IDB WORKING PAPER SERIES Nº IDB-WP-01193

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Cataloging-in-Publication data provided by the
Inter-American Development Bank
Felipe Herrera Library
The value of biodiversity in economic decision making: applying the IEEM+ESM approach to conservation strategies in Colombia / Onil Banerjee, Martín Cicowiez, Žiga Malek, Peter H. Verburg, Renato Vargas, Sean Goodwin.
p. cm. — (IDB Working Paper Series ; 1193)
Includes bibliographic references.
1. Biodiversity conservation-Economic aspects-Colombia. 2. Ecosystem services-Colombia. 3. Environmental economics-Colombia. 4. Conservation of natural resources-Colombia-Decision making. 5. Land use-Colombia. I. Banerjee, Onil. II. Cicowiez, Martín. III. Malek, Žiga. IV. Verburg, Peter H. V. Vargas, Renato. VI. Goodwin, Sean. VII. Inter-American Development Bank. Environment, Rural Development and Risk Management Division. VIII. Series.
IDB-WP-1193

JEL Codes: C68 Computable General Equilibrium Models; E21 Consumption, Saving, Wealth; Q15 Land Use, Irrigation, Agriculture and Environment; Q2 Renewable Resources and Conservation; Q5 Environmental Economics.

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Applying the IEEM+ESM Approach to Conservation Strategies in Colombia

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Abstract

In this paper we evaluate the economic, natural capital and ecosystem services impacts of strategies for conserving Colombia's rich natural capital endowment. Specifically, we consider Government program proposals for establishing Payment for Ecosystem Services (PES), implementing more sustainable silvopastoral systems and expanding habitat banking. We develop and apply the Integrated Economic-Environmental Modeling (IEEM) Platform linked with spatial Land Use Land Cover (LULC) and Ecosystem Services Modeling (IEEM+ESM) to shed light on the multi-dimensional impacts of these programs from the perspective of sustainable economic development and intergenerational wealth. Advancing the state-of-the-art in integrated economic-environmental modeling, our framework for the first time integrates dynamic endogenous feedbacks between natural capital, ecosystem services and the economic system to fully capture how changes in natural capital and ecosystem service flows affect the economy and vice versa. Our approach quantitatively models the economy, natural capital and ecosystem services as one integrated and complex system at a high level of spatial resolution across Colombia's 32 Departments. We demonstrate how valuing biodiversity in public policy and investment analysis can make the difference between an investment that is economically viable and one that is not. Without accounting for the value of biodiversity, the proposed PES and habitat banking programs are not economically viable. Including the value of biodiversity, both PES and habitat banking become strong investment propositions with a net present value of US$4.4 billion and US$4.9 billion, respectively. The economic and environmental benefits of enhancing Colombia's natural capital base and future ecosystem service supply are demonstrated and regionally differentiated, which provides a strong empirical evidence base to inform the spatial targeting of policies to maximize economic, environmental and social outcomes.

JEL Codes: C68 Computable General Equilibrium Models; E21 Consumption, Saving, Wealth; Q15 Land Use, Irrigation, Agriculture and Environment; Q2 Renewable Resources and Conservation; Q5 Environmental Economics.

Keywords: Integrated Economic-Environmental Modeling (IEEM) Platform; dynamic computable general equilibrium (CGE) model; ecosystem services modeling; land use land cover modeling; natural capital; payment for ecosystem services; habitat banking; Colombia.

1. Introduction

The Government of Colombia signed a peace agreement with the Revolutionary Armed Forces of Colombia in November of 2016, after over 50 years of civil conflict. As is the case with many other post-conflict countries, this period of recovery places mounting social and economic pressure on Colombia's natural capital base. Drawing from the experience of other post-conflict countries, following the resolution of conflict, deforestation and natural resource extraction intensify and the return of displaced people coupled with ineffective land use planning drive environmental degradation (Suarez et al., 2017).

In the case of Colombia, vast swaths of high biodiversity areas were off limits due to the presence of civil conflict. With the onset of peace, these areas of tropical forest and other ecosystems and the valuable ecosystem services (ES) they provide are now effectively open for business (Hanauer and Canavire Bacarreza, 2018; Prem et al., 2020). Colombia requires programs and policies to manage the return of the millions of displaced people to the rural environment and provide sustainable livelihood opportunities for them to build local economies that enhance natural capital and wealth. The alternative to an organized resettlement process that is embedded in local productive potentials and sustainable bio-economies is short-term extractive and destructive practices that while they may be effective in feeding families in the short-run, they undermine inter-generational wealth and the development prospects that households seek to ensure (Banerjee et al., In press)

To guide public policy in this post-conflict period, it is critical to have tools to objectively evaluate new policy and investment portfolios according to their contribution to a nation's wealth and sustainable development and their three dimensions, namely manufactured capital, human capital and natural capital. Economic performance metrics must go beyond conventional ones such as Gross Domestic Product (GDP) to capture impacts on natural capital stocks, ES and wealth. As Sir Partha Dasgupta asserts in the latest Inclusive Wealth Report, without metrics of wealth, it is not possible for governments to assess whether or not their economic development policies are sustainable (UNEP, 2018, p. 2018). The measure of wealth used in this paper is an adjusted form of genuine savings, which takes into account household savings, natural capital stocks and environmental quality. With regards to measuring and valuing biodiversity, we follow the approach outlined previously (HM Treasury, 2020) and use proxy measures to quantify and value biodiversity, specifically, changes in stocks of natural capital and flows of ecosystem services and their value.

This paper presents a highly innovative decision support system that integrates dynamically endogenous feedbacks between the economy and its constituents, natural capital and both market and non-market ES. Our approach brings the value of biodiversity into economic decision making by linking the Integrated Economic-Environmental Modeling (IEEM) Platform with high resolution land use land cover change (LULCC) and ES modeling to address the challenge of generating indicators that speak to all dimensions of wealth and sustainability, all consistent and compatible with a country's System of National Accounts (European Commission et al., 2009). We apply this approach to the analysis of three specific post-conflict strategies for conservation, developing local bio-economies and rebuilding rural livelihoods, namely establishing a Payment for Ecosystem Services (PES) program, investments in more productive and sustainable silvopastoral systems, and expanding habitat banking for natural capital restoration and conservation.

The structure of this paper is as follows. The following two sub-sections of the introduction provide an overview of some of Colombia's challenges related to natural capital and rural livelihoods in this post-conflict period and government plans for addressing them. Section 2 describes the methodological approach for implementing the linked IEEM and ES Modeling (IEEM+ESM) approach. Section 3 begins with a description of the scenarios to be implemented, followed by results and analysis. Section 4 draws on and deepens this analysis with a discussion of the key findings, conclusions and policy insights arising from this work. The detailed Supplementary Information appendices to this paper describe in more detail methodological aspects and data sources.

1.1. Natural capital in the Colombian context

In Colombia and other post-conflict countries, government investment is focused squarely on security and social and economic recovery, which increases pressure on natural capital and deforestation (Bustos and Jaramillo, 2016; Conca and Wallace, 2009; McNeish, 2017). This is of national and global concern as Colombia is home to 10% of the planet's biodiversity and is one of the most biodiverse countries, second among all by some measures (CONPES, 2017; Moreno et al., 2019). Over half of the country is forested and it has the greatest abundance of water resources among countries in Latin America and the Caribbean (World Bank, 2015).

Colombia's conflict had its most profound impact on 170 municipalities across 36% of the nation's territory. These municipalities are named post-conflict subregions, where public investment has been prioritized. In the post-conflict period, these municipalities face the most intense pressure on natural capital as displaced people return home and attempt to rebuild their livelihoods. Many of these municipalities coincide with areas of exceptionally high biodiversity and natural capital values (Calderon et al., 2016).

Colombia's armed conflict has had spatially diverse impacts on the environment and deforestation. In some areas, landmines and the prohibition of access has resulted in de facto conservation (Álvarez, 2003; Dávalos et al., 2011; Fergusson et al., 2014). Abandonment of land in the San Lucas mountain range, other areas in the Amazon, and Orinoquía, for example, has led to forest regrowth and improvements in biodiversity (Baptiste et al., 2017). However, in the past 25 years, the country lost 5.2 million hectares of forest cover, 3 million hectares of which were deforested in municipalities affected by the armed conflict (Departamento Nacional de Planeacion, 2017a). Even Colombia's protected areas have not been spared, with deforestation spiking in the post-conflict period and accounting for 11% of the national total in 2017. Deforestation, land degradation and soil erosion have been estimated to cost the country on average 0.7% of GDP annually (Sanchez-Triana et al., 2007). Deforestation has impacts on local microclimates and contributes to climate change. By 2014, 55% of Colombia's 23.7 million tons of CO_2 equivalent emissions came from deforestation and land use (IDEAM et al., 2008).

Although each post-conflict zone in Colombia has its own development dynamic, overall, clearing for agriculture and livestock drive deforestation and was responsible for 65% of the deforestation over the previous decade (World Bank, 2015). In the Amazon, poor displaced migrants push their way into the forests, extract high value timber, burn the remnant forest and plant subsistence crops. After 2 or 3 years of cultivation, the soil becomes unproductive and farmers move to adjacent areas to repeat the process. Cleared areas are purchased cheaply and consolidated for extensive cattle ranching, which was responsible for 50% of the land cleared between 2005 and 2012 (Etter et al., 2006; Nepstad et al., 2013; Pares, 2018). Deforestation in the country is also closely related to illegal activities, which have proliferated due to weak governance in parts of Colombia's territory. This lawlessness and the presence of armed groups have led to the transformation of forests to illicit crops, the illegal extraction of minerals, illegal logging, and the construction of informal roads. Since the Peace Accord, Colombia's coca production has tripled, accounting for a staggering 70% of the coca cultivated globally (UNODC, 2019).

1.2. Government plans for post-conflict rural development and natural capital

The Peace Accord establishes commitments aimed at rehabilitating the rural environment and livelihoods through Integrated Rural Reform and providing alternatives to the cultivation of illicit crops and natural capital degradation. Colombia's Green Growth Strategy aims to increase economic growth and competitiveness while conserving natural capital. There are three principal components to the strategy, which are: (i) the efficient use of natural capital including water and soil resources, energy efficiency, and material and residual intensity; (ii) development of new economic opportunities through enhancing forest-based economies, a transition toward energy efficiency, and strengthening bio-economies, and; (iii) improving labor competitivity and formalizing the entrepreneurial sector.

Green Growth was formally adopted in Colombia's National Development Plan (2014-2018) "Todos por un Nuevo País", aligned, consistent and compatible with Paris Agreement targets, Nationally Determined Contributions and the Sustainable Development Goals (Departamento Nacional de Planeacion, 2017a). This has been reaffirmed within the new National Development Plan 2018-2022 "Pacto por Colombia, Pacto por la Equidad" (Departamento Nacional de Planeacion, 2017a, 2017b; DNP, 2019). Reducing deforestation is a critical element of the strategy, along with reducing greenhouse gas emissions by 20% with respect to the emissions projected for 2030 and by up to 30% should additional financing mechanisms become available (DNP, 2016).

To contribute to the financing of these interventions, the Colombian government established the Sustainable Colombia Fund, a multi-donor fund that aims to significantly reduce deforestation and promote sustainable development in Colombia. Specifically, it aims to promote conservation and sustainable use of biological diversity; support rural development; support public policy enforcement that promotes climate change mitigation and the reduction of deforestation; support capacity building in armed conflict-affected areas, and; incorporate climate change as a cross-cutting topic in the development agenda (IDB, 2019).

Within this framework, the Colombian Government has proposed PES as a sustainable way of promoting economic alternatives to populations affected by the armed conflict. As such, PES has been included in the thematic portfolios of the Colombia Peace Fund and the Sustainable Colombia Fund. The proposal for a PES program specifically aims at reducing deforestation and it places emphasis on regions that are part of the Forests for Peace Program. This PES program is designed to create territories that integrate biodiversity conservation with productive projects that will benefit populations in post-conflict areas (CONPES, 2017; DNP, 2019).

One of the main tenets of the PES program is its focus on areas of strategic ecosystem value, post-conflict zones and areas with illicit crops. The PES program is designed to be implemented in three stages, with an impact on 150,000 hectares between 2017 and 2019; 350,000 hectares between 2020 and 2025; and 500,000 hectares between 2026 and 2030 for a total of 1,000,000 hectares. The program will operate in 366 of the 1,122 municipalities of Colombia, of which 96 were heavily affected by the armed conflict (CONPES, 2017; DNP, 2019).

2. Methods

2.1. The IEEM Platform for Colombia

The IEEM Platform advances the state-of-the-art in decision making frameworks, enabling policy makers to understand the full range of economic and environmental implications of new public policy and investment proposals. IEEM for Colombia (IEEM-COL) is calibrated with Colombia's recently published natural capital accounts under the SEEA framework (United Nations et al., 2014). While conventional economic impact analysis quantifies the effects on standard indicators such as GDP, income, and employment, the IEEM Platform captures impacts on stocks of natural capital, environmental quality, wealth and well-being, which is central to the discussion on potential post-conflict development prospects for Colombia. With a country's natural capital accounts presenting a snapshot of past natural capital use, IEEM is the first future-looking framework that integrates natural capital accounts in the SEEA format, has environmental modeling modules to capture the dynamics of each environmental asset and ES, and enables one to ask, 'what if' questions of how a given policy or investment will impact the three pillars of sustainable development, namely society, economy and environment.

At the core of IEEM is a dynamic computable general equilibrium (CGE) model. The theory, structure and strengths and limitations of CGE modeling for public policy and investment analysis are discussed in a body of literature that has developed over the last 4 decades (Burfisher, 2017; Dervis et al., 1982; Dixon and Jorgenson, 2012; Kehoe, 2005; Shoven and Whalley, 1992). The IEEM Platform is publicly available[1]. IEEM's mathematical structure is documented in (Banerjee and Cicowiez, 2020). IEEM's database is an environmentally-extended Social Accounting Matrix (SAM). The construction of the IEEM database is described in (Banerjee et al., 2019b). A user guide for a generic version of IEEM, applicable to any country with the corresponding database, is available in (Banerjee and Cicowiez, 2019).

2.2. Linking IEEM with spatial land use land cover and ecosystem services modeling

A key methodological contribution of this work is the integration of dynamic endogenous feedbacks between natural capital, ES and the economic system as proposed in Banerjee et al., (2020b, 2020a). To achieve this, we link IEEM with LULCC and ES modeling (IEEM+ESM) to model the economy, natural capital and ecosystem services as one integrated and complex system. While the one-way workflow between IEEM, LULCC and ES modeling has been implemented before (Banerjee et al., 2020a), where a policy experiment is implemented in IEEM, which in turn impacts LULC and ES supply in the future, this is the first implementation of the workflow that endogenizes feedbacks between future changes in ES supply and how these changes affect agent behavior in the economy represented by IEEM and subsequent demand for land.

The endogenous IEEM+ESM workflow is outlined in Figure 1. The three models, IEEM, LULC and ESM are run iteratively in 5-year time steps for the analytical period of 2020 to the year 2040. In this application, we use a multi-regional version of IEEM-COL, which disaggregates Colombia's 32 Departments. The first step in the workflow is to generate a baseline projection for

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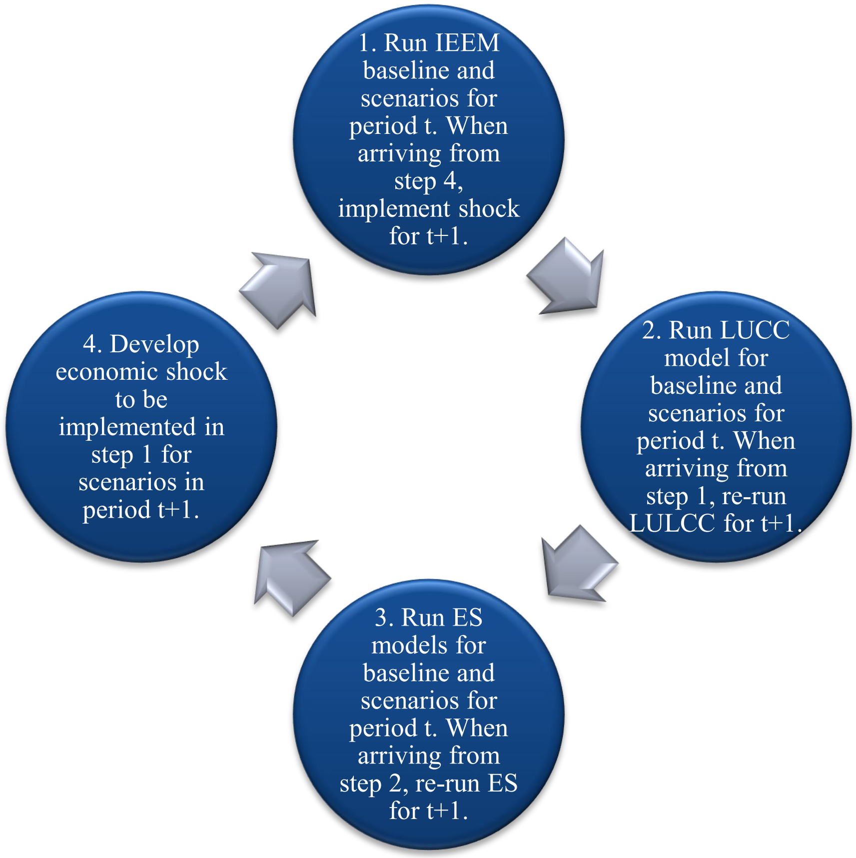
[1] All IEEM models, databases and documentation will be available here: https://www.iadb.org/en/topics/environment/biodiversity-platform/the-idbs-biodiversity-platform%2C6825.html

the first time period. IEEM produces results for the first period in terms of impacts on economic indicators, natural capital and demand for land. The projected estimates of demand for land for the first period are allocated spatially with the LULCC model and a Land Use Land Cover (LULC) map is produced for the beginning of the period t and the end of the period t+5. Our analysis is high resolution in that we model each of Colombia's 32 Departments individually over a 300 by 300-meter spatial grid.

ES models, in this case, carbon storage, sediment retention, nutrient retention (a proxy for water quality) and water supply, are parameterized based on the best available local and global data. The ES models are run for the period t and t+5 based on the LULC maps generated in the previous step. ES model results are generated for each of Colombia's 32 Departments. Based on the changes in ES supply calculated as the difference between the scenario and the baseline, an economic shock is estimated to account for the economic impacts of changes in future ES supply. In the next iteration, this shock is introduced in IEEM in t+6 to t+10, and the iteration cycle begins again. These iterations continue in 5-year steps until 2040. While this workflow could be used to endogenize the impact of changes in a range of ES supply, in this application we focus on erosion mitigation ES and how they interact with the economy.

Figure 1. The IEEM+ESM workflow with dynamic endogenous feedbacks.



Source: Authors' own elaboration.

With regards to calculating the economic impact of changes in ES supply, changes in ES supply affect the economy through various mechanisms. Increased erosion for example reduces agricultural productivity (Borrelli et al., 2017, 2017; Panagos et al., 2018, 2015; Pimentel, 2006; Pimentel et al., 1995). Increased soil erosion and nutrient run-off affect water quality, which can have implications for water treatment costs, human health and tourism values (Aguilera et al., 2018; Banerjee et al. 2019; Keeler et al., 2012; O'Neil et al., 2012; Paerl and Huisman, 2008; STAC, 2013). In this paper, we focus on how changes in erosion mitigation ES affect the economy through their agricultural productivity impacts.

We estimate the impact of changes in erosion on agricultural productivity based on a survey of the literature. Severe erosion is considered to occur where erosion is greater than 11 tons per hectare per year. In our business-as-usual projection, we identify the number of pixels exhibiting severe erosion. We estimate the land area subject to severe erosion as the number of pixels with severe erosion multiplied by the spatial resolution of the LULC map. Next, we identify the number of pixels in each scenario that exhibit severe erosion and multiply it by the spatial resolution of the LULC map. If the area of severe erosion is greater in the scenario than in the baseline, erosion is increasing as a result of the scenario.

Based on Panagos et al. (2017), we relate the presence of severe erosion to a reduction in agricultural productivity of 8%. To create a feedback between changes in ES and IEEM, we apply equation 1 to the business-as-usual case and to each scenario:

$$LPL_d = \frac{SER_d}{TAA_d} \cdot 0.08 \qquad \text{equation 1}$$

Where:

- LPL_d is the land productivity loss by subscript *d* Department;
- SER_d is the agricultural land area (hectares) subject to severe erosion of >11t/ha/year in each Department;
- TAA_d is the total agricultural area, both crop and livestock, by Department, and;.
- 0.08 is the agricultural productivity shock a la Panagos et al. (2017).

We implement this agricultural productivity shock in IEEM and implement iterative runs of all three models as described above.

The estimation of the wealth impacts of the conservation strategies explored herein is an important element of this paper. We use an adjusted form of genuine savings to focus on the economic and environmental impacts on changes in wealth and less emphasis on the third pillar of wealth, namely human capital. Changes in human capital are often measured by changes in investments in education, which do not vary across the business-as-usual case and scenarios in this study. Genuine savings is calculated as in equation 2:

$$GenuineSAV_t = GNSAV_t - DeprCapStock_t - DeplForStock_t - DeplMinStock_t - EmiVal_t$$

equation 2.

Where:

- $GNSAV_t$ = Gross National Savings ($GNDI_t - PrvCon_t - GovCon_t$);

- $GNDI_t$ = Gross National Disposable Income;
- $DeprCapStock_t$ = depreciation of reproducible capital stock;
- $DeplForStock_t$ = depletion of forest stock;
- $DeplMinStock_t$ = depletion of mineral stock, and;
- $EmiVal_t$ = Cost of damage from CO_2 emissions; US$30 per ton of CO_2.

For natural capital, the value of depletion is defined as in equation 3.

$$\sum_{i=t}^{t+T-1} \frac{qdepl_t \cdot unitrent_t}{(1+intrat)^{i-t}} \qquad \text{equation 3.}$$

Where:
$qdepl_t$ = quantity of the resource extracted;
$unitrent_t$ = unit rent in year t, the value of which is endogenous in IEEM, and;
$intrat_t$ = interest rate (4% as in (Lange et al., 2018)).

