reflected country-level *ΔY*-baseline differences (with partly extremely high levels of extrapolated *ΔY* e.g., 13.7 for Zimbabwe, 5.8 for Brazil), mapped outcomes gave an informative picture of continent-level effect variation (Figure 9a). In South America and Asia, input *ΔY* values translated into particularly high forest loss, while modeled loss was comparably lower in Africa.

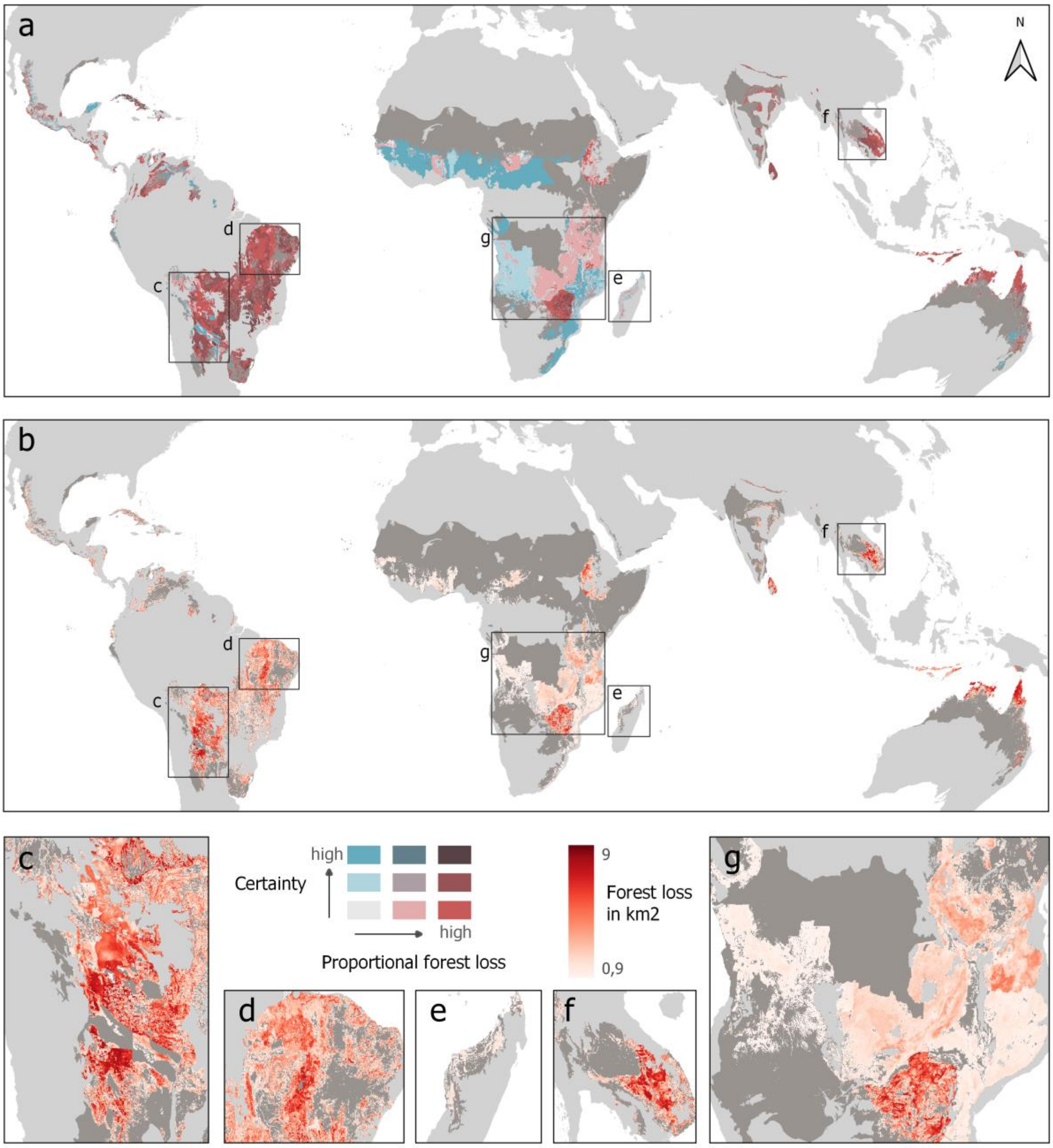

__Figure 9: Modeled forest loss from intensification spillovers__ based on continuing yield change patterns. Predictions draw upon a hypothetical scenario of extrapolating past 10 years' yield change 20 years into the future. The effect of population density was disregarded, and all other model parameters (nonStap, suit, IPL, special, accessibility) remained unchanged. Proportional forest loss and certainty represent the mean posterior estimate and the posterior standard error (comprising both parameter uncertainty and predictive uncertainty) (a). Forest loss in km^2 was calculated by multiplying the modeled proportional forest loss per grid cell by forest cover in 2020 (b). Insets show zoom-in to deforestation hotspots in the South American Gran Chaco & Chiquitano (c), Cerrado & Caatinga (d), African Miombo and Mopane woodlands (e), Madagascar (f) and Indochina tropical dry forests (g).

Influences of effect modifiers manifesting at finer spatial scales (*IPL*, *suit*, and *access*) led to pronounced regional differences. This was especially notable in large countries such as Brazil and Argentina where modeled forest loss covered wide value ranges despite equal continent-, and country-level baseline conditions (Figure 9a). There was no correlation of uncertainty and modeled forest loss magnitude but especially in South American and Southeast Asian deforestation hotspots, a considerable amount of grid cells exhibited both high modeled forest loss and high model certainty (Figure 9a). In India and Australia, predictions were generally more uncertain (Figure 9a). Forest loss predictions in km^2 based on present forest cover in 2020 showed high overall dynamics (Figure 9b). Especially in deforestation hotspot regions in South America and Southeast Asia, forest loss was predicted to stay high, yet with fine-scale differences tracing back to both variation in present forest cover and fine-scale effect modifiers (Figure 9c,d,f). In contrast, modeled forest loss was lower in Madagascar and large parts of African Miombo woodlands (Figure 9e,g).

5. Discussion

Spillovers of agricultural intensification are divers and complex, but my results imply that overall, intensification fails to spare land in the world's TDF. Over the study period, higher yields have reinforced rather than reduced forest loss, thus supporting the existence of a rebound effect. At the same time, my results underline the diversity of intensification outcomes as yield change was positively correlated with dispersion of forest loss. Hence, land sparing or rebound effect is not an explicit "either-or" choice but is highly context dependent. In my analysis, I identified economic, agroecological, and sociocultural factors together with continent-level baseline conditions that impact land system dynamics and diversify intensification spillovers.

5.1. Conditioning factors of intensification spillovers

The dominant influence of market opportunities in commercialized agriculture hampers land sparing

To scrutinize the effect of market dynamics and price elasticity on the outcomes of intensification, I included share of non-staple crops in the model as a measure of high agricultural profitability and international market integration. In line with many studies[16,24,25,31–34,39,44,63,64], my results demonstrate that globally, under high shares of non-staple/commodity crop production, intensification reinforces deforestation instead of promoting land sparing. These findings add to the general consensus that commercialized commodity agriculture producing for international markets is the major driver of cropland expansion[58,107,140]. Since global integration of commodity markets through trade has decoupled demand from local consumption limits[140], efficiency gains directly increase returns to land. Land use expansion is especially responsive to commodity prices[20] so that high profitability of commodity cultivation logically acts as an incentive to expand the crop frontier under increased productivity.

