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Understanding and modelling the ambiguous impact of off-farm income on tropical deforestation

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ABSTRACT
Few land-allocation models consider the impact of off-farm income on tropical deforestation. We provide a concept to integrate off-farm income in a mechanistic multiple-objective land-allocation model, while distinguishing between farms with and without re-allocation of on-farm labor to obtain off-farm income. On farms with re-allocation of labor we found that off-farm income reduced farmers' financial dependency on deforestation-related agricultural income leading to less tropical deforestation. The influence of off-farm income covered two aspects: availability of additional income and re-allocation of on-farm labor to off-farm activities. The labor effect tended to reduce deforestation slightly more than the income effect. On farms without re-allocation of on-farm labor we showed how farmers can use off-farm income to purchase additional labor to accelerate deforestation. Our study highlights the importance of considering off-farm income in land-use models to better understand, model and possibly curb tropical deforestation.

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KEYWORDS
Smallholder farms; land allocation; multiple objective optimization; robust optimization

Introduction

The expansion of agriculture and forestry is a key driver of tropical deforestation (Pendrill et al., 2019). Scientifically, such re-allocation of natural forest to human-modified land is part of land-use science (e.g. Walker, 2004), which investigates how humans shape and change the Earth's land cover, where 'understanding and modelling' is central to the discipline (Müller & Munroe, 2014). To learn about and possibly avoid future deforestation we need land-use models, but adequately capturing the underlying socio-economic processes and conditions that drive land-use change poses a challenge. For example, new conceptual approaches are rare (O'Sullivan et al., 2016; Verburg et al., 2019) and few land-use models can account for non-agricultural aspects such as off-farm income, which influence both the livelihoods and land allocation decisions of farm households (Antle et al., 2017; Janssen & van Ittersum, 2007).

Ignoring important underlying socio-economic conditions may lead to unrealistic projections of future land allocation, a fact that may have caused biased modelling results for the Amazon, where land-use models largely failed to predict the amount of deforestation (Dalla-Nora et al., 2014). For example, in South America smallholder farms dominate tropical agriculture (Affholder et al., 2013), for which the regional socio-economic conditions are very important. Smallholder farms are commonly managed by family members, building on the principle of transfer of ownership to the next generation (Van Vliet et al., 2015). Such farms often have limited access to resources, for example,

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labor or capital, which distinguishes them from market-oriented, more intensively managed farms, which are less resource constrained. Some farmers with limited access to labor resources have to re-allocate current on-farm labor to obtain off-farm income, while other farmers receive specific types of off-farm income without re-allocation of on-farm labor (e.g. from farmer-owned businesses, remittances from abroad or pensions). For our conceptual study we will consider both types of smallholder farms and call them either farms 'with re-allocation of labor' or farms 'without re-allocation of labor'.

The availability of off-farm income as an important underlying socioeconomic condition will influence deforestation processes on farms with re-allocation of labor and farms without re-allocation of labor differently. For example, Vosti et al. (2000) showed how farmers may use off-farm income to invest in additional deforestation by establishing an intensive agricultural production system, when enough labor is available. An example for a study raising doubts about any influence of off-farm income on deforestation is Hübler (2017), who found no significant effect of financial support on the level of poverty-related deforestation.

On farms that have to re-allocate labor to obtain off-farm income, the ability to pursue deforestation activities decreases. In addition, alternative revenue sources such as off-farm income directly decrease the need for income from deforestation-based agriculture on subsistence-oriented farms. In economic terms, off-farm income will increase the opportunity costs of on-farm agricultural activities, likely leading to a reduction of agricultural expansion of such farms (Araujo et al., 2019). For example, Shively and Pagiola (2004) found that additional (off-farm) income reduced deforestation on farms in the Philippines. Empirical studies by Vasco et al. (2020) showed a clear inverse relationship between the number of days worked off the farm and the level of deforestation. Araujo et al. (2019) parameterized a theoretically grounded model with empirical data from the Brazilian agricultural census. They also obtained clear evidence that off-farm income contributes to a reduction in deforestation. Similarly, Ojeda Luna et al. (2020) provided statistical evidence that governmental grants have reduced deforestation. Such grants offer farmers a secure income source. In line with the results of many statistical studies, Bluffstone (1995) confirmed that the area of natural forest is more stable when assuming farmers have access to off-farm income, using a mechanistic utility-based optimization model. Based on a multiple-objective robust optimization approach, Knoke et al. (2022) analyzed the influence of uncertainty on the acceptability of sustainable agricultural intensification and considered off-farm income as a side aspect. Similar to other studies, their research ignored the ambiguous character of off-farm income, neither analyzing income and labor effects separately nor considering the influence of the type of off-farm income on deforestation.

In light of this existing knowledge, future concepts for land-use models need to acknowledge that off-farm income will probably influence the level of deforestation, but that the influence will likely depend on both farm type and type of off-farm income. For example, in Ojeda Luna et al. (2020), off-farm income included wages from permanent or seasonal work outside the farm, income from farmer-owned businesses, and also remittances and pensions. This shows that not all off-farm income requires reallocating on-farm labor. Farmers could instead use this income to purchase labor or invest in intensive agricultural practices, as demonstrated by Vosti et al. (2000). This would constitute a typical rebound effect, whereby programs that increase off-farm income with the intent of reducing deforestation can inadvertently enhance deforestation. Similar rebound effects have been documented, for example, for agricultural intensification (García et al., 2020; Phelps et al., 2013). While agricultural intensification should spare land for conservation, the resulting enhanced yields often provide a strong incentive to expand the agricultural area. In this context, the influence of off-farm income on deforestation rates is ambiguous, for example, depending on the type of the off-farm income.

Dynamic mechanistic models, which can project plausible deforestation rates by accounting for off-farm income, are currently rare. We help address this research gap by presenting a new model concept considering off-farm income for satisficing decisions. Our aim is to support learning of how to integrate off-farm income as an important non-agricultural component of household conditions (Janssen & van Ittersum, 2007) into land allocation models. To model possible effects of off-farm income on tropical deforestation, we will develop a mechanistic land allocation model, which can consider off-farm income either for farms with re-allocation of labor or farms without re-allocation of labor. Our main research question is:

How well can we reproduce the existing empirical evidence of the influence of off-farm income on tropical deforestation using a mechanistic land allocation model?

