Received: 20 September 2019 | Revised: 25 December 2019 | Accepted: 12 January 2020

DOI: 10.1111/gcb.15003

PRIMARY RESEARCH ARTICLE

Global Change Biology WILEY

Accounting for multiple ecosystem services in a simulation of land-use decisions: Does it reduce tropical deforestation?

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Funding information
German Research Foundation, Grant/Award Number: PAK 823/4/5; Naturaleza y Cultura Internacional; Universidad Técnica Particular de Loja; Universidad Nacional de Loja

Abstract

Conversion of tropical forests is among the primary causes of global environmental change. The loss of their important environmental services has prompted calls to integrate ecosystem services (ES) in addition to socio-economic objectives in decision-making. To test the effect of accounting for both ES and socio-economic objectives in land-use decisions, we develop a new dynamic approach to model deforestation scenarios for tropical mountain forests. We integrate multi-objective optimization of land allocation with an innovative approach to consider uncertainty spaces for each

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objective. These uncertainty spaces account for potential variability among decision-makers, who may have different expectations about the future. When optimizing only socio-economic objectives, the model continues the past trend in deforestation (1975–2015) in the projected land-use allocation (2015–2070). Based on indicators for biomass production, carbon storage, climate and water regulation, and soil quality, we show that considering multiple ES in addition to the socio-economic objectives has heterogeneous effects on land-use allocation. It saves some natural forest if the natural forest share is below 38%, and can stop deforestation once the natural forest share drops below 10%. For landscapes with high shares of forest (38%–80% in our study), accounting for multiple ES under high uncertainty of their indicators may, however, accelerate deforestation. For such multifunctional landscapes, two main effects prevail: (a) accelerated expansion of diversified non-natural areas to elevate the levels of the indicators and (b) increased landscape diversification to maintain multiple ES, reducing the proportion of natural forest. Only when accounting for vascular plant species richness as an explicit objective in the optimization, deforestation was consistently reduced. Aiming for multifunctional landscapes may therefore conflict with the aim of reducing deforestation, which we can quantify here for the first time. Our findings are relevant for identifying types of landscapes where this conflict may arise and to better align respective policies.

KEYWORDS

biodiversity, ecosystem services, Ecuador, land allocation, landscape restoration, robust optimization

1 | INTRODUCTION

Ecosystem functions (EF) are ecological processes and structures that determine the capacity of ecosystems to provide ecosystem services (ES; Groot, Wilson, & Boumans, 2002). Integrating EF into land-use decisions is an important challenge to secure the provisioning of ES (Daily et al., 2009; Defries, Foley, & Asner, 2004; Foley et al., 2007; Goldstein et al., 2012; Nelson et al., 2009; Schößer, Helming, & Wiggering, 2010). ES result from EF that support human well-being (Fisher, Turner, & Morling, 2009) and have become an important utilitarian argument to justify nature conservation (Balmford et al., 2002; European Union, 2013; Fisher & Brown, 2015; MEA, 2005; Polasky et al., 2012). Payments for ES are seen as an innovative means to curb deforestation and to reduce the global loss of biodiversity (Wunder et al., 2018). However, while the concept of ES has stimulated an enormous amount of research, major challenges still remain regarding how to use this scientific knowledge to support real-world decision-making (Bennett et al., 2015; Guerry et al., 2015; Martinez-Harms et al., 2015; Ruckelshaus et al., 2015). Despite recent concepts linking ES with biodiversity to support conservation and sustainable use of natural resources (Díaz et al., 2018), few studies have gone beyond conceptual synthesis to quantify the consequences for nature conservation of integrating ES into decision-making, especially for tropical landscapes. For example, it is unclear how enhancing the capacity of a tropical landscape to provide ES would influence deforestation.

Deforestation still poses a major global challenge (Bebbington et al., 2018). The current level of forest loss driven by human activities could cause species extinction rates of 18%–40% by 2100, depending on whether the immediate protection of existing habitats in biodiversity hotspot areas is achieved (Pimm & Raven, 2000). Yet, many biodiversity scenarios only focus on the impact of climate change and ignore the influence of land-use/land-cover (LULC) change (Titeux et al., 2016). Tropical deforestation is a large-scale phenomenon and part of global change (Geist & Lambin, 2002). It is a relevant example for considering the influence of multiple ES on land-use decisions. Policies to reduce deforestation have been studied extensively (Angelsen, 2010) because deforestation and forest fragmentation can have far-reaching negative consequences. However, forest clearing may also sustain the livelihoods of local people, particularly in the tropics, where small-scale farming prevails (Affholder, Poeydebat, Corbeels, Scopel, & Tittonell, 2013).

Given the global importance of tropical deforestation, simulating decisions about the level of deforestation is important to obtain plausible future LULC trajectories for biodiversity or climate change scenarios and to test how decision-making may be improved to mitigate deforestation. This study investigates under which conditions accounting for ES in simulated land-use decision-making can contribute towards conserving tropical forests. Our study also attempts to overcome several shortfalls

associated with previous tropical LULC change models, including lack of transparency and validation (Rosa, Ahmed, & Ewers, 2014).

Various studies have used optimization approaches to integrate a variety of ES in land-use decision-making (Bagdon, Huang, & Dewhurst, 2016; Estrella, Cattrysse, & van Orshoven, 2014; Kaim, Cord, & Volk, 2018). Results of such studies have shown that incorporating ES can substantially change the allocation of land to different LULC types (Bateman et al., 2013). However, such optimization approaches have rarely tested the consequences of optimizing multiple ES in conjunction with socio-economic aspects of tropical deforestation. This is an important gap because tropical forests maintain important ES which are not accounted for in private land-use decisions (Foley et al., 2007). To make informed decisions about tropical land-use, it is necessary to better align short-term private benefits (e.g. derived from agricultural commodities) with the ecological consequences of land-use change (Defries et al., 2004; Foley et al., 2007; Guerry et al., 2015).

While higher levels of biodiversity usually enhance EF (Binder, Isbell, Polasky, Catford, & Tilman, 2018; Cardinale et al., 2012; Soliveres et al., 2016) and ES (Isbell et al., 2011; Rey Benayas, Newton, Diaz, & Bullock, 2009) at the plot scale, considering ES at the landscape scale does not necessarily help to conserve biodiversity. Some ES may be best provided by less biodiverse LULCs managed specifically for those ES. For example, Dawson and Martin (2015) have shown that tropical forests in western Rwanda failed to provide some key services, such as firewood and construction timber, which are better provided by non-native forest plantations. Ferreira et al. (2018) demonstrated how focusing on carbon sequestration may fail to protect the most biodiverse tropical forests because less biodiverse natural forests have higher carbon stocks. Thus, a clear understanding of the consequences of considering multiple ES in decision-making for the fate of natural tropical forests is still lacking.

Modelling the consequences of considering multiple ES and socio-economic objectives simultaneously in decision-making is challenging due to the uncertainties associated with measuring and predicting future provision of these ES and socio-economic benefits. Most multiple-criteria and optimization-based approaches do not satisfactorily address the possible influence of uncertainty on land-use decisions (Knoke et al., 2016), which may undermine 'science-based' decision-making (Hamel & Bryant, 2017). Uncertainty is more commonly considered in economic studies (Matthies, Jacobsen, Knoke, Paul, & Valsta, 2019). Some authors show that uncertainties may provide an incentive for land owners to conserve (agro-) biodiversity as a means to obtain natural insurance (Baumgärtner, 2007; Baumgärtner & Quaas, 2010; Di Falco & Perrings, 2005). The conservation of biodiversity may thus constitute an insurance value (Finger & Buchmann, 2015). However, it is difficult to predict how the typical behaviour of potentially risk-averse decision-makers will influence the actual conservation of biodiverse natural ecosystems.

Our study hypothesizes that the following conditions will lead to scenarios with reduced deforestation rates: (a) considering multiple ES in addition to socio-economic aspects in land-use decisions and (b) accounting for increasing uncertainty in the level of ES.

2 | MATERIALS AND METHODS

2.1 | The concept: Modelling three decision-making perspectives

Our study simulates real-world decision-making about allocating tropical land to LULC types, building on mathematical programming methods (Schreinemachers & Berger, 2006). We use a reference point method to consider multiple objectives (Estrella et al., 2014) combined with robust optimization to integrate uncertainty about future conditions (Ben-Tal, El Ghaoui, & Nemirovski, 2009). A reference point is the most desired value for an objective (seen as an ideal point; see Estrella et al., 2014), which can be achieved for a single objective and a single decision-maker, but not necessarily for all objectives and all decision-makers simultaneously (Yu, 1973; Zelany, 1974). Therefore, our model seeks a compromise that reduces trade-offs between the different objectives but also accounts for the attitudes of different decision-makers.