The effect of market dynamics and price elasticity varied by continent. Share of non-staple crop production most markedly increased risk of rebound effect in South America. This result reflects the wave of large-scale, industrialized agricultural expansion that has occurred in South American dry forest regions and triggered the most rapid rates of deforestation since 2000[95]. Today, agricultural frontiers in South American TDF are increasingly driven by capitalized corporate commodity farming, especially in the Dry Chaco[141,142], the Chiquitano forests[101], or Venezuelan Llanos[69]. Usually, these highly capitalized, well-organized farmers operate with little direct government intervention[142] – a facilitating condition for rebound effects that can turn the spread of large-scale, highly capitalized commodity farms into an escalating driving force of contemporary deforestation frontiers.

In Africa, the effect of non-staple crop production shares was smaller und uncertain which is not surprising, given subsistence or smallholder land use is more widespread in Africa than commodity farming[95,104,143]. Accordingly, African deforestation frontiers are mostly associated with conditions typical for smallholder regions i.e., high prevalence of shifting agriculture and small field sizes, and thus less responsive to incentives from global commodity markets[107]. Yet, recent events such as emerging large-scale plantations and increasing industrial operations in the Miombo forests suggest this pattern may be changing[26,104], and pressure on forests induced by international trade is becoming more prevalent[107]. Moreover, expanding African frontiers indicate strong similarities to South American frontiers regarding environmental, institutional, and other contextual conditions and might be further accelerated by recently documented knowledge transfer, cooperation, and public and private sector linkages between the two continents' TDF regions[103]. The increasing influence of distant markets in Africa, manifesting in both expanding commodity farming for export and intensification from increasing foreign investments[104], is an alarming trend that might trigger strong rebound effects and resulting deforestation.

In Asia, model results, though associated with high uncertainty, contradicted rationale 1: In contrast to the other regions and the global average, high levels of production share of non-staple crops reduced intensification-related forest loss. This is surprising given Asian TDF faces similarly high threats from rapidly expanding commodity frontiers as South America, and encompasses several commodity frontier hotspots such as Indochina TDF and Southern Vietnam lowland dry forests[96,99,144]. These unexpected results might be due to the applied distinction of staple crops and non-staple crops. While major agricultural export in Asia indeed traces back to "classical" non-staple/commodity crops such as palm oil, rubber and coffee[107,145], also rice is strongly associated with international market destinations[145]. However, in my study, rice was classified as staple-crop, since it is one of the most important food crops with more than 80% of the world's rice produced and consumed by small-scale farmers[146]. This discrepancy might confound model results of the effect of production share of non-staple crops in Asia.

Given commercialized commodity production crucially shapes the outcomes of intensifying practices, it might appear counterintuitive that the model obtained the same results when conditioning on intensification only within staple crops. Still, findings are plausible because Ewers et al. documented how land sparing effects of staple crops enabled by risen yields were counteracted and partly canceled by a tendency of increasing cropland areas for non-staple crops, arguably because intensification frees up labor, capital or land for other crops[39].

Today, smallholders producing food crops for households or local markets have been more and more supplemented and replaced by industrialized agribusinesses[107]. Even the remotest areas can be integrated in global markets, and agricultural frontiers are mainly driven by the expansion of large-scale highly capitalized farming targeted at exporting agricultural commodities[5,58,142]. Although in the last decades, commodity frontier dynamics played a more important role in driving deforestation in the wet tropics[95], a geographic shift away from Brazilian rainforests towards tropical forests elsewhere was recently observable[147].

Clearly, this trend weakens the fundamental assumption of the Borlaug hypothesis of land sparing relying on inelastic demand of agricultural products. Given staple production for closed local markets is increasingly replaced by commodity production for globalized markets, above-described findings pose a major challenge to achieve land sparing under current trends of global agriculture.

Agroecological or accessibility constraints lower the risk of rebound effect in the concerned areas

In support of rationale 2, my results suggest that land sparing is more likely under conditions of restricted land availability determined by agroecological suitability and accessibility. Low suitability had a moderating effect on rebound effect-induced forest loss which is consistent with case studies observing how intensifying technologies in productive lowlands are likely to discourage forest clearing in the less productive uplands[35–37]. Provided that intensification in lowlands satisfies demand for food-stuffs, abandonment of less suitable cultivation in uplands can be motivated by more labor-intensive technologies attracting labor away from the forest margins[35,36], or by declining populations in uplands[107].

Furthermore, my results suggest that remotely located areas face lower risk of rebound effect. This finding highlights the importance of neighborhood effects on agricultural dynamics and adds to the theory of agglomeration economies arguing that the likelihood of an area being converted to agriculture is strongly linked to the socioeconomic conditions of a location's surrounding[28]. In the South American Dry Chaco, land clearing dynamics have been crucially associated to the proximity to already cleared areas, and especially systems oriented to the production of international commodities have shown to attract investment to places near to already developed areas[148]. Given agricultural intensification increases profitability and incentives to invest in agricultural expansion thus spurring the growth of supply chain infrastructure[28], these neighborhood effects of agglomeration economies can trigger strong rebound effects.

However, while suitability and accessibility constraints have shown to decrease the risk of intensification-induced forest loss for an individual location, my results do not provide insights about their impact on broad scale land dynamics. An alternative interpretation could be that these fine-scale features determine only the spatial distribution of forest loss without interfering in broad scale drivers of land use change[149].

Finally, although limited accessibility in the tropics has effectively restricted agricultural expansion in the past and thereby facilitated land sparing, this constraint is diminishing with the emergence of commodity frontiers. Increasingly, large-scale agribusinesses have the capital to overcome accessibility constraints and build extensive networks of roads that in turn facilitate additional clearing[107,142].

Economic incentives likely outrank policy-imposed restrictions

Against my expectation formulated in rationale 3, land protection and governance quality did not assist in explaining intensification outcomes. First, the lack of identified effects might be due to the coarse country-level resolution of my data on governance and land protection. Second, impact of land protection can be offset by leakage effects[64], describing how land use zoning leads to displacement of production outside the regions subject to zoning[12]. Third, although Ceddia et al. documented a significant effect of governance type on intensification spillovers[27], other studies argue that economic factors can be a much stronger deforestation force compared with domestic legal frameworks[150], which is worrisome given market barriers are more and more diminishing. Especially in Africa, some of the prevailing main agronomic constraints are expected to be overcome within the next few years through improved governance, economic liberalization, market deregulation, and investments into agricultural modernization, technology, and infrastructure[103]. Steadily, most governments have shifted from a role of planning to one of facilitation[107] or of nonintervention[142]. With regard to governing intensification spillovers, such dominating influence of globalized markets over domestic governance would critically confine the scope of management opportunities in favor of land sparing.