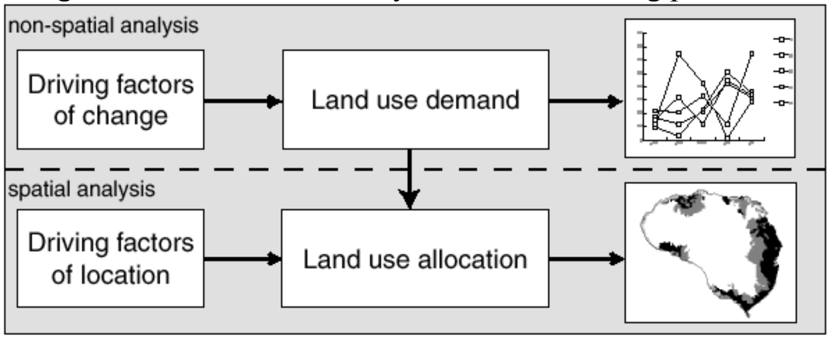
For example, for t=2020, …., 2040 and T = 21, the equation is solved as follows:

$$\frac{qdepl_{2014} \cdot untrent_{2014}}{(1+intrat)^0} + \frac{qdepl_{2015} \cdot untrent_{2015}}{(1+intrat)^1} + \cdots + \frac{qdepl_{2035} \cdot untrent_{2035}}{(1+intrat)^{21}}$$

2.3. Overview of the LULCC modelling framework

The bridge between IEEM and changes in ES is made through LULCC modeling. IEEM demand for land is spatially allocated with the LULCC model, which is used to generate baseline and scenario-based projected LULC maps. These maps are the variable of change used in the ES modeling. We use the CLUE (Conversion of Land Use and its Effects) modelling framework to spatially allocate LULCC using empirically quantified relationships between land use and location factors, in combination with the dynamic modelling of competition between land use types. CLUE is among the most widely used spatial LULCC models and has been applied on different scales across the globe. The version of the CLUE model family we use is the Dynamic CLUE (Dyna-CLUE) model, which is appropriate for smaller regional extents compared with global LULCC modeling (Veldkamp and Verburg, 2004; Verburg et al., 2002; Verburg and Overmars, 2009).

Figure 2. Overview of the Dyna-CLUE modeling procedure

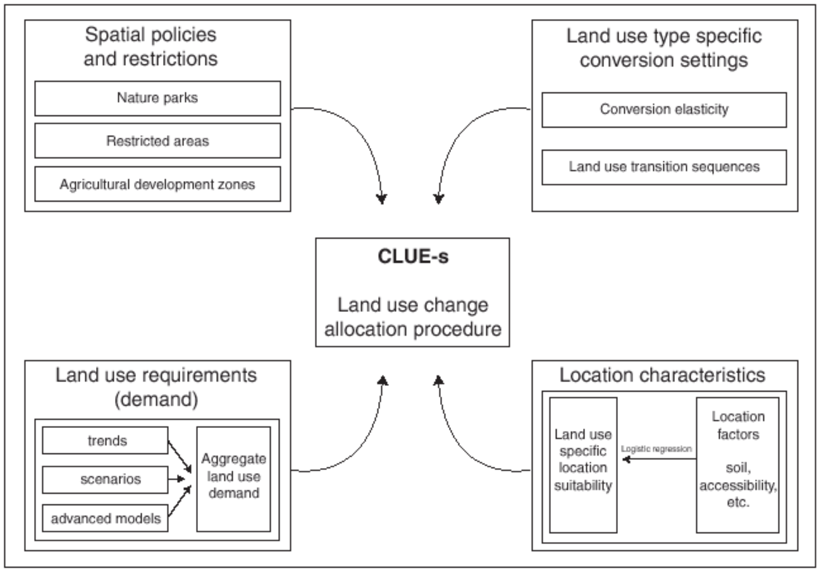


Source: (Verburg et al., 2002).

The model is sub-divided into two distinct modules: a non-spatial demand module and a spatially explicit allocation procedure (Figure 2). The non-spatial module calculates the area change for all land use types at the aggregate level and in this case it is an input derived from IEEM. IEEM demand for land is spatially explicit at the level of Colombian Department. Within the second part of the model, these demands are translated into land use changes at different locations within the study region using a raster-based system.

Figure 3 provides an overview of the information required to run Dyna-CLUE. This information is subdivided into four categories that together create a set of conditions and possibilities for which the model calculates the best solution in an iterative procedure. Detailed information on the suitability analysis and all Dyna-CLUE model parameters and procedures is provided in Supplementary Information section 1.

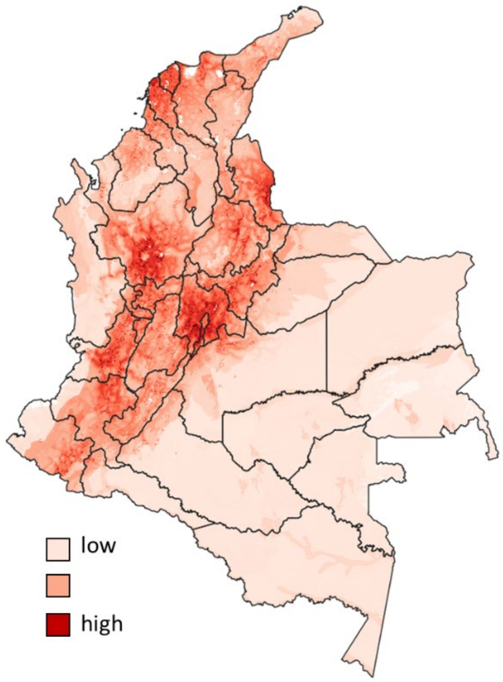
Figure 3. Overview of the information flow in the Dyna-CLUE model.



Source: (Verburg et al., 2002).

For the land use demand module, different model specifications are possible ranging from simple trend extrapolations to complex economic models, such as in this case with the linkage of Dyna-CLUE with IEEM. The results from the demand module need to specify, on a yearly basis, the area covered by the different land use types, which is a direct input for the allocation module. In this study, annual demands for forest, forest plantation, cropland and grazing areas were provided by IEEM. This demand is allocated based on a combination of empirical estimations, spatial analyses and dynamic modelling. In an intermediate step to the allocation of demand for land, CLUE calculates probability maps for each land use type (example for cropland in Figure 4).

Figure 4. Spatial suitability for cropland based on the logistic regression. The scale low to high refers to low suitability (0) to high suitability (1).



Source: Authors' own elaboration.

2.4. Ecosystem services modeling

The Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) suite of models are used to calculate spatially explicit changes in ES supply. InVEST combines LULC maps and biophysical information to calculate ES, with the option to add additional parameters to assist in ES valuation. InVEST is one of the most widely used open-source ES modeling tools and is well documented with a large user community (Sharp et al., 2020).

A wide variety of ES can be calculated through the InVEST suite, whether biophysical or socio-cultural in nature. In this paper we parameterize and apply four InVEST ES models to calculate changes in ES supply across the baseline projection and all scenarios. These models are the following: sediment delivery ratio model used to calculated the Revised Universal Soil Loss Equation and sediment export; carbon storage model used to calculate carbon storage and carbon sequestration potential; annual water yield model used to calculate water supply, and; nutrient delivery ratio model, which is used as a proxy for the water purification potential of landscapes in absorbing nitrogen and phosphorus. Detailed information on the ES models used and all model inputs are documented in Supplementary Information section 22.

In addition to the ES modeled, we also evaluated how policy scenarios impacted biodiversity by calculating composite Biodiversity Intactness Indices—BII—(Hudson et al., 2017; Newbold et al., 2016). The BII is a coefficient based on the average abundance of species originally present across undistributed habitats (Newbold et al., 2016). Our estimations are based on the PREDICTS database, an extensive database collecting case study information on the relationship between land use and biodiversity, with over 32 million observations from 32,000 locations and covering 50,000 species (Trustees of the Natural History Museum, 2020). For Colombia alone, the database had a collection of 285 locations (Echeverría-Londoño et al., 2016) where the relationship between land use change and biodiversity have been monitored and assessed. Using calculated mean BII values, we assigned BII coefficients to different land use types and calculated the composite BII. This approach enabled composite BII comparisons across scenarios through time.

3. Scenario design, results and analysis

3.1. Business as usual projection

We evaluate the Colombian Government's plan to establish a PES Program to preserve high conservation value ecosystems, restore degraded ecosystems and implement sustainable silvopastoral production systems. As a parallel restoration and conservation strategy, we also examine the expansion of habitat banking in Colombia following the Terrasos Habitat Bank model (Fundepúblico and Terrasos, 2020).

In this analysis, all scenarios are compared to a business-as-usual (abbreviated as BASE in figures and tables) projection. In the business-as-usual case, Colombia's economy is projected to the year 2040 without the implementation of any new public policies or investments. The base year of IEEM-COL is 2014, which is the most recent year for which complete National Accounts data are available. For the period from the 2014 to the year 2020, we draw on observed data on Colombia's economy, including for example, observed growth rates for real GDP at factor cost. For the period 2020 to 2040, we draw on projections from the latest International Monetary Fund's World Economic Outlook (IMF, 2019) to impose GDP growth rates.

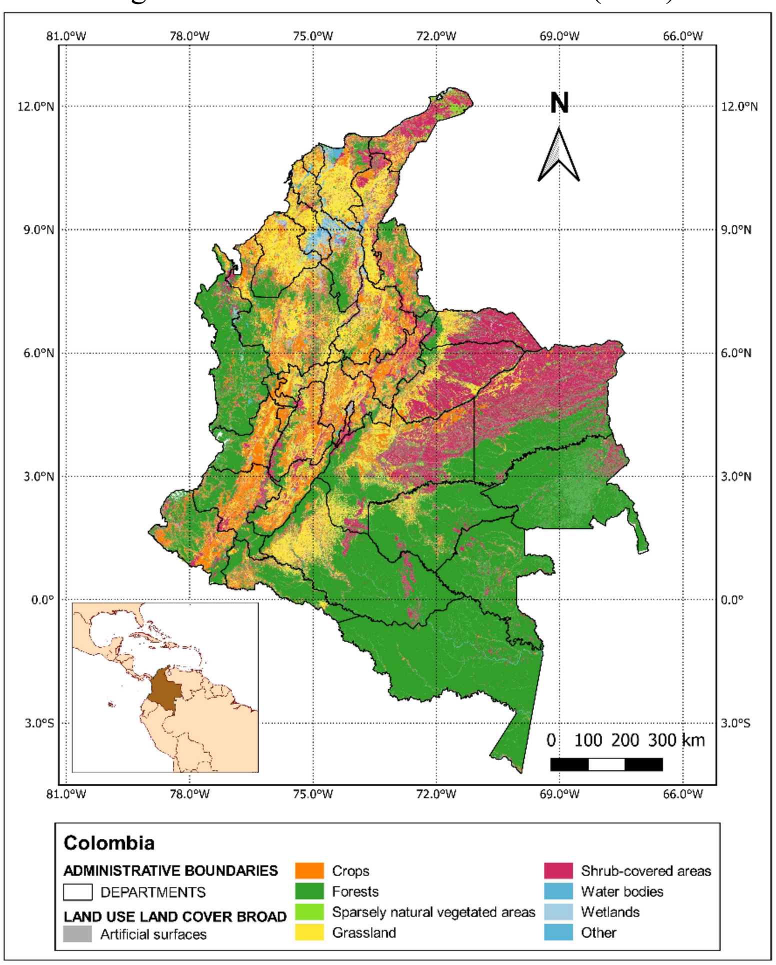
In the business-as-usual scenario, GDP growth is exogenous and imposed by endogenously adjusting total factor productivity. In all policy scenarios on the other hand, GDP growth is endogenous. In addition, we assume that government demand for government services, transfers from government to households, and domestic and foreign government net financing are all kept fixed as shares of GDP at their base-year values. Taxes are fixed at their base-year rates, which means that they will grow at a similar pace to the overall economy. Population projections were obtained from Colombia's National Administrative Department of Statistics. The supply of agricultural land grows by the rate of deforestation, which, for the base-year, varies between 0.02 and 1.8 percent per year across all of Colombia's 32 departments. The flows from extractive natural capital assets such as petroleum and minerals grow at the same rate as GDP, which captures the dynamics of new discoveries.

At the macro level, IEEM, like any other CGE model, requires the specification of equilibrating mechanisms known as model closures for three macroeconomic balances, namely the: (i) government closure; (ii) savings-investment closure, and; (iii) balance of payments closure. For the business-as-usual projection, the following closures are used: (i) the government's accounts are balanced through adjustments in the direct tax rate; (ii) the savings-investment balance is achieved with private domestic investment equal to household savings as a fixed share of GDP at the base-year value. Private foreign investment is financed through the balance of payments. Government investment is a fixed share of the government budget, which in turn is a fixed share of GDP at its base-year value, and; (iii) the real exchange rate equilibrates the balance of payments by influencing export and import quantities and values. The non-trade-related payments in the balance of payments, specifically, transfers and non-government net foreign financing and foreign direct investment, are non-clearing and kept fixed as shares of GDP[2].

[2] Furthermore, in the BASE scenario, we impose exogenous projections for all non-trade items in the current account of the balance of payments, such as transfers. In the capital account, we impose exogenous projections for government and non-government foreign borrowing. In turn, this means that foreign savings follows an exogenous path, which is equal to the sum of government and non-government foreign borrowing and foreign direct investment. Consequently, the real exchange rate will adjust to balance the inflows and outflows of foreign exchange, and as a result, exports and imports will adjust.

Regionally disaggregated land areas are required to calibrate IEEM's land market module. LULC in the business as usual scenario is derived from Colombia's Third National Agricultural Census (DANE, 2016). The land use indicated in the census was compared with Colombia's LULC map for 2012, which is based on the CORINE Land Cover Inventory (Figure 5). This inventory of 44 land cover classes has a spatial resolution of 25 hectares, was initiated in 1985 with a 1990 reference year, and updates have been produced in 2000, 2006, 2012, and 2018. It is common that there are differences in the land use areas in the census compared with the spatial information drawn from an LULC map. We calibrate the IEEM land market module based on census data (Table 1) but ensure that as far as deforestation is concerned, the rate of deforestation does not exceed the available standing forest for any given year in the base LULC at the Departmental level.

Figure 5. Land use land cover classes (2012).



Source: Authors' own elaboration, based on CORINE (IDEAM, 2010).

Land use in the base year of IEEM is determined as follows. Crop areas reported in the agricultural census are equivalent to 8,476,711 ha. This area is regionally disaggregated to Colombia's 32 Departments according to data from Evaluaciones Agropecuarias Municipales (MADR, 2019). The total livestock area is 34,426,622 ha (DANE, 2016) and is regionally disaggregated according to data on herd size from the Livestock Census (ICA, 2019). The total area of forest plantations and natural forests are 584,802 ha and 58,971,012 ha, respectively. Both are regionally disaggregated based on data from IDEAM (IDEAM, 2020).

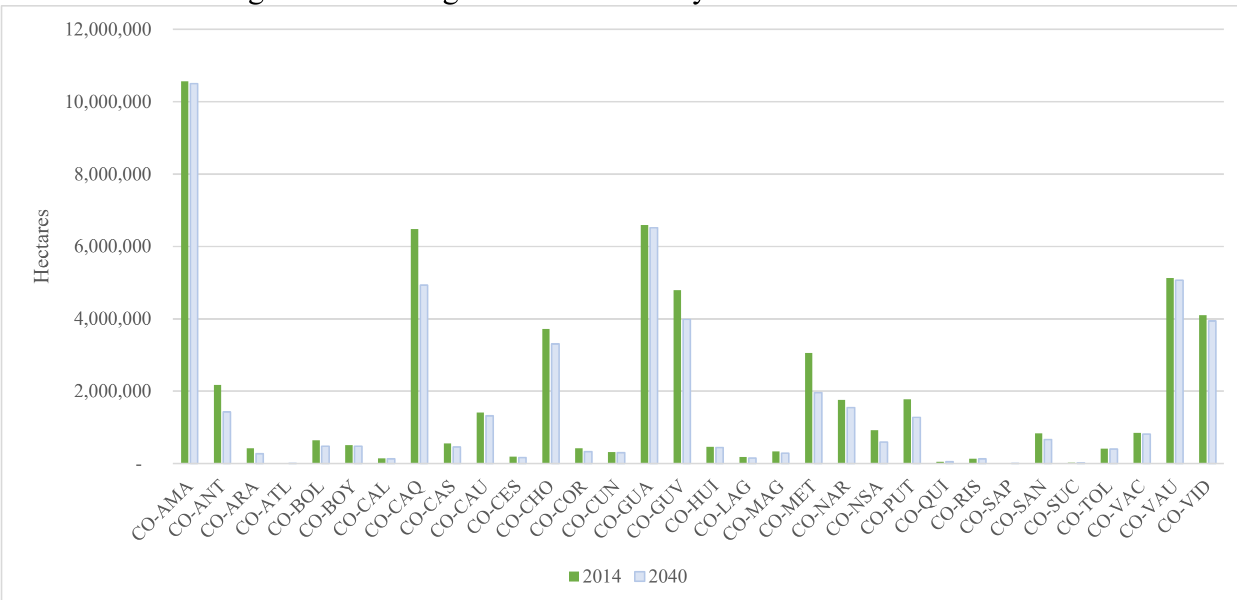
Table 1. Land use in the business-as-usual scenario and projected to 2040 in hectares.

Land use	Base 2014 (Ha)	Base 2040 (Ha)
Crops	8,476,711	9,038,276
Livestock	34,426,622	40,912,934
Forest Plantation	584,802	608,042
Forest	58,971,012	51,923,135

Source: Authors' own elaboration based on IEEM projections.

Establishing the baseline projection of deforestation for each Colombian Department was undertaken in two steps. First, the Departmental distribution of deforestation was drawn from IDEAM for the period 2014 to 2018 (IDEAM, 2020). This period was chosen to avoid the spike in deforestation that has arisen during the post-conflict period. The forward projection of deforestation was based on IDEAM's projections from 2020 to 2030, which estimated average deforestation at the national level, equivalent to 389,154 ha in 2030. Based on this figure, we estimate the rate of deforestation by Department and apply it to the standing forest stock each year to project deforestation by Department to 2040 (Figure 6). Table 1 shows starting LULC in 2014 and projected land use in 2040.

Figure 6. Standing forest in the base year and 2040 in hectares.



Source: Authors' own elaboration based on IDEAM (2019 and 2020).

3.2. Policy scenario design

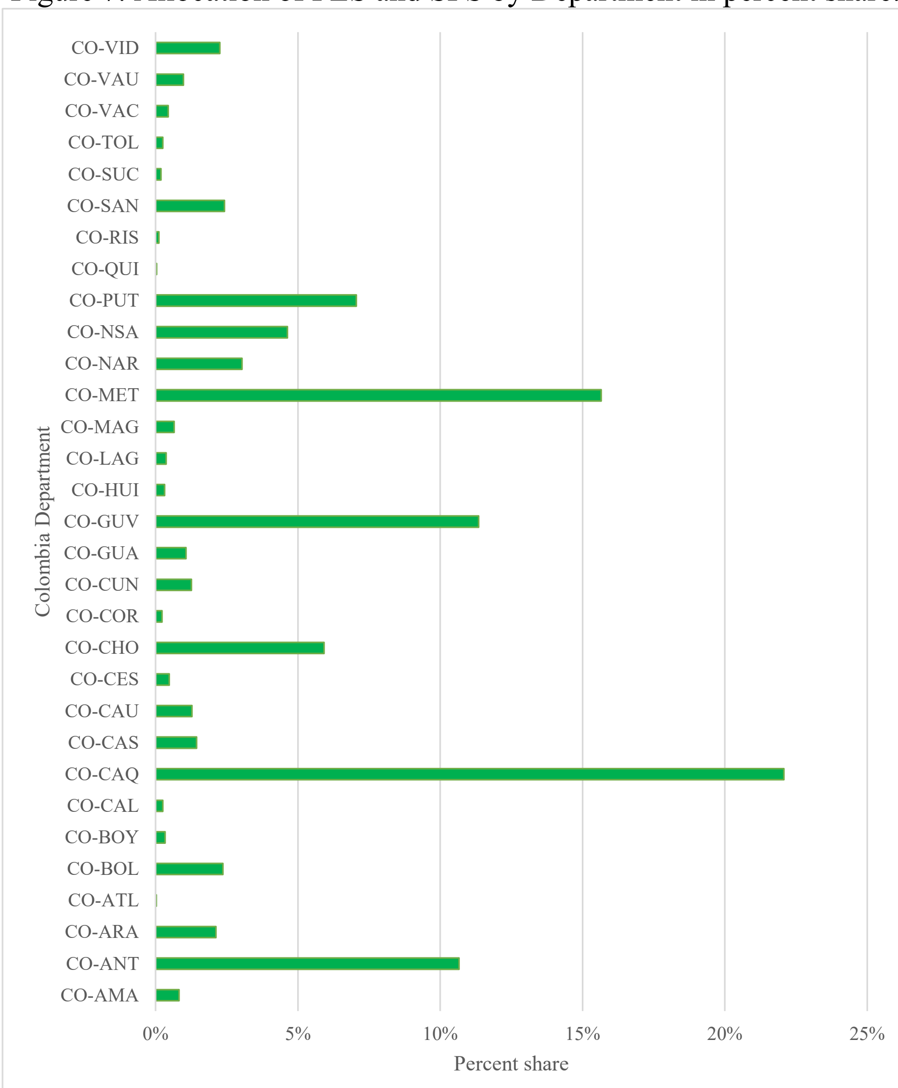
Three scenarios are designed and implemented in IEEM-COL to assess a Government plan developed by the National Council for Social and Economic Policy (CONPES) to establish a PES Program (CONPES, 2017; DNP, 2019). The Program seeks to establish one million hectares of PES over the next 14 years, allocating half of the area to strict preservation and the other half to restoration and the implementation of more sustainable agricultural and livestock systems. Our scenarios simulate: (i) establishing 500,000 ha of PES across the country; (ii) restoring 125,000 ha of degraded pasture areas with more productive silvopastoral systems (SPS), and; (iii) the joint implementation of the two previous scenarios. Landowners are beneficiaries of the Program, which is funded by the Government.

The allocation of PES and SPS across Colombian Departments follows the shares shown in Figure 7, which is proportional to the base levels of deforestation in each Department. A fourth scenario evaluates the impacts of a parallel conservation strategy through the expansion of habitat banking following the Terrasos Habitat Bank model (Fundepúblico and Terrasos, 2020).

