



ORIGINAL ARTICLE

# Confronting sustainable intensification with uncertainty and extreme values on smallholder tropical farms

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## Abstract

Sustainable intensification of agricultural lands might reconcile the conservation of tropical forest with food production, but in-depth assessments considering uncertainty and extreme values are missing. Uncertainty prohibits mapping probabilities to potential future states or ranking these states in terms of their likelihood. This in turn hampers the assessment of possible decision outcomes. Here, we use simulations to investigate how uncertainty may influence the social acceptability of alternative land-use strategies to halt tropical deforestation (including sustainable intensification), based on indicators representing farmer satisfaction. The results show how extreme values (worst values) for indicators of farmer satisfaction may undermine the adoption of sustainable intensification. We demonstrate that a pure forest conservation strategy leads to lower food production, but outperforms a sustainable intensification strategy that maintains food security. Pure forest conservation performed better, i.e., could secure higher farmer satisfaction, than sustainable intensification across a range of indicator groups. This suggests strong barriers to achieving sustainable intensification. Using agricultural subsidies breaks the dominance of pure forest conservation by enhancing the economic returns of sustainable intensification. We discuss the importance of access to labor and farmers' preferences for the use of already cleared lands, which achieved the worst values under sustainable intensification and conclude that any assessment of land-use strategies requires careful consideration of uncertainty and extreme values.

**Keywords** Land allocation · Tropical deforestation · Agricultural intensification · Farmer preferences · Off-farm income · Multiple objective robust optimization

## Introduction

Agriculture represents an unrivalled threat to the natural environment, putting ever-increasing pressure on planetary boundaries (Gerten et al. 2020), with tropical deforestation being among the most prominent negative consequences of agricultural activities (Erb et al. 2016). Sustainable intensification could reconcile tropical forest conservation with agricultural production (Beltran-Peña et al. 2020; Brandt et al. 2018; Godfray and Garnett 2014). While sustainable

intensification is not restricted to any single agricultural system (Pretty and Bharucha 2014), a standard definition is to increase agricultural yields and associated economic returns per unit of cleared land and time, without harming the underlying natural resources or integrity of other ecosystems (Cassman and Grassini 2020). By 2018, only around 9% of the world's agricultural lands had undergone sustainable intensification (Pretty et al. 2018). Deforestation remains a major problem, particularly in the tropics (Seymour and Harris 2019; Silva Junior et al. 2021), with dramatic consequences for global biodiversity (Gomes et al. 2019). Zero deforestation is thus an undisputed objective in recent studies and global policies (Erb et al. 2016; Gomes et al. 2019). To support approaching the path toward zero deforestation, we demonstrate the importance of accounting for uncertainty when assessing land-use strategies. We analyze alternative land-use trajectories in the Andes of Ecuador

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to achieve food security by increasing future pasture yields per unit of already cleared land, as an example for sustainable intensification (Pretty and Bharucha 2014).

Uncertainty implies that we lack important information (Lindley 2006), which will only become known in the future, meaning that we face multiple futures when making decisions today. Lacking information may include not knowing the future preferences of key stakeholders or decision-makers (Knoke et al. 2016) and how plurality of perceptions will influence what is desirable and what not (Pereira et al. 2020). In addition, when dealing with long-term decisions, we are often neither able to associate any specific probability to possible states of nature, nor to prioritize these future states in terms of their importance or likelihood. Uncertainty is often discussed in association with Knight (1921), who was the first to clearly distinguish risk and uncertainty in an economic context. The concept of risk considers random variables with known probability distributions to describe states of nature and associated decision outcomes, while “Knightian uncertainty” implies that information about probability distributions is unavailable (Bewley 2002). Examples of economic studies on the theory of “Knightian uncertainty” include Bewley (2002) as well as Baumgärtner and Engler (2018). Bewley (2002) showed that aversion to uncertainty exists, because people prefer situations of risk with known probabilities over situations of uncertainty, with vague or missing information about probabilities. Baumgärtner and Engler (2018) developed a new axiomatic foundation to quantify and model such uncertainty aversion.

Uncertainty forms a common decision environment for climate change related (Lawrence et al. 2020) or forestry problems (Radke et al. 2020), but is so far often unaddressed in the assessment of land-use strategies. The concept of uncertainty is strongly associated with extreme values (minima or maxima) and extreme value theory (Embrechts et al. 1999). For example, the construction of dams and dykes to protect citizens against flooding requires consideration of maximum values of sea levels and not statistical average values (Cirillo and Taleb 2020). Similarly, a smallholder farmer cannot use average expected economic returns for decision making, as smallholder farms lack resources to compensate for potentially much poorer than expected economic outcomes. For these farms, extreme values represented by worst cases are relevant for decision making. Reliable assessments of sustainable intensification must account for such worst-case values for multiple indicators of farmer satisfaction, such as economic performance for various time preference levels, labor demand or farmers' perceptions of specific land-use/land-cover (LULC) types. To integrate uncertainty of each indicator into decision-making a large range of possible futures must be considered (Lempert et al. 2003), without relying on any stochastic information, such as probabilities, weightings or priorities

(Lawrence et al. 2020). Approaches to integrate uncertainty into decision-making include information-gap decision theory (Ben-Haim 2006; Hayes et al. 2013) and robust optimization (Ben-Tal and Nemirovski 2000), but the influence of uncertainty on the acceptability of sustainable intensification for farmers has yet not been investigated. To help fill this gap we develop a novel approach to assess land-use strategies against uncertainty.

For our analysis, we devise possible land-use trajectories to achieve sustainable intensification. The implicit aim of these land-use trajectories is to increase productivity of agricultural land to reduce the need for agricultural expansion and hence spare land for nature (Latawiec et al. 2014; Phalan et al. 2011). However, agricultural intensification in itself is unlikely to reduce or halt deforestation. In contrast, due to rebound effects it may even accelerate deforestation (Ceddia et al. 2013; García et al. 2020; Phelps et al. 2013). Innovative concepts are thus needed to combine preservation of tropical forest with agricultural intensification. A higher independence of farmers from agricultural income is an essential precondition to reduce or halt deforestation. For example, alternative revenue sources such as off-farm income would directly reduce the need for income from deforestation-based agriculture (Shively and Pagiola 2004; Araujo et al. 2019). In addition, labor reallocated to obtain off-farm income limits the ability of farmers to pursue deforestation activities (Vasco et al. 2020).

Another alternative to support greater financial independence of farmers from deforestation-related agriculture is conservation payments, which are financial payments to land owners conditional on the preservation of natural forest (Benítez et al. 2006). Unlike typical off-farm income, such as wages from work outside the farm (Ojeda Luna et al. 2020), conservation payments are directly targeted towards forest conservation. Experimental evidence on the effectiveness of conservation payments in reducing deforestation is encouraging (Andersson et al. 2018; Jayachandran et al. 2017). However, assessing the level of payment needed to halt deforestation is complex. Existing approaches tend to simplify the assessment, for example by treating tropical forest and agricultural land uses as mutually exclusive alternatives (Fisher et al. 2011; Warren-Thomas et al. 2018). The immediate and complete clearing of all forests owned by tropical farmers, however, is rarely a realistic scenario (Ruslandi et al. 2011). Instead, farmers are likely to convert tropical forest to agricultural land more gradually. This type of behavior may be better captured by portfolio approaches, which consider multiple land-use alternatives simultaneously to account for typical land-use diversification patterns of smallholder farmers (Ochoa et al. 2019). Portfolio-theoretic approaches to land-use problems would suggest the optimal allocation of land shares to LULC types to achieve a given objective (Macmillan 1992).

To help address the above described research challenges our study provides a new method to assess sustainable intensification, including alternative optimized land-use trajectories controlled by indicators representing farmers' satisfaction, the indicators' uncertainty, off-farm income, conservation payments and agricultural subsidies. We then present a method to investigate the influence of the uncertainty of decision outcomes on the assessment of indicators of farmer satisfaction from alternative optimized land-use trajectories. The aim of the new method is to elicit the acceptability of sustainable intensification for tropical farmers faced with uncertainty.