In our model, decision-makers determine the optimal land-use allocation based on the ability of LULC types to contribute to various objectives (input values from here onwards). For example, for the objective *carbon in planta*, we have measured input values ranging among LULC types between 12.5 and 125.2 Mg/ha. The decision-makers, however, are uncertain about the extent to which the LULC types can meet these objectives in the future. Our approach accounts for this uncertainty through the so-called uncertainty spaces, which contain a range of possible input values. When determining the optimal land-use allocation we rule out compensation among objectives: higher performance in one objective cannot compensate for poor performance in another. Instead, we minimize the maximum distance between the reference point and the actually achieved level across all objectives and all the input values contained in the uncertainty spaces (Zhang, Liang, & Zhang, 2018). Our aim is to find a compromise for future land allocation that best satisfies all objectives under uncertainty (see Methods S1 for further justification of our distance function).

We apply the approach to the widespread problem of pasture expansion into tropical forests, which is common in South America (Garrett et al., 2018; Wassenaar et al., 2007). While many studies use secondary data, we integrate in situ data in our model, that is, plot-level field, modelling and survey data of long-term ecological, social and economic studies in a real landscape in southern Ecuador (Knoke et al., 2014; Richter, Beck, Rollenbeck, & Bendix, 2013). This landscape is located in the transition zone of the Tumbes-Chocó-Magdalena and the Tropical Andes hotspot of vascular plant (Brummitt & Lughadha, 2003) and bird species richness (Liede-Schumann & Breckle, 2008; Orme et al., 2005; Methods S2). Most of this biodiversity is harboured by native mountain rainforests (Richter et al., 2013) and is threatened by deforestation activities which are common in the whole Andes (Aguirre, Palomeque, Weber, Stimm, & Günter, 2011). These circumstances form an ideal opportunity to study the consequences of optimizing multiple ES and socio-economic objectives.

We provide an innovative and dynamic perspective on the relation between the conservation of natural forests and maintaining

multiple ES. Our study extends the static land-use allocation model developed previously (Knoke et al., 2014, 2016). While the previous studies ignored deforestation and the landscape context and were limited to a fixed area of abandoned lands, we now consider the whole landscape composition and allow for an expansion of non-natural land in our optimizations. This is a precondition to model deforestation. We assume an initial landscape composition comprising 19% abandoned lands, 31% traditional low-input pasture and 50% natural forest (based on the land-use in 2015, derived from Curatola Fernández et al., 2015 for an area of 25 × 25 km^2). We also test the impact of different initial landscape compositions on deforestation levels. We simulate gradual changes in the landscape composition in 5-year time steps, consisting of a reallocation of area proportions to various LULC types, where the optimized future composition will form a long-term target for decision-makers. Our approach is dynamic because it uses the simulated landscape composition of the preceding time step to update the current landscape composition at the beginning of a new time step (Methods S3).

The model components are summarized in Figure 1. To evaluate and simulate the effect of considering ES in addition to socio-economic objectives in land-use decisions, we develop three different decision perspectives. These perspectives represent three *groups* of hypothetical decision-makers, each with a different set of objectives representing their preferences. The first group considers socio-economic objectives only (SE scenario, Figure 1) and obtains the perspective of farmers managing their own land. The second group considers both ES and socio-economic objectives (ES-SE scenario, Figure 1), and the third considers biodiversity in addition to the socio-economic objectives (B-SE scenario, Figure 1). The direct integration of biodiversity is an alternative to aiming at the conservation by integrating multiple ES. We thus contrast the decisions resulting from optimizing socio-economic objectives with the land-use allocation of two alternative decision perspectives, which in addition to the socio-economic objectives also consider objectives for either (a) maintaining multiple ES or (b) biodiversity conservation.

Within each decision perspective, no objective or group of objectives has priority over the others: all objectives are weighted equally. Weights depend on the individual stakeholder values assigned to the different objectives. These values are not static in time, differ among stakeholders and are also different between local and global scales. While some studies in similar analyses use stakeholder based weighting, we have refrained from this as such may lead to a strong bias introduced by the involved stakeholders and current priorities. We therefore use the arbitrary setting of equal weights and test the influence of specific objectives and of weighting single indicators higher than others by sensitivity analyses (Figure S1; Table S1; see Section 3.5).

Based on the different objectives, each group allocates land to seven LULC types (illustrated in Figure 2). These include traditional LULC types (Curatola Fernández et al., 2015) as well as alternative land-use types that aim to rehabilitate abandoned land or to improve low-input pastures: afforestation either with (native) *Alnus acuminata* Kunth or (exotic) *Pinus patula* Schltdl. & Cham. and recultivation towards intense pasture management. The ability of the LULC types to provide socio-economic benefits or multiple ES, or to maintain biodiversity, is quantified through a large number of indicators, which are used as input coefficients in the model (Figure 1) and described in Knoke et al. (2014). Specific subsets of these indicators also serve as the decision criteria of the three decision perspectives (Tables 1–3). The proportion of land allocated to each LULC type under each decision perspective form the choice variables, which are optimized according to different objectives as reflected by the decision criteria (Figure 1).

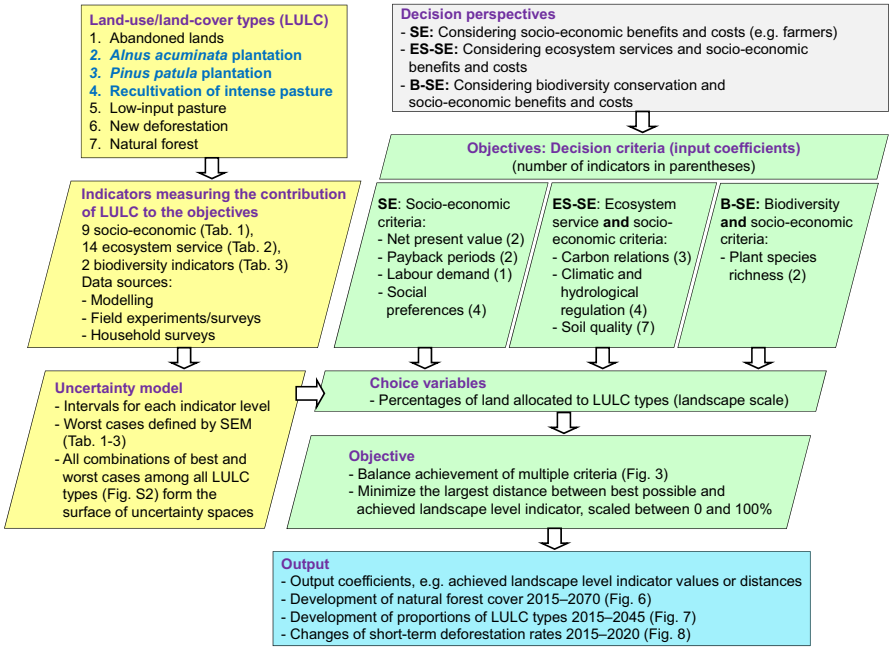


FIGURE 1 Overview of the optimization model components. Yellow fields represent land-use/land-cover (LULC) types and associated decision parameters (indicators used to quantify objectives and their uncertainty, where *SEM* is the standard error of the mean of these indicators). LULC types used to rehabilitate abandoned lands or to improve low-input pasture are shown in blue font. Green fields depict the subsets of indicators considered by the three decision-making perspectives and the components used to simulate the decision-making process. The blue box outlines the types of results obtained



FIGURE 2 Land-use/land-cover (LULC) types (a–g). Abandoned: Areas without any active use, which were previously used for pasture or where pasture established after deforestation failed (resulting in succession areas, e.g. with bracken fern, i.e. *Pteridium arachnoideum* (Kaulf.) Maxon and *Pt. caudatum* (L.) Maxon). *Alnus* plantation: Afforestation of low-input pasture or abandoned lands with *Alnus acuminata* Kunth as a native tree. *Pinus* plantation: Afforestation with *Pinus patula* Schltdl. & Cham. as an exotic tree species. Intense pasture recultivation: Conversion of low-input pasture (with *Setaria sphacelata* (Schumach.) Stapf & C.E. Hubb. ex Moss or *Melinis minutiflora* P. Beauv.) or abandoned lands to pasture with subsequent intense management. Low-input pasture (common practice in the study area): pasture with low-input management, characterized by low fertilizer and labour inputs. New deforestation: conversion of natural forest to low-input pasture. This land-use has different *socio-economic indicators* than the existing low-input pastures. For example, upfront revenues are received from clearing the timber, but very high labour input is required. Natural forest: with low-input management (tropical mountain rain forest)

The simulated decisions of the three perspectives aim for a compromise land allocation to improve levels for each single indicator. Land is allocated to the seven LULC types with the objective of balancing the achievement of indicators comprising the relevant decision criteria for each perspective (Figure 1). Our optimization procedure compares the distances between the most desirable level of each indicator achievable by a single LULC type (set as the reference point) and the levels actually achieved by a given landscape composition, and then minimizes the largest distance (Diaz-Balteiro et al., 2018; Romero, 2001; Stewart, 1992; Tamiz, Jones, & Romero, 1998) across all indicators and uncertainty scenarios (see Section 2.3).