CONPES (2017) has estimated the value of the payments for specific ES based on the opportunity cost of agriculture and cattle ranching as reflected in the Third National Agricultural Census

(DANE, 2016). Areas designated for strict preservation will receive between 318,000 and 477,000 Colombian Pesos (COP)/ha/year (between US$84 and US$126, USD of May, 2020) in PES payments while restoration activities will receive a payment of between 159,000 and 317,999 COP/ha/yr (between US$42 and US$84). Payments for strict conservation represent 75% of the estimated opportunity cost of forgone land uses and restoration activities will pay up to 50% of the opportunity cost of forgone land uses.

Figure 7. Allocation of PES and SPS by Department in percent share.



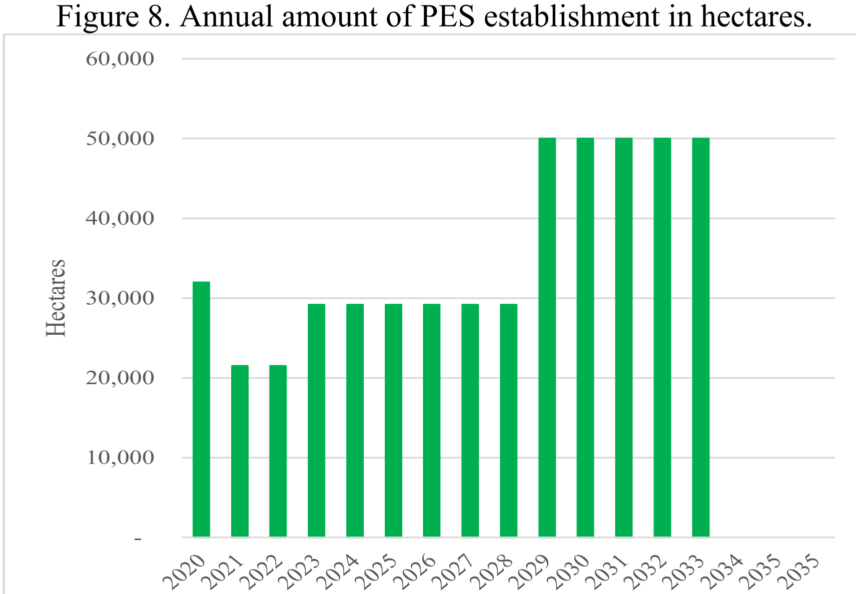
Source: Authors' own elaboration based on data from Ministry of the Environment and Sustainable Development. Note that Bogota's Federal District is aggregated with Cundinamarca throughout this paper.

The following describes the scenarios in greater detail:

(i) Payment for Ecosystem Services (PES): This scenario implements 500,000 ha of PES for strict preservation, beginning in 2021 and concluding in 2034 as shown in Figure 8. In this scenario, we take an optimistic approach and assume that one hectare of strict conservation of PES avoids the deforestation of one hectare of forest. In this scenario, we also assume improvements in government allocation of resources to monitoring and enforcement of deforestation, which accounts for the greater level of efficacy in PES contributing to avoided deforestation. This means that 500,000 ha of PES will avoid deforestation of 500,000 ha of forest into perpetuity, assuming payments and compliance are maintained, which are prerequisites of a PES program (Börner et al., 2017, Wunder et al., 2008, Engel et al., 2008, Wunder, 2005). No additional avoided deforestation is assumed past the year 2034 once all PES agreements have been established.

The fact that the establishment of PES implies just a one-time reduction in deforestation highlights the importance of complementary measures that can have dynamic impacts on reducing deforestation. Such measures include reducing pressures for the expansion of agricultural land through more productive and sustainable productive practices, and mechanisms for funding additionality in conservation, including for example, habitat banking. Both mechanisms are explored in subsequent scenarios.

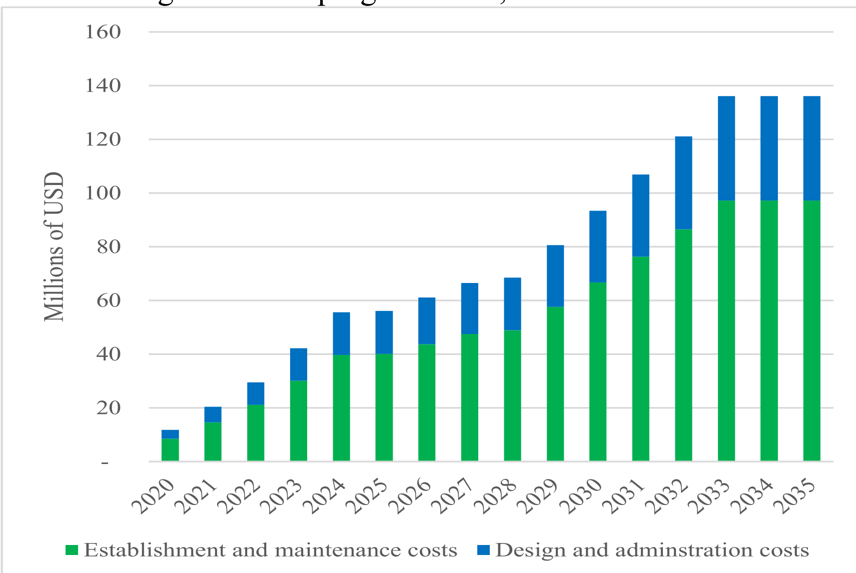
Figure 8. Annual amount of PES establishment in hectares.



Source: Authors' own elaboration based on CONPES, 2017.

PES establishment costs are presented in Figure 9. These costs include establishment and maintenance costs and are treated in IEEM-COL as direct transfers from the Government to property owners. PES design and administrative costs are also included and are financed by the Government. The CONPES Plan presents various mechanisms for financing PES, specifically: water use taxes; transfers from the energy sector; a 1% transfer of current income from municipal and departmental governments, which in 2019 was estimated as 900 billion pesos; a carbon tax, and; international grant financing (CONPES, 2017)

Figure 9. PES program costs, millions of USD.

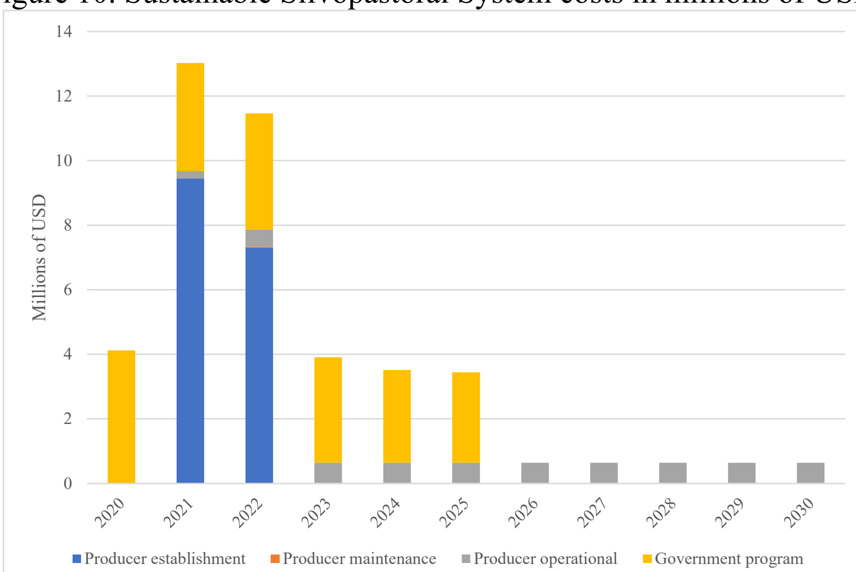


Source: Authors' own elaboration based on (CONPES, 2017).

(ii) Silvopastoral Systems (SPS): This scenario implements sustainable silvopastoral systems (SPS) to restore degraded pasture lands and enhance livestock productivity for meat and milk production. As the establishment of PES in some areas can result in a reduction in the current as well as potential supply of land for crops and livestock, the purpose of this scenario is to explore investments that can reduce demand for agricultural land, reduce pressure for new deforestation and generate revenue to finance the PES program. The data and estimates used to inform the productivity gains and costs in this scenario are based on Rodríguez (2017) who conducted an economic analysis of investing in SPS to improve productivity and reduce greenhouse gas emissions in Colombia (Rodríguez, 2017).

Within this scenario, we implement a total of 125,000 ha of SPS with two levels of productivity gains considered to account for variability in productivity due to soils, climate and other biophysical conditions. We implement 17,500 ha of high yielding SPS, which are expected to result in a milk production productivity gain of 2.9 times and meat productivity gain of 3.1 times. We implement 87,000 ha of average yielding SPS, which result in both a milk and meat productivity gain of 2.2 times. Trees are sparsely planted throughout the total 125,000 ha, with their biomass being equivalent to 10,000 ha of forest. The remaining 10,000 ha of the total 125,000 ha are assumed to remain under traditional livestock practices. Livestock producers are responsible for establishment, maintenance and operational costs, while the Government is responsible for other program costs (Figure 10). Livestock producers receive a total payment in the amount of US$5,012 million between 2021 and 2036 to cover some of the establishment, maintenance and operational costs incurred.

Figure 10. Sustainable Silvopastoral System costs in millions of USD.



Source: Authors' own elaboration based on Rodríguez, 2017. Note that costs remain constant at their 2026 values on to 2040.

(iii) COMBI: The COMBI scenario is the joint implementation of the PES and SPS scenarios.

(iv) Payment for Ecosystem Services and endogenous estimation of livestock Total Factor Productivity (PES+SPSe): This scenario implements the establishment of PES as in the PES scenario and endogenizes livestock productivity such that GDP in the scenario tracks GDP in the business-as-usual scenario.

(v) Habitat Bank Scenario (HAB): This scenario implements the expansion of a habitat banking system based on information supplied by Fundepúblico and Terrasos (2020). The additional area brought under habitat banking is 500,000 ha where 80% of the area will be designated as strict conservation and 20% as restoration. In IEEM and the LULCC modeling, the areas of strict conservation will be unmanaged forest, primarily tropical and tropical dry forests. Target areas will include the Caribbean coast region, the Cauca and lower Magdalena region and the center region on the Tochecito valley. Specifically, areas were distributed in equal parts among the Departments in each of these regions. For the Caribbean Region, areas were established in Departments of Atlántico, Bolivar, Cesar, Laguajira, Magdalena, Sucre. In the Valle Tochecito, areas were established in Tolima and Quindio. In the Andean and Pacific Region, areas were established in Cauca. The 200,000 ha of restoration areas will require activities including planting of native trees, installation of fences and ongoing monitoring over a period of 30 years. The cost for restoration or preservation is US$3,275/ha with an additional cost of US$1,607/ha for administration and overhead for a total cost of US$4,882.

There are two mechanisms through which the establishment of the habitat bank will affect the economy. The first is through avoided deforestation, which will be equivalent to the amount of the area conserved and restored, which is 500,000 ha. As with the PES scenario, we also implement a government reallocation of resources to enhance the effectiveness of the monitoring and enforcement of measures to reduce deforestation. The second is through reduced transaction costs for the mining sector, which is anticipated to be the primary clients of the habitat bank at least initially. Mining sector firms will engage in habitat banking to offset conservation liabilities for activities that generate environmental impacts. Habitat Banking is an attractive alternative for these firms, since conservation and restoration activities typically hinder their competitive advantage by deviating resources to the identification of compensatory areas. This reduction in transaction costs is modeled as a reduction in factor use to simulate more efficient operations. The cost of the program is covered by an increase in Government expenditure, which is financed through a special payment made by the mining sector to the Government. The Government revenues raised by this payment are set to an amount equivalent to the business-as-usual costs of mining sector conservation off-setting. The reduced transaction costs generated through habitat banking are equivalent to the business-as-usual cost of conservation offsetting and the savings generated through reduced firm factor use arising from engaging in habitat banking.

The initial investment will occur in year 2021. Avoided deforestation will occur linearly between 2021 and 2035. Legal and administrative structuring will take place in years 2021 and 2022. Operations will begin in year 2023, including restoration activities, which will take place over a 13-year period, until year 2035. Preservation activities also begin in year 2023. The habitat bank guarantees conservation of the 500,000 ha over a 30-year period. Biodiversity credit sale will begin on year 2023, progressively increasing until all credits sold by year 2030. Seventy percent of all required financing will be from domestic private investment and 30% will be from external debt.

For all of the above non-business as usual scenarios, we change the macroclosures as follows: (i) for the savings-investment balance, instead of imposing a fixed GDP share for private investment, investment spending (including its GDP share) is endogenous, adjusting to make use of available financing in the context of exogenous household savings rates; (ii) for the government balance, the treatment depends on the simulation design; specifically, the clearing variable is changed as part of the simulation design, and; (iii) for the balance of payments, the treatment is the same as in the business as usual scenario with the real exchange rate balancing the account.

Beyond the macro balances, the scenarios also differ from the business-as-usual scenario in that the following payments are fixed at the levels generated in the BASE scenario, instead of as fixed shares of GDP: domestic government financing (fixed in domestic currency, implicitly indexed to the Consumer Price Index, the model numeraire), and; private and government transfers and financing from the rest of the world (fixed in foreign currency).[3] The reason for this is that in the BASE scenario, it is assumed that many variables follow GDP as a constant share. For example,

[3] For the BASE scenario, imposing GDP shares has the advantage of generating a balanced evolution of targeted indicators. However, for non-base scenarios (which will be compared to the base and to each other), it is not reasonable to assume that, for example, in response to changes in the exchange rate or GDP, payments in foreign currency automatically are adjusted sufficiently to stay unchanged as shares of GDP. Fixing these payments in foreign currency has the additional advantage of leveling the playing field across the different simulations – they are to an identical extent able to rely on payments from the rest of the world – and, unless otherwise noted, the level of foreign liabilities is identical at the end of the simulation period.

if GDP increases in the BASE scenario, remittances will need to increase in order to keep the ratio to GDP constant. This is a reasonable assumption to generate a business-as-usual scenario, but not a good assumption for the policy scenarios themselves. For example, if we simulate an agricultural productivity shock that has a positive impact on GDP, there is no reason why remittances should also increase. This is why we change how some variables behave in the scenarios, including remittances in this example.

Instead of assuming that these variables' proportion to GDP is constant, we assume that in real terms they evolve the same as in the BASE scenario. In other words, the same value of remittances in this example continues to enter the country, regardless of what happens to GDP as a result of the agricultural productivity shock. This feature is critical for a sensible interpretation of the results. Specifically, scenario impacts therefore are solely attributable to the change in agricultural productivity and not confounded by other features such as changes in remittances. The same type of reasoning applies to other payments that change their behavior rule between BASE and non-BASE scenarios.

3.3. Results

As shown in Figure 1, the IEEM+ESM workflow begins with implementation of the business-as-usual and scenarios in IEEM for the first time-step. IEEM results are used to drive change in LULC, which then translate into impacts on ES supply. Changes in future ES supply, specifically erosion mitigation ES in this study, have a direct impact on the economy and economic agents. Given this workflow, the presentation of results begins with demand for land from IEEM, how it is spatially distributed with the LULCC model, how LULCC translates into changes in future ES supply, and then finally the resulting impacts on the economy, which accounts for changes in erosion mitigation ES supply and its value. An overview of LULC in Figure 11 shows Colombia's original 2014 LULC, our projected LULC in the BASE in 2020 and all scenario LULC in 2040. While changes in LULC in Figure 11 are difficult to detect at the scale presented, these changes drive impacts on ES supply, which are evident in subsequent figures.

In Figure 11, the business-as-usual and five scenarios differ in 2050 primarily in terms of the amount of cropland and grazing land and their spatial distribution, which can be seen in more detail on a local scale (see, for example, Figure 13 focusing on Valle de Cauca). All scenarios project land use change trends that have been observed in Colombia in the past decades. The main process identified, largely driven by the demands estimated by IEEM, is conversion from forest to grazing on the Amazon frontier. Although this is the predominant process of forest loss in our scenarios, we also observe some formation of grazing land inside the forest, far away from the forest edge, but usually close to roads, for example, in the department of Amazonas. Encroachment of cropland into forest is more common in the forests in the Pacific regions. Other processes, such as conversions from cropland to grazing and vice versa occur at a minor scale as defined by IEEM, and mostly in departments on the Pacific coast and in the Andes. Forest and shrub cover loss is occurring on a smaller scale in the Llanos region in central Colombia towards the border with Venezuela.

In Figure 12 we highlight the areas converted from forest to other uses by scenario by 2040. LULCC is modeled individually for each of Colombia's 32 Departments; such detailed LULCC modeling at the national scale is uncommon. This approach enables a detailed analysis of LULCC, which is the main driver of changes in ES supply, as well as the spatial targeting of the policies implemented. As an example, Figure 13 presents LULCC across scenarios for the Department of Cauca in Colombia's southwest. This figure, for example, highlights how the differences in areas converted to cropland across scenarios. Smaller changes in conversion to grazing are detected in PES and HAB, for example, when compared with the business-as-usual scenario. Figure 14 shows the annual change in deforestation (Panel A), crops (Panel B) and livestock (Panel C) areas. These changes in land use fundamentally drive changes in future ecosystem services supply and economic outcomes.

Figure 15 provides a visual overview of the performance of each scenario in terms of the ES production potential. Scenarios in these charts are compared against each other with total ES values for all scenarios presented as a normalized index. Table 2 provides a summary overview of scenario impacts on ES supply compared to business-as-usual. Overall, most scenarios have a positive impact on future ES supply. Overall, most scenarios are beneficial in terms of erosion mitigation ecosystem services. SPS and COMBI tend to reduce erosion mitigation ecosystem services, which is mostly driven by a different share of cropland and livestock areas, despite similar deforestation trends. Croplands can have higher rates of erosion than grassland, which is what is driving this reduction in the case of SPS and COMBI. Several departments also exhibited a loss of soil erosion mitigation services. Detailed results for all ecosystem services analysis are included in Supplementary Information section 3.

It is important to note that while some departments showed a loss in ecosystem services, in some cases the reduction in this ecosystem service was attributable to small differences between business as usual and the scenarios, though the calculated percent difference can be large. For example, a 10 hectare increase in erosion in the business-as-usual scenario compared with a 14 hectare increase in a scenario translates into a scenario impact of 40%.

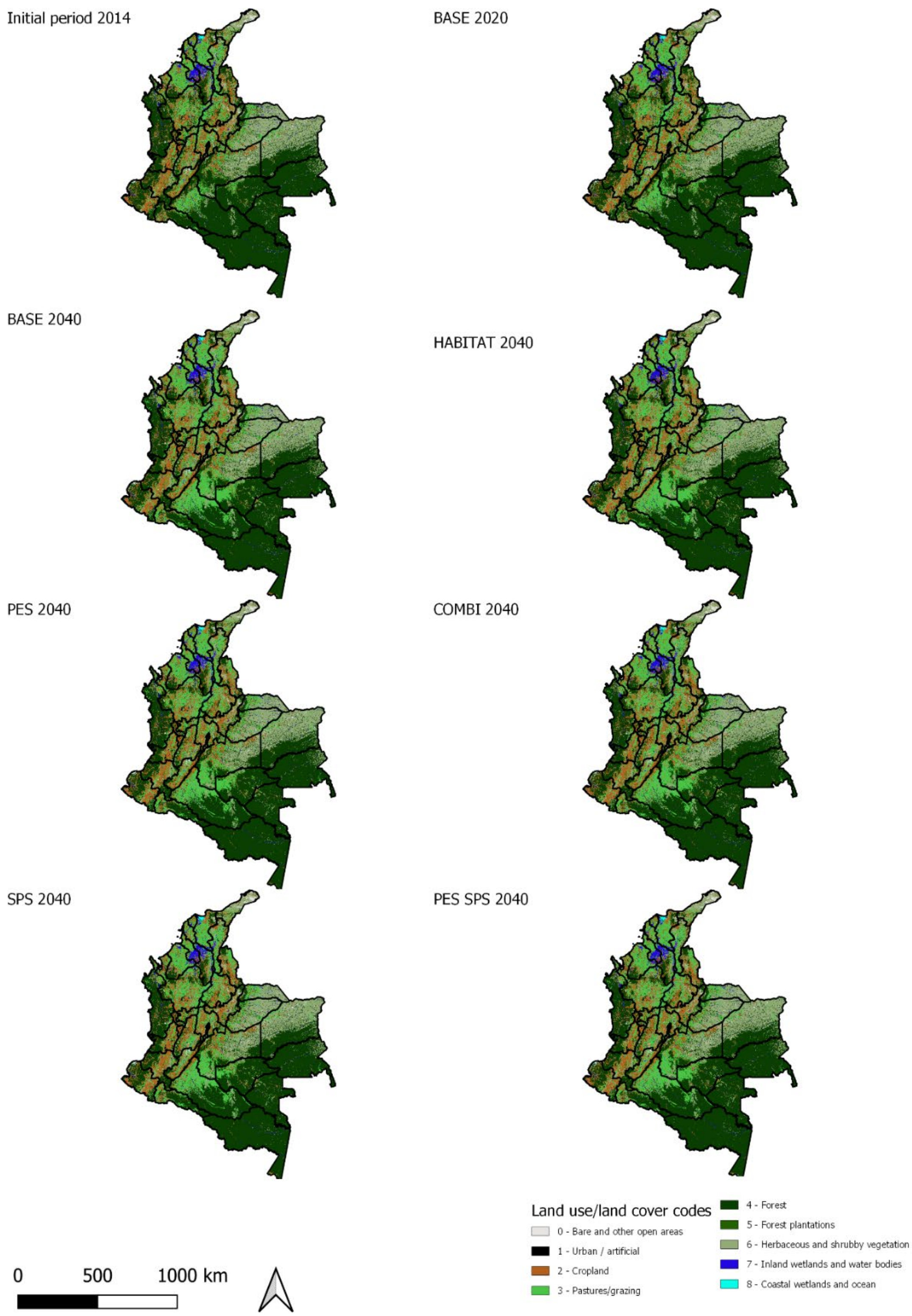
Table 2. Scenario impact on overall ES supply in percent.

	PES	SPS	COMBI	PES+SPSe	HAB
Soil erosion mitigation	3.3	-12.5	-4.0	11.4	16.7
Carbon storage	6.3	0.01	6.1	6.8	7.2
Nutrient (nitrogen) storage	7.3	4.9	10.3	6.0	29.4
Nutrient (phosphorus) storage	4.9	0.1	6.1	7.2	18.8
Annual water yield	6.4	0.6	5.4	6.3	4.8
Biodiversity Intactness	6.4	0.1	6.6	7.3	8.2

Source: IEEM+ESM results.