## Material and methods

### Concept of land allocation under uncertainty

With our concept, we assume that tropical farmers face a range of plausible futures when making decisions, but that they cannot associate a probability to such futures and the resulting decision outcomes. We thus include an uncertainty of level 3 in our assessments, given a frequently used classification system. Walker et al. (2010) have defined four levels of uncertainty for all situations between determinism and complete ignorance (Fig. 1) and termed level 3 and level 4 as "deep uncertainty". In contrast, more recent publications consider level 4 (with unknown futures, outcomes and rules to assess outcomes) as the only level representing deep uncertainty (van Dorsser et al. 2020). Instead of distinguishing risk from uncertainty, Walker's framework considers a progressive transition of the level of uncertainty, where the classical concept of risk represents one of those levels.

We consider smallholder farmers as decision-makers who are averse to uncertainty (Cerroni 2020). This means that farmers would prefer landscape compositions associated with less uncertain outcomes over those associated with more uncertain outcomes. Consequently, farmers will organize their land-use activities so that they obtain a high worst-case land-use performance. To achieve this, they strive to minimize the largest difference between what they most desire and what is possible to achieve across multiple futures. This largest difference quantifies the magnitude of the uncertainty of decision consequences that a farmer is confronted with in our concept. In their decisions on land management farmers would allocate land to LULC types to reduce such uncertainty of decision outcomes, for example by land-use diversification, which is typical for farmers (Di Falco and Perrings 2005; Ochoa et al. 2019). Decision outcomes depend on the landscape composition and result from the corresponding contributions of various LULC types to indicators of farmers' satisfaction (see Table 1 for the indicators used). To incorporate uncertainty in our analyses we always consider an optimistic and a pessimistic possible future contribution (measured by input indicator levels) of each LULC type, without being able to decide which of both levels is more likely. Various combinations between optimistic and pessimistic indicators are possible among our LULC types forming the possible futures that farmers are confronted with, which means that our assessment builds on many sets of input information levels, which however do not possess any probability. With our concept we abandon any probabilistic consideration or treatment of input or output information.

In light of the mentioned understanding of level 3 uncertainty, our analytical concept consists of an assessment from

	Context	Level of uncertainty				Ignorance
		1 "A clear enough future"	2 "Alternate futures with probabilities"	3 "A multiplicity of plausible futures"	4 "Unknown future"	
Determinism						
	System model	Single model	Single model with probabilistic parameterization	Several models, with different structures	Unknown system model; awareness that we don't know	
	System outcomes	Point estimates and confidence intervals for each outcome	Several sets of point estimates and confidence intervals for each outcome, a probability is attached to each set	Known range of outcomes	Unknown outcomes; awareness that we don't know	
	Weights on outcomes	Single estimate	Several sets of weights, a probability is attached to each set	Known range of weights	Unknown weights; awareness that we don't know	

**Fig. 1** Levels of uncertainty. The matrix shows the different levels of uncertainty between determinism and complete ignorance. Adopted from Walker et al. (2010) with slight alterations

**Table 1** Considered criteria to model farmer satisfaction and associated indicators

Criteria to model farmer satisfaction	Indicators	Studies supporting the importance of the criteria and associated indicators
Economic return [US\$ per hectare]		
	(1) Net present value (sum of cash flows discounted with <b>5%</b> discount rate) combined with <b>high</b> off-farm income	For economic return effects: Connally and Shapiro (2006), Clough et al. (2016), Coomes et al. (2008), Hoekstra (1985), Rahman et al. (2017)
	(2) Net present value ( <b>5%</b> discount rate) combined with <b>low</b> off-farm income	For off-farm income effects: Araujo et al. (2019), Bluffstone (1995), Shively and Pagiola (2004)
	(3) Net present value ( <b>8%</b> discount rate) combined with <b>high</b> off-farm income	
	(4) Net present value ( <b>8%</b> discount rate) combined with <b>low</b> off-farm income	
Limited access to capital [number of years]	(5) Payback period (time until farmers receive invested money back, assuming <b>5%</b> discount rate)	Coomes et al. (2008), Holmes et al. (2017), Rahman et al. (2017)
	(6) Payback period ( <b>8%</b> discount rate)	
Limited access to labor [labor days per hectare per year]	(7) Labor demand combined with <b>high</b> off-farm income, requiring <b>high</b> off-farm labor	For labor demand: Angelsen and Kaimowitz (1999), Angelsen (2010), Pichon (1997), Tschakert et al. (2007), van Zonneveld et al. (2020)
	(8) Labor demand combined with <b>low</b> off-farm income, requiring <b>low</b> off-farm labor	For off-farm income effects: Vasco et al. (2020), Bluffstone (1995), Shively and Pagiola (2004)
Stated land-use preferences [number of choices]	(9) Number of times <b>Mestizo</b> farmers (during interviews) selected a land-use type as being the most or second most preferable land-use option for converted land, <b>without</b> any financial support from subsidies (this set of land-use preferences was not used for “subsidized sustainable intensification”); ‘Mestizo’ refers to farmers of mixed Spanish and indigenous descent, whereas ‘Saraguro’ are indigenous people who traditionally inhabited the Andean uplands of southern Ecuador	Gosling et al. (2020), Knoke et al. (2014), Pohle et al. (2010), Rahman et al. (2017)
	(10) Number of times <b>Mestizo</b> farmers selected a land-use type as being the most or second most preferable option for converted land <b>with</b> support from subsidies	
	(11) Number of times <b>Saraguro</b> farmers selected a land-use type as being the most or second most preferable option for converted land, <b>without</b> support from subsidies (this set of land-use preferences was not used for “subsidized sustainable intensification”)	
	(12) Number of times <b>Saraguro</b> farmers selected a land-use type as being the most or second most preferable option for converted land, <b>with</b> support from subsidies	

the perspective of farmers, building on three forest conservation strategies for which farmers obtain forest conservation payments (Fig. 2): one strategy with only conservation payments (pure forest conservation) and two strategies fostering adoption of sustainable intensification to conserve natural forest but also maintain food security (with and without agricultural subsidies). For all conservation strategies, we assume that farmers have access to off-farm income. We obtain the trajectories (i.e., the change in land-use patterns over time) as an important input for our assessment when following each forest conservation strategy using a dynamic land allocation model (Knoke et al. 2020b), which is based on mathematical programming (Berger 2001; Schreinemachers and Berger 2006). This allocation model accounts for multiple socioeconomic indicators, their uncertainty, off-farm income, conservation payments and agricultural subsidies.

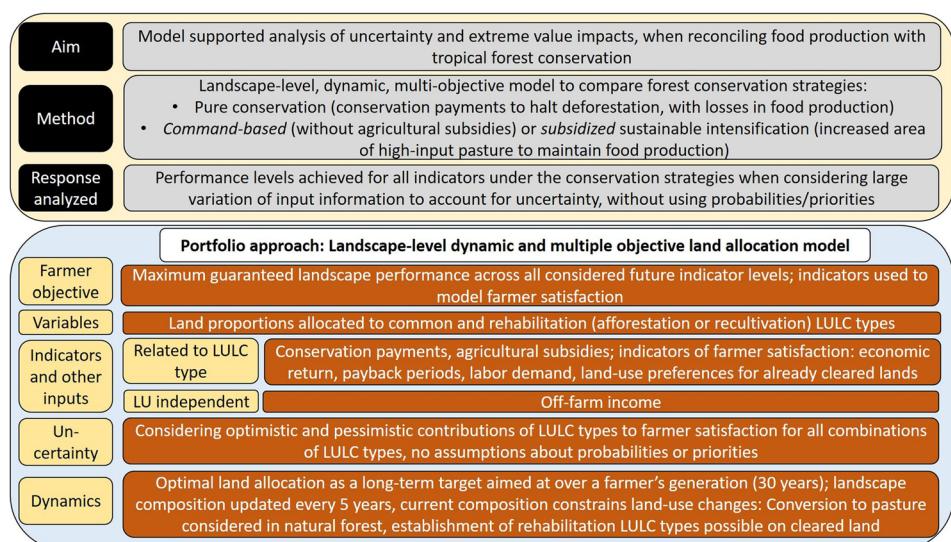
The land allocation model combines compromise programming and robust optimization to simulate target landscape compositions pursued by farmers over one generation. Compromise programming uses reference points (Estrella et al. 2014) to minimize trade-offs across multiple objectives. A reference point represents a most desirable outcome level, which cannot be achieved for all objectives simultaneously so that the distance between actually obtained outcomes and the reference points forms an objective to be minimized. Robust optimization guarantees minimum outcome levels across variable input information contained in uncertainty sets (Ben-Tal and Nemirovski 2000). Considering one generation as a planning horizon appeared intuitive to us, as smallholder farms often build on the principle of transfer of ownership to the next generation (van Vliet et al. 2015). Adelaja et al. (2011), for instance, used a planning horizon of 30 years for a young farmer. In addition, plausible land-use trajectories achieved when using a planning horizon of

30 years support our assumption (such trajectories being described in “Results”).