Considering uncertainty for each indicator is important (Methods S4) as decision-makers have different attitudes towards risk (i.e. different risk preferences), which influences their decision-making. We assume that land-use decisions will build on beliefs about, rather than exact knowledge of, future indicator levels. The input values to quantify indicator levels cannot be predicted with certainty because environmental, market and socio-economic conditions change over time. Decision-makers' beliefs about the future will vary and depend, among other factors, on their degree of risk-aversion. To account for such uncertainty, we implement uncertainty spaces through our uncertainty model (Figure 1; Figure S2). Uncertainty spaces are represented by discrete scenarios systematically combining best- and worst-case values for each indicator for each LULC type based on the mean and standard error of the mean (*SEM*). All uncertainty scenarios are considered simultaneously in our optimization to ensure that the simulated future land allocation will provide feasible solutions over the whole uncertainty space (Ben-Tal et al., 2009), thus satisfying the requirements of a group of decision-makers who would consider the included input values.

The model output shows how the allocation of land to the seven LULC types changes. This comprises annual deforestation rates over a 5-year period (short term) and how the landscape composition and the natural forest cover develop over a 30-year period (farmer generation) and a 55-year period (long term), respectively. We present here the results for the 55-year period to allow for comparison with deforestation predictions of a stochastic model (Thies, Meyer, Nauss, & Bendix, 2014). The longer time period also allows us to analyse the dynamics of the modelled loss of natural forest over a longer timeframe.

2.2 | Indicators as decision parameters

Most of the indicators (Tables 1–3) considered in this study have been defined in Knoke et al. (2014). This includes indicators to quantify supporting (biomass production, soil quality) and regulating services (carbon, climate and water), as well as food and timber provisioning services, which are economically valued, and the social preferences of the local people. In addition to the indicators already published in Knoke et al. (2014), in this study, we also integrate indicators for biodiversity and labour requirement. The indicators show mainly weak correlations (Table S2).

The selected socio-economic indicators (Table 1) include economic return as the *net present value* (NPV) for two discount rates, *labour required* to establish and maintain the land-use types, and the often problematic issue of access to money, considered in the form of *payback periods* (time until the invested money is received back) for the two different discount rates. However, we not only considered economic criteria but also what the farmers would actually prefer, by addressing their *social preferences* for new LULC types. *Social preferences* are indicators representing the cultural benefit of the rehabilitation LULC types. They quantify the compatibility of each LULC type with tradition and also their contribution to the aesthetics of the landscape, or preserving cultural heritage (Knoke et al., 2014). The Mestizo farmers of mixed Spanish and indigenous

TABLE 1 Input values for socio-economic indicators and their uncertainties (quantified by their standard error of the mean, *SEM*) considered in the optimization model to simulate decisions based on socio-economic criteria (SE scenario)

Land-use/land-cover type, *l*								
Indicator, *i*	**Unit**	**Abandoned**	***Alnus* plantation**	***Pinus* plantation**	**Intense pasture recultivation**	**Low-input pasture**	**New deforestation**	**Natural forest**
Net present value (NPV) 5% discount rate[a]	US$/ha	0 (±0)	1,435 (±649)	1,322 (±586)	1,060 (±234)	1,318 (±111)	1,765 (±332)	427 (±73)
NPV 8% discount rate[a]		0 (±0)	619 (±394)	561 (±373)	485 (±132)	1,113 (±93)	1,471 (±321)	343 (±62)
Payback 5% discount rate[b]	Years	0.0 (±0.0)	16.0 (±3.0)	16.0 (±3.0)	10.0 (±2.0)	0.0 (±0.0)	0.3 (±0.8)	0.1 (±0.7)
Payback 8% discount rate[b]		0.0 (±0.0)	16.0 (±4.0)	16.0 (±4.0)	13.0 (±4.0)	0.0 (±0.0)	0.2 (±0.7)	0.1 (±0.6)
Labour requirement[b]	Days ha^{-1} $year^{-1}$	0.0 (±0.0)	9.4 (±1.2)	9.4 (±1.2)	16.6 (±1.1)	4.4 (±0.4)	13.4 (±6.8)	2.0 (±0.3)
Saraguro preference without subsidy[a]	Number of answers with preference rank 1 or 2	4 (±2)	14 (±3)	12 (±3)	4 (±2)	5 (±2)	Not assessed (see Methods S5)	
Saraguro preference with subsidy[a]		0 (±0)	19 (±3)	9 (±3)	8 (±3)	3 (±2)		
Mestizo preference without subsidy[a]		5 (±2)	19 (±4)	15 (±3)	10 (±3)	12 (±3)		
Mestizo preference with subsidy[a]		0 (±0)	16 (±3)	17 (±4)	12 (±3)	14 (±3)		

Note: The 'Number of answers with preference rank 1 or 2' reports how many respondents have rated a LULC type as best or second best during interviews. Data are adopted from Knoke et al. (2014) and from additional studies of the authors (Tables S3–S5; Methods S5). *SEM*, given in parentheses, has been used to quantify the uncertainty of socio-economic indicators as the possible undesirable deviation (worst cases) from the measured indicator levels for each LULC type, *l*, and indicator, *i*. The term 'Mestizo' refers to farmers of mixed Spanish and indigenous descent. Indigenous Saraguros are Quichua people who traditionally inhabited the Andean uplands of southern Ecuador.

Abbreviation: LULC, land-use/land-cover.

[a]Higher indicator values are considered better.

[b]Lower indicator values are considered better.

descent and the indigenous Saraguros (Quichua people from the highlands of southern Ecuador) participating in the household interviews hold their lands privately. During the interviews, the farmers were asked to rank five of the LULC types: three rehabilitation types (intense pasture recultivation and the two types of afforestation), low-input pasture and leaving the land abandoned. Each was ranked with and without the assumption of receiving subsidies (Methods S5).

The selection of the socio-economic indicators was informed by previous studies (Angelsen & Kaimowitz, 1999; Börner et al., 2010; Janssen & van Ittersum, 2007). We use a mix of sources: direct preferences of farmers concerning various LULC types, which were recorded in interviews, and calculated indicators, which build on household surveys, field experiments and simulations (Table 1). Household surveys provided information on market prices and labour requirement, which we combine with productivity data from field experiments and simulations (Knoke et al., 2014). This provides a consistent method to evaluate the economic performance of each LULC type, including the new LULC types (e.g. intense pasture recultivation and afforestation) that could not be quantified by farmer experience. Farmers were thus not asked directly for the performance of LULC types against some indicators, as we wanted to quantify these indicators from a neutral perspective. To validate our selection of socio-economic indicators, we compared the deforestation rate simulated by the model to past deforestation observed in the study area, and to the future deforestation rate predicted by a locally valid stochastic model (Thies et al., 2014). Here, we assume that a set of socio-economic objectives that produces a deforestation trend similar to past and predicted deforestation rates will best reflect the objectives driving farmers' actual decision-making.

Indicators for multiple ES (Table 2; see Methods S5 for more details) have also been defined in Knoke et al. (2014) and describe *carbon relationships*, *climatic regulation*, *hydrological regulation* and *soil quality* (Table S3). We assume that these EF provide benefits for humans and thus regard them as ES. *Carbon relationships* quantify the uptake of carbon and its accumulation. The indicators used, such as *biomass production* or *carbon* stored in plants or soils (Table 2), quantify primary EF that are a precondition for provisioning (food, fodder and timber), regulating (storage of atmospheric

TABLE 2 Input values for indicators for ecosystem services (ES) and their uncertainties, used to simulate decisions combining the multiple ES with the socio-economic indicators from Table 1 (ES-SE scenario)