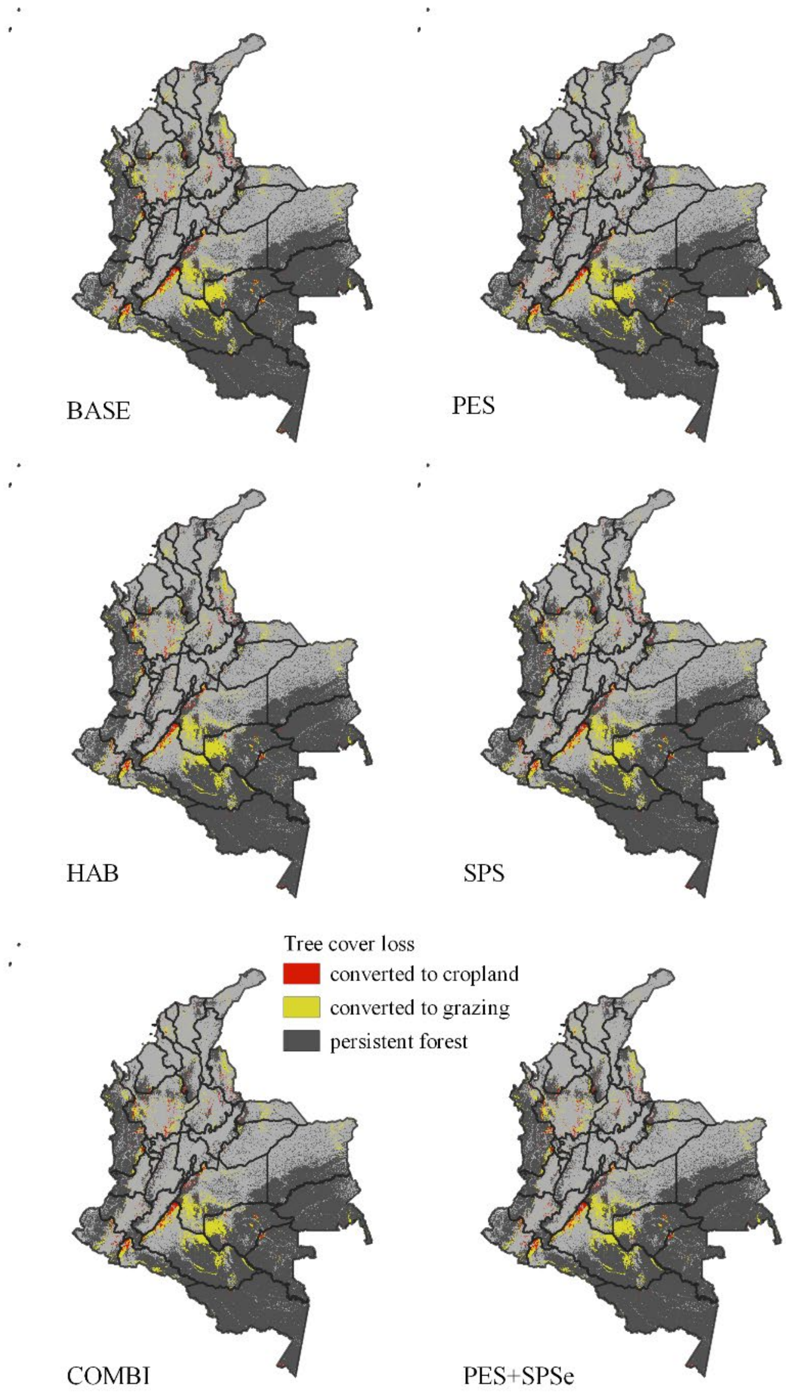
Figure 16 summarizes changes in erosion mitigation ecosystem services between all scenarios and the business-as-usual case in 2040. Positive values indicate that the scenario has a positive impact on erosion mitigation ecosystem services. Negative values indicate that there was a reduction in erosion mitigation ecosystem services.

Figure 11. LULC maps for initial land cover (2014), business-as-usual in 2020, and all 2040 scenarios.



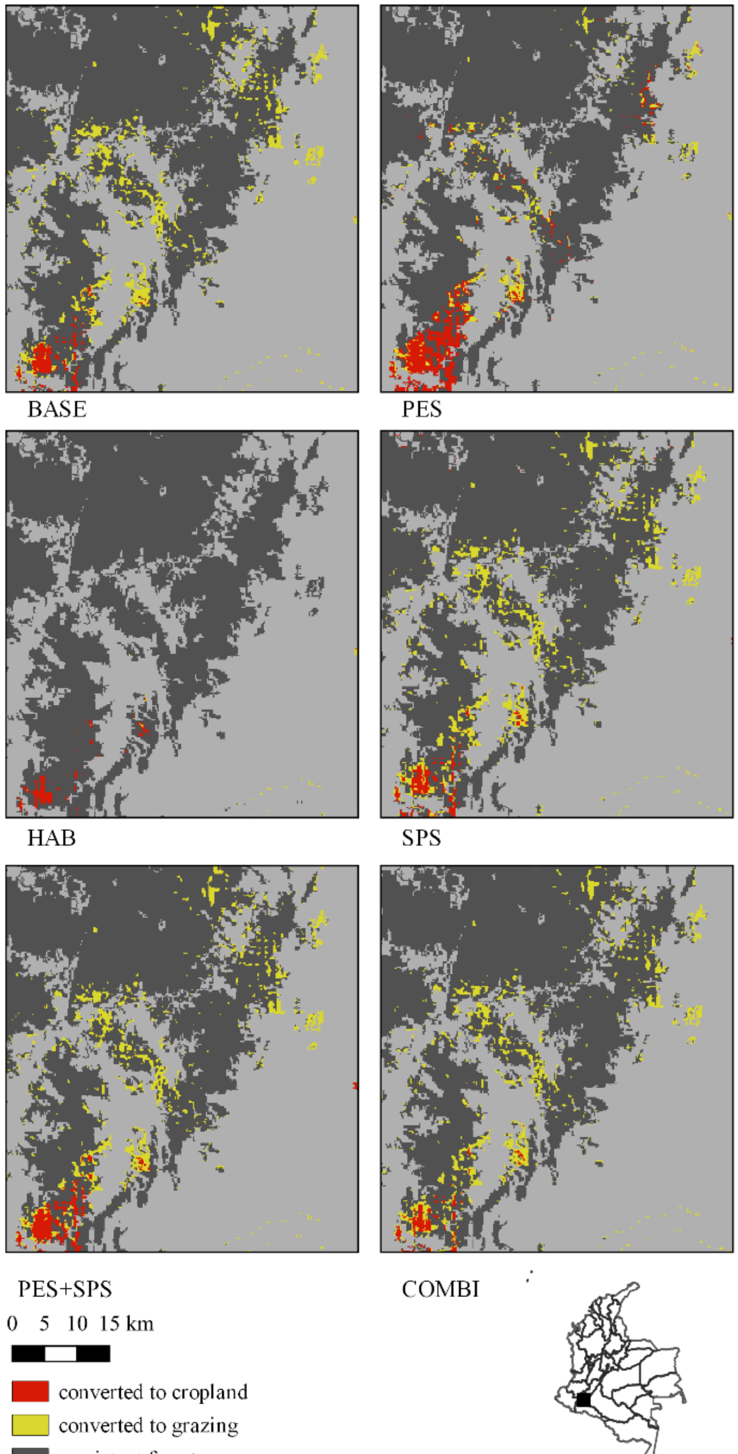
Source: IEEM+ESM results.

Figure 12. Scenario impact on land use and land cover, highlighting converted areas by scenario by 2040.



Source: IEEM+ESM results.

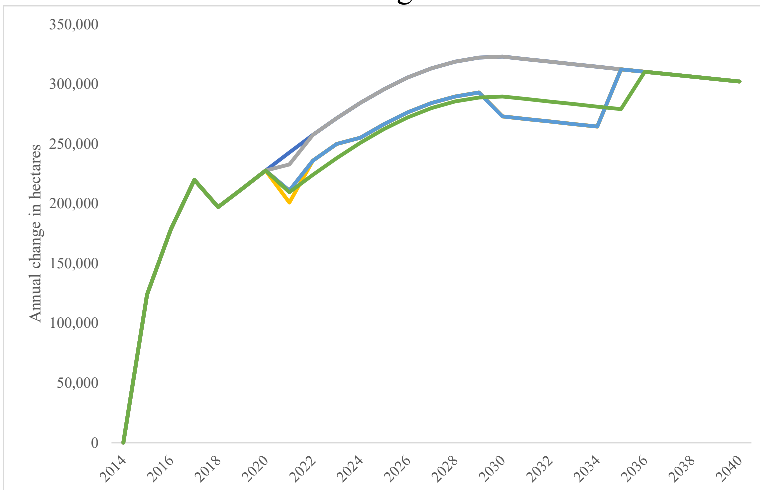
Figure 13. Detailed scenario impacts on LUCC, Department of Cauca.



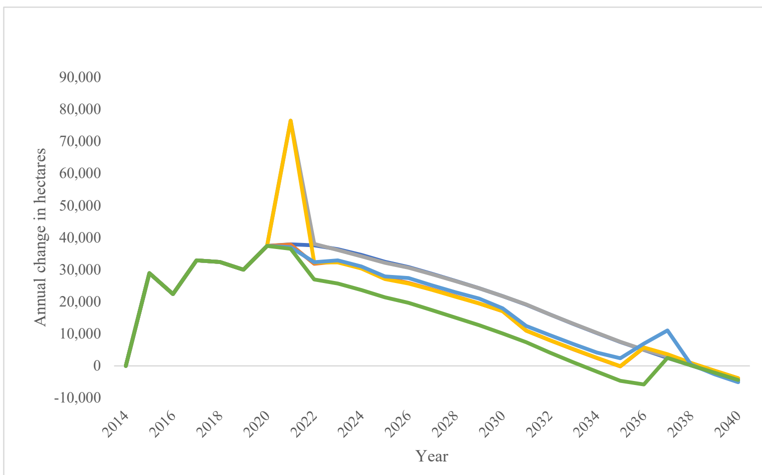
Source: IEEM+ESM results.

Figure 14. Annual change in deforestation, cropland and livestock for Colombia.

Panel A. Annual change in deforestation.



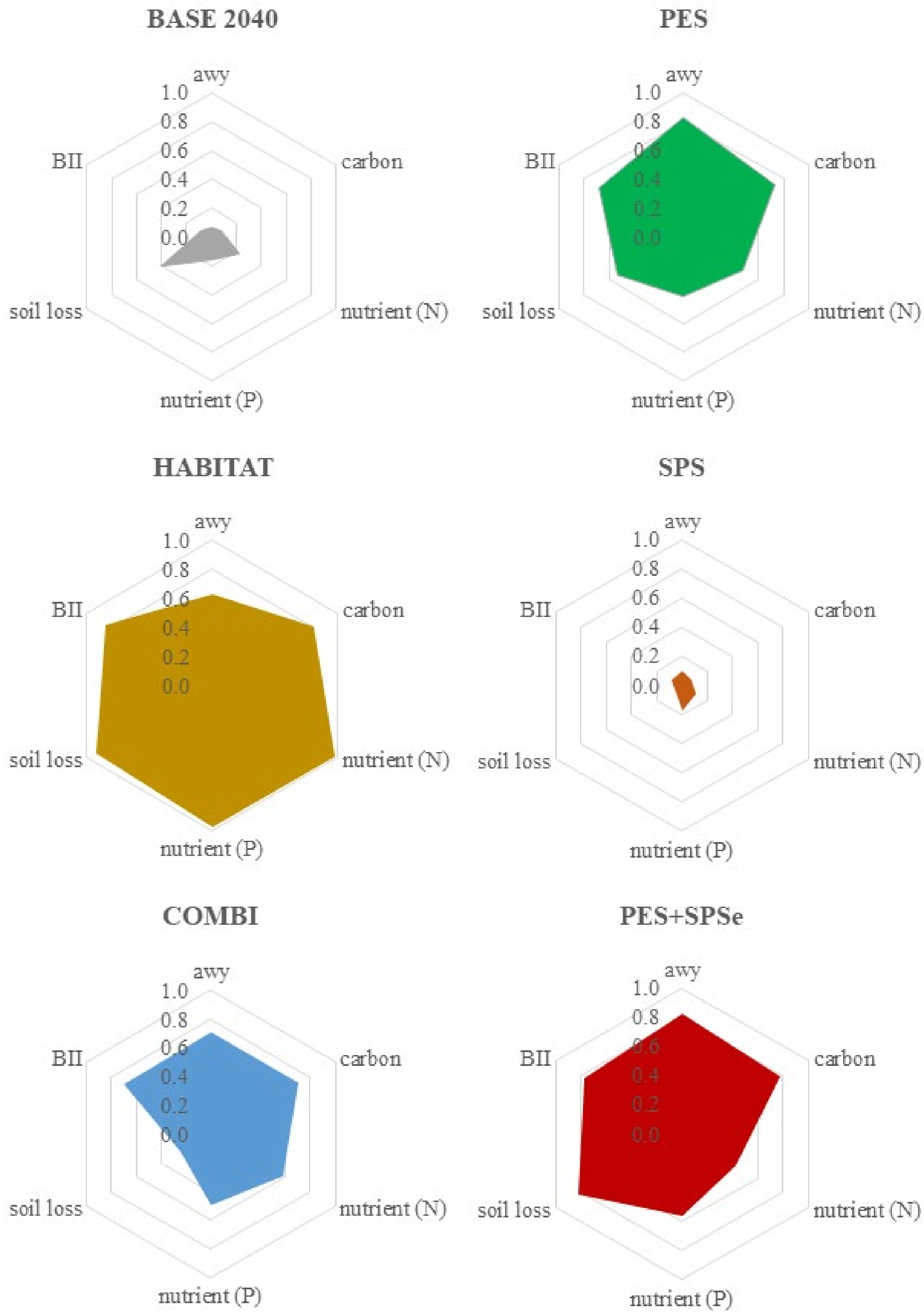
Panel B. Annual change in crops in hectares.



Panel C. Annual change in livestock in hectares.

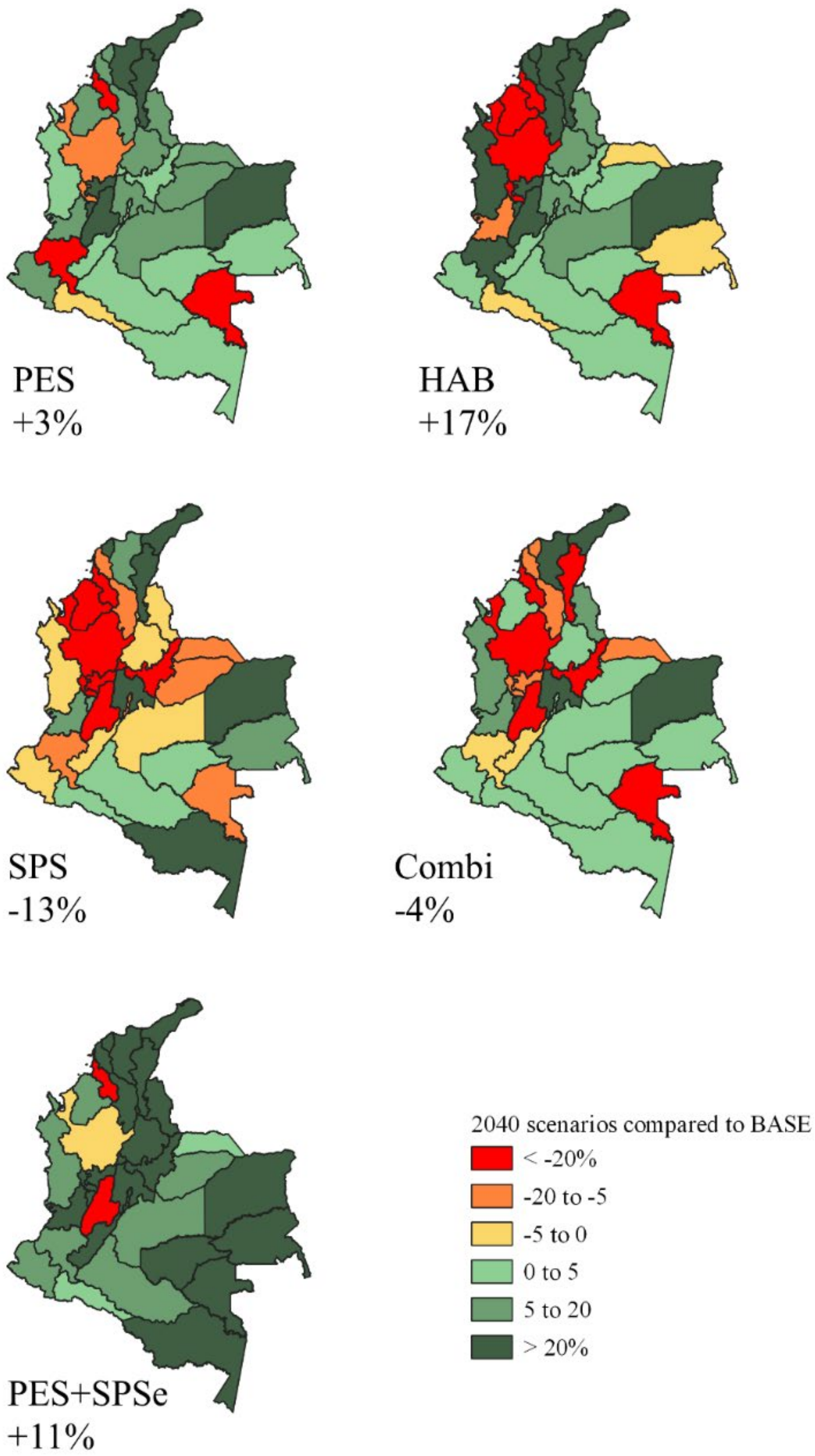
Source: IEEM+ESM.

Figure 15. Summary of scenario performance in terms of ES (scenarios compared against each other). Total ecosystem service values for all scenarios presented are here all normalized (between 0-1) for illustrative purposes. AWY is annual water yield and BII is Biodiversity Intactness Index



Source: IEEM+ESM results.

Figure 16. Changes in erosion mitigation services in 2040 as a difference from base in %. Numbers next to the scenario name describe the change on a national level for the scenario.



Source: IEEM+ESM results.

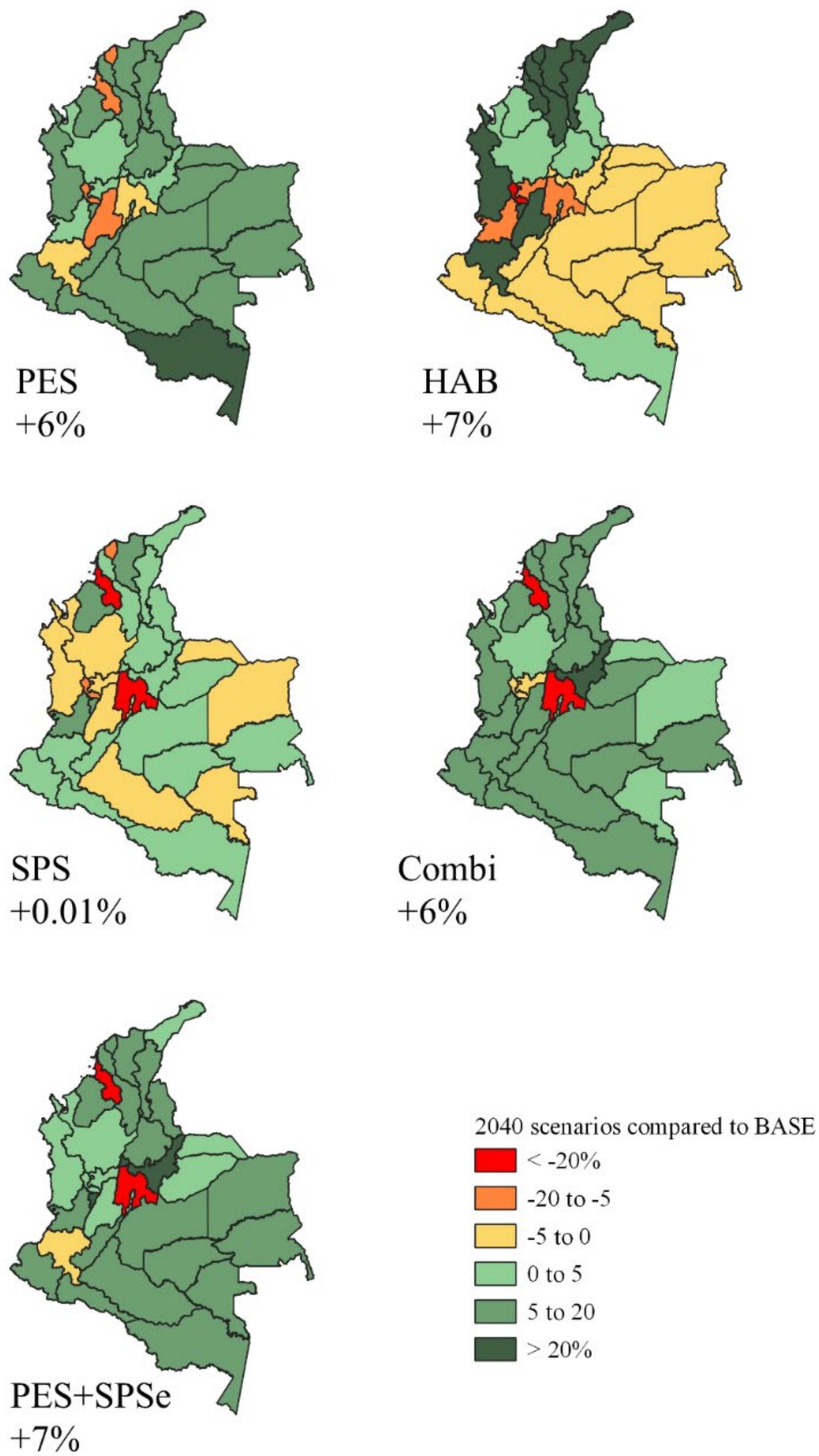
Figure 17 evaluates scenario impacts on carbon storage. Positive values indicate that the carbon storage potential in a scenario is higher than in the busines-as-usual scenario. Negative numbers indicate that the scenario has a lower carbon storage potential compared to business as usual. All scenarios result in increased carbon storage compared to business as usual, with HAB and PES+SPS being the most beneficial. While the habitat banking scenario map may appear to show that it has generated less benefits than others, this is attributable to the fact that yellow regions were generally on the lower end of the interval band classification, though the overall outcomes were positive.