Input information comprises modeled and measured data quantifying the performance of various LULC types against multiple decision criteria (which we refer to as indicators of farmers’ satisfaction) that previous studies have shown to be relevant for land-use decisions. Indicators include net present value (NPV) and labor demand (with both criteria associated with either a high or low level of off-farm income), payback periods, and the land-use preferences of local farmers (Table 1; Table S1). We model pasture-based land-use systems in tropical mountain rainforest areas, using the example of the Ecuadorian Andes. The LULC types include the highly biodiverse natural system (tropical mountain rainforest), the replacement systems (existing and newly established low-input pasture), and rehabilitation options for abandoned lands (two types of afforestation and recultivation toward intense pasture management). As a high-input land use, intensive pasture management facilitates the simulation of intensified agricultural land use.

The model accounts for uncertainty of input information in two main ways. First, it incorporates multiple indicators without any weightings (to represent uncertainty associated with the future preferences of farmers). Second, the model integrates discrete scenarios that capture potential fluctuations in performance of each LULC type against each indicator. These scenarios are generated in the absence of any probability information. A robust optimization accounting for all scenarios drives the simulated allocation of land shares to LULC types. The aim is to minimize the maximum distance between the most desirable and actually achieved indicator levels over all scenarios. The model assumes that farmers show satisficing behavior, i.e., will be content with less than the maximum expected outcome, if a moderate outcome is guaranteed across all (including worst) scenarios

**Fig. 2** Schematic overview of study framework. The upper part (yellow background) outlines the specific study aims, methods and analyzed results, while the lower part (blue background) summarizes the model components. LULC means land use/land cover



(Hey et al. 2017). The resulting compromise land allocation has been described as the nearest possible approach to a so called Rawlsian perfectly equilibrated solution (Uhde et al. 2017; Tamiz et al. 1998).

The model's output is the future landscape composition (percentage of area covered by each LULC type) simulated for multiple periods based on 5-year (period length based on Simmonds et al. 2013) time steps, from which we can calculate annual deforestation rates (annual change in the area covered by natural forest divided by its initial share in the study area). The adopted model is dynamic and accounts for the influence of changes in the landscape context (i.e., the initial composition of the forested landscape). The approach uses a recursive process by reapplying the same optimization algorithm (described below) updated with the landscape composition simulated in the previous 5-year period to obtain an adapted long-term target of the landscape composition for the next 5-year period.

## Input data, study region and land-use strategies

The sustainable intensification land-use strategies expand the share of high-input pasture on already converted land to ensure the same level of food production that would have otherwise been achieved through deforestation-based land management (Figure S1). Expansion of high-input pasture is either enforced by appropriate constraints in the model to simulate a command-based (using laws and regulations) strategy (called “command-based sustainable intensification”) or incentivized by agricultural subsidies (called “subsidized sustainable intensification”). The alternative trajectory (called “pure forest conservation”) assumes off-farm income and conservation payments to stop deforestation, but tolerates any associated losses in food production. For all trajectories we derived and assessed target landscape compositions optimized with the land allocation framework described in Fig. 2 and under “[Devising land-use trajectories](#)”.

Input data used to analyze the pure forest conservation and sustainable intensification strategies are representative of a region covering 62,500 ha in the Andes of Ecuador (Curatola Fernández et al. 2015). Knoke et al. (2014) described and documented the modeling of the socioeconomic indicators used to simulate farmer decision-making for this region. Table 1 shows how we combined the previously described indicators with indicators related to off-farm income. We obtained input information for our land allocation model from field experiments, newly developed plot-level models, extensive household surveys, remote sensing data on historical land use (Knoke et al. 2014, 2016, 2020b) and existing literature on off-farm income (Ojeda Luna et al. 2020).

The land-use preferences of the local people regarding the best use of cleared land form part of the criteria used to evaluate the acceptability of the alternative land-use trajectories (see Table 1, Figure S2 and Supplementary Table 1). Such land-use preferences may capture more intrinsic or cultural values that are important for farmers' decision-making (but difficult to measure with other socio-economic indicators derived from a cost–benefit analysis) (Plieninger and Huntsinger 2018). These preferences and values will therefore determine local people's perception and acceptance of such novel LULC types (Pohle et al. 2010).

To measure the food production associated with our land-use trajectories, we analyzed the dietary energy (from meat and milk) provided by the simulated land-use compositions (see Supplementary Information for details) (Figure S1). We took the baseline level of food production from the deforestation-based scenario (in which farmers do not receive any conservation payments nor have access to off-farm income). We then computed the additional area of high-input pasture needed to reach the same level of food production under the sustainable intensification strategies as provided by the deforestation scenario. On this basis, we compared the performance of sustainable intensification (with and without subsidies) to enhance food production with the performance of the pure forest conservation strategy.

## Simulation of uncertainty

We considered  $Y_{iu}$  as an uncertain decision outcome, showing the contribution to farmer satisfaction indicators  $i$  achieved by a given landscape composition  $\omega$  for a discrete uncertainty scenario  $u$ . Such landscape composition  $\omega$  consists of the land shares allocated to the seven LULC types;  $\omega = \{a_{\text{aband}}; a_{\text{alnus}}; a_{\text{pinus}}; a_{\text{inten}}; a_{\text{pastu}}; a_{\text{defor}}; a_{\text{fores}}\}$ .

Included LULC types are abandoned lands, *Alnus* and *Pinus* plantations, intense and low-input pastures, and new deforestation areas and natural forests. The level of  $Y_{iu}$  depends on the contributions of the single LULC types  $y_{liu}$  under a given uncertainty scenario and on the area share  $a_l$  allocated to the LULC types l.

$$Y_{iu} = \sum_l a_l \cdot y_{liu} \quad \text{with} \quad \sum_l a_l = 1 \quad a_l \geq 0 \quad (1)$$

Each uncertainty scenario  $u$  considers a different set of input coefficients  $y_{liu}$ , representing one plausible future. By defining the most desirable indicator levels as reference points for each uncertainty scenario, we then computed the relative distance  $D_{iu}$  between the most desirable indicator level  $Y_{iu}^*$  (i.e., the reference point) and the actually achieved level  $Y_{iu}$ .

$$D_{iu} = \frac{|Y_{iu}^* - Y_{iu}|}{\max\{y_{liu}\} - \min\{y_{liu}\}} \cdot 100 \quad (2)$$

As a min–max normalized distance,  $D_{iu}$  characterizes the relative underachievement level across all possible futures  $u$ . These relative distances facilitate computing which achievements are feasible under a given individual uncertainty scenario. Based on  $D_{iu}$  we then derived a performance index  $P_{iu}$  for a given landscape composition  $\omega$ .

$$P_{iu} = 100 - D_{iu} \quad (3)$$

To obtain an assessment under uncertainty, our simulation experiments used long-term landscape compositions  $\omega$  for various land-use trajectories, optimized with the land allocation framework described in Fig. 1 (see Table S2 for compositions obtained). Concerning such landscape compositions  $\omega$ , we assume the following preference relationship:

$$\omega_1 \geq \omega_2 \text{ iff } P_1 \geq P_2, \quad (4)$$

$$P = \min\{P_{iu}\}, \quad (5)$$

where  $P$  is the guaranteed performance level for given landscape compositions and sets of uncertainty scenarios across all indicators. We assume that farmers prefer land-use compositions that guarantee higher performance under uncertain future conditions.