Indigenous or community land management facilitates land sparing in South America

In Indigenous or community managed lands in South America, intensification is likely resulting in land sparing. In contrast, rebound effect is more probable in the absence of Indigenous/community management (representing any other tenure regime), thus supporting rationale 4. These findings are in accordance with most case studies identifying positive effects of Indigenous/community land management on nature conservation and forest loss prevention[68,69,151].

Indigenous or community land use systems often entail characteristics that make them less prone to the drive to increase profitability, thereby fostering land sparing instead of rebound effects. First, many Indigenous-led management approaches are compatible with, or actively support, ecosystem conservation, by “accompanying” natural processes of preserving and restoring ecosystems, and developing innovative ways to design conservation reserves, environmental policy instruments, and management programs[117]. Second, traditional Indigenous or community land use is often based on collective ownership, and fulfils the requirements for successfully managing common-property resources[68]. These conditions include clearly defined boundaries, collective management, the recognition of rights to organize, monitoring systems, sanctions, and conflict resolution mechanisms[152].

Surprisingly, the conditioning effect of Indigenous/community land management on the intensification outcome was considerably lower and more uncertain in Africa and Asia. One explanation for Africa could be the prevalence of slash and burn farming of local community-managed agriculture in TDF. When land is abundant, this farming practice is associated with extensive forest loss[60,107,153]. Another reason could be that, although large parts of the continents' land is covered by various forms of customary rights by Indigenous and local communities, many areas are not formally recognized as either owned by or designated for Indigenous/local communities[154]. For much land, the legal recipient of the formal title is unclear and tenure is often overlapping with public or private territories[10]. These ambiguities and the resulting uncertainty affect land management decisions and tend to undermine the positive conservation impacts that are usually associated with Indigenous/community management[68,151].

So far, many common land theories and conservation frameworks have not appropriately reflected the critical role of Indigenous and local communities in providing sustainable pathways to land-related challenges. Urbancic further argues that to reverse the trends of deforestation, perception of nature and property has to shift away from a Western anthropocentric view closer to the Indigenous worldview[155]. For these reasons, land formalization, and increased acknowledgment of Indigenous peoples' unique ties with nature and land use approaches can play an important role in facilitating sustainable intensification outcomes[10,69].

The specialization trap does not manifest itself in the modeled effects

Rationale 5 - predicting higher risk of rebound effect to resource specialized low-income countries because of market power asymmetries - was not supported by my results. The outcome differs from previous findings, documenting how productivity increases trigger a stronger rebound effect in low income countries than in high income countries[44], cause displacement of agricultural land to low-income countries[63], or spare the largest part of land with potential for forest regenerations in the global North[15].

My seemingly contradicting results might trace back to the relative homogeneity of countries included in my study. Although countries differed by stage of economic development and role of primary sector, most countries in the dry tropics held lower positions in global supply chains and are not among the ones most clearly documented as displacing environmental costs to other places (US, EU, Canada, Japan)[5,45,75]. Indeed, many included regions are hotspots of deforestation embodied in international trade[5]. Given this unbalanced distribution within susceptibility to the specialization trap, the model likely had difficulties to statistically explore and identify effects of trade patterns on intensification spillovers.

Still, impact of trade patterns on intensification spillovers should be further scrutinized because the increasing integration of the world via international trade requires explanations for forest loss beyond national dynamics[22,58]. It is well documented that globalization is accelerating the separation between places of production and consumption, most often implying a geographic displacement of land use from the global north to the global south[5,19,156]. As a consequence, tropical forests experience ongoing and intensifying pressure from agricultural expansion while the global deforestation rate was reported to be decreasing[5,156]. This trend is accelerating, especially since increasing demand for livestock products and biofuels generated new international trade flows and pressures on tropical forests[39,107], so that some of the major current sustainability challenges are predictable consequences of structural trade patterns, hampering sustainability through displacing extractive frontiers[74]. For this reason, critical sociological perspectives related to world system theories, such as the specialization trap and ecologically unequal exchange[72,76,78] can play an important role in understanding intensification outcomes as social-ecological traps[85] and should be better integrated in land system theories on spillovers and displacement[12].

Market opportunities supersede rural population change as main driver of forest dynamics

Finally, the uncertainty in the modeled effect of rural population density on forest loss might be due to a general change in the drivers of tropical deforestation. While before the 1990s, deforestation was mostly attributed to shifting cultivators and smallholders in rural landscapes[107,140], today, agricultural expansion is rather driven by urban and global demand[7,143]. This shift reflects that contemporary deforestation frontiers are better explained by economic incentives than by local demand[57,107,142], thus highlighting another weakness of the Borlaug hypothesis of land sparing.

5.2. Limitations

My study has some limitations mainly associated with operationalizing intensification and related land outcomes, as well as challenges linked to input data.

Using yield growth as measure of intensification implies a simplified, monodimensional representation of land-use intensity[157,158]. It considers only the output per land unit, resulting in two major shortcomings. First, it does not distinguish among land productivity increased through technological improvements, through higher inputs per land unit (e.g., labor and capital-based inputs, or technology), or through higher frequency of land use (e.g., multiple harvests)[12]. For this reason, some authors have suggested to consider more precisely technological progress in agriculture by the measure of total factor productivity (i.e. the efficiency of the overall mix of production factors (land, labor, and capital) due to improved technologies, farmer's skills, and knowledge)[44,60,159]. Indeed, Rodríguez García et al. obtained slightly different results for yield and total factor productivity when using both measures of intensification in their analysis[44]. Second, by hiding the practice behind increased output per land unit, yield does not tell whether intensification occurred in a sustainable way, thus potentially missing crucial impacts on biodiversity and ecosystem properties[157,160,161]. Intensification that degrades the environment and surrounding natural systems through agrochemical pollution, altered species or carbon emissions incurs significant environmental costs, even if it spares land[160]. Therefore, closer consideration would be needed to scrutinize whether taken together, environmental costs outweighed the benefits of land sparing. Although these limitations constitute substantial simplifications in my analysis, they do not directly compromise my findings – anyways already questioning the strategy towards land sparing.

Another difficulty comes from measuring the extent of spared land or rebound effect-triggered cropland expansion. In my study, I used forest loss as a proxy for cropland expansion resulting in three shortcomings. First, there is no explicit data on land sparing since cropland abandonment is not included in my study. Only implicitly, land sparing is represented by comparably lower rates of forest loss given certain yield growth and considering changes in demand from rural population. Second, beyond expansion into forests, cropland may also replace other lands such as existing farmland or pasture[26]. Yet, this inaccuracy is negligible as the largest share of new cropland areas in the tropics actually comes at the expense of forests[60,109,110], and consequences for forest ecosystems are of most interest when scrutinizing conservation impacts of potential land sparing[13,14,45]. Third, reported forest loss might be due to land-cover changes other than cropland expansion. Here, particularly wildfires are an intrinsic part of the natural dry forest ecosystem[48]. However today, many fire events can be traced back to anthropogenic causes, often signaling clearance for agricultural purposes[48,143]. Therefore, fires in TDF, though occurring also naturally, are often part of frontier-making processes. Apart from that, the most important driver of deforestation other than cropland expansion is the creation of pasture lands for cattle ranches. Especially in South America, cattle farming spurred vast deforestation, often outranking cropland expansion as proximate cause of forest loss[107,162]. Yet also here, forest clearing for pasture is often connected to cropland expansion forming a coupled frontier: forests are initially cleared for ranching, but farmers shift to cropping once they have acquired enough capital[163]. As a result, cropland expansion indirectly drives deforestation by displacing grazing lands and pushing pasture forward into the forest frontier[31,109,164] so that eventually, forest loss remains a valid proxy for cropland expansions in the tropics.