Our main contribution is a mechanistic framework to integrate different types of off-farm income into a robust multiple-objective optimization model suggested by Knoke et al. (2020), considering satisficing as a principle of farmer decision-making. This includes showing how off-farm income may be accounted for when minimizing the distance to reference points for multiple farmer objectives, instead of maximizing profits or utilities. Empirically, we analyze the impact of different off-farm income types on deforestation trajectories, while describing income and labor effects on deforestation separately.

Materials and methods

Simulation of farmer decision-making

We simulated land-use trajectories for typical Andean forested landscapes in South Ecuador, with pasture as the major replacement system established after clearing of natural forest. Curatola Fernández et al. (2015) measured historical deforestation rates between ~1.5% (1975–1987) and 0.8% (1987–2000) for our study area, while Tapia-Armijos et al. (2015) reported rates between 0.75% and 2.86% p.a. (1976–1989; 1989–2008) for a larger region containing our study area. Manchego et al. (2017) measured deforestation rates of 1.4% p.a. for the dry forest in South Ecuador (2008–2014).

We simulated future land-use trajectories and associated deforestation rates, building on Knoke et al. (2020) as our baseline model. Our planning horizon was $h = 30$ years (see e.g. Adelaja et al., 2011), divided into six periods (length $p = 5$ years). The Supplementary Demonstration program illustrates how we modelled land-use trajectories for farms with labor re-allocation to achieve off-farm income. We devised the landscape composition at the end of each period. Land allocated to a specific land-use/land-cover (LULC) type l is modelled using proportions, a_l^{start}, a_l^{end} and a_l^{target}, which represent landscape shares covered by l at the beginning and end of each period as well as at the end of h (a_l^{target}). The landscape composition at the end of each previous 5-year period (a_l^{end}) provides the start landscape composition (a_l^{start}) for each current period (see sections A. and B. in Supplementary Demonstration Program for Period 2015–2020 to Period 2040–2045).

$$a_l^{end} = a_l^{start} + \left(a_l^{target} - a_l^{start}\right) \cdot \frac{p}{h} \tag{1}$$

with

$$\sum\nolimits_l a_l^{start} = \sum\nolimits_l a_l^{end} = \sum\nolimits_l a_l^{target} = 1; a_l^{start}, a_l^{end}, a_l^{target} \geq 0 \tag{2}$$

A long-term target landscape composition was obtained by optimization, with the vector ω describing the long-term future proportions (a_l^{target}, cells AQ1585-AQ1591 in Supplementary Demonstration Program) of seven LULC types, being our decision variables. The LULC types include abandoned lands, Alnus and Pinus plantations on previously abandoned lands as well as recultivation of previously abandoned lands to intensive pasture management, low-input pastures, deforestation by forest conversion to low-input pasture and natural forest.

$$\omega = \left\{a_{abandon}^{target}; a_{Alnus}^{target}; a_{Pinus}^{target}; a_{int.pastu}^{target}; a_{pastu}^{target}; a_{defor}^{target}; a_{fores}^{target}\right\} \tag{3}$$

To obtain ω we used reference points to implement satisficing decision-making (Wierzbicki, 1982). A reference point is an extreme aspiration level, representing the most desirable outcome of a land-use decision for a specific objective, which cannot be achieved for all objectives simultaneously (thus called the utopic or ideal point). In fact, reaching such a point would maximize farmers' satisfaction, while the distance to a reference point (cells AO48-AO1583 in Supplementary Demonstration Program) quantifies the size of farmers' dissatisfaction. The actual unattainability of all reference points simultaneously implies that decision-makers can only approach them. By minimizing the maximum difference between reference points and achieved solution (see below for an explanation) we mimic satisficing behavior. Assuming satisficing behavior is typical for goal-programming methods (Orumie & Ebong, 2014; our model follows the goal programming concept in a wider sense) and a realistic assumption concerning farmer decision-making, in contrast to efficiency maximizing behavior. This has been shown recently by Findlater et al. (2019) even for large-scale commercial grain farmers in South Africa.

With our method we assume that tropical farmers have multiple objectives and face multiple futures, for each of which a reference point exists. Multiple futures mean that we do not know exactly how much our LULC types will contribute to the farmers' objectives in the future, so that we consider multiple possible contributions within our optimization model (and call them multiple futures, see section E. in Supplementary Demonstration Program). Farmers strive to achieve the best compromise outcome of their decisions across their multiple objectives (Tamiz et al., 1998) and the considered possible futures. They do so by minimizing their dissatisfaction with the current landscape composition, while ruling out compensation among achievement levels for different objectives or futures. Technically, we mimic this farmer decision-making by searching for an allocation of land proportions to LULC types which minimizes the maximum distance ($max\{D_{iu}\}$) between the reference points (Y^*_{iu}) and the actually achieved decision outcomes (Y_{iu}) across all objectives (i) and futures (u) integrated into the optimization process.

We use min-max normalized distances so that the different objectives become comparable (Figure 1). A distance D_{iu} expresses farmers' dissatisfaction and is computed as:

$$D_{iu} = \frac{Y^*_{iu} - Y_{iu}}{Y^*_{iu} - Y_{iu*}} \cdot 100 \tag{4}$$

D_{iu} not only depends on the reference points (with the reference point Y^*_{iu} being an ideal and Y_{iu*} an anti-ideal point), but also on the allocation of land proportions (a_l) to LULC types (l). Note that the most desirable Y^*_{iu} (reference point) may either be the maximum or the minimum under future u (cells AG48-AG1591 and AH48-AH1591 in Supplementary Demonstration Program). The minimum is desirable, for example, when labor requirement or payback periods are the objectives. This implies that the numerator and the denominator of D_{iu} are both negative (zero is also possible in case of the numerator), resulting always in a positive relative distance. Eq. 4 thus applies for objectives where 'more is better' and for objectives where 'less is better'. The decision outcome for a specific landscape composition is computed as a weighted mean (cells AK48-AK1583 in Supplementary Demonstration Program).

$$Y_{iu} = \sum\nolimits_l a_l \cdot y_{liu} \tag{5}$$

with

$$y_{liu} = \begin{cases} E(y_{li}) & \textit{as the optimistic indicator level} \\ E(y_{li}) \pm 3 \cdot SEM_{li} & \textit{as the pessimistic indicator level} \end{cases} \tag{6}$$

The weighted mean considers the allocated land proportions a_l as weights of each contribution y_{liu} (cells Z48-AF1583 in Supplementary Demonstration Program) of an LULC type l to the objective i under a specific future u. $E(y_{li})$ (see 'Input Scores' in Supplementary Demonstration Program) is the expected contribution of a LULC type l to the objective i.