The assessed landscape compositions stem from optimizations with our land allocation model for our three land-use trajectories described later. Their assessment under uncertainty reveals the full range of resulting landscape indicator outcomes and thus provides detailed information on the performance and acceptability of the trajectories analyzed.

To simulate the mentioned discrete uncertainty scenarios, we combined optimistic and pessimistic input indicator levels among the seven LULC types, leading to a set of  $2^7 = 128$  scenarios for each of the 12 indicators shown in Table 1. Optimistic and pessimistic indicator levels form intervals accounting for three times the standard error of the relevant indicator (Table S1). Using three times the standard error to construct such intervals represents an assumption for the possible range of worst cases, but not a prediction. This assumption is informed by model calibration experiments, which found that using a multiple of three times the standard error to obtain worst cases allowed for simulating land-use scenarios that best fit the observed historical land-use trajectory (Knoke et al. 2020b), see Fig. 5b for an example. Empirically, the standard errors stem from measuring, sampling or model prediction errors, heterogeneity of sites, unanticipated future environmental changes, unpredictable market development and damages by calamities, such as fire (Knoke et al.

2016). The obtained 1,536 future scenarios (12 indicators  $\times$  128 uncertainty scenarios) possess no probability, as the uncertainty scenarios cover any possible combination between optimistic and pessimistic levels among all LULC types, even those being most unlikely (e.g., all indicators either with optimistic or with pessimistic levels). Given our construction of the uncertainty scenarios, any  $P_{iu}$  will be equal to or larger than  $P$ , independent of the indicator or uncertainty scenario considered. This holds for all indicator levels included by the intervals formed by optimistic and pessimistic indicator levels.

We finally consider  $P$  (5) as a preference function of decision-makers being averse to uncertainty. The use of the before defined intervals implies that the worst indicator level among all  $P_{iu}$  is the minimum (guaranteed) landscape contribution to farmers' satisfaction for all input indicator levels included in the intervals used.

## Devising land-use trajectories

The three considered land-use trajectories (pure forest conservation, command-based sustainable intensification and subsidized sustainable intensification) evolve from a simulation of land allocation processes depending on farmers' preferences. The land-use trajectories were developed prior to the assessment of the full range of their uncertain outcomes. Without considering any conservation payments or agricultural subsidies our land allocation approach describes the recent deforestation trajectory in the study region appropriately, pursuing the historical trend in a plausible way (see Fig. 5b in “Reducing farmers' dependency on agricultural income”).

We use our land allocation model to derive long-term target landscape compositions which minimize the maximum distance  $\beta$  between the reference points and the actually achieved indicator levels. The reference points are the most desirable indicator levels in each uncertainty scenario.

$$\min_{\omega} \beta, \quad (6)$$

where  $\beta$  depends on

$$\omega = \{a_{aband}; a_{alnus}; a_{pinus}; a_{inten}; a_{pastu}; a_{defor}; a_{fores}\}, \quad (7)$$

$\omega$  describes the simulated land allocation to the specific LULC types  $l$  in percent for the desirable long-term landscape composition, which minimizes  $\beta$  across all indicators and uncertainty scenarios.

The value of indicator  $i$  under uncertainty scenario  $u$  at the landscape level depends on the allocation of land proportions  $a_l$  to each LULC type  $l$ , see (1):

To consider all indicators and uncertainty scenarios, we require numerous constraints of the type:

$$\beta \geq \left| Y_{iu}^* - Y_{iu} \right| \cdot \frac{100}{\max\{y_{liu}\} - \min\{y_{liu}\}} \quad \forall i \ \forall u, \quad 0 \leq \beta \leq 100. \quad (8)$$

$\beta$	Maximum relative distance between the best possible and the achieved contributions to all indicators, associated with the optimal allocation of area proportions to the LULC types across all uncertainty scenarios
$\omega$	Set of allocated area proportions to seven land-use/land-cover (LULC) types $l = \text{abandoned, Alnus plantations, Pinus plantations, recultivation to intense pasture, low-input pasture, deforestation, or natural forest}$
$Y_{iu}$	Landscape level indicator value (i.e., contribution of a specific landscape composition to a specific indicator) for indicator $i$ under uncertainty scenario $u$
$a_l$	Area proportion of a landscape allocated to a specific land-use/land-cover (LULC) type $l$
$y_{liu}$	Contribution of LULC type $l$ to an indicator $i$ under uncertainty scenario $u$
$\max\{y_{liu}\}$	Maximum land use-related level of indicator $i$ among all LULC types in a given uncertainty scenario $u$
$\min\{y_{liu}\}$	Minimum land use-related level of indicator $i$ among all LULC types in a given uncertainty scenario $u$

Consistent with our preference function (5), the objective is to improve the guaranteed performance across all indicators. In this way, the optimization algorithm seeks to maximize the minimum performance level achieved by all indicators, even in worst-case scenarios for each of the different land-use strategies. The optimization algorithm thus minimizes directly over  $\beta$  (Knoke et al. 2020b), which corresponds to maximizing the guaranteed performance  $P$ . For more details see Methods S1. The described optimization model provides solutions that are robust against uncertainty by securing the feasibility of our constraints (8) across all indicators  $i$  and uncertainty scenarios  $u$ . Our optimization assumes that farmers would allocate land to certain LULC types with the aim to either maximize (net present values, and land-use preferences of two local groups of farmers)

or minimize (labor demand and payback periods) several indicators simultaneously (Table 1 and Table S1).

For our optimization, the same uncertainty scenarios as described under “Simulating uncertainty” form uncertainty spaces for each indicator, ensuring a land allocation with acceptable performance for all input information included in these uncertainty spaces (i.e., all input values falling within the intervals formed by the optimistic and pessimistic estimates). Multiple constraints rather than one objective function encapsulate our indicators and uncertainty scenarios. Such a constraint-wise representation of uncertainty is a convenient and reliable assumption in robust optimization methods (Gorissen et al. 2015). Given all indicators under multiple possible futures, it is clear that a single LULC type cannot achieve the most desired outcomes for all uncertainty scenarios included. Consequently, the optimization algorithm seeks an acceptable compromise land-use allocation by selecting an appropriate mix of LULC types to maximize the guaranteed performance across all indicators and uncertainty scenarios.

## Off-farm income, conservation payments and agricultural subsidies

To account for the influence of off-farm income on farmers’ land-use decisions, we implemented two effects (Methods S2). First, off-farm income decreases the economic dependency of farmers on land use-related income (concerning the net present value, NPV). Second, off-farm income limits the opportunity to carry out agricultural activities and hence generate land use-related income (concerning labor availability). As a result, off-farm income guarantees certain performance levels independent of the allocation of land. For example, such income secures elevated farm income, exceeding the land use-related minimum. However, the simulated off-farm income requires additional labor, always exceeding the minimum required labor for land-use activities.

We represented off-farm income by the NPV of income streams earned off the farm for various uncertainty scenarios. We used a common proportion of the off-farm income of 30% (Ojeda Luna et al. 2020), depending (in our model) on the land use-related income achieved at a given time. In Ojeda Luna et al. (2020), a representative study for our model case, off-farm income included wages from permanent or seasonal work outside the farm, income from farmer-owned businesses, and also remittances and pensions. In addition to the off-farm income itself, we considered the labor in days necessary to obtain the off-farm income. In our simulations, we assume that farmers reallocate labor previously used for on-farm agricultural activities to off-farm activities. We consider the impact of uncertainty concerning the labor required for off-farm income using an average and

a worst-case scenario, based on the average and worst-case scenarios for on-farm income.