Another major weakness of my study is the spatial resolution of input data and temporal resolution of my model. Many variables (yield change, production share of export and non-staple crops, proportion of protected areas, governance scores, resource specialization and income class) are only available on country level. The use of aggregated information over such large units hampers the explanation of spatially explicit land use dynamics occurring at finer scales. Further, the temporal resolution in my analysis constitutes one timestep encompassing 20 years (2001-2020). Such temporal aggregation bears the risk to miss finer temporal dynamics and especially neglect potential time lags of the scrutinized effects. To minimize this, I performed robustness checks that supported the assumed constancy of modeled effects.

Additionally, there are sources of potential errors linked to the datasets I derived my variables from. First, data on forest cover and annual forest loss from Global Forest Watch based on the remote-sensing derived global forest dataset by Hansen et al.[96] entails some inherent weaknesses. Of particular importance for my study is the uncertainty in forest-grassland transition areas where tree cover is on the margin of the remote sensing definition of forest. Besides, remote sensing forest data cannot discriminate between sources of forest loss, thus equally reporting conversion of natural ecosystems and harvesting of non-native plantations. Also, I did not include forest gain data because they were unavailable for my full analysis period, are less certain than forest loss, and include forest plantations. Having said that, the utilized data on forest cover and loss have an overall accuracy of more than 80%, which is further increased through aggregating on a coarser grid[96]. Second, the FAOSTAT dataset has been criticized for containing inconsistencies among countries in compiling information and estimates of yields, outputs, and area of farmland[165], although FAO has officially outlined rules for collecting data and defining measures[111]. Nevertheless, it remains the only global long-term, cross-country dataset, and a comparative analysis with and without countries with the lowest-quality data revealed that substantive findings remained the same, thus promoting the use of FAO data despite the mentioned limitations[43].

Finally, there are aspects that were out of the scope of this work but that represent important issues requiring further investigation. First, higher quantity of agricultural production does not guarantee less hunger. Most famines are caused by a lack of access to food, rather than too little food[166]. To more specifically address these issues, focus needs to shift from agricultural production to food production, food security, or food sovereignty[167]. Second, land is source and focus of multiple meanings and values[10], and provides more valued goods than the ones considered in my analysis. Different believes and perspectives influence claims regarding the use and expected benefits of land[168] and especially in multifunctional landscapes with rich cultures and histories, reducing land use decisions to production and conservation does not comply with this diversity of notions connected to land[166,167]. Third, transformations of land use systems have important consequences for local livelihoods that were not taken into account in my study such as risk of increased social inequality and conflicts[26]. Addressing social justice is practically and ethically complex[64], and the goal of optimizing land use regarding production and conservation might be coherent with, but is distinct from improving local livelihoods. Especially when ecosystem conservation is set as target, additional measures such as increasing nonagricultural job opportunities for marginalized groups should be crucially considered[64].

Generally, the challenge is to move on from thinking about higher yields as a unidimensional land-use strategy, being shaped by the dichotomous interplay of market incentives on one hand and restrictive regulations on the other hand[152]. Instead, the debate of land sparing versus rebound effect could gain from more solution-based approaches such as enhancing productivity through sustainable intensification or agroforestry[14,169,170].

Moreover, common-pool resource theory could contribute to more adequately dealing with the wide diversity of institutional arrangements that humans craft to govern, provide, and manage common-pool resources[152]. Given the role of forests in climate change mitigation and carbon sequestration, the biodiversity they contain, and their contribution to rural livelihoods, efforts regarding just and effective land use solutions could benefit from a perspective towards more stewardship of land as a global commons[171].

5.3. Facilitating land sparing under today's challenges

Despite some conceptual and data-related limitations, my study has contributed to identifying and estimating causal pathways of how intensification relates to deforestation in TDF. While many studies remain confined by disciplinary boundaries[45], I seeked to integrate concepts across disciplines to do justice to the fundamentally interdisciplinary nature of land systems science. The systemic perspective I applied to account for complexity of land systems provided insights on mechanisms occurring at multiple scales and allowed comparison across space. For this purpose of statistically investigating complex social-ecological systems, the multilevel Bayesian approach has proven advantageous, particularly because epistemic uncertainties and prior knowledge are naturally incorporated. Causal pathways derived inform about mechanisms but also about their robustness or associated uncertainties.

Gained insights should feed into future strategies and policy recommendations to balance land-use tradeoffs – especially because available evidence suggests that given likely rates of technological progress and future growth in demand for land-based products, the world is still far from "peak cropland"[20]. At the same time, many TDF regions fall into early stages of emerging deforestation frontiers[89]. Given policies and management that prevent undesired, irreversible impacts bring more overall benefits than trying to restore land afterwards[172], there is urgent need for forward-looking sustainability planning. Here, avoiding undesired spillovers of agricultural intensification plays a key role but counteracting interventions can only be successful when they are contextual and adaptive, and are based on their overall expected impacts, instead of focusing only on the direct local land impact[10]. My results revealed that there are critical conditions that make places more susceptible to rebound effects of intensification so that some general conclusions can be derived.

Most importantly, improved productivity will in itself not halt deforestation but, under most prevailing conditions and trends of global agriculture, rather motivate agricultural expansion and accelerate deforestation with devastating consequences for forest ecosystems in the dry tropics. Major effort to prevent such rebound effect must address economic incentives of commercialized commodity agriculture, because relying on market mechanisms risks turning intensification into an escalating driving force of cropland expansion due to the drive to increase profits inherent in commercialized production systems. While it must be acknowledged that local governance requires robust legal frameworks to curb market opportunities, strong restrictions on land use will be crucial to limit rebound effects of commodities with globalized markets and elastic demand[64]. Furthermore a shifting focus from agricultural production to food security might serve as a conceptual basis for strategies[167], especially given non-staple production contributes little to improving food availability[26]. Supporting alternative agricultural systems and emphasizing autonomy of local, small-scale production as argued by the concept of food sovereignty[173], can be the groundwork for action.

Generally, policies to reduce the risk of rebound effects among smallholders or local communities must be fundamentally different than the ones targeted at industrial-scale, export-oriented agriculture[64,140]. In the case of staples grown by smallholders, supporting them to increase their yields might be more appropriate. For example, replacing extensive slash and burn farming systems is a precondition for slowing forest loss from shifting cultivation in many TDF regions but must necessarily be accompanied by actions controlling for rebound effect from economic incentives[60,153,174]. Moreover, yield-enhancing measures should be intentionally directed toward certain areas and not others, reflecting the findings on mechanisms of land restrictions. Indigenous and community-management can to some extent serve as a guidance for strategies against rebound effect, building on their often fundamentally different relation to nature and successful common-property management of ecosystems. With globally, up to 65% of the world's land area being covered by various forms of customary rights by Indigenous Peoples and local communities but only a small part of it formally recognized[154], land formalization can play an important role.