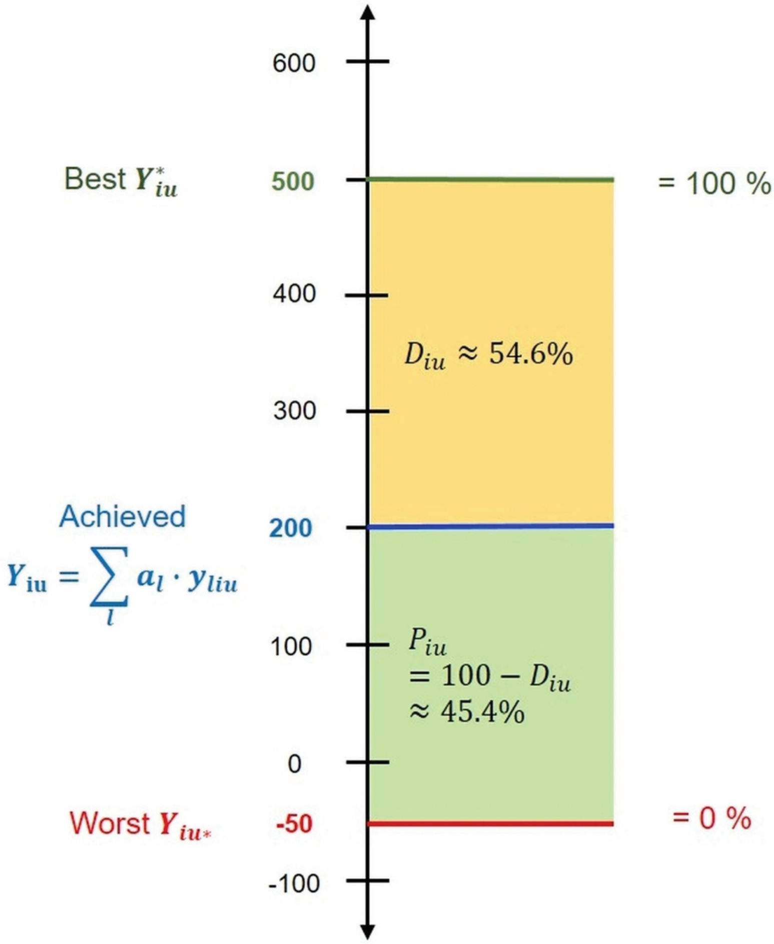

Figure 1. Schematic to show the normalization of a distance between the best decision outcome and the actually achieved decision outcome (here 200) for objective i and future u, assuming 500 as the ideal and −50 as the anti-ideal reference point. For instance, in this illustrative example 500 could represent the net present value (NPV, measured in US$/ha) of the most profitable LULC type, whereas −50 would be the NPV of the least profitable LULC type. The achieved decision outcome (200 US$/ha) represents the weighted mean of the NPVs of all LULC types comprising the landscape composition.

To mimic the land allocation of farmers who aim to minimize their dissatisfaction with the current landscape composition, our objective function for optimizing the long-term landscape composition was (cell AQ1584 in Supplementary Demonstration Program):

$$D = \min max\{D_{iu}\} \tag{7}$$

with

$$D \geq \frac{Y^*_{iu} - Y_{iu}}{Y^*_{iu} - Y_{iu*}} \cdot 100 \qquad iu \tag{8}$$

The following area constraint applied (cells D28 and F28 in Supplementary Demonstration Program):

$$a^{start}_{fores} = a^{target}_{fores} + a^{target}_{defores} \tag{9}$$

which means that natural forest may only be converted to low-input pasture by deforestation directly, while alternative LULC types may subsequently be established on previously converted land.

We assume that off-farm income affects the net present value (NPV, sum of all discounted future cash flows) of an agricultural and forested landscape and the available labor to establish and manage different LULC types. For simulating the possible impact of both effects on land allocation, we assume satisficing farmer decision-making; no fixed constraints on NPV or labor were used. We distinguish between farms with re-allocation of labor to obtain off-farm income and farms without re-allocation of labor (see 'Off-farm Income' in Supplementary Demonstration Program).

Farms with re-allocation of labor to obtain off-farm income

For the NPV (index n for NPV) of a smallholder farm with re-allocation of labor we consider the contribution of the off-farm income as follows:

$$Y_{nu} = O_{ntu} + \sum\nolimits_l a_l \cdot y_{lnu} = \sum\nolimits_l a_l \cdot (O_{ntu} + y_{lnu}) \tag{7}$$

O_{ntu} is the NPV of the off-farm income for future u, which develops over time t. The distance D_{nu} then changes compared to the previously introduced D_{iu} to account for the influence of off-farm income.

$$D_{nu} = \frac{Y^{*o}_{ntu} - \sum_l a_l \cdot (O_{ntu} + y_{lnu})}{Y^{*o}_{ntu} - Y_{nu*}} \cdot 100 \tag{8}$$

where $Y^{*o}_{ntu} = Y^{*}_{nu} + O_{ntu}$, so that Y^{*o}_{ntu} is the maximum total NPV theoretically achievable by the farmer under future u (reference point), consisting of the maximum land-use related and the off-farm income NPV.

Obtaining off-farm income requires farm households here to re-allocate labor to off-farm activities, because we assume these farms have only limited access to additional labor and capital. To integrate the labor (index w) required off the farm we write:

$$Y_{wu} = O_{wtu} + \sum\nolimits_l a_l \cdot y_{lwu} = \sum\nolimits_l a_l \cdot (O_{wtu} + y_{lwu}) \tag{9}$$

O_{wtu} is the off-farm labor required under future u, which changes over time t, as the off-farm NPV does. Similar as for D_{nu}, the distance D_{wu} changes compared to the previously introduced D_{iu} to consider the influence of off-farm labor.

$$D_{wu} = \frac{Y^{*}_{wu} - \sum_l a_l \cdot (O_{wtu} + y_{lwu})}{Y^{*}_{wu} - Y^{o}_{wtu*}} \cdot 100 \tag{10}$$

where $Y^{o}_{wtu*} = Y_{wu*} + O_{wtu}$, so that Y^{o}_{wtu*} is the maximum labor theoretically required under future u (anti-ideal point), consisting of the maximum land-use related labor and the labor necessary for off-farm activities.