To account for off-farm income we modified the constraints used in the existing land allocation model for the indicators NPV ( $n$ ) and labor demand ( $w$ ) as follows:

$$\beta \geq (Y_{nu}^{*o} - Y_{nu}^o) \cdot \frac{100}{\Delta_{nu}^o} \quad \forall i \quad \forall u, \quad 0 \leq \beta < 100, \quad (9)$$

$$\beta \geq (Y_{wu}^o - Y_{wu}^{*o}) \cdot \frac{100}{\Delta_{wu}^o} \quad \forall i \quad \forall u, \quad 0 < \beta \leq 100. \quad (10)$$

$Y_{nu}^{*o}$	$Y_{nu}^{*o} = Y_{nu}^* + O_{nu}$ , is the maximum (most desirable) net present value (NPV, sum of discounted future cash flows) including off-farm income.
$O_{nu}$	is the NPV of off-farm income ( $n$ for NPV), changing over time $t$ , for uncertainty scenario $u$
$Y_{nu}^o$	Achieved NPV including off-farm income for a given land allocation, $Y_{nu}^o = \sum_l a_l \cdot (O_{nu} + y_{lnu})$ . $O_{nu}$ is the NPV of off-farm income ( $n$ for NPV), changing over time $t$ , for uncertainty scenario $u$
$\Delta_{nu}^o$	Difference between most desirable NPV including off-farm income and least desirable NPV excluding off-farm income, $\Delta_{nu}^o = Y_{nu}^{*o} - Y_{nu}^*$
$Y_{wu}^o$	Required labor for on- and off-farm activities, $Y_{wu}^o = \sum_l a_l \cdot (O_{wu} + y_{lwu})$
$O_{wu}$	Off-farm labor ( $w$ for work) required to obtain the off-farm income, changing over time $t$ , for uncertainty scenarios $u$
$Y_{wu}^*$	Lowest (most desirable) land use-related labor demand among all LULC types in a given uncertainty scenario $u$
$\Delta_{wu}^o$	Difference between least desired (maximum) land use-related labor demand plus labor to obtain off-farm income and lowest (most desired) land use-related labor, $\Delta_{wu}^o = Y_{wu}^o - Y_{wu}^*$ .
$Y_{wu*}^o = Y_{wu*} + O_{wu}$	Is the maximum (least desirable) land use-related labor demand plus labor to obtain off-farm income, changing over time $t$ with changing $O_{wu}$ , for uncertainty scenario $u$

We assumed that conservation payments are conditional to the conservation of natural forest. To calculate

the conservation payment needed to halt deforestation, we enhanced the on-farm NPV of natural forests only, keeping the NPV of the alternative LULC types at their initial levels, until our model simulated constancy of the natural forest's future area (i.e., a cessation of deforestation). We then converted the necessary additional NPV into equivalent annual payments (annuities). With the same method, we computed the necessary agricultural subsidies to incentivize farmers for expanding the high-input pasture area.

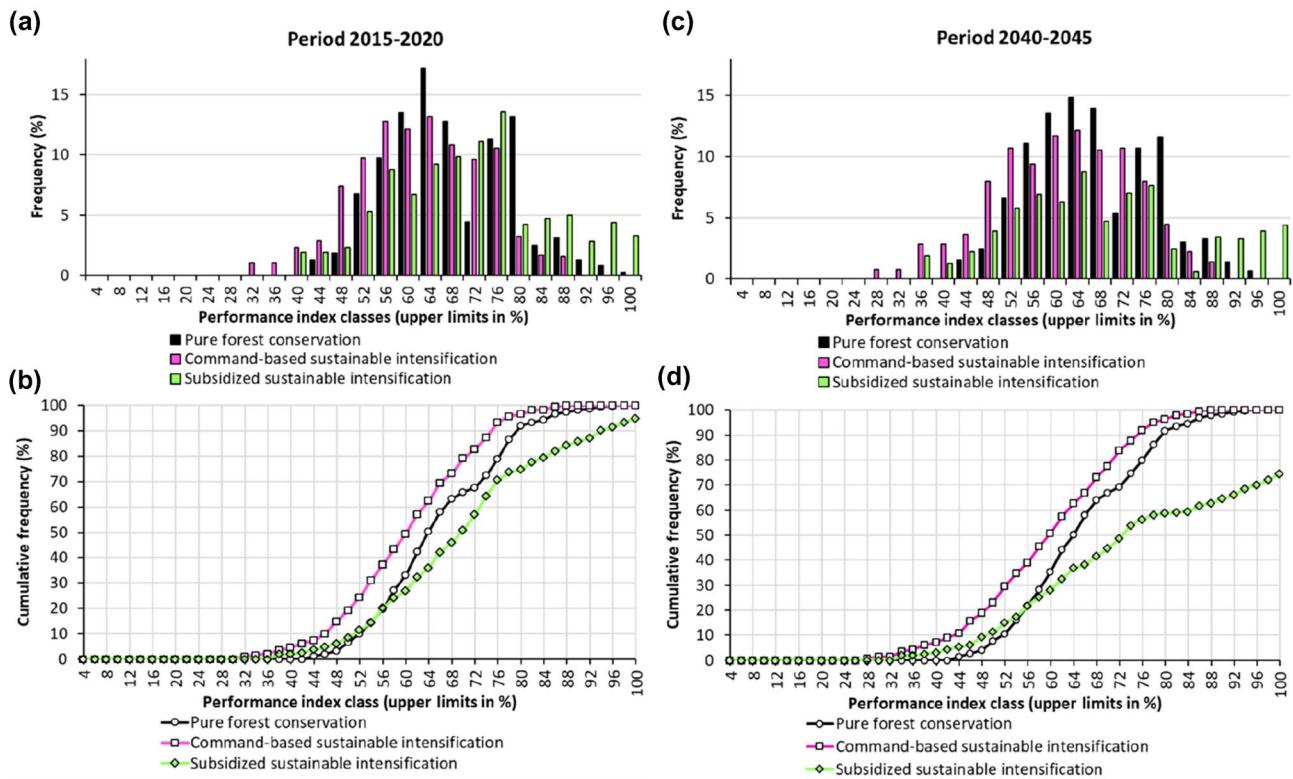
## Results

### Performance profiles

Our experiment to assess different long-term landscape compositions from the perspective of smallholder farmers facing uncertainty resulted in worsened performance profiles for command-based sustainable intensification (without agricultural subsidies), when compared to pure forest conservation (forest conservation in both strategies achieved through conservation payments). Figure 3a, c shows how the frequency distributions of the performance indices for sustainable intensification are shifted to the left compared to the distributions of the performance indices achieved by pure forest conservation, indicating that simulated farmer satisfaction decreases.

For pure forest conservation, the worst-case value was 43% compared to 32% for command-based sustainable intensification (period 2015–20); or 43% compared to 28% (period 2040–45). On top of that, for all performance thresholds that a farmer could demand (x-axis), the number of simulated performance indices greater than such a threshold is always higher for pure forest conservation than for sustainable intensification (Fig. 3b, d). This shows clearly that the performance profile of pure forest conservation dominates the performance profile of sustainable intensification without agricultural subsidies under uncertainty.

Incentivizing the expansion of high-input pasture by agricultural subsidies (strategy “subsidized sustainable intensification”) breaks the dominance of pure forest conservation over sustainable intensification (Fig. 3). The simulation experiment shows that including agricultural subsidies enhances the performance of “subsidized sustainable intensification”. The intersection between the cumulative frequency distribution of the “subsidized sustainable intensification” and “pure forest conservation” strategies signifies that the former land-use strategy offers a better opportunity of achieving high (> 56%) performance levels than the latter (Fig. 3b, d). Compared to the sustainable intensification strategy without subsidies, sustainable intensification with subsidies performed much



**Fig. 3** Performance profiles of land-use trajectories: frequency distributions (upper panel) and cumulative distribution functions (lower panel) showing the variation of performance indices obtained for target landscape compositions when halting deforestation. The figure contrasts three strategies: either accepting (pure forest conservation strategy) or compensating food production losses by expanding intensified agriculture. “Command-based sustainable intensification” means using laws and regulations and “subsidized sustainable intensification” means inclusion of agricultural subsidies to incentivize the expansion of high-input pasture. The input information for each indicator and land-use/land-cover (LULC) type consisted of optimistic and pessimistic indicator levels, which were combined in 128 uncertainty scenarios for each of the 12 considered indicators. Performance was measured for these 12 indicators used to model farmers’

stronger. In fact, in some cases the strategy with subsidies achieved a performance level higher than the maximum (which we still considered as 100%) achievement level under the strategy without subsidies.