Land-use/land-cover type, *l*							
Indicator, *i*	**Unit**	**Abandoned**	***Alnus* plantation**	***Pinus* plantation**	**Intense pasture recultivation**	**Low-input pasture/ new deforestation**	**Natural forest**
Biomass production (aboveground)[a]	Mg ha^{-1} $year^{-1}$	9.2 (±1.3)	6.1 (±0.6)	7.1 (±0.4)	6.6 (±0.3)	1.2 (±0.2)	9.2 (±0.6)
Carbon in planta[a]	Mg/ha	33.0 (±2.9)	24.5 (±2.3)	29.6 (±1.4)	25.8 (±3.4)	12.5 (±1.2)	125.2 (±15.7)
Soil organic carbon stock[a]	Mg/ha	87.3 (±5.3)	91.7 (±6.8)	93.5 (±4.6)	96.3 (±5.1)	91.8 (±4.9)	100.0 (±8.7)
Evapotranspiration[a]	mm/year	928 (±3.8)	1,597 (±4.1)	1,410 (±1.1)	1,167 (±5.1)	1,186 (±5.8)	1,580 (±5.0)
Momentum flux[a]	kg m^{-1} s^{-2}	0.018 (±0.0003)	0.285 (±0.0156)	0.294 (±0.0004)	0.026 (±0.0004)	0.023 (±0.00003)	0.42 (±0.0119)
Overland flow[b]	mm/year	75 (±3.7)	38 (±0.8)	29 (±1.5)	77 (±2.9)	75 (±2.8)	0 (±0)
Area-specific discharge[b]	mm/year	927 (±6.9)	283 (±4.0)	471 (±2.7)	695 (±6.1)	677 (±7.0)	300 (±5.0)
pH (in deionized H_2O; hydroxonium concentration used for optimization[b])		4.5 (±0.09)	4.3 (±0.04)	3.6 (±0.13)	4.1 (±0.09)	4.5 (±0.18)	3.8 (±0.06)
Soil organic carbon concentration[a]	%	9.5 (±0.2)	7.9 (±0.7)	6.8 (±0.8)	11.7 (±0.4)	10.6 (±0.6)	8.0 (±0.47)
Base saturation[a]	%	11.5 (±2.6)	30.4 (±1.8)	6.4 (±1.2)	11.9 (±1.3)	16.9 (±1.3)	9.0 (±1.8)
Carbon concentration in microbial biomass[a]	mg/kg	1,088 (±51)	1,065 (±80)	576 (±75)	1,359 (±65)	1,065 (±102)	1,025 (±80)
Carbon mineralization rate[a]	g CO_2-C/kg SOC	3.9 (±0.18)	3.1 (±0.13)	3.7 (±0.49)	3.2 (±0.27)	3.5 (±0.31)	3.2 (±0.32)
Nitrogen mineralization rate[a]	mg N kg^{-1} day^{-1}	2.3 (±0.27)	2.7 (±0.49)	1.9 (±0.31)	3.0 (±0.12)	1.0 (±0.22)	3.6 (±0.71)
PO_4-phosphorus concentration[a]	mg/kg	0.5 (±0.09)	1.3 (±0.22)	5.8 (±1.21)	6.0 (±1.79)	0.6 (±0.13)	1.1 (±0.24)

Note: Data are adopted from Knoke et al. (2014) and from additional studies of the authors (Table S3; Methods S5). *SEM*, given in parentheses, has been used to quantify the uncertainty of ES as the possible undesirable deviation from the measured indicator levels for each land-cover type, *l*, and indicator, *i*.

Abbreviation: *SEM*, standard error of the mean.

[a]Higher indicator values are considered better.

[b]Lower indicator values are considered better. For the pH indicator a high hydroxonium concentration corresponds to high acidity and low pH value and vice versa.

TABLE 3 Results of statistical simulations (based on iChao2 and Jackknife2 methods) for biodiversity indicator input values and their uncertainties based on species–area relationships

Land-use/land-cover type, *l*							
Indicator, *i*	**Unit**	**Abandoned**	***Alnus* plantation**	***Pinus* plantation**	**Intense pasture recultivation**	**Low-input pasture/new deforestation**	**Natural forest**
Species richness (iChao2)	Number	199.1 (±8.9)	40.6 (±1.8)	468.4 (±76.4)	61.7 (±8.3)	138.7 (±15.7)	1,345.4 (±23.3)
Species richness (Jackknife2)	Number	216.2 (±16.4)	45.4 (±6.7)	311.4 (±19.9)	64.2 (±7.3)	137.6 (±12.5)	1,457.4 (±42.0)

Note: These input values and uncertainties are used to simulate decisions in the B-SE scenario, in which biodiversity and SE indicators (Table 1) are combined. The dataset is based on a new evaluation of data in Peters et al. (2010) and on additional studies of the authors (Table S3; Methods S5). *SEM* has been used to quantify the possible undesirable deviation from the measured indicator levels for each land-cover type, *l*, and indicator, *i*, and is given in parentheses. See Figure S6 for graphical representation of species–area relationships. Higher indicator values are considered better.

Abbreviation: SE, socio-economic; *SEM*, standard error of the mean.

carbon) and life supporting (formation of organic matter to improve soil quality) ES. The ES *climate regulation* is supported by other important EF. Changes in the energy balance, surface roughness and evapotranspiration link the atmospheric to the hydrological function. To quantify such effects, we calculate water and momentum fluxes (turbulence production). *Hydrological regulation* is important to assess the potential of LULC types for reducing undesired effects of water, such as erosion. These ES are covered by the indicators *area-specific discharge* and *overland flow*. Indicators of *soil quality* evaluate the long-term soil productivity, capturing plant productivity and soil biodiversity. This above information has been adopted from Knoke et al. (2014, pp. 3–5), where more detailed information is provided.

Biodiversity indicators quantify vascular plant species richness (Table 3). Data for the indicators *species richness iChao2* and *species richness Jackknife2* were obtained by examining vegetation plots on natural and anthropogenic sites within the study region (Peters, Diertl, Gawlik, Rankl, & Richter, 2010) and were re-evaluated for our study. Terrestrial vascular plant species and their ground coverage (in %) were recorded. Epiphytes, hemi-epiphytes, lichens and bryophytes were not sampled. For the statistical modelling of the species–area relationships, the open-source software R and its packages vegan and SpadeR were used and species data were transformed to presence–absence values. Species richness was quantified by iChao2 and second-order Jackknife indices. For both calculations, the frequencies of unique and duplicated species were used to estimate the number of undetected species (Table S3; Methods S5).

2.3 | Robust optimization of multiple criteria

Robust optimization of the allocation of land to LULC types produces solutions that remain feasible for a large range of input values. We consider the measured and modelled input values for the indicators (Tables 1–3) as knowledge available for our decision-makers. However, we also model deviations from these expected input values in the form of worst cases, which are also considered in decision-making. We assume that more cautious, risk-averse decision-makers will account for more pessimistic worst cases in their decisions, while for less risk-averse decision-makers worst cases will be more optimistic.

Figure 3 illustrates the key concepts of our robust optimization approach. It shows examples of the relative distances between the indicator levels achieved by a given LULC composition and the reference point for each indicator (set to 100%), which are the basis for our optimization. To determine the level of an indicator achieved at the landscape scale by a given LULC composition, we computed the sum of the area-weighted indicator values of each of the LULC types included in that landscape. We then normalized these landscape scale indicators from 0% to 100% based on the highest and lowest values for single LULC types to obtain the distance between the achieved level and the reference point (Figure 3). Table S6 shows the maximal landscape level values, when each single indicator is maximized separately.

The nature of a given indicator determined whether the reference points were represented by the maximum or minimum value achieved in the various LULC types. For example, the highest NPV among all LULC types was 1,765$/ha for new deforestation (Table 1): this value forms the 100% level and the minimum (lowest NPV, $0/ha for abandoned land) is set to 0%, because for this indicator high values are desirable. In contrast, for *labour requirement* and *payback periods* lower values are desirable and their minima thus form the 100% level, while their maxima are set to 0%.

The variation of the landscape scale indicator levels shown in Figure 3, that is, the varying distances to 100%, is due to the uncertainty scenarios considered, which reflect the potential variation in the indicator levels achieved by each LULC type in best and worst cases. For example, in the worst-case scenario, the current landscape composition would only achieve a performance level of ≈1% for *social preferences*. However, after the optimization