Farms without re-allocation of labor

We assume that for farms without re-allocation of labor their initial farm NPV remains unchanged, because they will use the off-farm income to purchase additional labor. In this scenario, off-farm income would rather increase the farm NPV long-term, by facilitating enhanced agricultural expansion. We assume off-farm income comes from exogenous sources that do not commit on-farm labor, such as financial assets held by the farmer. We can then assume that additional labor O_{wtu} becoming available for the farm will reduce the labor required from members of the farm household.

$$Y_{wu} = -O_{wtu} + \sum\nolimits_l a_l \cdot y_{lwu} = \sum\nolimits_l a_l \cdot (-O_{wtu} + y_{lwu}) \tag{11}$$

For the resulting distances we write:

$$D_{wu} = \frac{Y^*_{wu} - \sum_l a_l \cdot (-O_{wtu} + y_{lwu})}{Y^*_{wu} - Y^o_{wtu*}} \cdot 100, \tag{12}$$

where

$$Y^o_{wtu*} = Y_{wu*} - O_{wtu}$$

General effects of off-farm income and information used for modelling

A general effect of off-farm income is the decreased dependency on land-use related income (concerning NPV). Another effect is that on-farm labor becomes scarcer, limiting the opportunity to achieve land-use related income. Off-farm income guarantees a certain achievement of the NPV, i.e. $P_{iu} = 100 - D$. Such off-farm income secures elevated total farm income ($O_{ntu} + Y_{nu*}$), always exceeding the land-use related minimum (Y_{nu*}), and thus guarantees a dissatisfaction D less than 100. The labor effect from off-farm income also means D is always greater than zero on farms with re-allocation of labor. Where off-farm income requires on-farm labor, total required labor ($O_{wtu} + Y_{wu*}$) will always exceed the minimum required labor for land-use activities (Y_{wu*}). This means that D can neither become 100%, nor zero, because: $O_{ntu} + Y_{nu*} > Y_{nu*}$ and $O_{wtu} + Y_{wu*} > Y_{wu*}$.

We used information from Ojeda Luna et al. (2020) to obtain 30% as a typical proportion of off-farm income (as a share of the total income of the farm household). These authors found shares of off-farm income among Ecuadorian farms between 18% and 31%. In addition to off-farm income as such, we computed the associated labor in days O_{wtu}. To estimate the worker days associated with a specific off-farm income we adopted a wage of US $10 per day, which is consistent with the modelling of other economic criteria used for our optimization, which have been described in Knoke et al. (2014).

Uncertainty

Our model integrates uncertainty by considering the multiple futures u for the optimization of the land allocation. Uncertainty becomes manifest by the likely variation in the expectations of the decision-makers concerning the future contribution of the LULC types to their objectives. Technically, we implemented the multiple futures by expected and pessimistic contributions of each LULC type, thus considering two possible contributions which form an interval. For the pessimistic scenario, the achieved contributions which deviate from the expected by three times their standard error (the standard errors, SEM_{li}, used are contained in the Supplementary Demonstration Program under 'Input scores'). The use of three times the standard error results from calibration experiments, which showed that this level of uncertainty allowed for deforestation trajectories over the last decades which best approached the previously measured deforestation (Knoke et al., 2022). The optimization of the land allocation considers all combinations of expected and pessimistic contributions among all considered seven LULC types so that $2^7 = 128$ uncertainty scenarios enter the optimization per objective.

To consider the impact of uncertainty concerning off-farm income and labor we also created an expected and a pessimistic scenario. We obtained the amount of off-farm income under each scenario by assuming that either the expected or pessimistic on-farm (land-use related) NPV were 70% of the NPV of the total household income and computed the remaining 30% as the off-farm related NPV.

Interaction across LULC types

Beneficial (e.g. fertilization by leaves shed on pastures) or adverse (e.g. shade) effects of adjacent LULC types on their neighbor LULC types were not considered. However, land-use diversification effects to buffer uncertainties are a main driver of the land allocation in our model (Knoke et al., 2016), which we consider a positive interaction across differently mixed proportions of LULC types.

Example study region, objectives and dynamic model nature

To demonstrate the modelling of the ambiguous impact of off-farm income on tropical deforestation, we used input information for a mountain rainforest landscape with pasture as a forest replacement system, located in the Andes of South Ecuador (Aguirre et al., 2011; Hartig & Beck, 2003). Land-use dynamics in this region are representative of pasture expansion into the tropical forest area all over Latin America (see, for example, Garrett et al., 2018). We consider tropical land allocation among seven representative LULC types. These LULC types comprise the highly biodiverse natural system (tropical mountain rainforest), the replacement system (existing and newly established low-input pasture) and abandoned lands, previously used as pasture or a result of failed pasture establishment. In addition, the model includes three LULC types to rehabilitate abandoned or degraded low-input pastures (see, Knoke et al., 2016 for a detailed description of all LULC types).

We use various decision criteria to describe the farmers' objectives, assuming that farmers would allocate land to certain LULC types with the tendency to either maximize (e.g. net present values and social preferences) or minimize (required labor and payback periods) several decision criteria simultaneously. We consider the perceptions of local people by integrating decision criteria capturing their stated preferences for LULC types on already cleared lands, such as low-input pasture, abandoned lands and three rehabilitative LULC types. These preferences were determined by asking local people to rank these LULC types during household interviews (Knoke et al., 2014). All decision criteria are described in detail in Knoke et al. (2020).

We have documented all input information with our Supplementary Demonstration Program, which contains all coefficients for the decision criteria and uncertainty scenarios. Based on this program the results presented in this paper are fully reproducible, when using OpenSolver, which is a freely available optimization software (Mason, 2012).

Results

Impact of off-farm income on the future landscape composition

Considering off-farm income on farms with labor re-allocation reduced the loss of natural forest compared to a baseline scenario (Figure 2a). To assess the impact of off-farm income, we used a baseline scenario that did not consider off-farm income for comparison (adopted from Knoke et al., 2020). The inclusion of off-farm income resulted in enhanced farm net present value at the cost of decreased available labor, as indicated by the achieved performance index for these decision criteria across the considered LULC and uncertainty scenarios (red color in Figure 2b).

On farms without re-allocation of labor, as per our assumption, off-farm income does not directly add to an enhanced farm NPV, but instead serves to purchase additional labor. Consistent with our assumption, the labor criterion improved on the farms without re-allocation of labor (yellow color in Figure 2b). This allows for enhanced agricultural expansion, associated with a higher loss of natural forest, as indicated by the lowest proportion of natural forest in the long-term target landscape composition for the farms without re-allocation of labor (Figure 2a).