Finally, land use strategies should adapt to region-specific trade positions[175]. This is especially important since novel global arrangements such as transnational cooperations and trade agreements often entail a considerable risk that environmental regulations will be corrupted or diluted by powerful special interests[64,176,177]. To avoid reinforcing inequalities and asymmetric trade patterns, governance interventions need to explicitly address these[10]. Attention to prevent social-ecological traps and asymmetries reproducing global socioeconomic inequalities and hampering sustainability through displacing extractive frontiers to economically less developed countries is thereby crucial.

Ultimately, not all trade-offs can be addressed by managing the supply-side of land systems, and there is a need for more effective approaches to managing demand and consumption grounded on acknowledging the limits of consumption that humanity can derive from land[10]. Major transformative changes in the global economy and altered consumption patterns are necessary to reconcile sustainability and the needs of a growing world population, but how such cultural shift and transformative change could take place remains an open question[73].

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Appendix

A. Yield change calculation

I operationalized agricultural intensification as country-level yield change, calculated in a three-step procedure: First, yearly yield changes of different crop groups were calculated separately compared to the mean of the two previous years. Since by definition, spillovers have a time lag of ≥ 1 time step, the time 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.

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

Second, yearly yield change on country level was compiled as average of crop group-specific yield change weighted by the respective proportion of harvested area in 2000 (HA_c). 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.

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

The resulting yield trajectories in Figure A.1 revealed that most countries experienced relatively steady yield dynamics over the entire study period, thus meeting the conditions to summarize yield over time without neglecting crucial patterns. Accordingly, as last step, I aggregated study-level country yield change (for staple crops, non-staple crops, and overall mean) as product of yearly 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 overall decline in yield (Figure A.2).

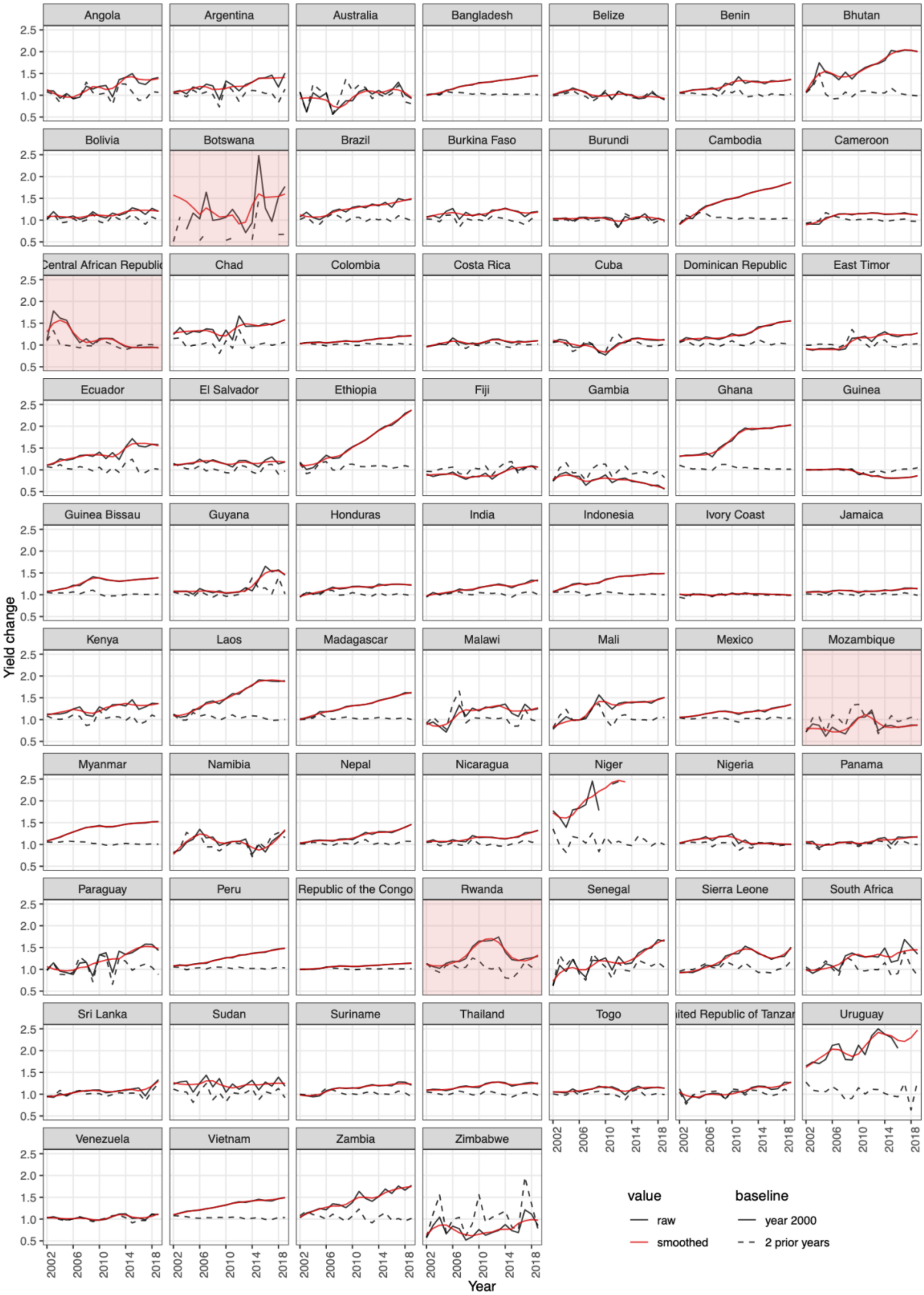

__Figure A.1: Yield change trajectories__. The curves represent country-level yield changes normalized to the value in 2000 regarding the starting year 2000 (solid line), or the mean of the two prior years (dashed line). Unlike those marked in red, all included countries show relatively steady yield increases (or decreases). Therefore, aggregating over the entire study period does not hide significant dynamics that would undermine my analysis.