Figure 18 and Figure 19 display percentage changes in water purification ecosystem services, specifically, nitrogen and phosphorus, comparing all scenarios with business as usual in 2040. Positive values indicate an increase in water purification ecosystem services and that less nutrients reach the waterways compared to the business-as-usual case. Negative values indicate a reduction in water purification ecosystem services and that more nutrients are delivered to the waterways in the scenario compared to the business-as-usual case. The results show that overall, all scenarios except SPS increase water purification ecosystem services when compared with business as usual; HAB being the most beneficial, both in terms of nitrogen and phosphorus retention.

Figure 20 presents the percentage change in water supply ecosystem services expressed as annual water yield volume in cubic meters (m^3) compared to business as usual in 2040. A positive value indicates an increase in water supply ecosystem services compared to business as usual, while a negative number indicates a decline in water supply ecosystem services compared to the business-as-usual case. On a national scale, all scenarios have higher water yield, and are thus more beneficial than the status quo in terms of water supply ecosystem services. Differences however are small due to slow moving hydrological processes.

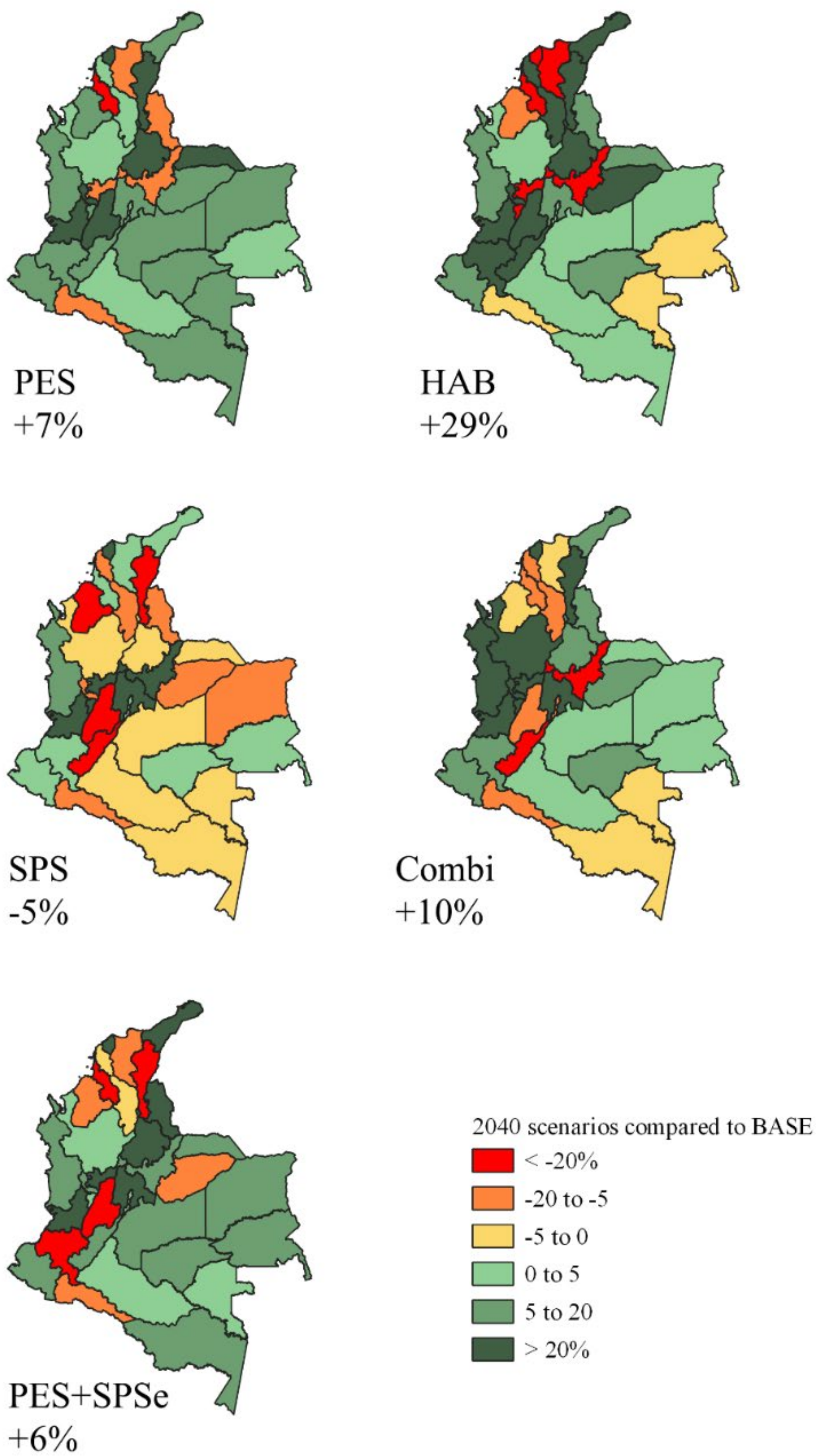
Figure 21 shows the scenario impacts on biodiversity compared to business as usual in 2040 expressed as a percent change in the BII. A positive number indicates that the scenario has a positive impact on biodiversity when compared with business as usual. A negative number indicates a reduction in biodiversity compared with business as usual. Overall, all scenarios have a positive impact on biodiversity.

Figure 17. Differences in carbon storage in 2040 as a difference from business-as-usual in percent. Numbers below the scenario name describe the change on a national level for the scenario.



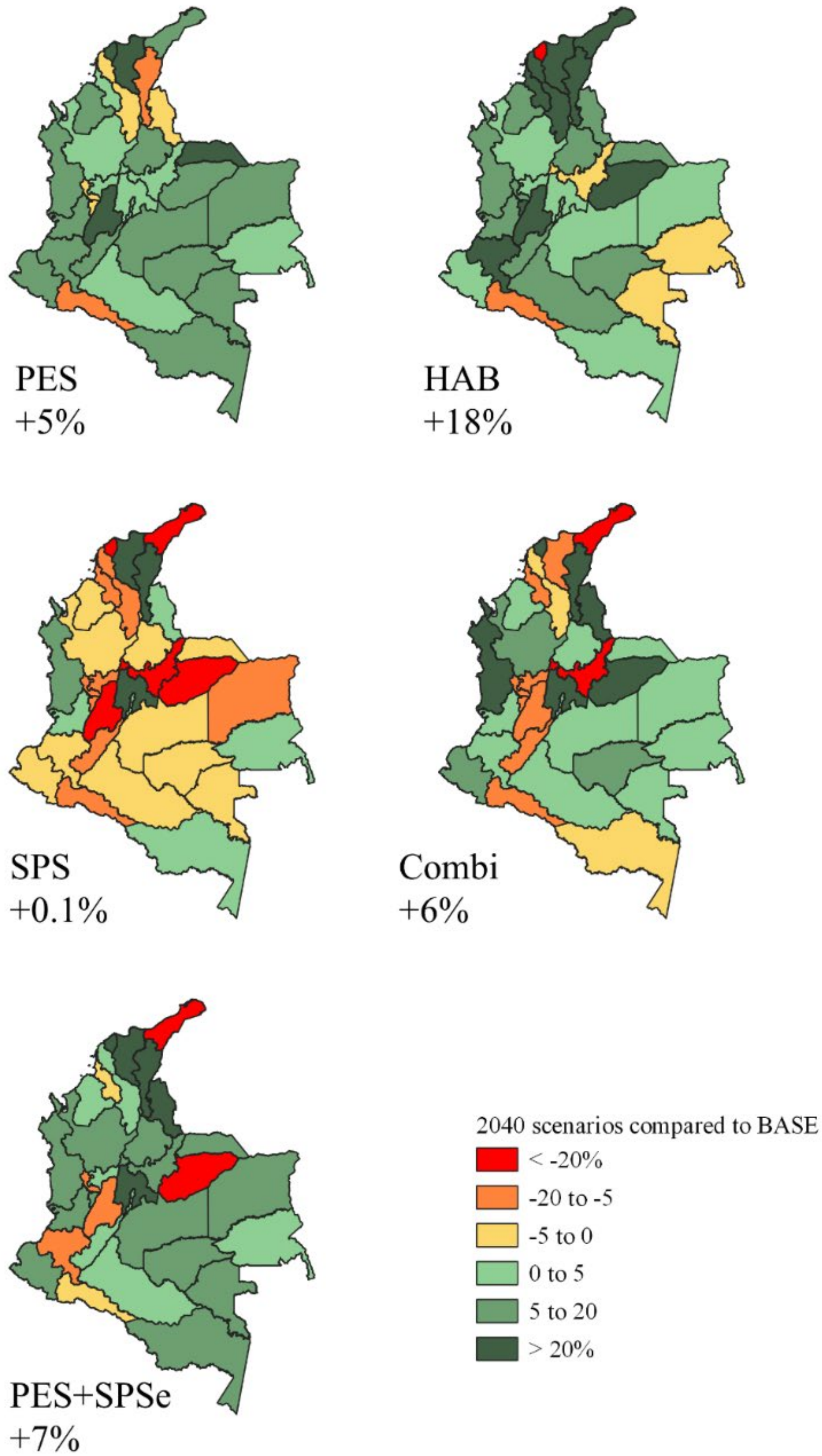
Source: IEEM+ESM results.

Figure 18. Differences in nitrogen retention in 2040 as a difference from business as usual in percent. Numbers below the scenario name represent the overall change.



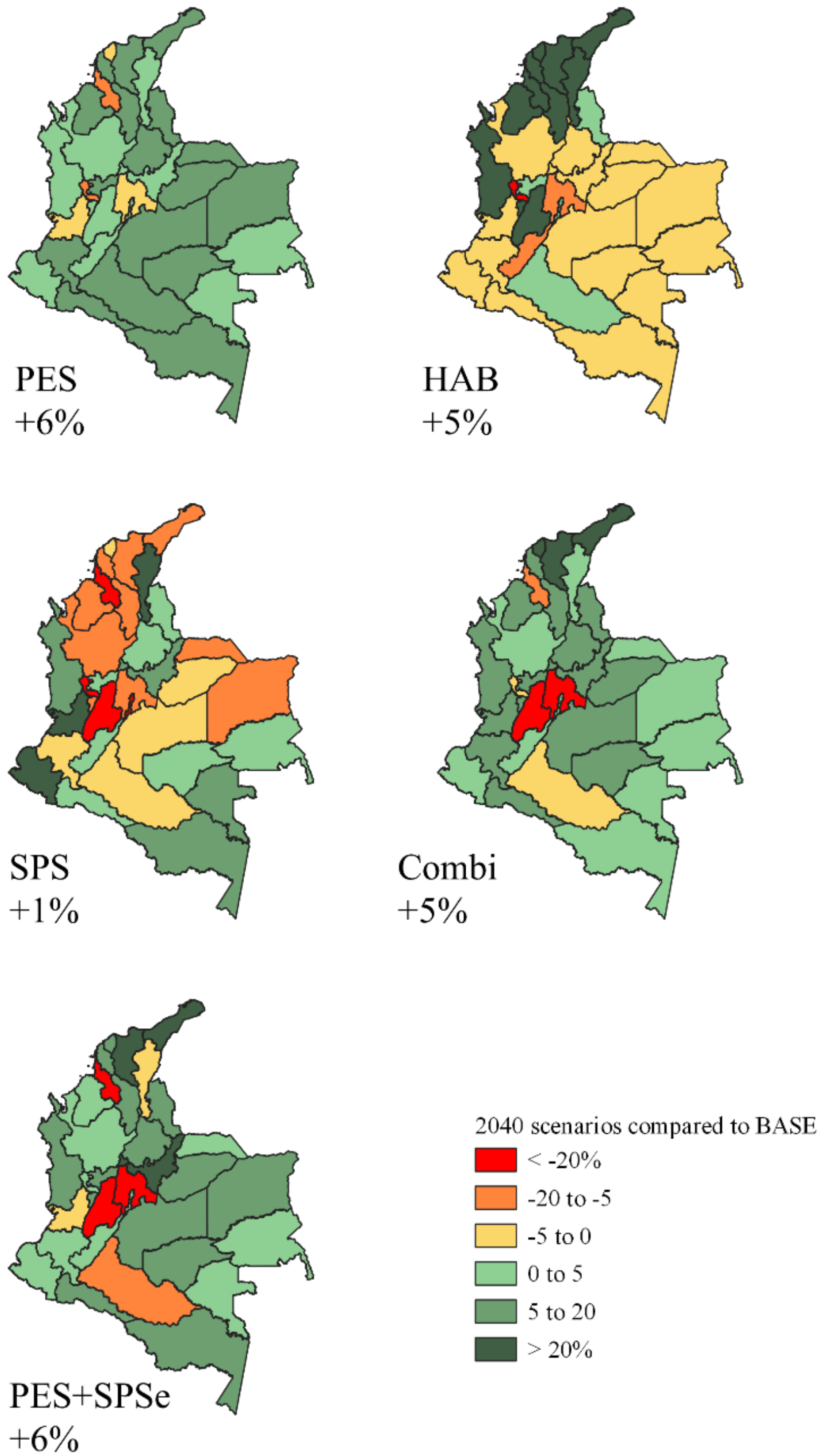
Source: IEEM+ESM results.

Figure 19. Differences in phosphorus retention in 2040 as a difference from business as usual in percent. Numbers below the scenario name represent the overall change.



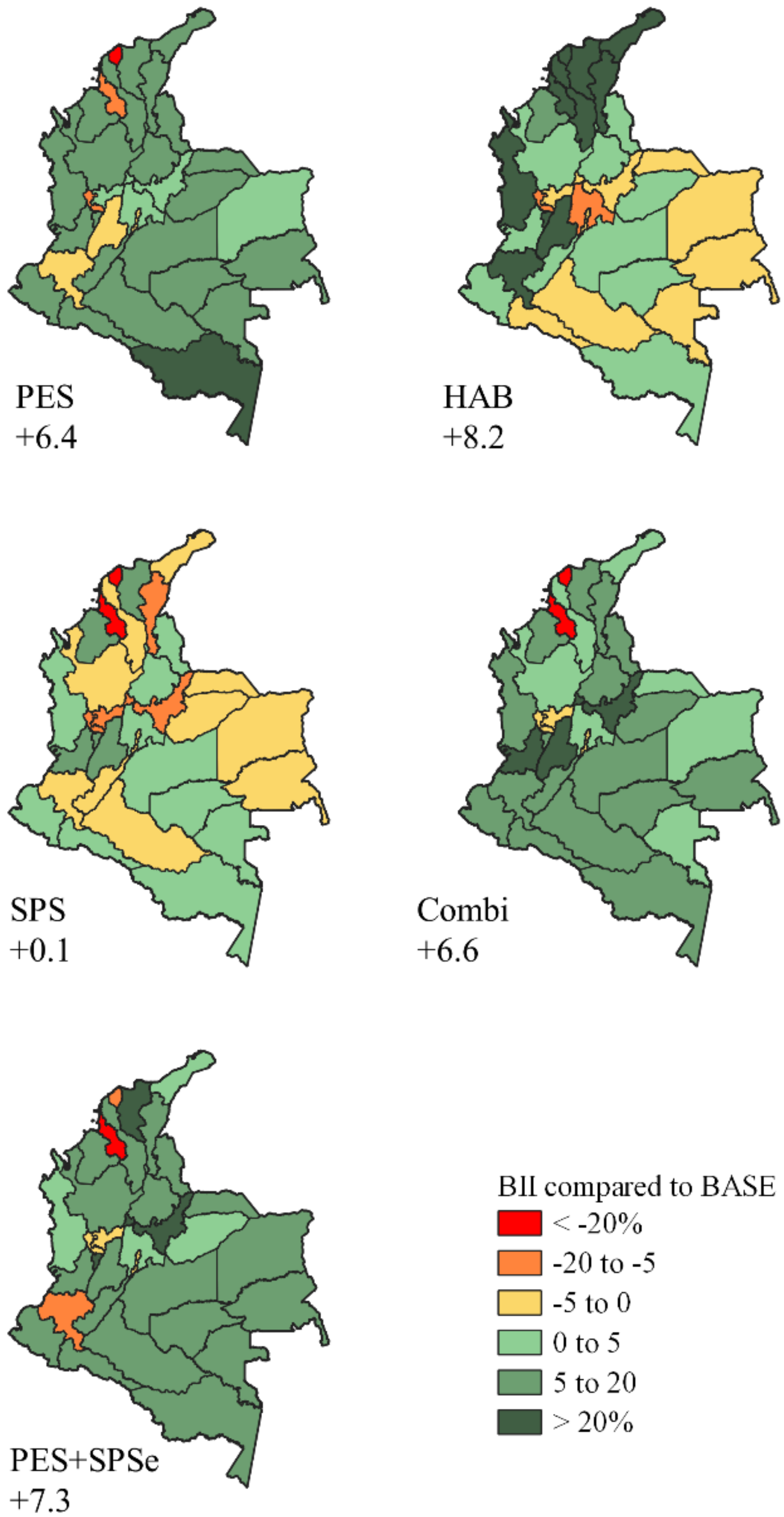
Source: IEEM+ESM results.

Figure 20. Differences in annual water yield in 2040 as a difference from BASE in percent. Numbers below the scenario name describe the change on a national level for the scenario.



Source: IEEM+ESM results.

Figure 21. Scenario impacts on the biodiversity intactness index compared to business as usual in 2040. Numbers below the scenario names define the difference in BII for scenario on the national level.



Source: IEEM+ESM results.

Table 3 shows scenario impacts on macroeconomic indicators as differences from business as usual in 2040. Results on the left side of the table include the value of erosion mitigation ES while results on the right do not. With the PES scenario generating competition for crop and livestock land, indicators are negative, US$262 million less GDP in 2040 compared with business as usual. With the importance of agriculture to the incomes of many households in the rural environment, household consumption contracts by US$188 million and despite the positive impact of increasing natural capital stocks with PES, the decline in income and savings pushes wealth downward by US$325 million. In the PES scenario, not taking ES values into account, GDP, wealth, private consumption and private investment are all more negatively impacted as the improvement in ES supply that PES generates is not considered. Table 4 shows by just how much ES, erosion mitigation ES in this case, contributes to each indicator across scenarios.

Table 3. Macroeconomic indicators, on the left, scenario impacts as difference between first and last year compared to business as usual, including ES values and, on the right, not including ES values, all values in millions of USD.

	PES	SPS	COMBI	PES+SPSe	HAB	PES*	SPS*	COMBI*	PES+SPSe*	HAB*
GDP	-262	694	549	0	188	-276	747	596	0	111
Genuine Savings	-325	125	-22	-216	1,607	-330	147	-3	-223	1,576
Private consumption	-188	725	444	-27	-237	-199	766	480	40	-299
Private investment	-244	76	-12	-130	134	-247	92	3	-182	114
Exports	-141	115	39	-69	237	-144	127	49	-80	217
Imports	-55	152	97	-1	166	-58	161	104	-3	151

Source: IEEM+ESM results. Superscript * indicates "not including ES values".

The implementation of SPS has a strong positive impact on GDP (US$694 million) and wealth is also lifted by US$125 million. Overall higher levels of production and consumption increase exports and imports. We know, however, from our ES analysis that SPS affects biodiversity, erosion, water quality, water supply and carbon storage and that these can generate negative economic impacts as well. When we compare SPS* with SPS, we see that by not valuing nature's services and their loss, we are over-estimating the positive economic returns to SPS (US$694 million vs. US$747 million), by US$53 million in fact when comparing just one point in time (Table 4). Cumulative impacts, of course, would be much greater.

The joint implementation of PES and SPS results in a boost to GDP of US$549 million and a relatively small negative impact on wealth (US$22 million). In this scenario, to some extent, double dividends are achieved with increased income, consumption and savings through heightened economic activity, coupled with enhanced natural capital stocks and ES supply. In PES+SPSe where tracking GDP is required by scenario design, the negative impact on wealth is driven by the decrease in deforestation, which reduces the supply of land available for crops and livestock, a reduction in crop and livestock growth and lower levels of savings and household consumption.

The establishment of habitat banking is a win-win across most indicators with a US$188 million boost to GDP and the largest impact on wealth by far with a US$1,607 million increase. Habitat banking not only increases natural capital stocks but shows some additionality where ES are concerned. Note that gains to the mining sector from habitat banking return to business-as-usual levels in 2036 and thus private consumption tends to reduce its pace of growth thereafter. This is the reason for the US$237 million decline in private consumption, given that this value is a snapshot of the indicator in the year 2040; cumulative values for each of these indicators would offer a different perspective. On the right side of Table 3, where ES are not valued, the habitat bank performs well in terms of GDP and wealth, but when comparing it with the left side of the Table, it is evident that ES values contribute significantly to the economy, by US$77 million and US$31 million to GDP and wealth, respectively. Table 4 presents how the inclusion of ecosystem services values affects each macroeconomic indicator for each scenario.

Table 4. The economic contribution of erosion mitigation ES to macroeconomic indicators as difference between first and last year compared to business-as-usual in millions of USD.