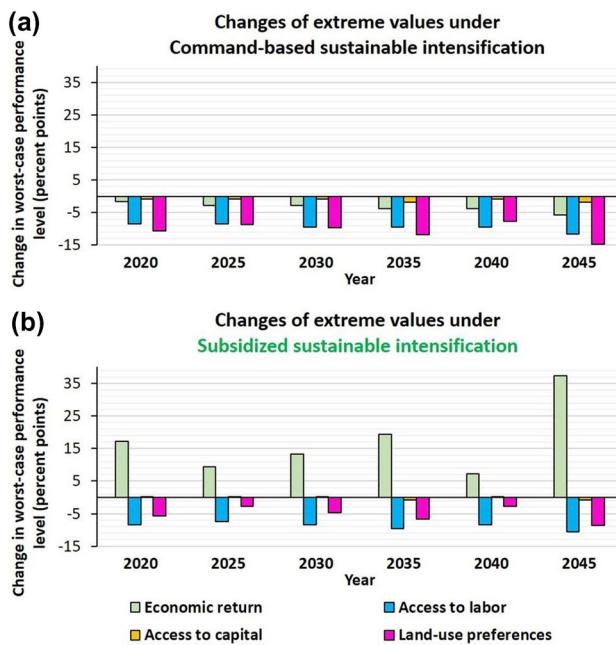
Analyzing the worst performances of the three forest conservation strategies across all indicators underlines the extremely low performance of the sustainable intensification strategy without subsidies from the perspective of smallholder farmers (Fig. 4a). However, compared with pure forest conservation, incentivizing the expansion of high input pasture through subsidies (subsidized sustainable intensification) enhanced the worst-case values by up to 37 percentage points for economic return (Fig. 4b). In contrast, labor demand worsened to the same extent as under command-based sustainable intensification. The

satisfaction, including economic return (net present value), limited access to capital (payback periods) and labor (labor demand), farmers’ land-use preferences for managing their cleared lands, and off-farm income (Table 1). Achieved indicator levels depend on the long-term land allocation in each strategy (Table S2). All landscape level indicator outcomes were scaled between zero (least desired indicator value) and 100% (most desired indicator value). **a** Frequency distribution of simulated performance indices for the initial period, 2015–20. **b** Cumulative frequency distribution of simulated performance indices for the initial period, 2015–20. **c** Frequency distribution of simulated performance indices for the last considered period, 2040–45. **d** Cumulative frequency distribution of simulated performance indices for the last considered period, 2040–2045

reductions of worst-case values against farmers’ land-use preferences were less severe under “subsidized sustainable intensification” than they were under the strategy without subsidies (Fig. 4a, b).

### Reducing farmers’ dependency on agricultural income

We tested the effect of both off-farm income and conservation payments on the expected level of deforestation. Our deforestation-based, business-as-usual scenario that we used to estimate the expected level of deforestation disregarded off-farm income, agricultural subsidies and conservation payments (Fig. 5a) and was adopted from Knoke et al. (2020b). Access to off-farm income reduced deforestation (Fig. 5b). Off-farm



**Fig. 4** Changes of extreme (worst) values for indicator groups used to model farmer satisfaction. The bars indicate the difference between extreme values achieved under pure forest conservation and extreme values resulting under either of the two strategies for sustainable intensification. **a** Enforcing an expansion of intense pasture management based on command and control, without agricultural subsidies, to compensate food production losses reduces extreme values for all indicators, with farmer land-use preference levels (indicators 9, 10, 11, and 12 in Table 1) for such a sustainable intensification scenario being most eroded. **b** Including agricultural subsidies to achieve “subsidized sustainable intensification” enhances extreme values for economic return and reduces farmer land-use preferences less strongly than the sustainable intensification scenario without agricultural subsidies. Land-use preferences are represented by specific indicators recorded under the premise “with subsidies” (indicators 10 and 12 in Table 1)

income representing 30% of all farm household income (see “Methods”) saved a 4% share of natural forest cover over a farmer’s generation. This corresponds to an average annual deforestation rate of 1.33% with and 1.73% without access to off-farm income. A 70% proportion of off-farm-income (as a proportion of all total household income) would suggest zero future deforestation according to our simulations. An annual conservation payment of US\$ 79 per hectare of natural forest sufficed in our model to halt deforestation (Fig. 5c) (pure forest conservation).

The optimal land-use scenarios to achieve the target landscape compositions anticipated a substantial increase of afforestation areas, either planted with an exotic or a native tree species, both on previously abandoned and low-input pasture lands. Such afforestation areas enhance landscape diversification and help farm households to buffer against future uncertainties. However, the recultivation of abandoned or low-input pasture lands toward intensive

(high-input) pasture management played only a minor role in the future landscape portfolios, especially when access to off-farm income was available. In our approach off-farm income and the labor-intensive high-input pasture competed for labour, explaining why intensive pasture management only covers a small area when farmers have access to off-farm income. Both trajectories for sustainable intensification (Fig. 5d, e) expanded high input pasture mainly by reducing the area for afforestation. Exotic *Pinus* plantations are reduced most under “subsidized sustainable intensification”.

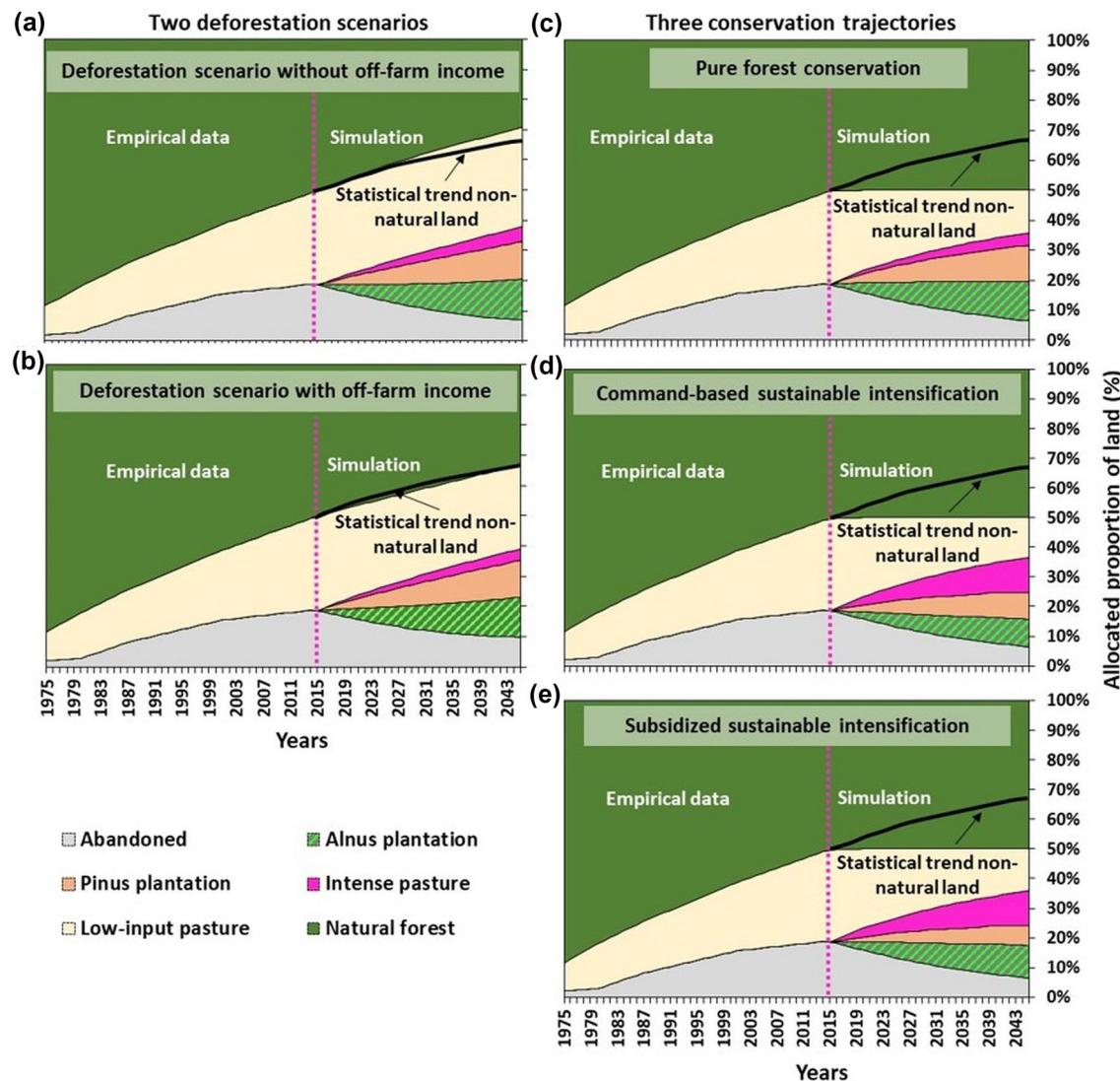
## Effect of conservation strategies on food production