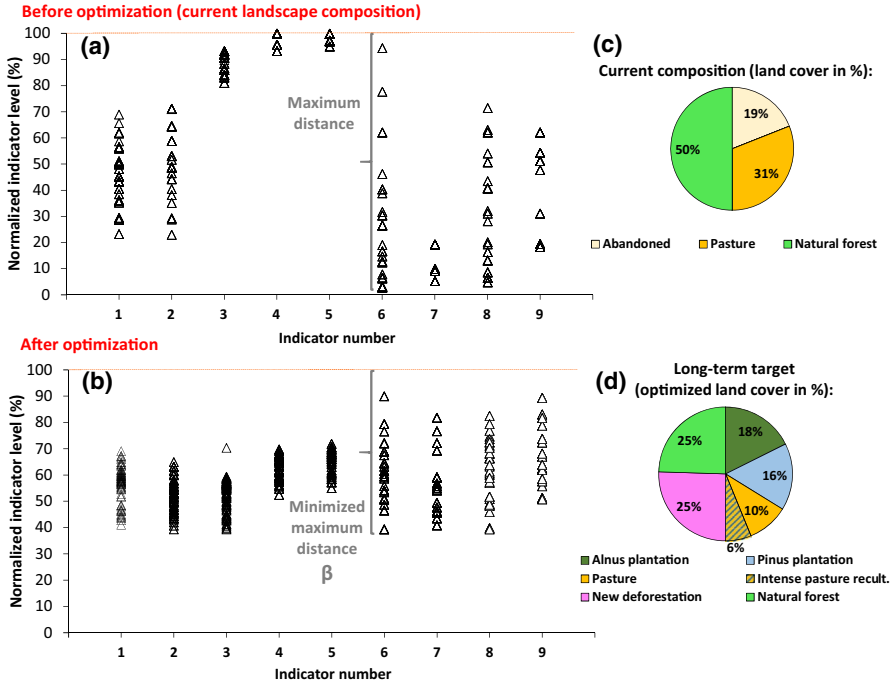


FIGURE 3 Explanation of the optimization procedure for the SE scenario. Triangles depict the possible distances between the reference point and actually achieved indicators values, scaled between zero and 100% for each uncertainty scenario (for an uncertainty space of size 3 *SEM*), (a) before and (b) after optimization. Distances for the nine socio-economic indicators are displayed for current and optimized long-term landscape compositions. The upper part (a) and (c) describes the current landscape composition, where rehabilitation land-use/land-cover (LULC) types are not present. The lower part (b) and (d) shows how the maximum distance, β, is minimized by re-allocating land to the considered seven LULC types (pie-chart in lower right). Shown indicators are: 1: net present value (NPV; 5% discount rate); 2: NPV (8% discount rate); 3: labour requirement; 4: payback period (5% discount rate); 5: payback period (8% discount rate); 6: Saraguro preferences without subsidy; 7: Saraguro preferences with subsidy; 8: Mestizo preference without subsidy; 9: Mestizo preference with subsidy. SE, socio-economic; *SEM*, standard error of the mean

procedure, this worst-case (guaranteed) performance level increases to ≈40%.

We model the uncertainty of our input values for each LULC type based on their *SEM*. The *SEM* mainly results from site variability and to a lesser extent from measurement and sampling errors. *SEM*s computed for economic indicators consider market price fluctuations and risk of fire or landslides and are relatively high. In contrast, Monte-Carlo simulations for hydrological and climate models resulted in lower uncertainties (Knoke et al., 2014). We assume that the numeric input values represent a group of decision-makers and thus reside in predefined intervals for all indicators (Gorissen, Yanıkoğlu, & den Hertog, 2015; Jalilvand-Nejad, Shafaei, & Shahriari, 2016). The intervals have the size $m{\cdot}SEM_{li}$:

$$y_{liu} = \begin{cases} y_{li} & \text{for best case} \\ y_{li} + m \cdot SEM_{li} & \text{for worst case, if less is considered better} \\ y_{li} - m \cdot SEM_{li} & \text{for worst case, if more is considered better} \end{cases} \quad y_{liu} \in U_i \,. \quad (1)$$

These intervals span the best (expected value), y_{li}, and worst cases for each uncertainty scenario, u, for the indicator i for a certain LULC type, l. We focus on the undesirable deviation of the input values by considering possible worst cases, which assumes that our decision-makers are motivated to avoid losses. Generating all possible combinations of best (expected) and worst cases across the seven LULC types creates our uncertainty scenarios, which provide the corner points (i.e. describe the surface) of multi-dimensional boxes representing our uncertainty spaces U_i for each objective (see Figure S2 for a simplified hypothetical example). All corner points are considered simultaneously during the optimization. We may thus expect that the optimal land allocation will represent a feasible solution for all input values included in the uncertainty spaces. We consider these optimized land allocations as compromise solutions, accounting for a group of decision-makers with different degrees of risk-aversion. Minimizing the maximum distance, β, as described in Figure 3, for a group of decision-makers may produce consensus solutions when decision-makers are uncertain or disagree in their opinions (Zhang et al., 2018).

We demonstrate the feasibility of our solutions by a simulation experiment based on sets of input values that were randomly chosen from within the uncertainty spaces. We use 500 hypothetical decision-makers per scenario, who consider randomly chosen worst cases, which deviate between m = 0 and 3 times the size of the *SEM* of the corresponding input values.

We have implemented our model as a linear program: The objective β depends on the future land proportions, a_l^f, allocated to each LULC type, l.

$$\min_{\left(a_l^f\right)} \beta, \tag{2}$$

s.t.

$$\begin{aligned} &\sum_l y_{liu} a_l^f \geq y_{iu}^* - \tfrac{\beta}{100} \cdot \left(y_{iu}^* - y_{iu*}\right) \quad \forall i,u, \text{if more is considered better} \\ &\sum_l y_{liu} a_l^f \leq y_{iu*} + \tfrac{\beta}{100} \cdot \left(y_{iu}^* - y_{iu*}\right) \quad \forall i,u, \text{if less is considered better} \end{aligned} \tag{3}$$

$$\beta \geq \begin{cases} \frac{y_{iu}^* - \sum_l y_{liu} a_l^f}{y_{iu}^* - y_{iu*}} \cdot 100 & \text{if more is considered better} \\ \frac{\left(\sum_l y_{liu} a_l^f\right) - y_{iu*}}{y_{iu}^* - y_{iu*}} \cdot 100 & \text{if less is considered better} \end{cases} \quad \forall i,u, \tag{4}$$

$$\sum_l a_l^f = 1; \quad a_l^f \geq 0, \tag{5}$$

$$a^c_{\text{natural forest}} = 0.50; \quad a^c_{\text{low- input pasture}} = 0.31; \quad a^c_{\text{abandoned}} = 0.19, \tag{6}$$

$$a_{\text{new deforestation}} + a^f_{\text{natural forest}} = a^c_{\text{natural forest}}, \tag{7}$$

$$a^f_{\text{low- input pasture}} \leq a^c_{\text{low- input pasture}}, \tag{8}$$

where a^f is the future and a^c is the current land proportion. The maximum input value y_{iu}^* (more is considered as better) or the minimum input value y_{iu*} (less is considered as better) from each uncertainty scenario are the reference points for our decision-makers (Inequalities 3). However, it is infeasible to always achieve the reference points, unless one LULC type provides the most desirable values for all indicators and uncertainty scenarios, which is not the case in our study. Consequently, our decision-makers must accept compromises and thus reduce their maximal requirements. The reduction is expressed by $\frac{\beta}{100} \cdot \left(y_{iu}^* - y_{iu*}\right)$. This is the maximal absolute distance to the reference points that the decision-makers would tolerate (Knoke et al., 2015). β is the maximum relative distance which they accept, if Inequality 3 is to be fulfilled for each indicator and uncertainty scenario. If decision-makers would accept β = 100, they would obtain the least desired input value, while requiring β = 0 would mean always demanding the reference point; realistic values are 0 < β < 100. However, the decision-makers would not reduce their requirements for desired indicator levels more than necessary. We thus need to minimize the maximum distance β when simulating decision-making (Methods S1).

To achieve a minimization of the maximum distance, we can reorganize our formulations so that a direct minimization of β is possible (Inequalities 4) and obtain a model formulation that allows for exact solutions (Estrella et al., 2014; Tamiz et al., 1998). The quotients on the right-hand side of Inequalities 4 quantify the individual relative distances between the achieved landscape level indicators, $\sum_l y_{liu} a_l^f$, and the reference point. We normalize these distances between 0% and 100% by dividing the absolute distance by the range of input values in one uncertainty scenario (Diaz-Balteiro et al., 2018). During sensitivity analyses to study the influence of weighting on the results, we included higher weights for each single indicator than for all other indicators. To achieve this, we multiplied the right-hand side of Inequality 4 by w_i, considering $\sum_i w_i = 1$ (Table S1). The sum of all allocated area proportions must be one and the area proportions also need to be non-negative (Equation 5).

Equation (6) represents the initial landscape composition in our example. The model runs in 5-year intervals, where the starting points of these intervals are updated with the landscape composition achieved in the previous interval (dynamic approach, see Methods S3). To compute annual changes within the 5-year intervals, we consider the optimized future landscape composition as a long-term target pursued over a farmer's generation (30 years) and divide the associated LULC changes by 30 years. We multiply the annual changes by five to determine the (interim) land-use composition at the end of each 5-year period. The LULC changes result from target area proportion (example in Figure 3d) minus current area proportion of LULC types (example in Figure 3c). Considering the new starting points at the beginning of each 5-year interval leads to periodic revisions of the long-term target.