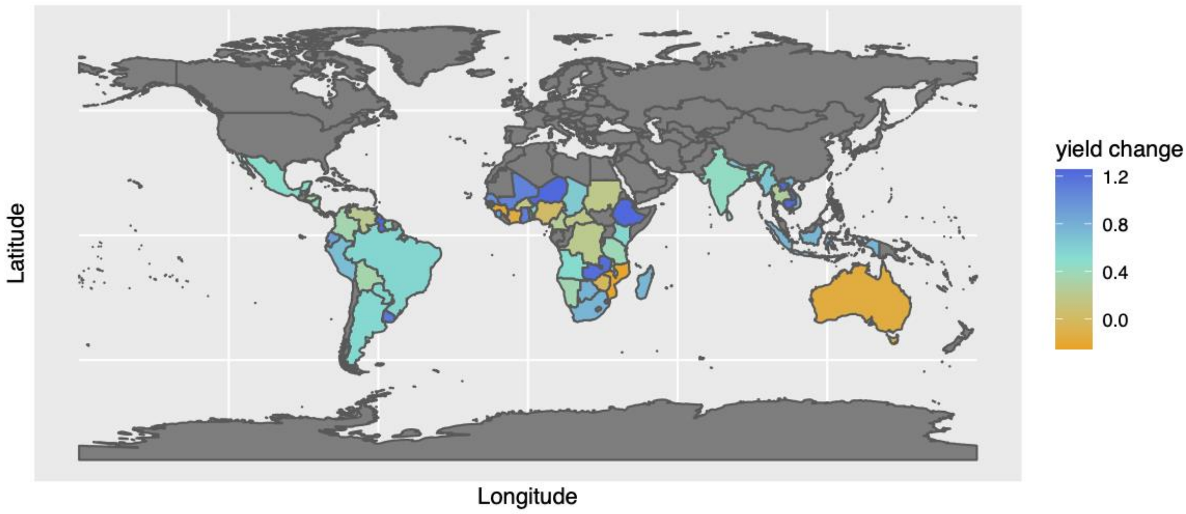

Figure A.2: Aggregated country-level yield change. Positive (negative) yield change represents increasing (decreasing) yield over the period 2000-2019. Only countries with TDF are included in the study.

B. Generalized propensity score

Hirano and Imbens[131] developed the propensity score for continuous treatments (GPS) as an generalization regarding propensity score for binary treatment[128]. In binary treatment context, the potential outcomes (*Y(1)* and *Y(0)*) are assumed to be independent of binary treatment (*D*) given the propensity scores (*e(X)*):

$$Y(1), Y(0) \perp D | e(X)$$

The key extension of the GPS is the weak unconfoundedness assumption, entailing that not joint independence of all potential outcomes is required, but instead conditional independence to hold for each value of the treatment[131]. Hence, with *T* as a continuous treatment variable, the potential outcome when *T=t* is unrelated to the treatment given the set of covariates:

$$Y(t) \perp T | X$$

With *r(t, x)* as the conditional density of the treatment given the covariates, the GPS is

$$R = r(T, X)$$

The GPS has a balancing property: within strata with the same value of *r(t, X)*, the probability that *T=t* does not depend on the value of *X*[131].

$$X \perp 1\{T = t\} | r(t, X)$$

Once GPS is estimated for each observation, it is used to statistically balance across the treatment range and adjust for dissimilar treatment exposure by including the inverse of the propensity scores as weights to the model[130].

C. Bayes theorem

The crucial principle of Bayesian inference is Bayes theorem where a probability distribution $P(\theta|D)$ is derived reflecting knowledge about the parameter, given both data and prior information.

$$P(\theta|D) = \frac{P(\theta)P(D|\theta)}{\int P(\theta')P(D|\theta')d\theta'}$$

Therefore, the likelihood $P(D|\theta)$, specifying how likely an observation of data D is for each value of parameters θ, is multiplied by a prior distribution $P(\theta)$, specifying prior knowledge about the probability distribution of unknown parameter values, and normalized by the term in the denominator, specifying the probability of the data averaged over $P(\theta)$[134]. In other words, Bayesian methods combine a model of the data with prior information with the goal of obtaining inferences that are consistent with prior knowledge and the empirical evidence[135]. These inferences are summarized by a set of simulations of the model parameters.

D. Beta distribution

Beta regression uses the beta distribution as the likelihood for the data,

$$Beta(y|\alpha,\beta) = \frac{y^{\alpha-1}(1-y)^{\beta-1}}{B(\alpha,\beta)}$$

where B() is the beta function. The shape parameters for the distribution are a and b and enter the model according to the following transformations to mean μ and precision ϕ.

$$\mu = \frac{\alpha}{\alpha+\beta}$$

$$\phi = \alpha + \beta$$

E. Predictor transformation

To facilitate meaningful parameter interpretation, I transformed predictor variables. Regarding key predictor variable *ΔY*, I performed a context-based standardization by subtracting 1, so that positive values indicate intensification while negative ones suggest decreasing productivity. All remaining predictors were conventionally standardized by subtracting the mean and dividing by the standard deviation. As a result, their coefficients can be interpreted in units of standard deviations which is helpful given standard deviations can be seen as a measure of practical significance roughly reflecting a typical difference between the mean and a randomly drawn observation[135]. For coding binary predictors (*IPL* and *special*), I used an indicator approach. Such approach must be applied with caution because it automatically implies that the absence of *IPL* and *special* is inherently more certain than their presence since conditioning on the latter includes one additional model parameter and thereby allows for more propagating uncertainty. However, in my study, the choice is reasoned to avoid boosting model run time due to non-linear syntax in model coding associated with the alternative approach of using index values for categorical variables. Furthermore, the assumption of both Indigenous land management and susceptibility regarding specialization trap adding more uncertainty to the intensification-deforestation-relationship can be contextually justified.

F. Predictive checks

Predictive checks constitute an important tool in Bayesian analysis because they inform about model performance. Prior predictive checks generate hypothetical data according to the prior specifications to assess plausibility of prior implications. In my case, prior settings proved appropriate because they bounded the range of possible prediction curves, while still allowing distributions that differ considerably from the observations (Figure F.1, left). Hence, priors successfully incorporated scientific knowledge into the model without predetermining modeling results. Posterior predictive checks provide insights about the reliability of the model by demonstrating how well it retrodicts the observations. Here, the final model demonstrated good predictive performance because comparing the replicated predictions sampled from the posterior predictive distribution to a random draw of observed data revealed high conformity (Figure F.1, right).

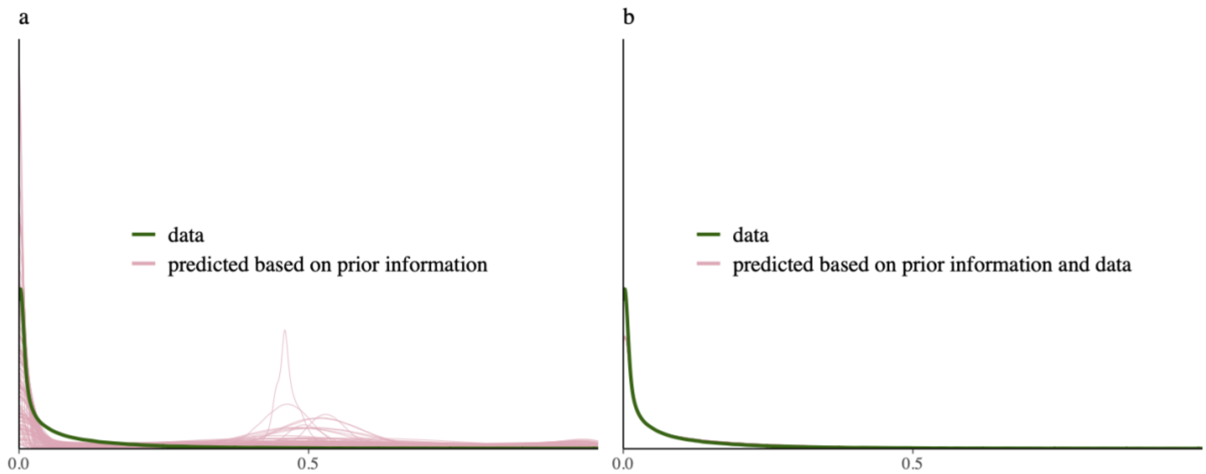

__Figure F.1: Predictive checks__. Comparing observations to a sample of 100 (a) prior model predictions generated according to prior specifications, and (b) posterior model predictions generated according to modeled posterior distributions based on priors __and data__, provided insights about plausibility of model settings and reliability of model results.