The proportion of the off-farm income (as a share of total household income) influenced the magnitude of the reduction (farms with re-allocation of labor) or enhancement (farms without re-allocation of labor) of the deforestation processes (Table 1).

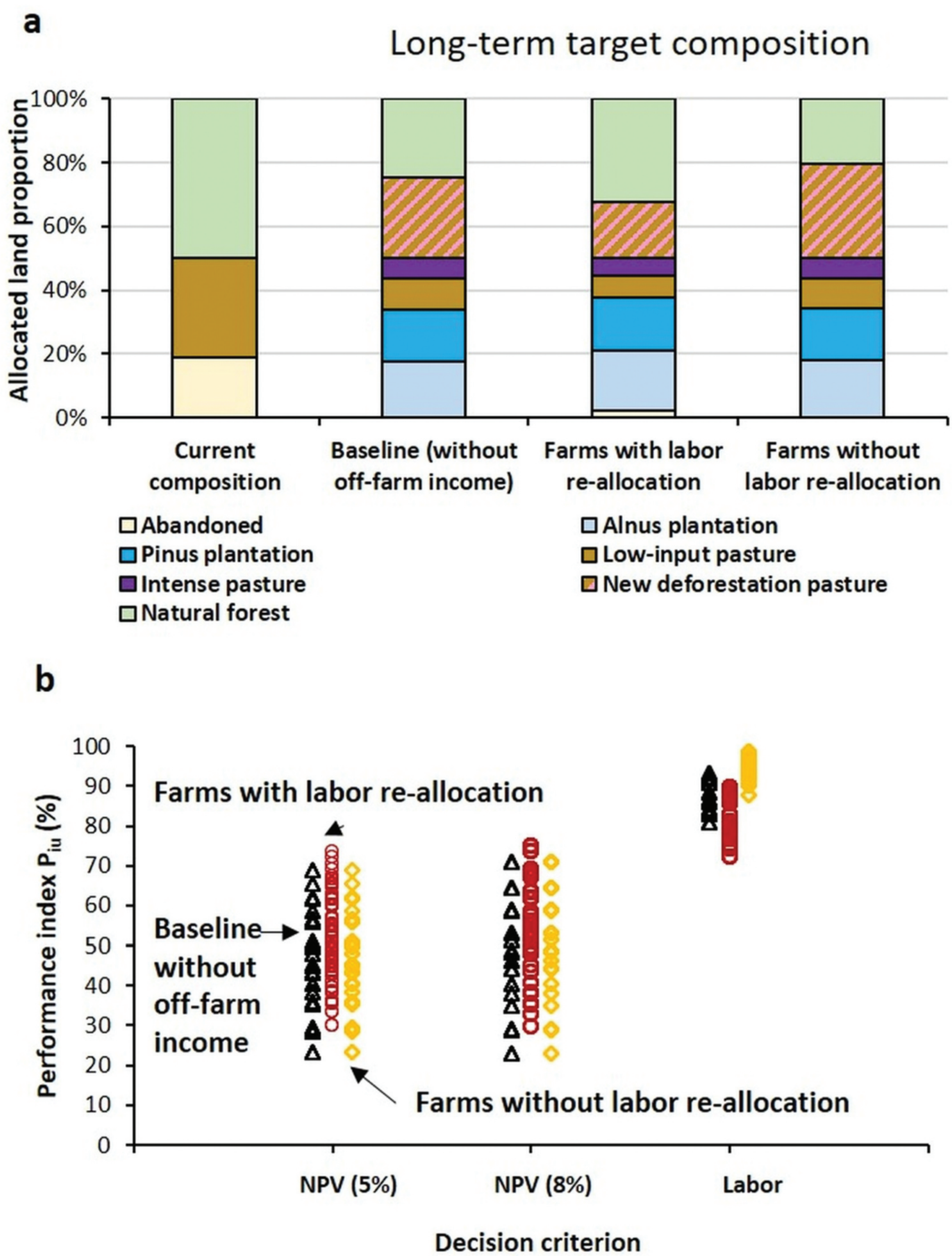

Figure 2. a. Current and optimized long-term target landscape compositions for various scenarios. The baseline scenario without consideration of off-farm income has been adopted from Knoke et al. (2020). b. Influence of off-farm income on distances between best and achieved decision outcomes for farms with and without re-allocation of labor, given the current landscape composition. We show only the decision criteria influenced by off-farm income (NPVs and required labor). The distances for the three objectives are important drivers of change, as the optimization seeks to minimize the maximum distance. As discount rates are uncertain (Weitzman, 1998) we considered net present values (NPVs) for two discount rates, representing more moderate (5%) and higher time preferences (8%). Each individual symbol represents one uncertainty scenario.

Assuming a proportion of off-farm income of 70% nearly halted the forest loss on farms with labor re-allocation. On farms without re-allocation of labor however, the same proportion of off-farm income would lead to the reduction of the current natural forest (50%) to 16.9%, meaning a forest loss of 33.1% points over 30 years.

Table 1. Influence of the proportion of off-farm income on the proportion of natural forest cover remaining after 30 years of simulation (initial forest cover is 50%).

	With re-allocation of labor		Without re-allocation of labor	
Proportion of off-farm income	Proportion of natural forest after 30 years	Natural forest lost over 30 years	Proportion of natural forest after 30 years	Natural forest lost over 30 years
[%]	[%]	[percent points]	[%]	[percent points]
0	29.1	20.9	29.1	20.9
10	30.7	19.3	28.6	21.4
20	32.2	17.8	27.9	22.1
30	33.1	16.9	27.1	22.9
40	34.7	15.3	25.8	24.2
50	38.7	11.3	24.1	25.9
60	44.4	5.6	21.4	28.6
70	49.5	0.5	16.9	33.1