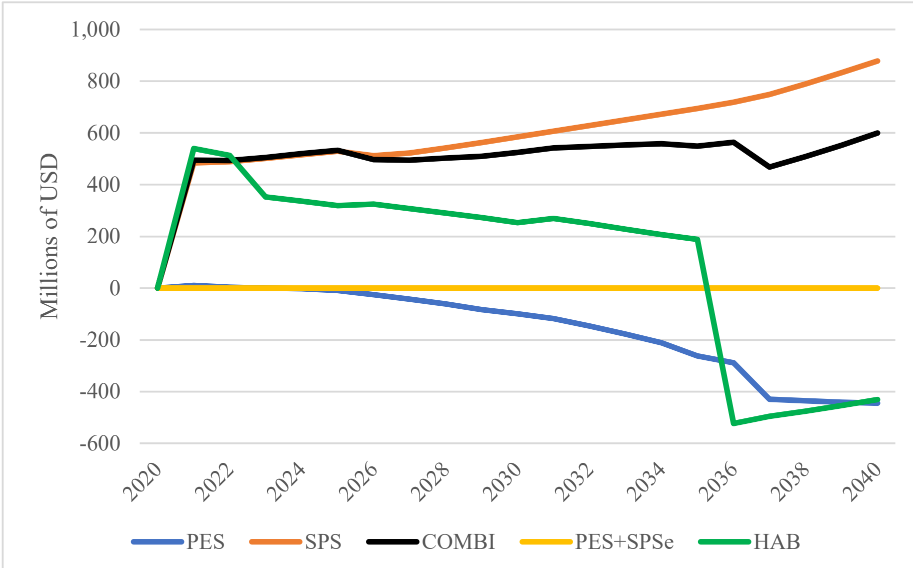
	PES	SPS	COMBI	PES+SPSe	HAB
GDP	14	-53	-47	0	77
Genuine Savings	6	-22	-19	7	31
Private consumption	11	-41	-36	-67	62
Private investment	4	-16	-14	51	20
Exports	3	-12	-10	12	20
Imports	2	-8	-7	2	15

Source: IEEM+ESM results.

Examining the cumulative value of indicators as a difference from business as usual provides a different perspective. Where Table 3 shows a decline in wealth arising from PES, the cumulative impact on wealth is quite positive generating an additional US$14 billion in wealth. Combined with silvopastoral systems, wealth reaches over US$19.5 billion. Habitat banking again presents clear gains of over US$16.6 billion. SPS alone, however, while a clear leader in Table 3 does not show such impressive gains where cumulative wealth is concerned.

The trajectories of two main indicators are shown in Figure 22 and Figure 23.

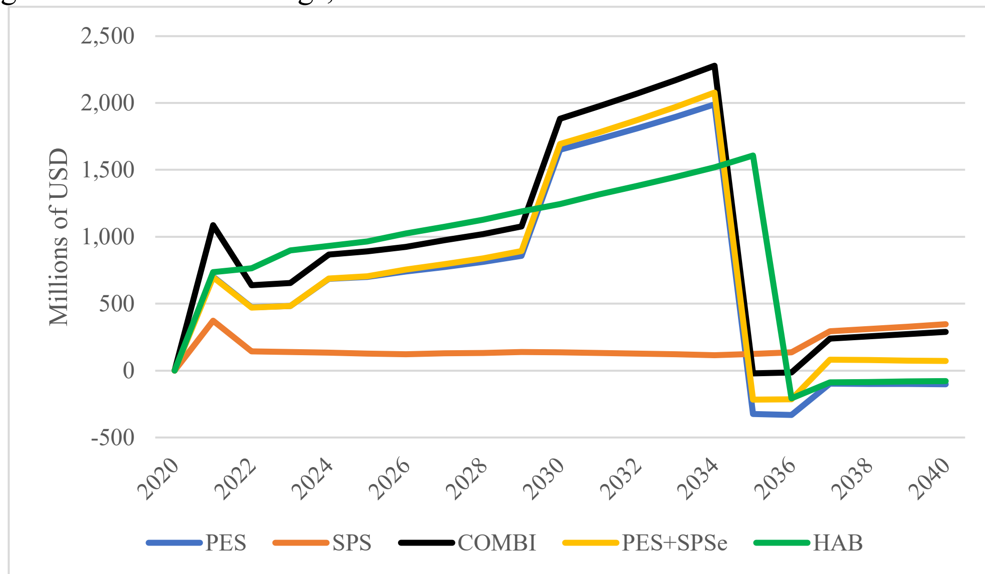
Figure 22. GDP at factor cost, difference from business as usual in millions of USD.



Source: IEEM+ESM results.

Figure 22 shows a smooth trajectory for the SPS scenario and the offsetting impact of SPS on the downward pull of PES on GDP in COMBI. In the case of habitat banking, there is an initial stimulus to the economy, a Keynesian effect, in the first two years (2021 and 2022) in which the habitat bank is established. This scenario shows gains that extend until 2035 after which there are no additional benefits as the program has achieved its intended purpose. Specifically, the drop in GDP in the HAB scenario in 2035 is explained by the fact that increases in productivity attributable to habitat banking and the Keynesian effect of increased public expenditure for program administration terminate in this year. Figure 23 is useful for highlighting the return to business-as-usual levels in wealth once the investments and policies have been fully implemented after 2034 for most scenarios and in 2035 in the case of the HAB scenario. Some indicators such as wealth drop slightly below business as usual due to the decrease in output, which in turn translates into a decrease in income, savings, and investment; the explanation in terms of decreased investment is directly related to changes in household income. In later periods, impacts on wealth tend to gravitate toward business-as-usual levels.

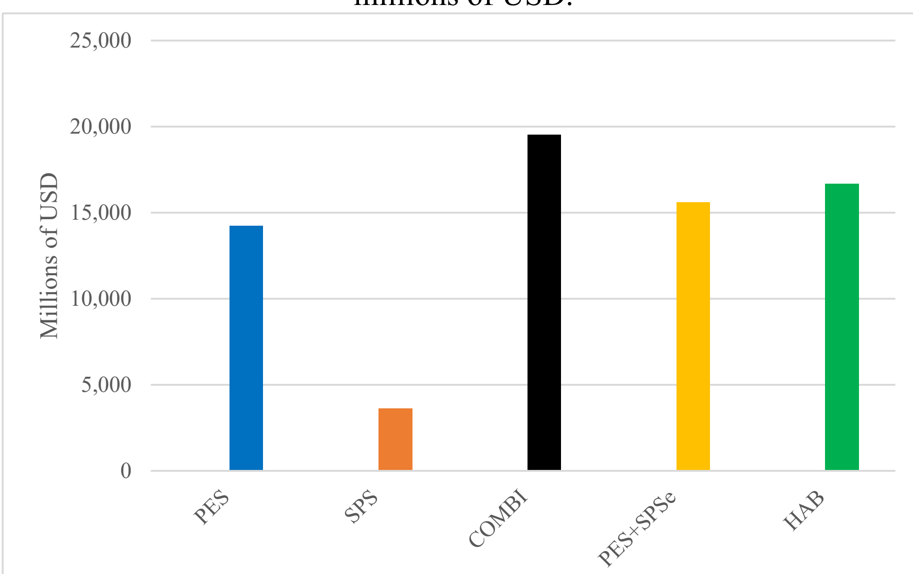
Figure 23. Genuine savings, difference from business as usual in millions of USD.



Source: IEEM+ESM results.

Cumulative wealth is presented in Figure 24 with all scenarios showing a positive impact and the greatest impact attributed to the joint implementation of PES and SPS.

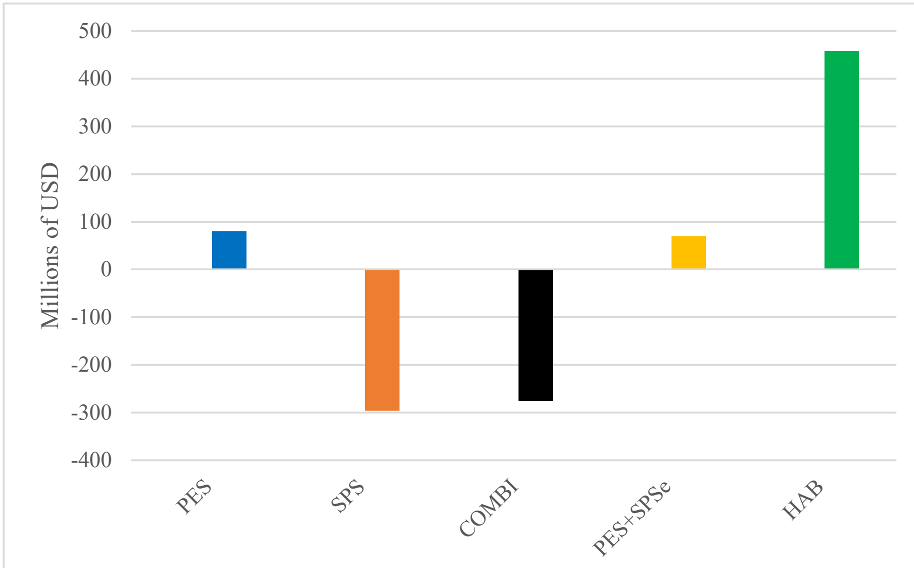
Figure 24. Cumulative wealth, difference between scenarios and business as usual until 2040 in millions of USD.



Source: IEEM+ESM results.

The significance of valuing natural capital and ES in policy and investment decisions is again demonstrated in Figure 25. In the case of implementing PES, ES contribute an additional US$80 million in wealth. Silvopastoral systems create some cumulative losses in ES and wealth, on the order of US$295 million. Habitat banking generates an increase of US$457 million in additional ES values and wealth.

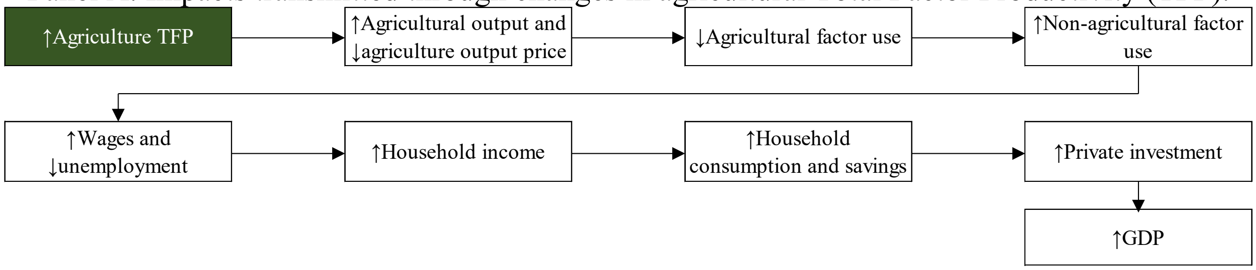
Figure 25. Difference in cumulative wealth when ES are valued. Values are expressed as the difference between scenarios and business as usual until 2040 in millions of USD.



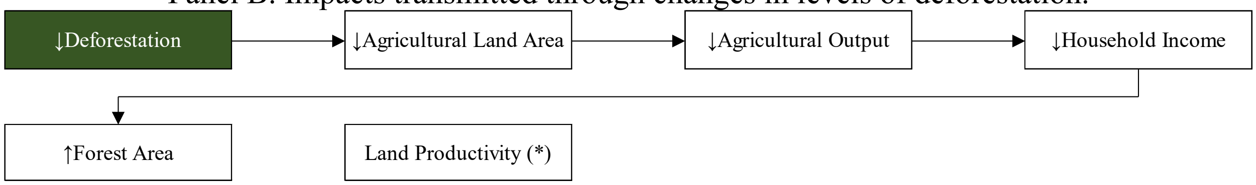
Source: IEEM+ESM results.

One of the distinct advantages of the IEEM+ESM approach is that all results generated by IEEM are entirely explainable within the consistent structure of the model and the assumptions and input parameters used. While a result may go against intuition or may not be pleasing, it can always be explained and assumptions adjusted where justified. Part of the modeling exercise involves tracing the results through their main transmission pathways to ensure that we capture the main features that we aim to represent through the modeling exercises. Figure 26, Panel A shows the transmission pathway for changes in agricultural productivity, which occur in the SPS, PES+SPSe and COMBI scenarios. In these scenarios, increases in agricultural productivity drive up agricultural output while reducing agricultural commodity prices. Factor use in the agricultural sector is reduced, which frees up factors for use in other economic sectors. Wages rise as a result, employment tends to fall, while household income, consumption and savings increase. Private investment also increases, all of which contribute to pushing GDP up higher than in the business-as-usual scenario.

Figure 26. Transmission pathways for agricultural productivity and deforestation.
Panel A. Impacts transmitted through changes in agricultural Total Factor Productivity (TFP).



Panel B. Impacts transmitted through changes in levels of deforestation.



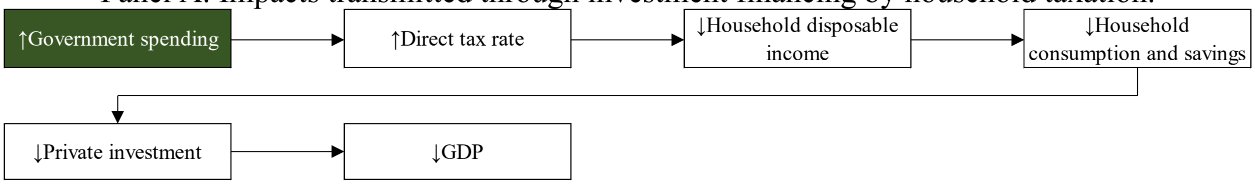
Source: Authors' own elaboration. Notes: (*) indicates an impact captured through ecosystem services modeling.

In the case of PES, HAB and COMBI, deforestation is reduced. The transmission pathways that are relevant here are that less deforestation results in less new land cleared for agriculture, a reduction in agricultural output and income, and an increase in standing forest stock. The changes in standing forest stock have an impact on ES supply, particularly by reducing erosion in watersheds where less forestland is cleared. This reduction in erosion is captured in our iterations between IEEM, LULC and ESM and is captured as an agricultural productivity impact, which follows a similar transmission pathway as in Panel A.

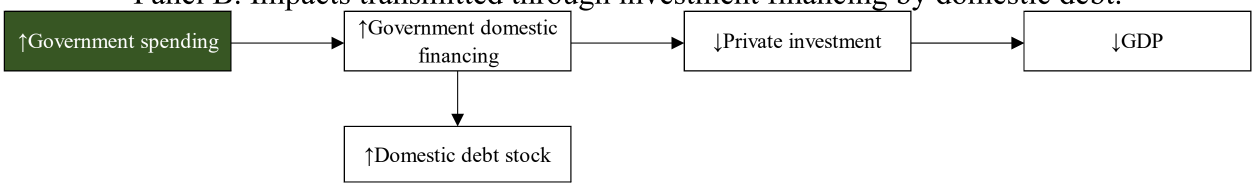
The way in which the investment costs are financed have a strong impact on IEEM results, as it should be. Figure 27 present these transmission pathways. Beginning with financing through changes in direct taxation (Panel A), government spending increases through an increase in the direct tax rate. This reduces the availability of household disposable income, consumption, savings and private investment, which then exerts a downward pressure on GDP. Where investments are financed through domestic debt (Panel B), the increase in government spending is achieved through domestic debt, which lowers the level of private investment. The reduction in the level of private investment can have lasting impacts on GDP. Finally, where increased government spending is financed through foreign borrowing, the foreign debt stock increases and the real exchange rate appreciates. This exchange rate appreciation can put downward pressure on exports, rendering them less competitive, though with a more powerful local currency, imports may increase as a result.

Figure 27. Transmission pathways for investment financing options.

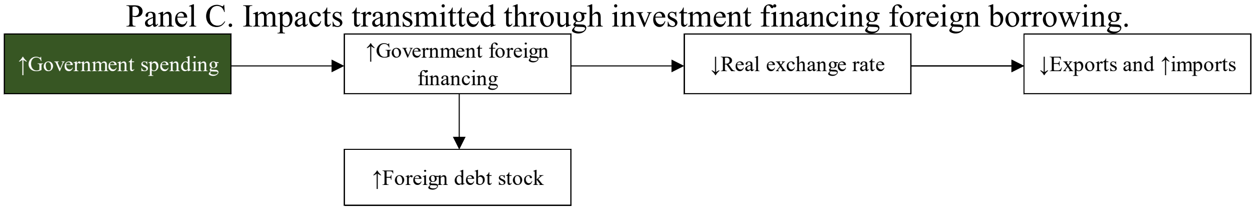
Panel A. Impacts transmitted through investment financing by household taxation.



Panel B. Impacts transmitted through investment financing by domestic debt.



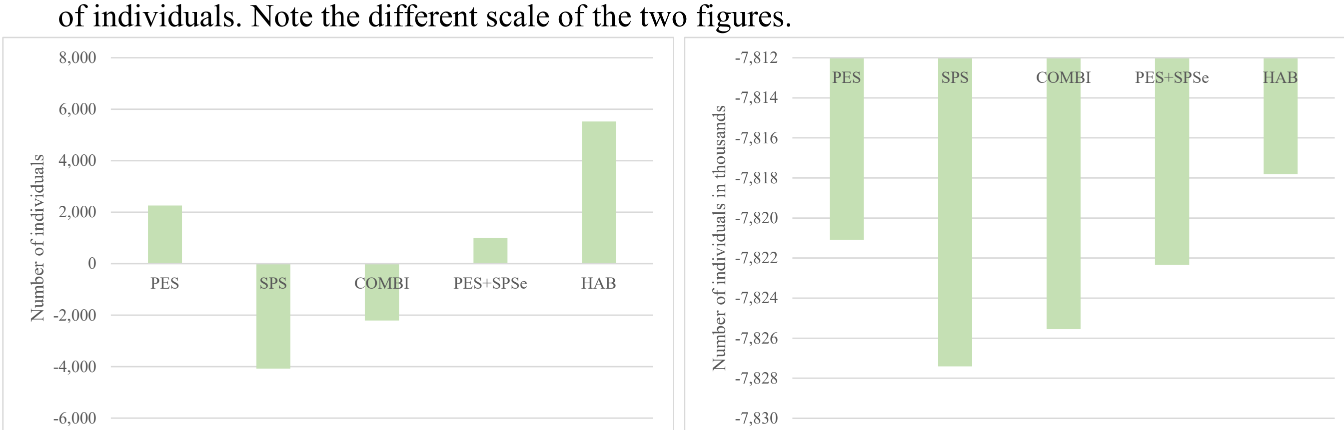
Panel C. Impacts transmitted through investment financing foreign borrowing.



Source: Authors' own elaboration.

Where we consider impacts on poverty, PES does not reduce poverty as quickly as in the business-as-usual scenario. By 2040, there are 2,259 more individuals than in the base, and 5,530 individuals more in the case of habitat banking (Figure 28, left). SPS on the other hand reduces more poverty by 2040, by 4,074 individuals.

Figure 28. On the left, impacts on poverty as difference from business as usual in 2040 in number of individuals. On the right, impacts on poverty as difference between 2040 and 2020 in thousands of individuals. Note the different scale of the two figures.

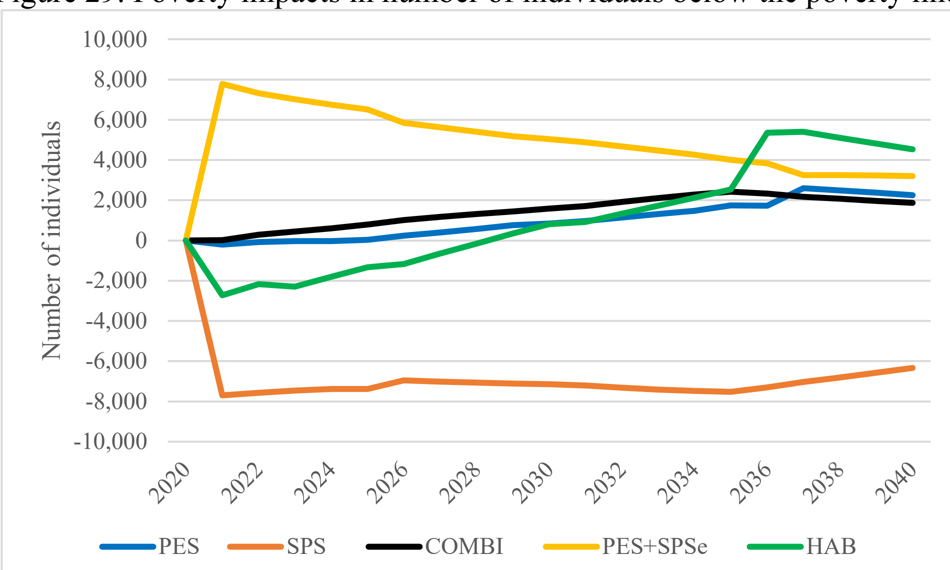


Source: IEEM+ESM results.

In the case of PES, the main driver for reduced poverty reduction is the decrease in crop and livestock land available for agricultural activities. Without a corresponding increase in factor productivity to compensate for reduced factor availability, the reduction in factor stocks causes an inward movement of the production possibility frontier. In the habitat banking scenario, poverty reduction is slightly slower also due to the decrease in crop and livestock land combined with the fact that habitat banking benefits dissipate beyond 2035.

Figure 29 shows the trajectory of poverty impacts, which is a more nuanced view of how the scenarios affect poverty. The figure shows that poverty reduction as a difference from business as usual does not occur in a linear way and a difference from business as usual and one direction can be reversed during the course of the time period of analysis; this is the case with the HAB scenario. In the case of both PES+SPSe and SPS, the impacts are abrupt in the initial 2 years and then show a tendency toward returning to business-as-usual levels through time. SPS is strongly poverty reducing with respect to business as usual while PES+SPSe shows poverty not declining as fast as in the business-as-usual scenario. PES poverty impacts deviate from business as usual slowly through the time period as does the joint implementation of PES and SPS, all indicating that poverty is falling a little more slowly than in the business-as-usual scenario. Habitat banking shows an initial dip below business as usual with an increase in 2035 once most investments and activities have concluded, though there is a movement back toward business as usual thereafter.

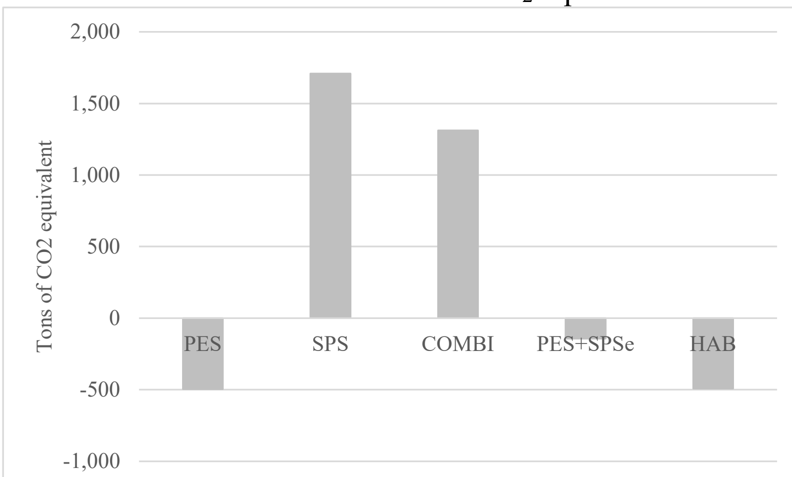
Figure 29. Poverty impacts in number of individuals below the poverty line.