Enhanced forest conservation through access to off-farm income and conservation payments strongly compromises the anticipated food production of the target landscape composition. While deforestation-based farming increased food production by 50%, halting deforestation implied a decline in food production by 18%, when comparing the simulated production levels of the years 2015 and 2045 (Figure S1).

## Costs of compensating food production losses

To compensate for food production losses, we would need 7.6 percentage points in more land covered by intensive pasture by the year 2045 compared to the optimized landscape trajectory (Fig. 3c), which means more than 4700 hectares for the landscape considered (which totals 62,500 hectares) (Fig. 6a). We found that both sustainable intensification strategies strongly reduced the conservation payments required to stop deforestation, from US\$ 79 (pure forest conservation strategy) to US\$ 46–47 per hectare natural forest per year (the required payments varied slightly from period to period).

The costs for achieving the conservation land-use trajectories differ between “pure forest conservation” and “subsidized sustainable intensification”. Due to additional agricultural subsidies “subsidized sustainable intensification” requires 75% higher total financial transfers to farmers than pure forest conservation, but the higher costs occur in the long run (Fig. 6b). During the earlier years of the considered timeline, “subsidized sustainable intensification” may even be more cost-efficient than pure forest conservation. To simulate this strategy, we only used land-use preferences (stated by farmers during household interviews) that were specific to the scenario where the three rehabilitation options would be subsidized (Table 1). Achieving the land-use trajectory necessary for sustainable intensification (without forcing the expansion) required increasing such subsidy payments to US\$ 220 (period 2015–20) and US\$ 390 (period 2040–45) per year for establishing one hectare of high-input pasture, which is more than two (or four) times the conservation payment required for one

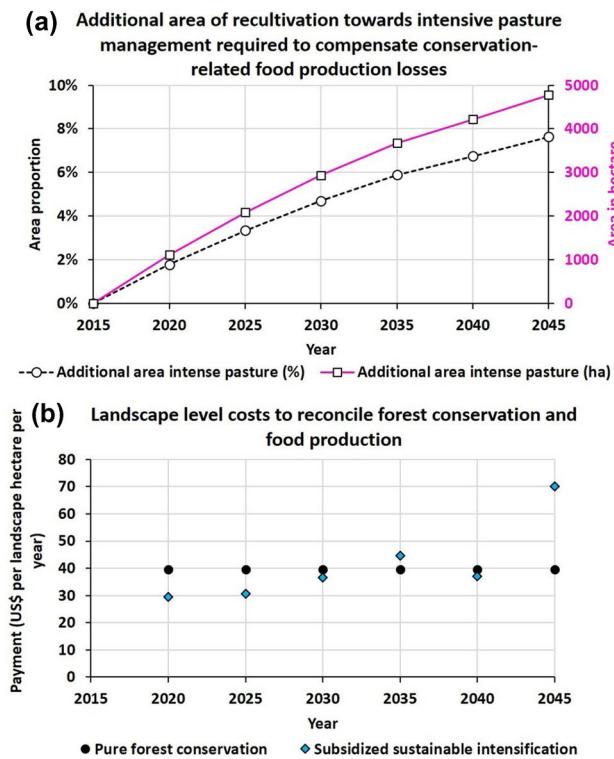


**Fig. 5** Historical development, statistically extrapolated trend for non-natural land and simulated trajectories of the proportions of land-use/land-cover (LULC) types over one farmer's generation. **a** Deforestation development on smallholder farms without access to off-farm income. **b** Deforestation development on smallholder farms with access to off-farm income. **c** Pure forest conservation: Development for farms with access to off-farm income accepting conservation payments for forest preservation. **d** Sustainable intensification without subsidies: development for farms with access to off-farm income accepting conservation payments for forest preservation, while simultaneously expanding high-input pasture to receive agricultural subsidies. The pink dashed line denotes the starting year of the simulation of the landscape composition development. “*Pinus plantation*” is an example of afforestation with an exotic tree species, while “*Alnus plantation*” represents an example of afforestation with a native tree species

hectare of natural forest to be preserved. However, the area of high-input pasture is initially relatively small, despite the simulated expansion. At the end of the first period, high-input pasture covers 3% and at the end of the last period 12% of the landscape, where the landscape always holds a constant cover of 50% of natural forest. For the example of the first period, costs account for agricultural subsidies across the whole landscape of US\$ 6.6 per hectare per year ( $0.03 \times \text{US\$ } 220$  per hectare per year). On 50% of the

taneously expanding high-input pasture to compensate for conservation-related food production losses under a command-and-control mechanism. **e** Subsidized sustainable intensification: development for farms with access to off-farm income accepting conservation payments for forest preservation, while simultaneously expanding high-input pasture to receive agricultural subsidies. The pink dashed line denotes the starting year of the simulation of the landscape composition development. “*Pinus plantation*” is an example of afforestation with an exotic tree species, while “*Alnus plantation*” represents an example of afforestation with a native tree species

landscape's area, the strategy requires US\$ 23 ( $0.5 \times \text{US\$ } 46$  per hectare per year) as conservation payments to preserve the natural forest, resulting in a total payment of US\$ 29.6 per hectare of the “subsidized sustainable intensification” landscape per year (Fig. 6b). For the first two 5-year periods, the interaction between agricultural subsidies and conservation payments would thus lead even to smaller costs than under the pure conservation trajectory. Over the other periods, the “subsidized sustainable intensification”



**Fig. 6** Additional area of intensive pasture management needed to compensate conservation-related food production losses under the sustainable intensification strategies and costs to achieve the land-use trajectories for an average hectare at landscape level. **a** Relative and absolute additional area of intensive pasture management needed to compensate for conservation related food gaps. **b** Conservation payments to achieve tropical forest conservation at 50% of the landscape's area and agricultural subsidies to incentivize an expansion of high-input pasture up to 12% land cover until 2045. While conservation payments to preserve natural forests show little variation over time, the required agricultural subsidies increased both per hectare and through expansion of the area of high-input pasture

strategy would at least not become much more expensive than pure forest conservation. Only in the last period, the costs for strategy “subsidized sustainable intensification” substantially exceed those for pure forest conservation.

## Discussion and conclusions

Our study provides for the first time a method to assess the influence of uncertainty on the potential acceptability of sustainable intensification. Our method uses a land allocation approach that helps to devise optimal land-use trajectories for alternative land-use strategies, so that we can always compare the best alternatives for achieving sustainable intensification or pure forest conservation. The subsequent assessment of the uncertainty of decision outcomes uses performance profiles from indicators of farmers' satisfaction for

whole landscapes, which is novel for estimating the potential acceptability of alternative land-use strategies. We hope that our optimization perspective to assess the acceptability of sustainable intensification for farmers can provide new impetus for further study and simulate decision-making by farmers to find sustainable and socially acceptable solutions to global land-use problems. For example, in future studies our approach could support developing nature–people scenarios, using the nature futures framework (Pereira et al. 2020). In our current study, we focused on farmer preferences, whereas including multiple ecological and biodiversity-related indicators (Knoke et al. 2020b) would enrich the results of assessing sustainable intensification, accounting for plural values of multiple stakeholders. Our current analysis already underlines the importance of cultural values (Chan et al. 2012) and suggests that problems with the adoption of methods for enhanced food production do not only relate to financial aspects as represented by the net present value.