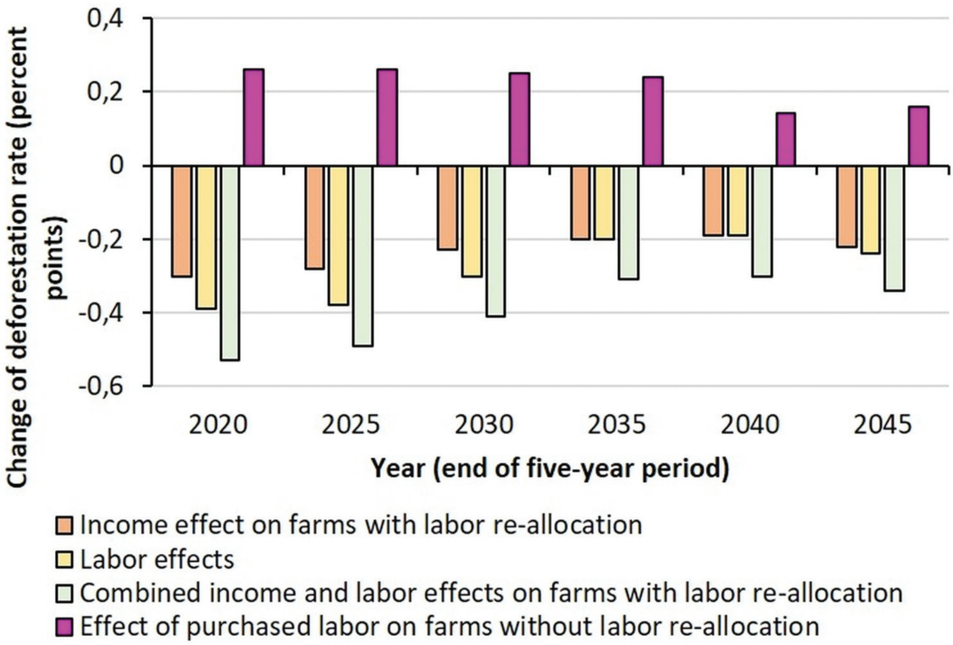

Figure 3. Changes of annual deforestation rates resulting from the consideration of off-farm income. Deforestation rates of the baseline scenario form the benchmark against which deforestation rates under the influence of off-farm income are assessed.

Changes of annual deforestation rates

All changes reported below (Figure 3) use the deforestation rates for the baseline scenarios (which did not consider off-farm income) as a benchmark (1.70%-1.98% p.a.). These deforestation rates were obtained for six five-year periods (see, Knoke et al., 2020, page 2415). For example, the baseline deforestation rate for the first period (annual average from 2015 to 2020) was 1.70% p.a.: considering off-farm income on farms with re-allocation of labor reduced the deforestation rate to 1.17%, but increased the deforestation rate to 1.96% on farms without re-allocation of labor.

Off-farm income reduced deforestation rates by 0.53 percentage points on farmers with labor re-allocation and increased deforestation rates by 0.26 percentage points on farms without re-allocation of labor, for the first period (Figure 3).

For the farms with labor re-allocation we can differentiate between income and labor effects, where the labor effect tends to have a slightly stronger impact on reducing deforestation rates than

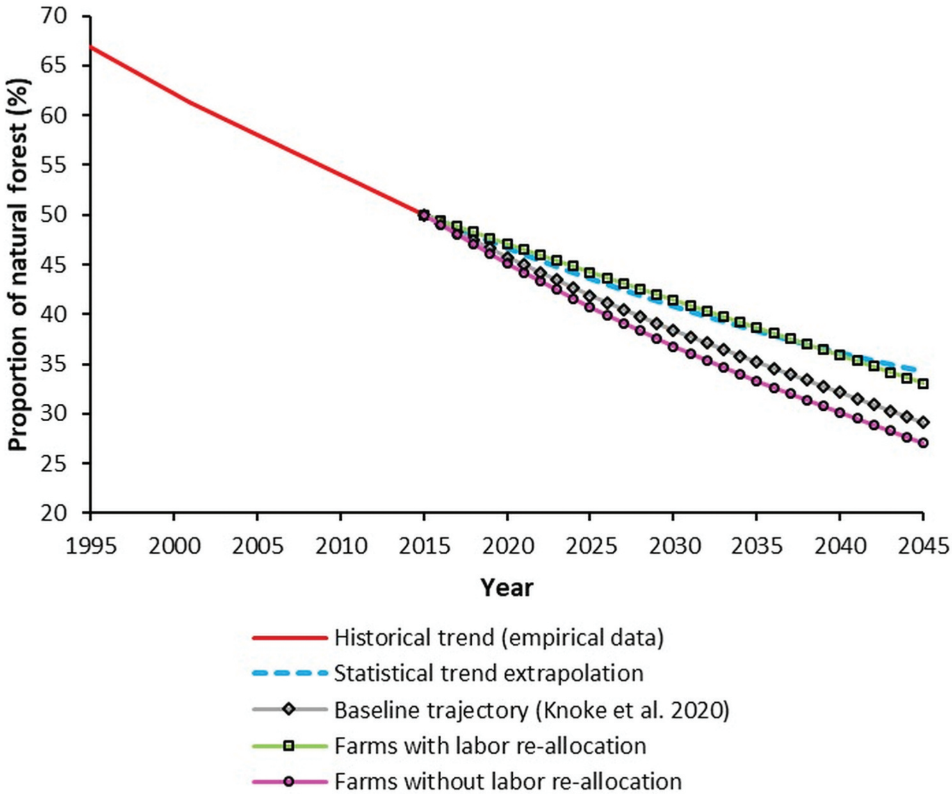

Figure 4. Trajectories of the proportion of natural forest under different scenarios.

the income effect (Figure 3). The direction of the influence of off-farm income on deforestation rates remained consistent over time, while the size of the influence tends to decrease over time.

Deforestation trajectories

Our different assumptions concerning farms with labor re-allocation and farms without re-allocation of labor led to diverging trajectories for the proportion of natural forest remaining in the landscape (Figure 4). Compared to the statistically extrapolated historical trajectory, the baseline scenario without considering off-farm income projected lower future proportions of natural forest until 2045. The trajectory for the farms with labor re-allocation hardly differed from the statistical trend extrapolation. The projected future proportion of natural forest was lowest when assuming a farm without re-allocation of labor.

Discussion

Comparison of model outcomes with empirical evidence from Latin America

The impact of off-farm income on farm management is variable and complex to analyze (e.g. Caulfield et al., 2021). Our model facilitates simulations of land-use allocation with and without inclusion of off-farm income in landscapes shaped by pasture expansion, where off-farm income either replaces farm income and leads to less agricultural expansion or is used to invest into resources for agricultural expansion, for example, by hiring additional labor. In Table 2 we contrast the model results obtained with empirical evidence.

Table 2. Results of our mechanistic land-use allocation model versus empirical evidence of the influence of off-farm income on tropical deforestation in Latin America.