Importantly, the area of new deforestation and future natural forest must be equal to the current natural forest area (Equation 7). Furthermore, the low-input pasture must not exceed its initial area (Equation 8) because new low-input pasture will only be established by deforestation, which is then named new deforestation. Conversion of new deforestation area into alternative land-use options within the next 5 years is ruled out by Equation (7), while abandonment of existing low-input pasture or its conversion to afforestation or intense pasture is possible. Frontline Analytic Solvers'® (V2017-R2 17.5.0.0) standard Linear Programming/Quadratic Engine was used to solve this program, but it would also be possible to run the optimization using open-source software (see example Program S1).

This modelling approach allows us to test the impact on deforestation decisions when considering (a) only *socio-economic indicators* (SE scenario); (b) ES indicators in combination with *socio-economic indicators* (ES-SE scenario); or (c) biodiversity indicators in combination with *socio-economic indicators* (B-SE scenario).

3 | RESULTS

3.1 | Static perspective: Robustness of the long-term landscape composition

Our robust optimization approach allowed us to find one solution for each decision perspective that satisfies all constraints (imposed by the Inequalities 3) for all sets of input values included in the uncertainty spaces. Figure 4 shows that all minimum performance levels for our simulated 500 decision-makers are greater than or equal to 100 − β, the performance level guaranteed by our robust solutions. As all sets of input values included in the uncertainty spaces were assumed to represent the beliefs of the single

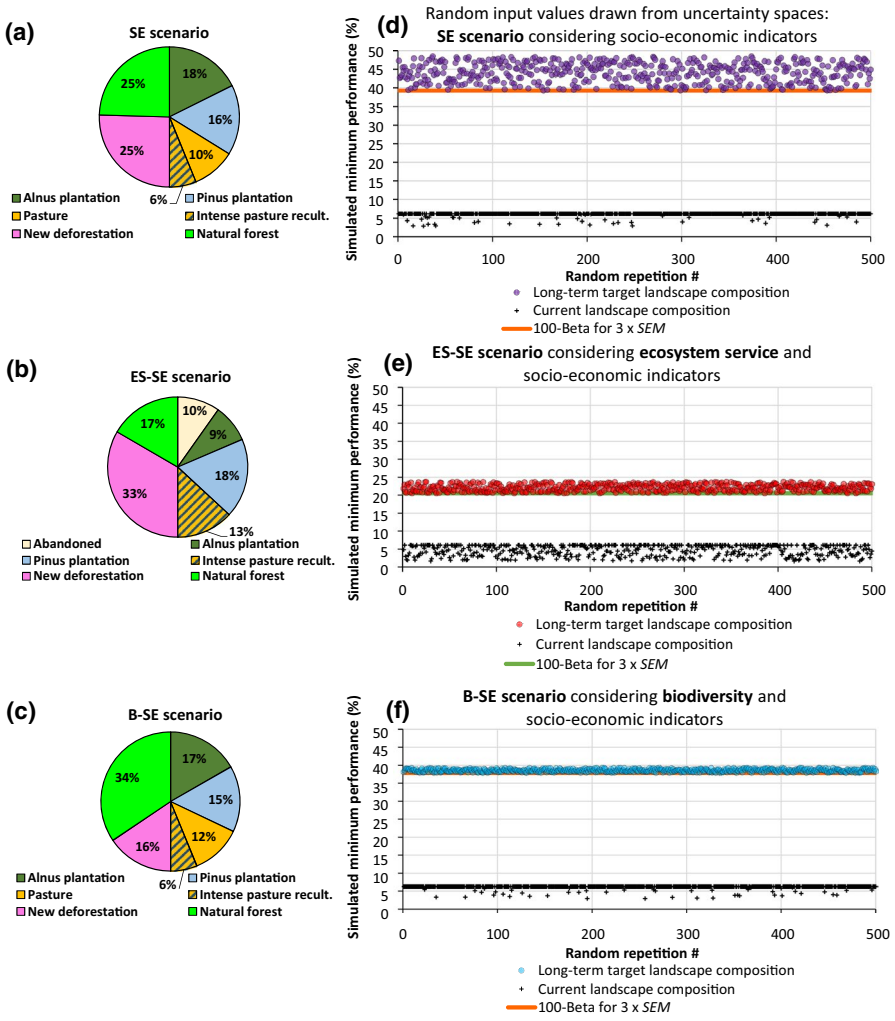


FIGURE 4 Robust allocation of land to land-use/land-cover types (a–c) and associated minimum performance levels (d–f) for hypothetical decision-makers represented by 500 sets of input values per decision perspective, randomly selected from the associated uncertainty spaces. The uncertainty spaces have a size of 3 *SEM*, while the simulated deviations of the worst cases from the expected values for our 500 decision-makers varied randomly between zero and 3 *SEMs*. ES, ecosystem services; SE, socio-economic; *SEM*, standard error of the mean

decision-makers, these solutions can be assumed satisfactory for our groups of decision-makers.

Decision-makers who seek to balance the achievement of socio-economic indicators (SE scenario) would aim to reduce the natural forest share in the landscape from 50% currently to 24.5% in 30 years. This means an annual deforestation rate of 1.7%. Under the SE scenario, decision-makers achieve a guaranteed performance level of 100 – $\beta \approx 39\%$ for all indicators and uncertainty scenarios.

Decision-makers accounting for ES indicators in addition to socio-economic indicators (ES-SE scenario) would reduce the proportion of natural forest from 50% to 16.6%. This amounts to an annual deforestation rate of 2.2%. Note that this very strong reduction of natural forest is partly a result of our static perspective (see the text below for changes under a dynamic perspective). The ES-SE decision-makers expand the converted land area and diversify the landscape more intensely than those in the other scenarios. The guaranteed performance level in the ES-SE scenario is 100 – $\beta \approx 21\%$.

Decision-makers in the B-SE scenario obtain a similar guaranteed performance level (100 – $\beta \approx 38\%$) as decision-makers in the SE scenario (100 – $\beta \approx 39\%$). Accounting for biodiversity indicators does not worsen the overall solution much. The B-SE scenario retains the most natural forest; its proportion decreases from 50% to 34.4%, representing a simulated annual deforestation rate of 1.0%, the lowest among the three decision-making perspectives.

3.2 | Landscape context influences deforestation

We have so far simulated deforestation for the current landscape context, with an initial natural forest proportion of 50%. However, the specific landscape context influences the simulated level of deforestation (Figure 5). For landscapes with an initial natural forest share of 38%–80%, the expansion of converted land in the ES-SE scenario leads to high deforestation rates. In fact, over this range of natural forest cover the ES-SE perspective shows the highest deforestation rates among the three decision-making perspectives. At either relatively low or very high shares of natural forest, considering multiple ES alongside socio-economic indicators reduces deforestation compared to the baseline SE scenario. At low forest shares, the elevated levels of some ES provided by natural forests are so important that further reduction of natural forest is greatly reduced or even ruled out; accounting for multiple ES would stop deforestation when natural

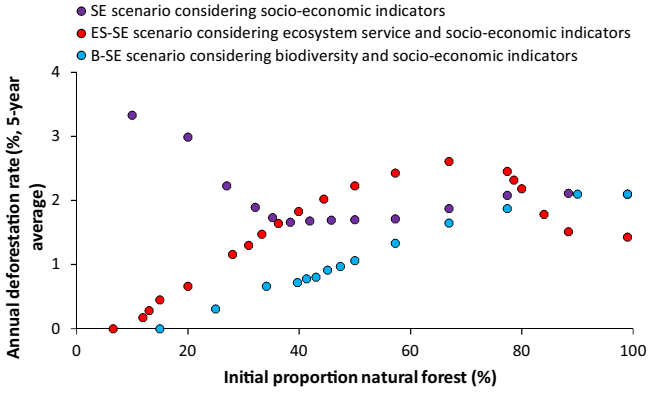


FIGURE 5 The influence of the initial natural forest proportion (landscape context) on deforestation. The simulated level of the annual deforestation rate (%) is higher when aligning multiple ecosystem services (ES) with socio-economic (SE) indicators than for the other perspectives, when we provide forested landscapes with natural forest proportions between 38% and 80%