Source: IEEM+ESM results.

CO_2 emissions from economic activity are shown in Figure 30. Establishing PES has a dampening effect on economic activity and therefore on the positive side, a reduction in CO_2 emissions on the order of 495 tons CO_2 equivalent by 2040. Silvopastoral systems increase emissions by 1,709 tons while the joint implementation of PES and SPS has an off-setting effect, though still increasing by 1,312 tons. The habitat banking scenario has the strongest positive emissions reduction potential, estimated at 491 tons CO_2. Note that these results to not include changes to emissions arising from changes in LULC.

Figure 30. Cumulative CO_2 emissions from economic activity in 2040 as a difference from business as usual in tons of CO_2 equivalent.

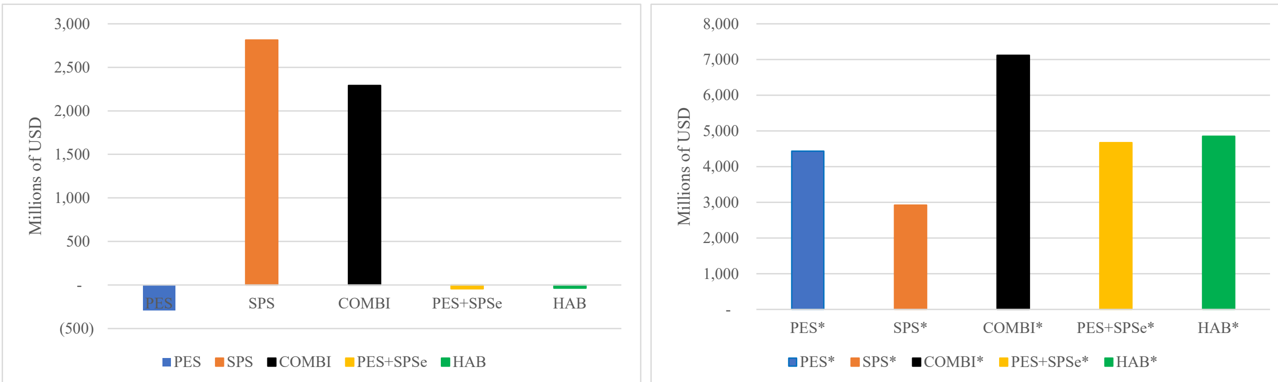


Source: IEEM+ESM results.

Calculating the Net Present Value (NPV) in a cost-benefit analytical framework is a standard approach to assessing the economic viability of projects from a public investment perspective. NPV is calculated here with a 12% discount rate, the standard discount rate used by some multi-lateral investment banks, such as the Inter-American Development Bank. NPV is calculated based on equivalent variation, which is the amount of income an individual would need to receive to be as well-off had an investment project not been implemented (Banerjee et al., 2019a). Figure 31 shows that when we consider household welfare alone, the implementation of PES results in an economically unviable project with an NPV of negative US$293 million. Coupling PES with silvopastoral systems results in a viable investment with an NPV of US$2,814 million. The habitat banking scenario is not economically viable with an NPV of negative US$37 million.

When we consider the value of natural capital and ES, we find that the bottom-line changes. The implementation of PES as well as habitat banking become very appealing investment opportunities with an NPV of US$4,432 million and US$4,852 million, respectively. The joint implementation of PES with silvopastoral systems results in an NPV of US$7,119 million, capturing the benefits of both enhanced conservation as well as productivity and rural income opportunities.

Figure 31. On the left, NPV calculated based on equivalent variation; on the right, NPV calculated based on equivalent variation and adjusted for changes in natural capital and environmental quality.



Source: IEEM+ESM results.

The discount rate chosen has an important impact on results where higher discount rates tend to discourage investments that generate benefits in the long-run versus the short-run. In the scenarios presented here, most benefits and costs are relatively evenly distributed across the analytical period. Given this distribution, a lower discount rate would tend to result in higher positive net present values and lower negative net present values.

4. Discussion and Conclusions

We developed and applied the IEEM+ESM approach to evaluating strategies for restoring and protecting Colombia's rich natural capital endowment through the implementation of a PES program, sustainable silvopastoral systems and habitat banking. Our approach is spatially explicit and directly integrates the value of biodiversity in economic decision making. The results demonstrate in an unambiguous way the importance of including natural capital and ES values in the cost benefit analysis used by Governments around the world. The methods developed here are now well-documented, peer-reviewed and replicable and are being implemented in other countries in the Latin American and Caribbean region and beyond.

In evaluating impacts of the different strategies, PES and HAB showed strong benefits in terms of future ES supply while SPS on average tended to negatively affect ES supply. The economic impacts of these changes in natural capital stocks and ES provision are clearly borne out in the economic indicators presented herein. With the large benefits that sustainable silvopastoral systems can provide in terms of rural livelihood development, a portfolio approach that would combine PES, sustainable silvopastoral systems and habitat banking would generate economic gains that are critical to maintaining the peace in post-conflict Colombia while mitigating environmental harm, maintaining ES supply and enhancing the productive natural capital base, which is foundational for future prosperity of the country. The evidence developed in this study generates a strong business case for financing such an approach.

Our analysis is highly detailed with regards to spatial impacts. This approach is particularly powerful where public policies and investments are regionally differentiated, but also to shed light on how impacts are geographically differentiated. All of the ES impacts show differences between departments, some more important than others. In the case of carbon ES, overall impacts are positive, however, some departments show a reduction in carbon ES while others compensate with an increase. Water quality ES show highly differentiated spatial impacts, especially in the case of the implementation of SPS. Biodiversity intactness, while generally improving across scenarios, also reveals spatially differentiated patterns. The spatial patterns for one ES are not necessarily the same as the spatial impacts of other ES. Knowing where the impacts on ES are the greatest and where communities may be most vulnerable to ES loss can help policy-makers target mitigating actions to reduce the loss of ES and strengthen the natural capital base, which as our analysis has shown, has a direct linkage with economic outcomes and wealth.

The impacts of PES compared with habitat banking are interesting to consider and provide evidence to support the importance of spatial targeting of PES programs. Both the PES and habitat banking scenarios aim to conserve half a million hectares. PES program distribution across the landscape was conducted based on the relative importance of deforestation in each department. On the other hand, the habitat banking scenario targeted specific regions of Colombia with high conservation value forest such as the Tropical Dry Forest and regions with high ES supply potential. The results of this analysis demonstrate that there are real advantages to spatial targeting in terms of maximizing economic and ES outcomes. These increases in ES flows translate into hard currency when evaluated from an economic standpoint and provide compelling evidence for increasing the importance of spatial targeting in PES design where the scientific underpinning of many PES programs is often lacking (Naeem et al., 2015).

The joint implementation of PES and SPS where we track GDP (PES+SPSe) provides some useful insights. With PES reducing deforestation and thus the supply of crop and livestock land, factor availability for agriculture is negatively impacted. This result highlights the importance of investing in agricultural productivity, which in this case would have compensated for some of the negative economic impacts that arose in implementation of PES+SPSe. In Colombia in particular, there is large scope for enhancing agricultural factor productivity as it is considered low when compared to factor productivity in neighboring countries.

In both PES and HAB scenarios, we implement a one-to-one relationship between the establishment of one hectare of PES and one hectare of HAB with one hectare of avoided deforestation. The implementation of PES or habitat banking alone is unlikely, however, to result in this one-to-one relationship. Ex-post evaluations of these programs have shown that these market-based instruments generate levels of efficacy that are often lower than expected, though generally consistent with other conservation tools based on the available evidence. There are a variety of reasons for this, including the bundling of various policy aims within the program and a lack of science-based fundamentals in program design. This growing literature on the effectiveness of PES and other instruments, both market-based and command and control offers numerous insights into how the efficacy of PES and similar instruments may be improved, including spatial targeting, differentiating payments for different services and measures implemented, and strong conditionality to name a few (Aguilar-Gómez et al., 2020; Börner et al., 2017; Burivalova et al., 2019; Ezzine-de-Blas et al., 2016; Naeem et al., 2015; Pattanayak et al., 2010; Snilsveit et al., 2019; Wunder et al., 2020).

This analysis has shown in an unequivocal way the importance of valuing biodiversity in the economic and cost-benefit analysis and decision making that Governments and multilateral institutions around the world undertake in assessing the viability of public policy and investment. Our results make the economics of biodiversity explicit and aligned to renowned economist David Pearce's assertion that "Economic valuation [of the environment] is always implicit or explicit; it cannot fail to happen at all" (Pearce, 2006, p. 4). We show in the case of habitat banking, for example, that valuing natural capital and biodiversity contributes over US$77 million to GDP in just one year. The cumulative impacts are impressive. PES and habitat banking contribute an additional US$14 billion and US$16.6 billion, respectively in wealth, which can help secure the peace in post-conflict Colombia for current and future generations.

Net Present Value calculations represent the 'bottom-line' for public policy and investment evaluated by governments and multilaterals. Public investments financed by multi-lateral development banks such as the Inter-American Development Bank need to be 'bankable', that is, generate returns on investment greater than a 12% rate of discount. Our results show just how fundamental the inclusion the value of biodiversity is in cost-benefit analysis and in NPV calculations. Investment in conservation through PES is not considered economically viable until the value of natural capital and ES are included in the analysis. This is the difference between funding and not funding a project. Without accounting for the value of biodiversity in economic analysis, the PES program is not considered economically viable. Including the value of biodiversity, PES becomes a strong investment proposition with an NPV just under US$5 billion. The consequences of valuing biodiversity in economic decision making are far reaching.

Acknowledgements

This study was prepared to inform the Dasgupta Review on the Economics of Biodiversity led by the UK's HM Treasury. The authors thank Javier Rojas Cala from Colombia's Ministry of the Environment and Andrés Camilo Alvarez-Espinosa, Sioux Melo, Leidy Riveros and Germán Romero from Colombia's National Planning Department for their collaboration in the development of the IEEM database for Colombia and various applications of the framework. Thanks to Robert Marks, Emily McKenzie and Felix Nugee and the Dasgupta Review Team for their constructive review of this paper. The authors thank Mariana Sarmiento and Jose David Taborda from the Terrasos Habitat Bank Team in Colombia for their contribution to the design of the habitat banking scenario. Thanks to Luke Brander for his insightful comments on the paper. Thanks to Kenneth J. Bagstad for his collaboration on development of the ecosystem services modeling data packets and for his constructive comments on the paper. The authors thank Annette Kilmer, Allen Blackman, Leandro Gaston Andrian, Gregory Watson, Carlos Salazar and Pedro Martel for their review and comments on the paper.

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Supplementary Information 1

Land Use Land Cover Change Modeling

Location suitability

Land use conversions are expected to take place at locations with the highest suitability for the specific type of land use. Suitability represents the outcome of the interaction between the different actors and decision-making processes that have resulted in a spatial land use configuration. The preference of a location is empirically estimated from a set of factors that describe the location characteristics of individual land use and land cover classes. In the CLUE modeling framework, the suitability is calculated by first developing a statistical model as a binomial logit model of two choices: convert location (raster pixel) into land a different land use type or not. The location suitability is assumed to be the underlying response of this choice. However, the location suitability cannot be observed or measured directly and has therefore to be calculated as a probability. The function that relates these probabilities with the biophysical and socio-economic location characteristics is defined in a logit model as follows:

$$\log\left(\frac{P_i}{1-P_i}\right) = \beta_0 + \beta_1 X_{1,i} + \beta_2 X_{2,i} \cdots + \beta_n X_{n,i}$$

where P_i is the probability of a land use type occurring on a specific grid cell with location i, and; X's are location factors specific to each application.

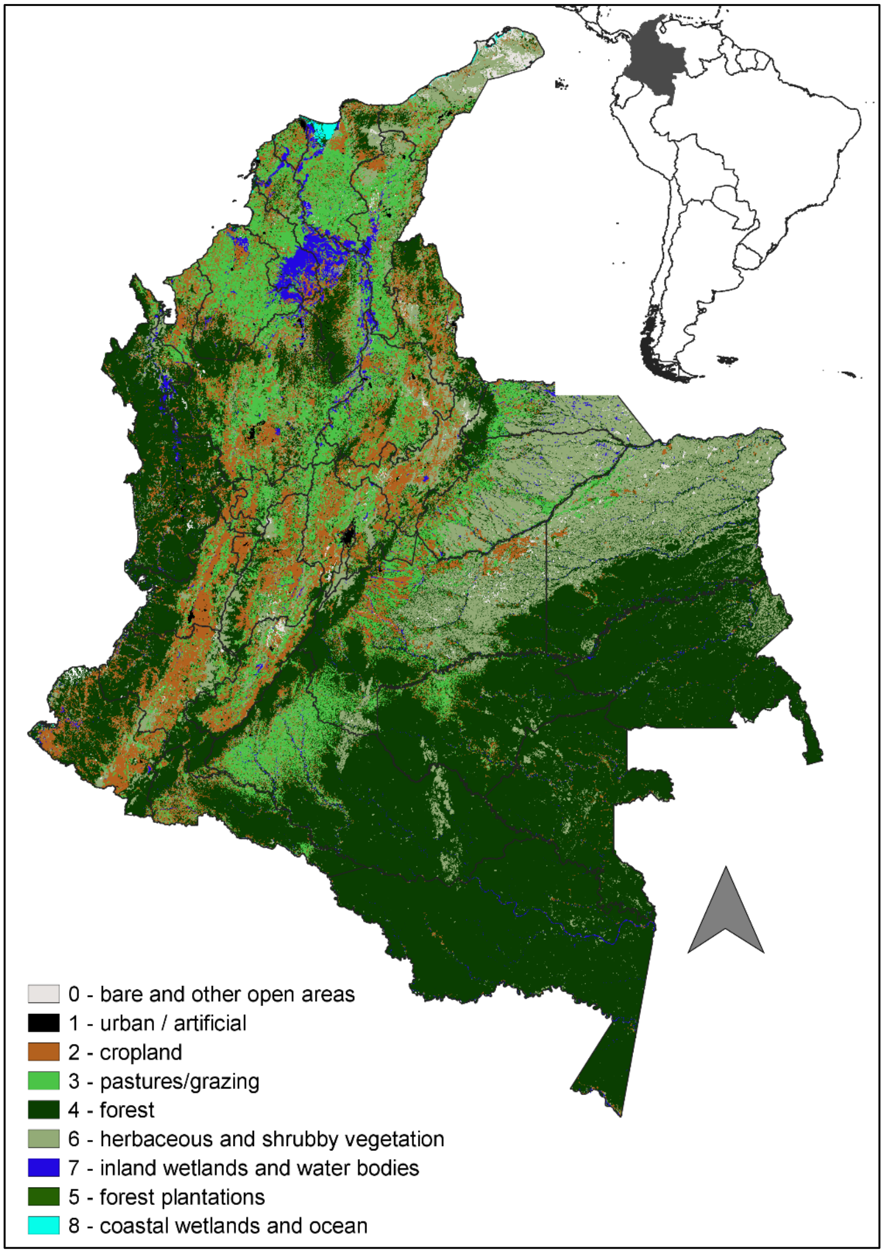
The coefficients (β) are estimated through logistic regression using the actual land use pattern as the dependent variable. This estimation procedure is implemented outside the CLUE modeling framework and can be done in most statistical packages. This method is similar to econometric analysis of land use change, which is very common in deforestation studies. In this approach, suitability includes socio-economic, biophysical and other factors that lead to rational behavior in land allocation but could also lead to deviations from economic rational behavior. This assumption makes it possible to include a wide variety of location characteristics or their proxies to estimate the logit function that defines the relative probabilities for the different LULC types.

Location characteristics relate to the location directly, such as soil and terrain characteristics, and climate. However, land management decisions for a certain location are not always based on location specific characteristics alone. Conditions at other levels, e.g., administrative level can influence the decisions as well. These factors are represented by accessibility measures, indicating the position of the location relative to important regional markets and by looking at the population distribution.

We used a wide variety of location factors to empirically study the occurrence of different (LULC) types in Colombia (Table SI 1). Most of them come from relatively recent global datasets, though, these are coarser than the 200-meter (m) resolution that was applied in this study. Therefore, all data was resampled to 200 m to match the native land cover resolution. We also analyzed how correlated the location factors are, in order to exclude highly correlated variables. The variables temperature and elevation were highly correlated (due to the effect of the Andes), however we kept them both, as they are both important driving factors for agricultural activities. The location factor 'land degradation' was used to allocate the silvopastoral systems in the SPS scenario, COMBI and PES+SPSe as this system was defined to be allocated in areas with high erosion. In these scenarios, we used the same suitability for the silvopastoral system as for pastures but increased the suitability in areas with high erosion by 0.1 and decreased the suitability in pasture systems in the same areas by 0.05.

We performed binary logistic regressions for the individual land use types (Figure SI 1), using forward conditional regressions, where we excluded all insignificant variables ($P<0.05$). First, we prepared balanced random samples of presence and absence of each land use type: we randomly selected 1,000 points where the specific land use type is found, constrained by a 1 km minimum allowed distance between sample points. We then selected 1,000 points where the specific land use type is absent. We used this balanced sample to collect information on the location factors, which we then used to perform binary logistic regression. The same procedure was performed for all land use types, except forest plantations, which were not mapped on the extent that would allow such a large sample. We therefore selected 350 presence and absence points each for forest plantations. To assess the quality of the regression models, we calculated the Area Under Curve (AUC) of the Receiver Operating Characteristic. In this way, we can also estimate how well our statistical model captures the suitability for a given land use type based on the location factors used.

Figure SI 1. Aggregated land cover map for the year 2014.



Source: Source: Authors' own elaboration, based on CORINE (IDEAM, 2010).

Table SI 1. Location factors used in the analysis.

Explanatory factor	Description	Unit	Original resolution	Source
Biophysical				
Temperature	Average temperature (mean of monthly means)	°C	1 km	(Hijmans et al., 2005)
Precipitation	Annual precipitation	mm	1 km	(Hijmans et al., 2005)
Potential Evapotranspiration	Annual PET	mm	1 km	(Trabucco and Zomer, 2009)
Altitude	Elevation above sea level	m	100 m	Provided by IADB
Slope	Derived from altitude	Slope degrees	100 m	Derived from altitude
Land degradation areas	Areas defined as moderately (moderada) to very severely (muy severa) eroded by Colombian ministry for Environment (only used to allocate the silvopastoral system)	Units identified with erosion	shapefile	Obtained from http://www.siac.gov.co/catalogo-de-mapas
Soil				
Drainage	Internal drainage of soils	class	1 km	(ISRIC, 2018)
Soil depth	Soil depth	cm	1 km	(Stoorvogel et al., 2016)
Sand and clay content	Share of sand and clay	%	1 km	(Stoorvogel et al., 2016)
Cation Exchange Capacity (CEC)	Proxy for nutrient retention capacity	cmol/kg	1 km	(ISRIC, 2018)
Soil pH	pH index measured in water solution	1-7	1 km	(ISRIC, 2018)
Organic content	Organic carbon content in the top 50 cm of soil	g /kg of soil	1 km	(Stoorvogel et al., 2016)
Socio-economic				
Population density	Distribution of human population	People/km^2	1km	(CIESIN and SEDAC, 2015)
Rural population density	Distribution of rural population	People/km^2	10 km	(CIESIN et al., 2011)
Market Accessibility	Indicator for the accessibility to markets.	Index	1 km	(Verburg et al., 2011)

Source: Authors' own elaboration.

Explaining the spatial distribution of land use types

Overall, our statistical models present a good fit explanatory ability. Cropland and shrubland are the only two classes, where the regression model fit is below 0.8, which can be explained by the land cover map not fully representing the diversity of these two LULC types. Cropland encompasses different crops, or crop types (annual vs. perennial crops). This means, that in regions where the main crops produced and their spatial distribution are considerably different from the main Colombian crops, the spatial distribution might not be sufficiently explained. Similarly, for crops with considerably different climate and soil requirements, the regression models might not be fully representative (e.g. crops that can grow in drier conditions vs. crops with high water demands). The same goes for pastures. Livestock grazing in Colombia is diverse, from extensive Andean grazing, to high-intensive lowland large-scale pastures. Similar to croplands, these different livestock systems are not distinguishable from the land cover maps. Nevertheless, the regression fits for both cropland and pastures are still considered to have sufficiently high ability to predict the occurrence of different land use types.

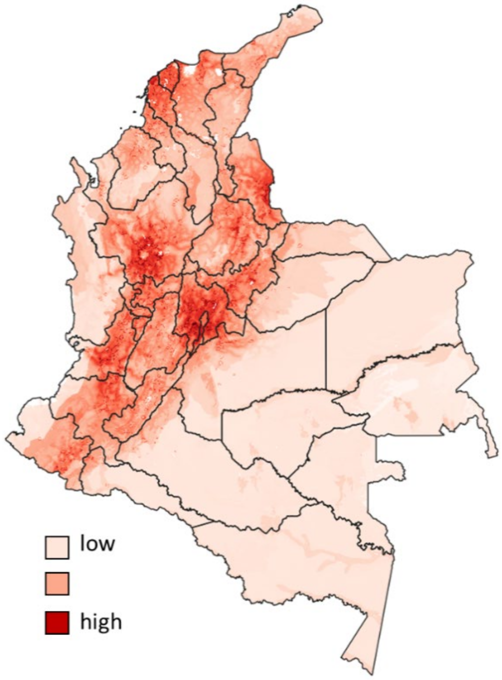
We can observe the influence of different socio-economic and biophysical characteristics on the spatial distribution of different land use types (Table SI 2). Cropland is more likely to be present in areas close to markets, lower population density, but higher rural population density. Biophysical factors do not play such a significant role, which can be again explained by the fact that different crops with different requirements in terms of soil and climate are represented in this class. Grazing areas also occur in areas with good market access, but seemingly poorer bio-physical conditions (lower organic content, higher pH and lower precipitation). Planted forests are also situated close to markets and are otherwise situated in areas significantly different from natural forests. Planted, as opposed to natural forests, are located close to markets, and on soils that are better drained and have a higher clay content. An example of how the regression model is used in CLUE to allocated future land use is demonstrated in Figure 4.

Table SI 2. Logistic regression models for land use types that are subject to changes in the Colombia study. Values present regression coefficients. For all variables P<0.05is valid. AUC values range between 0-1, and values over 0.5 mean that the model's predictive ability is better than random when describing the spatial distribution of the land cover types.