Expectation	Model result	Empirical evidence
Smallholder farming leads to deforestation	For all studied scenarios optimized long-term target landscape compositions showed conversion of natural forest into pasture (Figure 2).	"The imbalanced coincidence of abundant forestland, scarce off-farm assets, free household labour and time yields near-inevitable deforestation as colonos convert the resources at their disposal (land, forest) to on-farm investments (pasture) . . . " (Sloan, 2008, p. 432)
The proportion of off-farm income of total household income influences deforestation	The higher the proportion of off-farm income, the lower the loss of natural forest over 30 years on farms with re-allocation of labor (Table 1).	Off-farm work can draw away labor which would otherwise be used for deforestation (Barbier, 2010). As an example, Thapa et al. (1996) showed how off-farm income reduces women's participation in agriculture with this pressure on natural forest (see, also Barbier & Burgess, 2001). In Vasco et al. (2020), p. 38% more off-farm work reduced deforestation by 28%. Off-farm employment also reduces interest in clearing forest (Pacheco et al., 2011). Araujo et al. (2019) obtained an average reduction of deforestation by 0.07% for an increase of 1% in relative off-farm income on Brazilian farms. In addition, Reyes et al. (2018) showed that income generated from forest extraction is negatively correlated with off-farm income (see, also Ojeda Luna et al., 2020).
	The higher the proportion of off-farm income, the higher the loss of natural forest over 30 years on farms without re-allocation of labor (Table 1). Increased income without decreasing the on-farm labor force thus accelerates deforestation (Figures 2 and 3).	Support: Wealthy farmers choose more lucrative non-agricultural work and invest into agricultural activities (Murphy, 2001). They do not use off-farm income to replace farm income, but hire additional labor associated with high deforestation rates (Pacheco, 2009; Mena et al., 2006), Bennett et al. (2018) showed how additional financial resources becoming available boost deforestation. Generally, an increase in income accelerates deforestation (Culas, 2007). No support: Mullan et al. (2018) did not find that income changes alter the rates of forest clearing and concluded that the total labor force is not a significant determinant of cleared area.
Off-farm income on farms with labor re-allocation can halt deforestation	Deforestation would no longer be necessary to maintain or enhance the livelihoods of extensive farm households, when their income is dominated by off-farm income (proportion of off-farm income $\geq$ 70%, Table 1).	Some farmers who include off-farm income into their livelihood strategy apply deintensification and some ultimately step out of agriculture (Caulfield et al., 2021).
Increased income used to intensify agriculture with subsequent decreases of deforestation	The intense pasture LULC type is hardly affected by additional off-farm income. Even with labor and capital available, farmers tend to continue deforestation before intensifying agriculture. This highlights ambiguity about the social acceptability for farmers (Figure 3 and 4).	"The odds of deforestation decrease with herd size as stocking densities tend to increase most markedly only after colonos convert most of their forest cover to rough pasture." (Sloan, 2008. p. 431). Similar results published by Kaimowitz and Angelsen (2008).

Concerning farms with re-allocation of labor, available household labor is considered an important factor potentially limiting the size of deforestation. On such farms we simulated a twofold impact of off-farm income to reduce deforestation: 1) replacing agricultural income and 2) reducing available labor to conduct deforestation. Both potential impacts align well with empirical evidence. Income from forest-related activities (clearing or partial timber extraction) appears to be generally negatively correlated with off-farm income, as for example, shown by Reyes et al. (2018) for firewood extraction in Chile. There is further empirical evidence supporting the theory that off-farm income reduces deforestation (Table 2). For example, Araujo et al. (2019) showed an average reduction of deforestation by 0.07% for an increase of 1% in relative off-farm income on Brazilian farms. Similarly, our model suggested a reduction of the deforested area by 0.06% per 1% increase in relative off-farm income, when relative off-farm income accounts for 5% and a reduction by 0.41% when relative off-farm income comprises 50% of the total income. The impact of limiting the labor available for deforestation when off-farm income is obtained (Barbier, 2010) has been shown, for example, by Vasco et al. (2020), where 38% more off-farm work provided by Ecuadorian farmers reduced deforestation by 28%.

Concerning farms without re-allocation of labor, our model suggested higher levels of deforestation compared to farms either without off-farm income or with re-allocation of labor. This matches with an empirically observed livelihood strategy type in Latin America. Caulfield et al. (2021) identified farms generating significant amounts of off-farm income, but remained focused on commercial farm production. Such farms invested into chemical fertilizers, pesticides and mechanized tillage to expand their agricultural production. How additional financial resources becoming available to invest into agricultural LULC types can boost deforestation was shown by Bennett et al. (2018) for palm oil in the Peruvian Amazon. Similar results were published earlier by Pacheco (2009) for pasture systems in the Eastern Amazon, where wealthy farmers hired additional labor, resulting in deforestation of large areas at the same time.

The model results also fit with empirical socio-economic investigations in the study region. Under the baseline scenario (which excludes off-farm income) deforestation rates were higher than the trend extrapolated from historical observations of deforestation in the study region. Accounting for off-farm income on farms with re-allocation of labor approached the statistical trend best among the three scenarios considered. This is consistent with the fact that the poor, resource-constrained type of farms which receive off-farm income associated with re-allocation of labor prevail in our study region, where pure subsistence or hybrid subsistence and market economy livelihood strategies have been identified (Pohle et al., 2010).

However, a comparison with empirical evidence also shows some limitations of our mechanistic model. Using a multi-indicator survey in rural Andean regions of Bolivia, Ecuador, and Peru, Caulfield et al. (2021) found three livelihood strategies including off-farm income, but four livelihood strategies that did not incorporate off-farm income. The likelihood of including or excluding off-farm income is not addressed in our model. In their study, Caulfield et al. (2021) analyzed household characteristics such as age of household head and education level, which were important determinants of the livelihood strategies. Another example of factors not included in our model is the type of motivation of farmers (intrinsic or extrinsic), which may impact the level of deforestation (Rueda et al., 2019). Concerning off-farm income, Mullan et al. (2018) found neither an impact of income nor of available labor force on deforestation levels in an already heavily deforested region. They found only small immediate income gains by deforestation, but there was a long-term benefit for farmers through the accumulation of assets. Such more nuanced relationships under more specific conditions (e.g. heavily deforested landscapes) are not represented by our mechanistic model. In addition, spatial aspects such as distance to roads or cities, or the slope of the terrain, which may have an impact on deforestation levels (e.g. Mullan et al., 2018), are not considered by our model. Finally, our focus was on smallholder farms and we assumed satisficing behavior for both farm types, with and without re-allocation of labor, while the resulting deforestation levels might underestimate deforestation levels for larger, more commercially oriented farms. One can use an alteration of our model's objective function to maximize the achieved average performance across all decision criteria that farmers may have (see, for example, Diaz-Balteiro et al., 2018 for an explanation). Such a maximizing assumption enhances the modelled deforestation levels, with or without off-farm income, because such efficiency orientation suppresses land-use diversification.