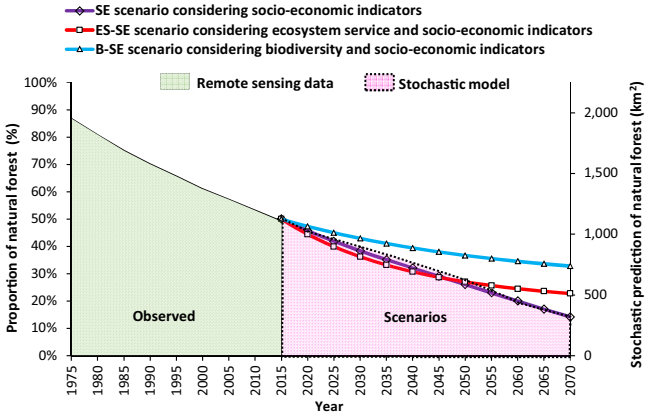


FIGURE 6 Decline in the area of natural mountain rainforest. The allocated proportions of land to natural forest in the study landscape (in %, left axis) depend on the perspective for decision-making on land-use/land-cover (LULC) change. Scenarios have been developed for a forested landscape in the southern Andes of Ecuador, where deforestation is common (Aguirre et al., 2011) and where LULC change has also been analysed via remote sensing (Curatola Fernández et al., 2015). Scenarios assume high risk-aversion for the considered decision-makers, accounting for possible indicator uncertainty with a worst-case scenario deviating by 3 *SEM*s (standard error of the mean) from the expected input value. Land was allocated among seven LULC types (abandoned lands, afforestation with either *Alnus acuminata* or *Pinus patula*, recultivation towards intense pasture management, low-input pasture, new deforestation and natural forest). Stochastic predictions of forest area (in km^2, right axis) refer to Thies et al. (2014) who provided forecasts for a larger region, which includes our study area (our area refers to Curatola Fernández et al., 2015). See Figure 7 for more information about the development of LULC composition over time

forest cover falls below 10%. At high forest shares, considering multiple ES also reduces deforestation levels. At very high forest shares, the model has the choice between only two options: retaining natural forest or new deforestation (as an interim step to establishing alternative LULC types). Considering multiple ES favours retaining the natural forest, because new deforestation with subsequent low-input pasture performs poorly for some of the ES indicators. In this situation, the alternative LULC types are not yet available to compensate for this deficiency because they cannot be established immediately, but instead require already cleared land.

3.3 | Dynamic perspective: Considering socio-economic indicators forms an expedient baseline

To account for the influence of a changing natural forest share on deforestation rates over time, we periodically updated the initial landscape compositions during the optimization procedure. This resulted in a dynamic modelling approach, where the starting conditions are updated every 5 years (see Section 2.1). Under this premise, the SE scenario results in continued deforestation of the highly diverse tropical Andean forest, where the proportion of the natural forest declines from 50% to only 14% within 55 years (Figure 6; Table S7). The favourable NPVs of the deforestation activities (represented by the LULC type 'new deforestation') drive land allocation (see Figures S1 and S3), while the high *labour requirement* for deforestation avoids even larger clearing of the natural forest. This scenario shows high agreement with available data (historical data and stochastic predictions) on LULC changes in the studied landscape when using 3 *SEM*s to derive worst-case values. The deforestation resulting from the SE scenario follows both the past trend in LULC change (1975–2015) and predictions by an independent, spatially explicit stochastic model (Thies et al., 2014; Figure 6 pink shaded area with dotted black frame). This trend (see Figure 7 for the development of the landscape composition) thus forms a plausible baseline scenario for our analyses.

3.4 | Influence of considering multiple ES or biodiversity

The ES-SE scenario (see Figure S4 for optimized indicators) reduces natural forest cover more than the baseline scenario during the first decades (Figure 6). However, the static long-term target of natural forest cover under this scenario (reduction of natural forest over a farmer generation to 16.6%) has provided a too pessimistic scenario. The dynamic model, considering the continuous change in the initial landscape composition, suggests a natural forest share of 28.9% after 30 years. The higher natural forest proportion obtained by the dynamic model reflects that deforestation in the ES-SE scenario depends highly on the landscape context (Figure 5), in which deforestation rates decline substantially with declining natural forest share.

The nevertheless strong reduction of the natural forest in landscapes with 38%–80% initial natural forest cover is associated with two interacting trends: (a) an expansion of the converted area

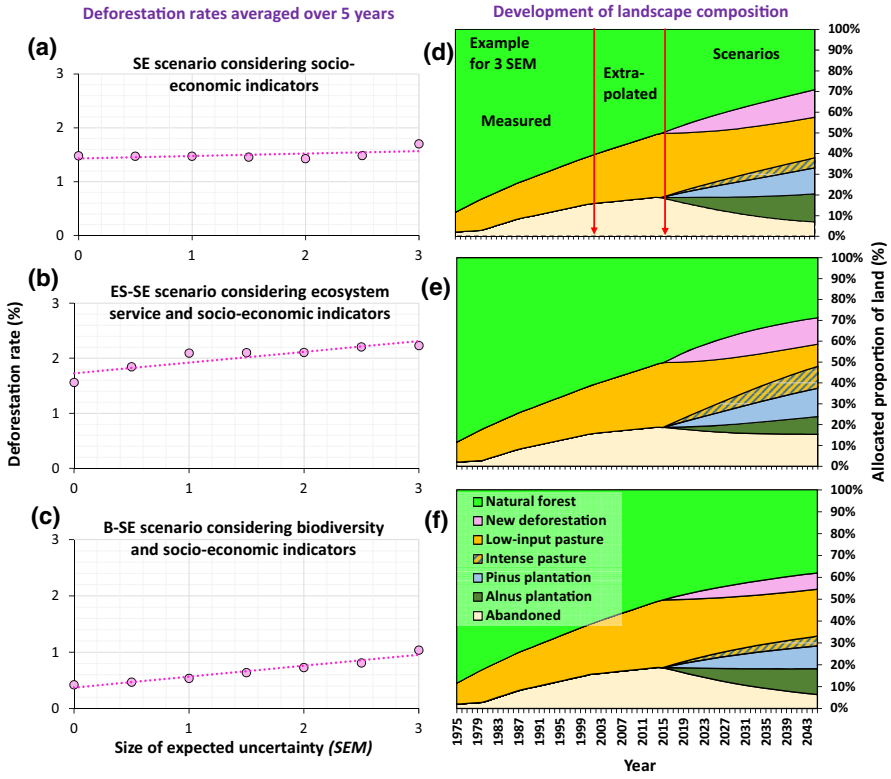


FIGURE 7 Short-term deforestation rates and development of landscape composition. (a)-(c): Scenarios for annual deforestation rates (averages for short-term consideration 2015–2020), when considering increasing uncertainty in decision-making (i.e. increasing degree of risk-aversion, indicated by the degree of uncertainty anticipated by decision-makers, as multiples of *SEM*). (d)-(f):Measured (Curatola Fernández et al., 2015), extrapolated (based on measured data) and modelled scenario data on landscape composition. (d) Considering socio-economic indicators, (e) considering indicators for multiple ecosystem services and socio-economic indicators, and (f) considering biodiversity indicators and socio-economic indicators. We refer to the year 2015 as the start situation, with 50% natural forest, 31% existing low-input pastures and 19% already abandoned land. The dashed line indicates a trend, the dots are the deforestation rates associated with the land-use scenarios. Seven LULC types (including land-use options for rehabilitation) and an anticipated indicator uncertainty of 3 *SEM*s have been considered for these scenarios.

as a whole and (b) a tendency towards greater LULC diversification indicated by increases in the landscape's Shannon diversity index (Figure 8b). While the increase in deforestation is largest when considering 3 *SEM*s to estimate worst cases, the Shannon index resulting from considering multiple ES and socio-economic indicators is not much higher than for the SE scenario. When high risk-aversion coincides with the aim of maintaining multiple ES, the first trend dominates. In this situation, the simulated LULC change predominately enhances the levels of indicators by expanding the area of converted land as a whole (to a greater extent than under the baseline scenario), rather than through diversification of LULC types.

Our last decision perspective (B-SE scenario) directly accounts for biodiversity as an objective in its own right, represented by two indicators estimating species richness of vascular plants, in addition to the socio-economic indicators (Tables 1 and 3). This reduces deforestation rates substantially and immediately (Figures 5–8). While the B-SE scenario still considers the socio-economic indicators, the compromise planning (see Figure S5 for optimized indicators) nevertheless greatly reduces deforestation so that the share of natural forest is still 33% after 55 years (Figure 6; Table S9). Remarkably, the B-SE scenario also reduces the compositional diversity of the landscape to conserve more biodiverse natural forest area (Figure 8b).

3.5 | Uncertainty, influential indicators and biodiversity levels

Our results highlight that considering larger uncertainty increases rather than decreases deforestation rates (Figure 7a–c). While the SE scenario hardly responds to greater uncertainties, both the ES-SE and the B-SE scenarios respond with increased deforestation rates under increased uncertainty.