G. Sampling diagnostics

Trace plots show the evolution of the parameter vector over the iterations of one (or more) Markov chains. To gain insights about reliability of the MCMC sampling process, they were checked regarding stationarity (i.e., chains moving around a stable central tendency), good mixing (i.e., chains rapidly exploring the full parameter region), and convergence (i.e., independent chains moving around the same region of high probability). All outlined criteria were met in my model runs (Figure G.1, based on final model, exemplary for all model runs).

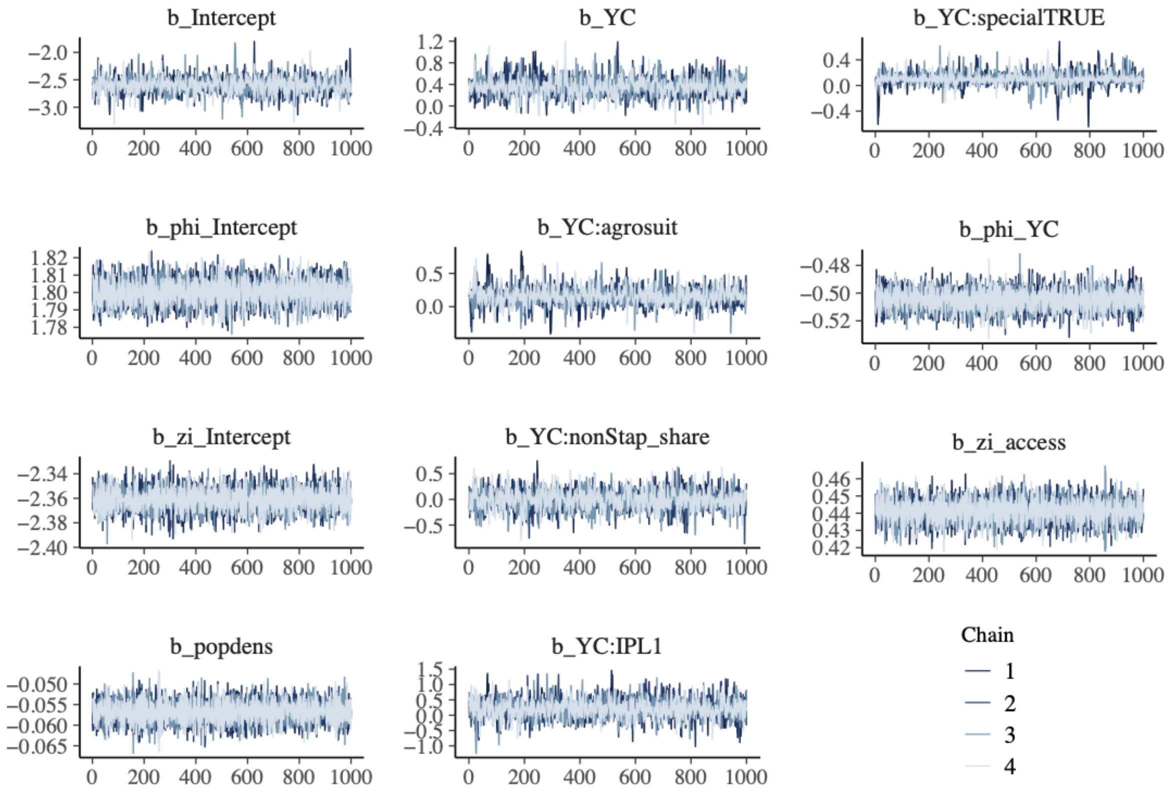

Figure G.1: Trace plots of effect parameter estimation in final model *exhibit stationarity, decent mixing and convergence of the independent Markov chains. These features indicate high sampling reliability.*

H. Robustness check

To check robustness regarding potential time lags of intensification impact on deforestation, I statistically investigated the effect of *ΔY* from earlier time periods (1981-2020 and 1991-2010) on forest loss in the study period (2001-2020). Resulting model estimates demonstrate that conditioning present forest loss on past yield change generated similar relationships. This strengthens the assumption that the temporal design of my analysis did not miss significant time lag effects of intensification on deforestation.

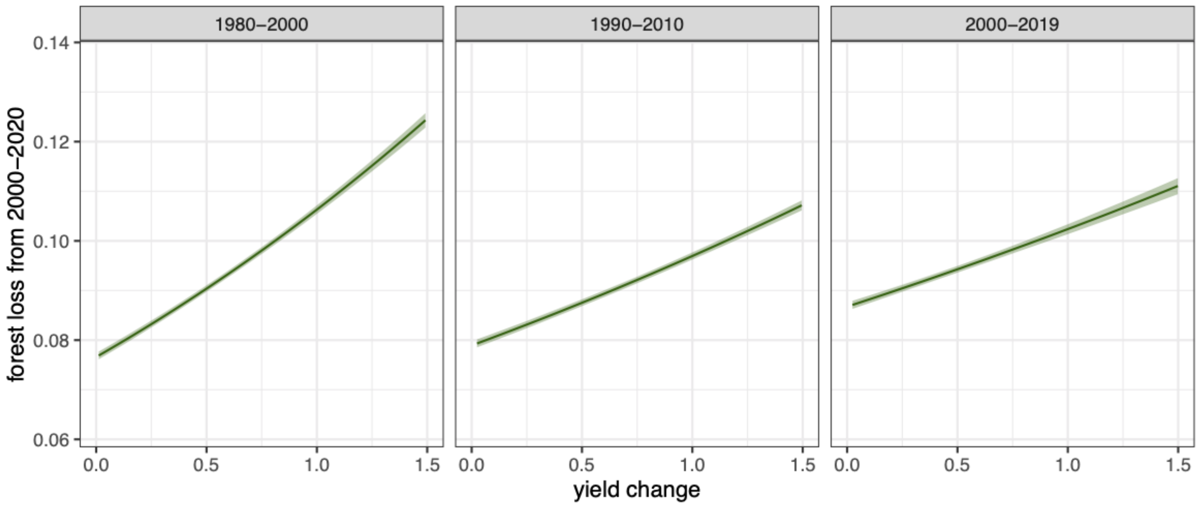

Figure H.1: Effect of ΔY from different time periods on forest loss in the study period*. The modeled effect of ΔY from past time periods had the same direction and was of comparable magnitude as the effect from the study period.*

I. Model summary

Table I.1: Summary statistics of final model. *Parameters are summarized using mean (estimate) and standard deviation (standard error) of the posterior distribution as well as two-sided 95% credible intervals. Bulk and tail ESS are diagnostics of the sampling efficiency, estimating the effective sample size that bulk and tail of the posterior distribution are informed by. All numbers are given in model scale (untransformed logit/log scale).*