Our results are relevant for reconciling food production with forest conservation and are representative of a large area. Land-use dynamics as in our Andean study region are typical for smallholders' pasture expansion into the tropical forest area all over Latin America. For example, several studies demonstrate the pressing challenge of dealing with pasture expansion into tropical forest (Garrett et al. 2018). Our focus for sustainable intensification were smallholder farms, the backbone of tropical agriculture (Affholder et al. 2013). Without smallholder farms, discussed as key contributors for ending hunger and undernutrition worldwide (Fan and Rue 2020), reconciling natural forest conservation with food production will not be possible. However, smallholder farmers face a special set of challenges and constraints, associated with their dependency on farm produce and family labor (van Vliet et al. 2015) as well as limited access to capital (Angelsen and Kaimowitz 1999; Angelsen 2010). As typically uncertainty-averse decision-makers, smallholder farmers will be inclined to strictly avoid poor outcomes of their decisions under uncertainty. Ignoring such uncertainties will leave efforts to establish sustainable intensification illusory, even if some studies promise much enhanced net present values from sustainable intensification of degraded pastures (Oliveira Silva et al. 2017).

The relevance of uncertainty for environmental decision-making is undisputed (Radke et al. 2020; Fasen et al. 2014; Lawrence et al. 2020; Knoke et al. 2021; Xu et al. 2019), but the consequences of this phenomena for solving the world's pressing land-use problems remain under-researched. To the best of our knowledge, no other study has yet assessed the possible distribution of farmer satisfaction levels across multiple indicators and uncertainty scenarios, showing such a strong potential reservation against sustainable intensification. This likely reservation resulted from poor worst-case

values of sustainable intensification for multiple indicators of farmer satisfaction. In addition, we have found that plot-scale intensification is potentially able to compensate for conservation-related food production losses. We revealed cost-synergies between agricultural subsidies and conservation payments during the transition phase toward target landscapes of sustainable intensification and showed the importance of accounting for off-farm income when devising appropriate land-use strategies.

### **Acceptance of sustainable intensification on smallholder farms**

Establishing intensive pasture management may pose significant problems for smallholders. In addition to accounting for the uncertainty of land-use decision outcomes, our analyses considered the low land-use preferences by local people for intense pasture management, which could form a major barrier to achieving enhanced, sustainable food production. While smallholder farmers are generally inclined to labor sparing activities (Pichon 1997; Baker et al. 2017), some farmers may also be unwilling to use large amounts of agrochemicals, not only because of financial reasons (high costs) (Nahayo et al. 2017), but also because of ecological concerns. In a study which provided the social preferences that we used in our optimization model, Knoke et al. (2014) document concerns about adverse ecological effects of intensive pasture. Farmers believe that agrochemicals damage or ‘sterilize’ their soils.

An agricultural redesign of classical agrochemical-driven land management types such as high-input pastures toward agroecosystems including trees could offer better and more acceptable solutions (Pretty 2018). For example, when farmers integrate agroforestry into their land-use activities they are less involved in deforestation, as shown by Rahman et al. (2017). Integrating nitrogen-fixing tree species that are native to the region, such as Andean alder (*Alnus acuminata*) in local pasture systems could help save artificial fertilizer and provide a range of ecosystem services, such as carbon sequestration (Riofrío et al. 2015).

Subsidies for high-input agriculture may support sustainable intensification, because they improve the worst-case values for economic return under sustainable intensification and break the dominance of pure forest conservation. Still, there remain groups of indicators (e.g., labor demand and land-use preferences for LULC types on cleared lands) which show decreased worst-case values under “subsidized sustainable intensification” compared with “pure forest conservation”. However, the much better economic returns of the target landscapes under “subsidized sustainable intensification” could enhance farmers’ wealth in the long term, making them more independent from land use-related

uncertain returns. This could change their attitudes toward uncertainty and increase the acceptability of “subsidized sustainable intensification”.

### **Plot-scale intensification**

We have demonstrated that plot-scale intensification may compensate the conservation-related food gaps by the expansion of high-input pasture. When implemented on parcels of limited size (Haber et al. 1990) and appropriately embedded into landscapes that also contain parcels with afforestation with native tree species, possible ecological problems associated with the agrochemicals used to manage high-input pasture could probably be overcome (Knoke et al. 2016). High-input pasture requires high on-farm labor and provides an economically beneficial land-use activity for farmers (Knoke et al. 2008), as an alternative to deforestation activities. The high labor demand of intensive pasture management could support protection of natural forests, as farmers would lack labor capacity for both intensive pasture management and deforestation. We have also demonstrated the crucial role of subsidies to incentivize the expansion of high-input pasture, which may break the dominance of pure forest conservation, causing sustainable intensification to at least become attractive for less uncertainty-averse farmers (Benítez et al. 2006).

### **Cost synergies by considering off-farm income**

The integration of off-farm income is a novel aspect that facilitated new results (Janssen and van Ittersum 2007), such as highlighting the importance of the use of and competition for the labor capacity among possible farmer activities, which otherwise would not have been possible to assess. For example, we could show enhanced cost-efficiency of conservation payments when considering off-farm income in combination with sustainable intensification. In our model approach we focused on smallholder farms, for which constraints such as labor capacity are important. On such farms, we considered in our land allocation model that forcing or incentivizing farmers to implement labor intensive LULC types such as high-input pasture binds labor, which in turn limits the capacity of farms for deforestation activities. This effect unfolded in our study on simulated farms where farmers have access to off-farm income, and need to allocate some of their labor capacity to the off-farm activities.

### **Research outlook**

Assessing the acceptability of innovative land-use strategies appears to be a much under-researched field. Ignoring

the acceptability of land-use alternatives for the concerned people will overestimate the potential of optimized land-use strategies. For example, Runting et al. (2019) have shown how optimal land allocation massively expanded forest plantations with intense management, accepting a reduction of the natural forest area to allow for more efficient conservation of the remaining natural forests. While the natural forests to be replaced were managed as community forests, thus providing benefits for local people, most benefits from the forest plantations were obtained by plantation companies. It is hardly likely that such a strategy of sustainable intensification would be acceptable for all people affected by the optimized land allocation concept. To assess the acceptability of land-use strategies we require indicators of farmer satisfaction that go beyond the classical net present value, which is so popular in the assessment of land-use projects (e.g., Fisher et al. 2011; Warren-Thomas et al. 2018; Butler et al. 2009; Knoke et al. 2020a).

In our study, off-farm income was important to reduce deforestation. However, off-farm income may have diverging implications on industrial farms (compared to smallholder farms), even bearing potential for enhanced deforestation (Vosti et al. 2000). For example, Chrisendo et al. (2021) have recently shown how off-farm income increased the likelihood of oil palm adoption. Our model approach can integrate such effects by considering the fact that off-farm income could facilitate purchasing additional labor capacity and/or investing in more capital-intensive forms of land use. Future studies should analyze sustainable intensification under uncertainty and off-farm income effects for industrial farms as well. In summary, our enhanced mechanistic portfolio approach has great potential to evaluate and explore sustainable land-use concepts, but also has some limitations. Among the limitations is the lack of spatial explicitness, which needs attention in future research. One could also further develop the combination of the mechanistic model with empirical research approaches, which could deliver valuable information on stakeholder opinions and preferences (Ochoa et al. 2019).

We conclude that using multiple futures to represent uncertainty in combination with landscape approaches facilitates new insights about the interplay of multiple farmer preferences, conservation payments, agricultural subsidies, off-farm income and tropical deforestation under uncertainty. Our approach to uncertainty highlights the extent to which strong farmer reservations could undermine the social acceptability of sustainable intensification. Social acceptability for smallholder farmers is crucial to consider in any analysis of land-use strategies, if we want to end hunger and undernutrition worldwide (Fan and Rue 2020).

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