There are groups of indicators which are particularly influential on deforestation rates. We demonstrate this by excluding specific indicator groups from the optimization process. For example, excluding the *soil quality* (Figure S1a) or NPV indicators (Figure S1b) reduces simulated deforestation, in some cases tremendously. Omitting NPVs would prevent any deforestation (Figure S1b), whereas omitting *labour requirement*, *social preferences* and *carbon relationships* would increase deforestation rates. An alternative indicator accounting for the option

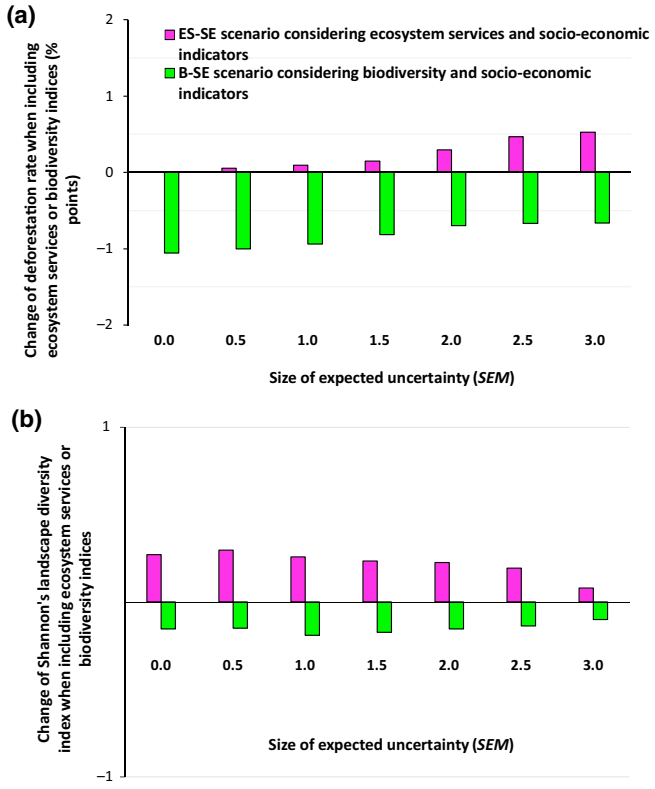


FIGURE 8 Changes in deforestation rates and Shannon's diversity. Difference in initial annual deforestation rates over the first 5-year period (2015–2020) and change in Shannon's landscape diversity indices achieved after 5 years. (a) Changes in deforestation from land-use decisions simulated for either the ES-SE scenario (considering ES and socio-economic indicators) or the B-SE scenario (considering biodiversity and socio-economic indicators) are compared with simulated decisions under the SE scenario considering only socio-economic indicators. (b) Differences after 5 years in the Shannon landscape diversity index; landscape compositions resulting from either the ES-SE scenario or B-SE scenario are compared with those arising from the SE scenario. ES, ecosystem services; SE, socio-economic

of a potential future commercial use of tropical plant species by the pharmaceutical industry would reduce deforestation (Methods S6; Figure S1c).

Higher weights for single indicators than for all other indicators can also alter the results (Table S1). Giving higher weights to either NPVs (enhances deforestation) or *labour requirement* (reduces deforestation) underlines the importance of these indicators. The ES-SE scenario is less sensitive to the weighting of single indicators than the SE scenario. Higher weights would either hardly change the proportion of natural forest in the long-term target landscape composition or would reduce it (e.g. when giving high weight to some soil indicators). Two out of 23 indicators present an exemption from this tendency: Giving higher weight to *carbon in planta* or to *nitrogen mineralization* significantly increases the future natural forest proportion. However, when perceiving all soil quality indicators as a bundle (including *nitrogen mineralization*), giving higher weight to this whole bundle would much reduce the future natural forest cover (Table S1).

Species richness for the exotic *P. patula* plantations was very high in contrast to the species richness in plantations with the native species *A. acuminata* (Table 3). However, alternative simulations with a reduced species richness in *P. patula* plantations based on expert opinion hardly changed the results (Methods S6; Figure S7).

4 | DISCUSSION

Our study has shown that, in a forested landscape like the one studied here, considering multiple ES may result in an initially substantial conversion of natural forest, especially if decision-makers perceive multiple indicators as highly uncertain. More than 30 years are needed until considering multiple ES in addition to socio-economic indicators leads to the same share of natural forest as obtained under the SE scenario. Aiming for multifunctional landscapes may therefore conflict with the aim of reducing deforestation.

The shares and characteristics of LULC types may differ for other land-use systems, but we can expect similar tendencies in other systems. For example, the increase in production levels (by expansion of anthropogenic land-covers in our case) under elevated uncertainty has been shown for other LULC systems as well, based on the example of food production (Fuss et al., 2015). This has yet hardly been shown when optimizing for multiple ES. In addition, previous studies have found that maintaining multiple ES is best supported by heterogeneity, for example through diversity in forest species and plant functional traits (Felipe-Lucia et al., 2018; Schuldt et al., 2018). This finding applies also for the landscapes scale, when various LULC types provide different ES to different extents (Plas et al., 2018). Our results are consistent with these previous studies. These important dynamics may save some natural forests, mainly if their current proportion is already low. However, if the forest cover is still substantial, ongoing forest loss is more likely.

With our modelling approach, we provide an alternative concept for considering ES and an uncertain future when simulating deforestation decisions. Our study integrates and bridges various perspectives and thus may help fill a current research gap (Bennett et al., 2015; Díaz et al., 2018). We do not focus our modelling of land-use decisions on monetary values (Bateman et al., 2013), but instead we use multiple criteria quantified by indicators from diverse sources of knowledge, which also include economic and social aspects. We thus refer to the fact that people perceive and value the benefits of ecosystems in multiple ways (Pascual et al., 2017). While we highlight the importance of the given landscape context and social preferences, our results challenge the pervasive expectation that aiming for a multitude of ES (Ingram, Redford, & Watson, 2012) and considering uncertainty (Cabral, Halpern, Costello, & Gaines, 2017) will always support conservation. We found this only to be the case under specific conditions, that is, in landscapes with either very high or very low forest shares.

When interpreting our results, it is important to keep in mind that our assessment builds on a common 'more is better' or 'less is better' ranking and on the assumption of risk-aversion. Considering a large variety of indicators, even if the demand for specific ES is unclear from today's perspective, may be justified, because forward-looking land-use planning may also include indicators for potentially useful ES. Since specific LULC types such as afforestation require longer time periods (e.g. 20 years to maturity), it is meaningful to start building up these forest resources already, even if the current demand for some of their ES is not so strong.

As the future demand for ES is uncertain, we have considered all indicators and uncertainty scenarios as equally important, following Walker, Lempert, and Kwakkel (2013). Sensitivity analyses for the ES-SE scenario have shown for most single indicators that the future natural forest proportion would hardly change or would even reduce, when we provide these single indicators with enhanced weights. Only when either carbon sequestration or nitrogen mineralization are single objectives with high weight, we obtain a long-term target landscape composition that contains more natural forest area than under the SE scenario. However, when multiple ES are equally important in a multifunctional landscape or when all indicators for soil quality are important as a bundle, the maintenance of ES and the conservation of natural forests will remain to be potentially conflicting aims.

Our results support the conclusion by Meyer et al. (2018) that biodiversity conservation is sometimes unlikely to be achieved indirectly by managing ecosystems for various particular ES (see Allan et al., 2015, for similar conclusions). We have shown trade-offs between considering a variety of ES and the conservation of megadiverse natural forests at the landscape level. We suggest care in using ES concepts independent from the landscape context to support the conservation of biodiversity indirectly. While the concept of ES is essential to maintain and enhance human well-being (e.g. Bennett et al., 2015), we see conservation-related applications of this concept mainly in human modified landscapes with low natural forest shares, where landscape-level diversification will also support biodiversity. However, in regions still comprising larger areas of high conservation value, where biodiversity in the natural ecosystem is considerably higher than in the corresponding anthropogenic replacement systems, concentrating on multiple ES alone might be insufficient to slow or prevent deforestation. Our approach may help to identify types of landscapes where a conflict between the goal of multifunctional landscapes and reducing deforestation may arise and to better align respective policies.

ACKNOWLEDGEMENTS

We thank the German Research Foundation (DFG) for supporting the study (Research Units 402 and 816, PAK 823/4/5), Naturaleza y Cultura Internacional (Loja, San Diego) and our Ecuadorian partner Universities in Loja (Universidad Técnica Particular de Loja, Universidad Nacional de Loja) for outstanding cooperation, the Ecuadorian Ministerio del Ambiente for granting research permits, the Ecuadorian Weather Service (INAMHI) for providing data, and the staff of the Estación Científica San Francisco and many students and workers for their support. We also thank the farmers of Imbana, Los Guabos, El Tibio and Sabanilla for their contribution to this study and Allyson Cappello for the language editing.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available in the Supporting Information of this article.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section.

How to cite this article: Knoke T, Paul C, Rammig A, et al. Accounting for multiple ecosystem services in a simulation of land-use decisions: Does it reduce tropical deforestation? *Glob Change Biol*. 2020;00:1–18. https://doi.org/10.1111/gcb.15003