Off-farm income as a means to halt deforestation

Given our results, very high off-farm income may lead to halting deforestation. This aligns with empirical research that showed that off-farm economic incentives can effectively reduce deforestation (Jayachandran et al., 2017; Jones et al., 2017) or even lead to stepping out of agriculture (Caulfield et al., 2021; Table 2). However, relying only on the beneficial effect of off-farm payments could be too simple, because reducing deforestation means potentially reducing rural food production. Consequently, when the farm's contribution to the total income becomes marginal, farm abandonment and rural outmigration become increasingly likely. In fact, Pohle et al. (2013) already documented a declining population in the study region, possibly linked to decreasing on-farm income.

Rural outmigration and depopulation is a world-wide phenomenon (Sauer et al., 2019). According to forest transition theory, rural outmigration can lead to reestablishment of forest (Rudel et al., 2005, 2020), but it may also exacerbate food insecurity for the people remaining in rural areas (Bhawana & Race, 2020). Extensive research in the humid tropics, however, has shown that farm abandonment and the associated urbanization will boost rather than halt tropical deforestation (Araujo et al., 2019; DeFries et al., 2010). The population growth in urban areas and the associated expansion of built-up lands (Andrade-Núñez & Aide, 2018) correlated positively with the levels of deforestation. DeFries et al. (2010) concluded that depopulated rural landscapes are likely to increase the pressure on natural forests, because increasing consumption levels go hand in hand with urbanization. From a global perspective, urbanization may encourage export-oriented large-scale industrial agriculture that increases tropical deforestation (DeFries et al., 2013). Such effects associated with off-farm income are not addressed by our model.

Using REDD+ initiatives (Ji & Ranjan, 2019) to finance conservation payments may reduce deforestation more than off-farm income, which is not conditional to forest preservation (Knoke et al., 2022). Further, supporting smallholder farms to implement more sustainable land-use systems is a desirable additional strategy to help reduce deforestation while avoiding outmigration and leakage effects (Knoke et al., 2008). It also represents an alternative strategy to channeling agriculture towards large-scale and environmentally damaging industrial practices to meet increasing urban demands (Pretty, 2018). Socio-ecological landscapes not only need to protect nature and wildlife (Warnock & Griffiths, 2015), but also integrate people and local communities as part of those landscapes (Steiner, 2008). For example, Stabile et al. (2020) suggested creating economic, environmental and social improvements through technical assistance provided for smallholder farmers in Brazil.

The risk of reduced food production represents a typical result of many local policies to reduce deforestation, which often lead to win-lose scenarios between forest conservation and agricultural production (Angelsen, 2010). Conservation-related food gaps could potentially be compensated for by agricultural intensification, for example, by expanding high input pasture in our study region. This option would also require on-farm labor and provide a gainful land-use activity for farmers (Knoke et al., 2008). However, little is known about the social acceptability of intensive agriculture by smallholder farmers. Mechanistic land-allocation approaches as demonstrated in the current study may help to study this issue more intensively (Knoke et al., 2022).

Conservation payments to control adverse effects of (other) off-farm income

As already shown by Ochoa et al. (2016), appropriate conservation payments vary quite considerably across different farm types. Our simulations showed that additional off-farm resources may accelerate deforestation on farms without re-allocation of labor. Consequently, off-farm income had divergent effects, depending on the farm type. Such effects need consideration when designing conservation strategies. On farms with re-allocation of labor, off-farm income might support lower payments required for conservation, while on other farms off-farm income might increase such required payments. It is important that conservation payments that guarantee forest preservation are coupled to any agricultural subsidies designed to intensify food production. Otherwise such subsidies will enhance the capacity of the farms for deforestation, relaxing their resource constraints (Pacheco, 2009; Bennett et al., 2018; Table 2) and leading to rebound effects (Phelps et al., 2013).

Uncertainty

Uncertainty is a strong argument to assume satisficing behavior for decision-makers (Jaillet et al., 2022), which is empirically supported, for example, by Findlater et al. (2019). The existence of large uncertainties in land-use decision-making (e.g. Knoke et al., 2022) supports the behavioral assumption underlying our land-use model. We extended the consideration of uncertainty also to the aspect of off-farm income. We quantified off-farm income as a proportion of the agricultural farm income for both expected and worst-case agricultural incomes. As natural forest was progressively replaced with more profitable (but also riskier) LULC types, the difference between the expected and worst-case agricultural incomes increased over time, and so did the difference between the expected and the worst-case off-farm incomes. This trend represented the increasing uncertainty of the off-farm income over time, which weakened the size of the off-farm effects. Given that the uncertainty surrounding future decision outcomes typically increases with growing time horizons, the observed conservative model behavior appears intuitive.

Conclusion

Concerning our research question *'How well can we reproduce the existing empirical evidence of the influence of off-farm income on tropical deforestation by using a mechanistic land allocation model?'* we think – despite the mentioned limitations – that our mechanistic modelling concept can satisfactorily reproduce some of the existing knowledge of how off-farm income may influence tropical deforestation. The integration of off-farm income into robust multiple-objective land allocation provides a new and suitable option to consider the influence of off-farm income on tropical deforestation.

We second Dalla-Nora et al. (2014) in their conclusion that sound ' . . . land use models are useful for representing plausible ways in which the future could unfold in the context of scenario development, and explore the effects of changes in certain factors'. In this sense, our approach to model processes of land allocation has provided a good basis to elucidate the conditions under which one could expect reduced tropical deforestation from off-farm income. We consider our study as a part of a continuous learning process, mainly consisting of the conceptualization of a sequence of land allocation models. This continuous modelling process allows us to understand the mechanistic links between input information for different LULC types and output information at farm or landscape levels, and also the drivers of land-use change. Ultimately this enhanced understanding may help inform policies and programs to achieve more sustainable land-use change.

Our current study was conceptual and documents what we have learned about integrating off-farm income into a mechanistic land-use model. While the basic model structure (without considering off-farm income) for a one-period (static) optimization is available as an R-package (Husmann et al., 2022), we have here provided an Excel version for a dynamic six-period optimization (see our Supplementary Demonstration Program). This program can be run with OpenSolver (Mason, 2012), so that it is possible to reproduce all results, without extensive programming knowledge.

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