Parameter	***Estimate***	***Standard error***	***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
popdens	-0.06	0.00	-07;-0.06	5437	2878
ΔY	0.44	0.01	0.41;0.46	3289	2941
ΔY:suit	0.06	0.00	-0.05;0.06	5218	2992
ΔY:nonStap	0.43	0.01	0.41;0.44	3779	3320
ΔY:IPL	-0.05	0.01	-0.08;-0.03	4749	2943
ΔY:special	0.29	0.01	0.26;0.31	3337	3032
phi_YC	-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(popdens)	0.14	0.07	0.07;0.32	1777	1869
sd(ΔY)	0.36	0.12	0.18;0.65	3452	2896
sd(ΔY:suit)	0.33	0.09	0.19;0.54	3682	3437
sd(ΔY:nonStap)	0.28	0.09	0.15;0.51	3580	2940
sd(ΔY:IPL)	0.48	0.12	0.30;0.75	4617	3584
sd(ΔY:special)	0.05	0.05	0.00;0.17	2509	2344
cor(Intercept,popdens)	0.18	0.34	-0.51;0.76	5029	2810
cor(Intercept,ΔY)	-0.40	0.20	-0.75;0.04	4243	2978
cor(popdens,ΔY)	-0.11	0.29	-0.64;0.45	4235	3320
cor(Intercept,ΔY:suit)	-0.28	0.21	-0.64;0.14	4083	2987
cor(popdens,ΔY:suit)	0.17	0.28	-0.39;0.68	3361	3072
cor(ΔY,ΔY:suit)	0.31	0.26	-0.27;0.75	2543	2672
cor(Intercept,ΔY:nonStap)	-0.15	0.23	-0.57;0.32	3904	2865
cor(popdens,ΔY:nonStap)	0.33	0.28	-0.27;0.81	3099	3183
cor(ΔY,ΔY:nonStap)	-0.06	0.26	-0.55;0.44	4594	3213
cor(ΔY:suit,ΔY:nonStap)	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(popdens,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:suit,ΔY:IPL)	0.40	0.22	-0.07;0.76	4331	3470
cor(ΔY:nonStap,ΔY:IPL)	0.05	0.29	-0.52;0.56	3025	3228
cor(Intercept,ΔY:special)	0.01	0.35	-0.63;0.67	7084	3149
cor(popdens,ΔY:special)	0.01	0.34	-0.64;0.66	5360	2852
cor(ΔY,ΔY:special)	-0.13	0.34	-0.73;0.57	5024	3239
cor(ΔY:suit,ΔY:special)	-0.00	0.36	-0.68;0.66	6626	2771
cor(ΔY:nonStap,ΔY:special)	0.06	0.33	-0.59;0.67	4341	2979
cor(ΔY:IPL,ΔY:special)	0.04	0.36	-0.65;0.68	4029	3525

J. Effect of yield change within staple-crops

When conditioning forest loss on *ΔY* calculated solely from staple crops, posterior *ΔY*-effect estimates were qualitatively the same as the model results relying on overall mean *ΔY*. Likewise, estimated interaction terms of effect modifiers *nonStap*, *suit*, *IPL*, and *special* affected the relationship of *ΔY* and forest loss in an analogous manner (Figure J.1).

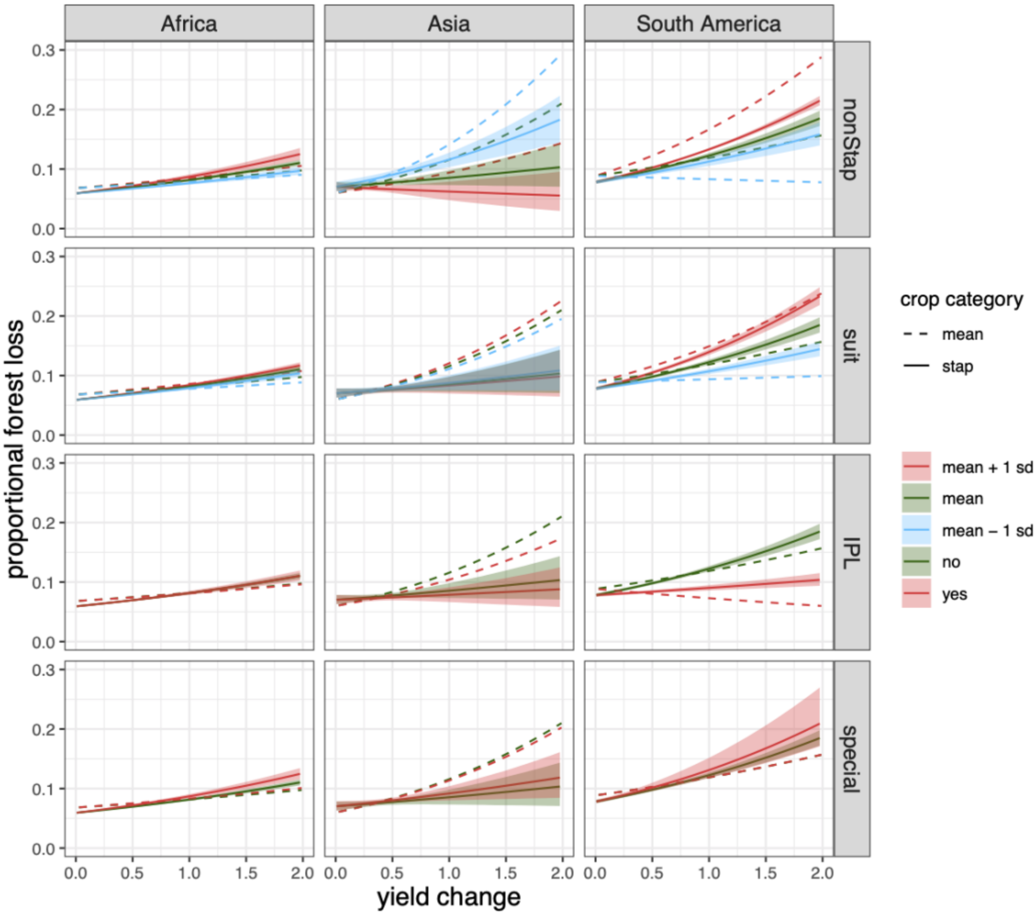

Figure J.1: Conditional effects of staple-crops yield change interactions on continent level*. Curves show the mean effect and the 95% credible interval of the posterior distribution for the average sample. Green curves are identical for every continent column.*

Erklärung

Ich erkläre, dass ich die vorliegende Arbeit nicht für andere Prüfungen eingereicht, selbständig und nur unter Verwendung der angegebenen Literatur und Hilfsmittel angefertigt habe. Sämtliche fremde Quellen inklusive Internetquellen, Grafiken, Tabellen und Bilder, die ich unverändert oder abgewandelt wiedergegeben habe, habe ich als solche kenntlich gemacht. Mir ist bekannt, dass Verstöße gegen diese Grundsätze als Täuschungsversuch bzw. Täuschung geahndet werden.

Berlin, 31.08.2021

Marie Pratzer