	Cropland	**Grazing**	**Forest**	**Planted forest**	**Shrubs and other vegetation**
population density	-0.00033	-0.00055			
rural population	0.00345	0.00323	-0.00596		-0.00163
market access	2.78217	2.299545	-2.63041	4.48505	-0.8484
organic content	-0.00465	-0.01001		-0.01773	0.00703
soil drainage			-0.24954	1.05954	0.67954
clay soil		0.022567	-0.05474	0.01933	0.05312
CECS	0.03884	0.043672	-0.04462	0.04992	
soil depth	-0.01276		0.011885		
sand			-0.03794		0.03613
soil pH		0.041388	-0.07242		-0.04586
elevation			-0.00343	0.00143	
slope		-0.03022	0.044379	-0.11525	
precipitation		-0.00055	0.000593	-0.00029	-0.00099
temperature		-0.28834	-0.51877		
PET		0.00699	-0.00271		
constant	0.21704	-6.8789	25.23958	-6.95029	-1.65359
AUC	0.787	0.812	0.843	0.893	0.741

Source: Authors' own elaboration.

Figure SI 2. Spatial probability for cropland in Colombia, based on the logistic regression above. Dyna-CLUE calculates such probability maps for each land use type and allocates future land use based on it. The scale low to high refers to values from 0 (low) to 1 (high).



Source: Authors' own elaboration.

Defining conversions

Land use type-specific conversion settings determine allowed conversions, and the likelihood (or difficulty) to convert a specific land use type. Two sets of parameters are needed to characterize the individual land use types: conversion elasticities and allowed land use transitions (Table SI 3). The first parameter set, the conversion elasticities, is related to the reversibility of land use change. Land use types with high capital investment will not easily be converted to other uses as long as there is sufficient demand. For example, forest plantations are unlikely be converted to another land use type after they have been established. Other land use types easily shift location when the location becomes more suitable for other land use types. Arable land often makes place for urban development while expansion of agricultural land occurs at the forest frontier. For each land use type a value needs to be specified that represents the relative elasticity to change, ranging from 0 (easy conversion) to 1 (irreversible change). These values are based on expert knowledge or observed behavior in the recent past.

Table SI 3. Conversion resistance of land use types in this study. Note, slight deviations from this table are possible in some regions and some scenarios.

Land use	Conversion resistance
bare and other	1
urban-artificial	1
Cropland	0.3
Grazing	0.3
Forest	0.4
forest plantations	0.4
shrub and other vegetation	0.2
inland wetlands	0.8
coastal wetlands	0.8
(SPS)	0.4

Source: Authors' own elaboration.

Allowed conversions depend on the observed behavior as well, but most importantly on the land use change processes we aim to study in a particular study area. In this study, we were only interested in the following conversions (summarized in Table SI 4below):

- Deforestation: forests can convert to cropland and grazing land.
- Plantations: forest plantations can occur on shrubland and other vegetation, and on other land use types (e.g. cropland and grazing), depending on the scenario and Colombian department.
- Multifunctionality (only SPS, combi, and PES+SPS scenarios): silvopastoral systems (grazing systems with planted trees), were allowed to occur on other pasture areas.
- Reforestation (some regions in the HAB scenario): in some regions, cropland and livestock areas were allowed to convert back to forest in areas with assigned habitat bank measures.
- Inter-agricultural change: in some regions and scenarios, cropland was allowed to convert to livestock (and/or vice versa).

Table SI 4. Allowed conversions for most regions and scenarios; 0 is not allowed while 1 is allowed. Note that in some regions and scenarios, the conversion matrix deviated from the one below. For example, if IEEM projected conversion from cropland to livestock, this conversion was enabled in that region. SPS was only allocated in scenarios SPS, COMBI and PES+SPSe.

	Bare and other	Urban-artificial	Cropland	Grazing	forest	forest plantation	shrub and other vegetation	inland wetlands	coastal wetlands	(SPS)
bare and other	**1**	0	0	0	0	0	0	0	0	0
urban-artificial	0	**1**	0	0	0	0	0	0	0	0
cropland	0	0	**1**	0	0	0	0	0	0	0
grazing	0	0	0	**1**	0	0	0	0	0	1
forest	0	0	**1**	**1**	**1**	0	0	0	0	0
forest plantations	0	0	0	0	0	**1**	0	0	0	0
shrub and other vegetation	0	0	0	0	0	**1**	**1**	0	0	0
inland wetlands	0	0	0	0	0	0	0	**1**	0	0
coastal wetlands	0	0	0	0	0	0	0	0	**1**	0
(SPS)	0	0	0	0	0	0	0	0	0	**1**

Source: Authors' own elaboration.

Demands for land (overview of IEEM inputs).

The CLUE modeling framework allocates future land use, which have to be calculated using external models. From IEEM, annual future land use demands in hectares for the period 2014-2040 were used for:

- Total forest area (and deforestation)
- Forest plantation
- Cropland
- Livestock (grazing)

IEEM used agricultural and forestry statistics to calculate future land use, which can differ considerably in some Colombian regions, due to the fact that land use and land cover maps derived by classifying remote sensing imagery, have uncertainties in the spatial extent and distribution of land use and land cover types. Nevertheless, the amount of deforestation, projected by IEEM (and subsequently allocated by CLUE), is based on observed past trends. To reduce these uncertainties, we allocated the exact amount (in hectares) of each land use change process, as projected by IEEM, instead of looking at relative change (in %). In the later sections, we present the difference in different land use types per scenario on a national scale.

LULC and CLUE considerations in the IEEM+ESM iterative process

The IEEM+ESM approach was implemented in 5-year time steps focusing on erosion mitigation services and their impacts on agricultural productivity and the economy. IEEM demands for future land use (amount of deforestation, cropland, livestock and forest plantations) were used for the year 2020 forward. All scenarios began with the same LULC base map in 2020, which was based on IEEM projections for 2014 to 2020. Once CLUE allocated demand for land for the first time-step, the sediment retention model was run to calculate areas where severe erosion increased or decreased relative to the business-as-usual scenario. The identification of these areas enabled an agricultural productivity shock to be calculated and applied in IEEM in the subsequent time-step. This iterative approach was implemented for three iterations between all three models for the periods 2025-2030, 2030-2035 and 2035-2040.

Such an iterative approach required that some modifications to model parameters had to be introduced on a region and scenario-specific basis. As an example, in regions and scenarios where IEEM projected cropland contraction we had to enable the conversion from cropland to livestock in the transition matrix for one iteration to enable CLUE to solve.

In Dyna-CLUE, each scenario and department were run independently. Interactions between departments are modeled and captured in IEEM. From a practical perspective, this translated into the implementation of each of the 6 scenarios independently for each of Colombia's 32 departments. While the demands and some parameters in the model might have been regionally specific, the location suitability was the same for all departments. Colombia is a large and diverse country, where some departments are situated high in the Andes, other on the coastline, and some in the Amazon. Additionally, the departments are of different sizes. As a result, each individual 5-year scenario run would have different run times, but on average, 5-year model runs, for an individual scenario and department, took approximately:

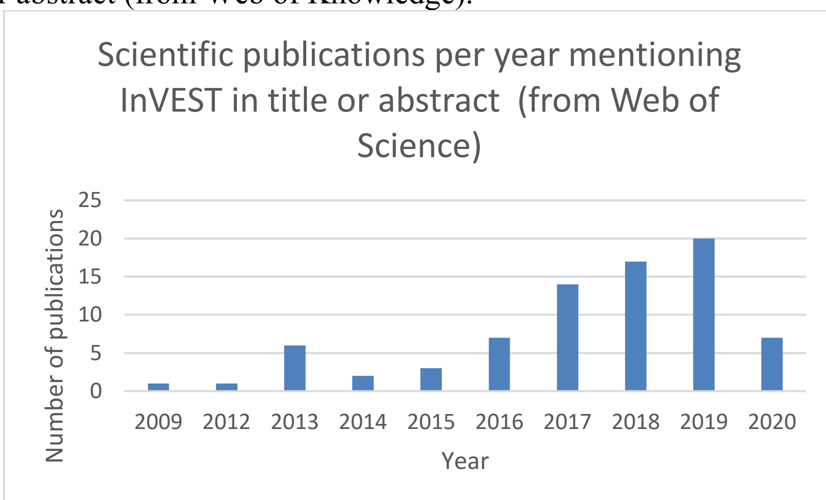
- 5-10 minutes for a small department (e.g. Quindío)
- 30-45 minutes for a medium department (e.g. Valle de Cauca)
- Up to 7h and 35 minutes for a large department (e.g. Amazonas).

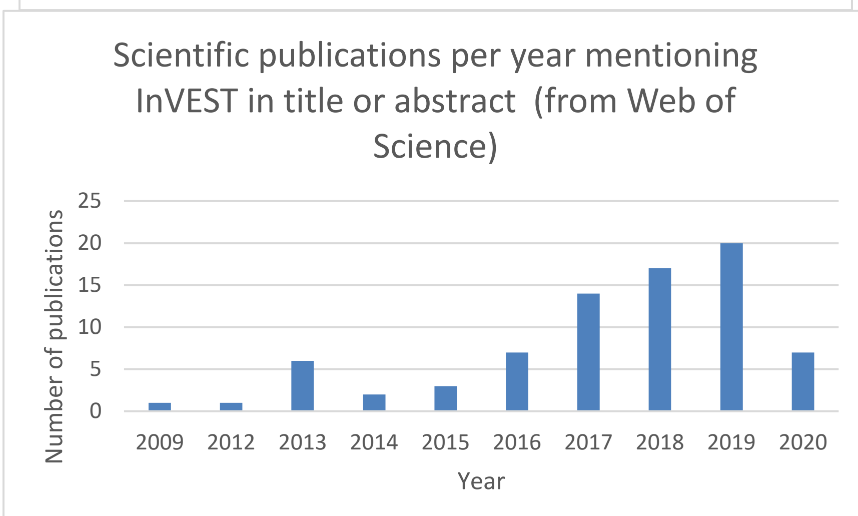
These long run times were mostly due to the fact, that we were operating on a relatively detailed spatial resolution, leading to a large total number of cells in larger regions, and consequently long allocation times. The amount of change projected usually does not matter (e.g. in Amazonas the amount of change was usually minor compared to other departments), because the model evaluates all locations (pixels) in the region when seeking the optimal solution.

Supplementary Information 2
Ecosystem Services Modeling

The Integrated Valuation of Ecosystem Services and Tradeoffs platform (InVEST) is a suite of models used to calculate spatially explicit changes in ES provision. InVEST combines LULC maps and biophysical information to calculate services, with the option to add additional parameters to assist in ecosystem service valuation. It is one of the most widely used open-source tools and has been growing in use also in scientific literature, as shown below in Figure SI 3.

Figure SI 3. Number of publications (y) per year (x) of scientific articles mentioning InVEST in either the title or abstract (from Web of Knowledge).





Source: Authors' own elaboration.

A wide variety of ES can be calculated through the InVEST suite, whether biophysical or socio-cultural in nature.

Brief description of ES models used

For this project, four models from the InVEST suite (3.7.0) were used to track changes in ES across scenarios. These included: sediment delivery ratio (SDR), used to calculated the Revised Universal Soil Loss Equation (USLE) and sediment export; carbon pools, used to calculate carbon storage and sequestration potential; annual water yield (AWY), used to calculate water supply; and nutrient delivery ratio (NDR), used as a proxy for water purification potential of landscapes in absorbing nitrogen and phosphorus.

All models were run using the InVEST python library (on Python 3.7). To increase the time efficiency of multiple model runs, the Joblib library (v0.14.1) was used to run scenarios concurrently. Once raw outputs were collected, they were processed using QGIS 3.10 in order to display the results on a regional level using the zonal statistics tool.

Description of biodiversity assessment.

To analyze how changes to LULC impact biodiversity levels, we calculated the composite biodiversity intactness index (BII). The BII presents the average abundance of originally present species across a broad range of species, and is defined as a coefficient for relative to the abundance in an undisturbed habitat (Hudson et al., 2017; Newbold et al., 2016).

We used the PREDICTS database (www.predicts.org.uk) (Trustees of the Natural History Museum, 2020), an extensive database collecting case study information on the relationship between land use and biodiversity (Hudson et al., 2017; Newbold et al., 2016). PREDICTS has 32 million observations from over 32,000 locations and covers more than 50,000 species. For Colombia alone, we used data from a collection of 285 locations where the relationship between land use change and biodiversity have been monitored and assessed (Echeverría-Londoño et al., 2016). Using mean BII values from Echeverria-Londoño et al. (2016), we were able to assign BII coefficients to different land use types and calculate the composite BII. Calculating a composite BII enabled us to compare different scenarios through time relative to the business as usual scenario.

While the BII might seem like a simple and straightforward approach, it is a data demanding synthesis that has been made possible by the extensive PREDICTS database, which is continuously being updated with new documented observations on the relation between biodiversity and land use.

Table SI 5. Biodiversity Intactness Index for different land use types, based on 285 observations in Colombia by Echeverria-Londono et al. (2016).

Land use	Biodiversity Intactness
Bare	0
Urban	0
Cropland	0.49
Pasture	0.59
Forest	1
Planted	0.79
Shrubs	0.8
inland wetlands	0
coastal wetland	0
Silvopastoral	0.75

Source: Authors' own elaboration. Notes: all values present a coefficient of the BII compared to a reference land use type, in this case forest. Note that bare and urban areas and wetlands do host considerable levels of biodiversity. These types, however, were not subject to change and were therefore not important for this analysis. Additionally, studies on converting these to or from these land use types were not available for Colombia.

Description of data inputs in summary tables, biophysical parameters used, summary of processing steps.

Sediment Delivery Ratio model

The model

In order to calculate sediment export and soil loss in Colombia, the Sediment Delivery Ratio (SDR) InVEST model was used. Key outputs sought included results of the Universal Soil Loss Equation (soil loss/pixel) as well as sediment export (soil export/pixel). The InVEST SDR model is based on the sediment connectivity algorithm proposed (Borselli et al., 2008)). Five main factors are used in its calculation: the energy from precipitation that is available to move particles (R), erodibility of soil (K), slope length (LS), as well as land-use cover factor (L) and practice factor (P) (Hamel and Guswa, 2015). Calculations are made at the pixel level through the use of GIS, and has been widely used at numerous regional and national scales (Hamel and Guswa, 2015; Zhou et al., 2019). The model is particularly useful to highlight priority areas for improving management practices (either in regional zones or watersheds) to minimize soil less and erosion, usually done through mapping of areas exceeding a certain threshold of soil loss or export depending on the use case (Bouguerra and Jebari, 2017). In our case, with results from the erosion ESM, we identify areas, which have moved from exhibiting severe erosion between the business-as-usual and a given scenario (defined as greater than 11 tons/ha/yr of soil loss (Panagos et al., 2018)) to no longer exhibiting severe erosion, and vice versa. The results of this process are used to estimate an agricultural productivity impact to be implemented in IEEM.

Data inputs

Table SI 6 presents the inputs of the SDR model. Data obtained from IEEM was resampled to 200 m resolution for greater detail between regions. The model was calibrated with default values for threshold flow accumulation, max SDR and k and IC0 parameters, as further calibration was not required for the specific results sought.

Table SI 6. Data inputs for InVEST SDR model.

Data input	**Data type**	**Source(s)**
Digital elevation model	Raster	See OPEN IEEM
Rainfall Erosivity Index (R)	Raster	OPEN IEEM
Soil Erodibility Index (K)	Raster	OPEN IEEM
Land-Use/Land-Cover	Raster	OPEN IEEM
Watersheds	Vector	(Sistema de Informacion Ambiental de Colombia, SIAC, 2013)
Biophysical table (USLE c and p factors)	Comma separated file (csv)	Included in Supplementary Information to this paper.
Threshold Flow Accumulation	Integer (default value 1000)	Borselli et al., 2008
Borselli k parameter	Float (default value 2)	
Borselli IC0 parameter	Float (default value 0.5)	
Max SDR value	Float (default value 0.8)	

Source: Authors' own elaboration.

Most data were provided by IEEM, however the completion of the biophysical table required first investigation and synthesis from existing data on Colombia and similar regions. The OPEN IEEM project is currently developing these tables and full data packets for the four ES models used in this analysis, with scope for including new ES through time. The main feature of the biophysical table is the assignment of each land use code with a cover-management factor (C) and support practice factor (P). The C factor accounts for "how specific crops on the land are managed relative to tilled continuous flow", while P accounts for "the effects of contour plowing, strip-cropping, or terracing relative to straight-row farming up and down on a slope" (Chacko et al., 2019, Sharp et al., 2020, Sediment Delivery Ratio Documentation). In the first instance, values were taken from literature from Colombia, and if no value could be found, these were then taken from the literature from similar climates (tropical) or regions (South America) and averaged where appropriate. The exact geographical source of the values used in the model are detailed where appropriate in the Supplementary Information. In all InVEST models that we used, all parameters were constant in the various model runs. Only the LULC maps were updated with new maps for each scenario.

Processing steps

Raw outputs were processed in QGIS in order to display regions that experienced greater than 11tons/ha of soil loss and sediment export. USLE and sediment export results are given in tons/pixel, and so each map was first divided by four using the raster calculator, and then converted to show all pixels that were greater than or equal to 11. Then, the zonal statistics tool was used to count the number of pixels with over 11tons/ha in each region of Colombia using a region shape file. A new column was then added to the sediment results database showing the percentage of change between the business as usual scenario in 2020 and all other scenarios in 2040 ((2040 scenario - business as usual scenario 2020)/(2040 scenario)). This enabled the visualization of changes between scenarios.

Carbon pools

The model

The InVEST Carbon pools model was used to calculate carbon storage and sequestration potential of landscapes in Colombia. This model is comprised of four main components of carbon: carbon in above ground biomass, below ground biomass, soil (or soil organic carbon, SOC) and dead organic matter (DOM). Carbon storage potentials for each of these carbon pools are used in the model for each LULC type used and are generally derived from the literature for studies implemented in similar regions and climates. The output is effectively an addition of each of these carbon sources over the landscape. In order to calculate sequestration, the future carbon pool is subtracted from that of an earlier time step. Uses of this model have included small, urban scale areas (Han et al., 2018), to forest systems (Chacko et al., 2019), as well as entire mixed landscape regions (Nelson et al., 2009).

Data inputs

The main inputs for this model are LULC maps for each scenario and time-step, as well as the carbon pools table outlining the carbon storage potential of each LULC code (Table SI 7). In lieu of local data, a literature search was undertaken to populate this table, averaged from multiple data sources were possible in order to reduce uncertainty. For some data points only organic carbon storage values could be found, while InVEST requires units in elemental carbon (C). These values were converted to elemental carbon with a default conversion rate of 0.37. Similarly, below ground carbon was calculated for forests on the basis of a 0.47 conversion rate for above ground to below ground C content in forests and 0.40 in grasslands (IPCC, 2006 ,Table 4.3).

Table SI 7. Data inputs for carbon model.

Data input	**Data type**	**Source(s)**
LULC map	Raster	IEEM
Carbon pools	Comma separated file (csv)	Literature review
Reference year	Integer	IEEM
Future LULC map	Raster	CLUE model
Future year	Integer	IEEM

Source: Author's own elaboration.

Most values were taken from default value tables produced by IPCC 2006 due to the lack of local data. This source provides data tables for either biomass or C values separated by land cover type, region and climate. Where possible, data was taken from tropical/wet climates in South America (Beck et al., 2018; Sánchez-Cuervo et al., 2012).Most values were taken from default value tables produced by IPCC 2006 due to the lack of local data. This source provides data tables for either biomass or C values separated by land cover type, region and climate. Where possible, data was taken from tropical/wet climates in South America (Beck et al., 2018; Sánchez-Cuervo et al., 2012).

Processing steps

The business-as-usual scenario 2020 map of total carbon storage, along with all 2040 scenario maps, were processed in QGIS using the zonal statistics tool to show results by department. Changes as a percentage by department were then calculated using Excel.

Nutrient Delivery Ratio

The model

The InVEST Nutrient Delivery Ratio (NDR) model was used to calculate the water purification potential of landscapes in Colombia in terms of nitrogen and phosphorus storage. The model maps nutrient sources from watersheds and their transport to the stream. As a result of this calculation it is possible to show where nutrients are most effectively stored in certain landscapes by virtue of their vegetative cover, elevation/slope, and placement in the hydrological cycle, thereby visualizing the ES of water purification. The InVEST NDR model does this by calculating a nutrient mass balance representing long-term processes of nutrient flows based on the nutrient sources associated with each LULC of each map pixel, and the retention properties (for example land cover, slope) of pixels belonging to the same flow path in a given hydrological system (Redhead et al., 2018). The model is generally used in order to compute changes in retention patterns under different land-use/cover scenarios, and has been readily applied over national (Redhead et al., 2018; Rukundo et al., 2018) and regional extents (Benez-Secanho and Dwivedi, 2019; Brown and Quinn, 2018).

Data inputs

Table SI 8 summarizes the data inputs for the InVEST NDR model. While most data were readily available, as with the other models the biophysical parameters required further searching in relevant literature. The biophysical table included the individual land use code, the nitrogen/phosphorus load (load_n/p), the efficiency that nitrogen/phosphorus is accumulated in the landscape (eff_n/p), as well as the critical length of the slope at which the nutrients will travel through the landscape (crit_len_n/p). These were primarily identified through literature on Colombia, however where this was not possible, literature from South America and similar (tropical) climates were taken. Where multiple data points were found, these were averaged where necessary in order to account for the high uncertainty when using secondary data.

Table SI 8.Data inputs required for the NDR model

Data input	Data type	Source(s)
DEM	Raster	OPEN IEEM
LULC Map	Raster	OPEN IEEM
Nutrient runoff proxy (annual precipitation)	Raster	(Hijmans et al., 2005)
Watersheds	Vector	(Sistema de Informacion Ambiental de Colombia (SIAC), 2013)
Biophysical table	Comma separated file (csv)	OPEN IEEM
Threshold flow accumulation	Integer	Default value (1000)
Borselli k parameter	Integer	Default value (2)
Subsurface critical length (nitrogen/phosphorus)	Integer	Default value (pixel length, 200m)
Subsurface maximum retention efficiency (nitrogen/phosphorus)	Integer	Default value (0.8/80%)

Source: Authors' own elaboration.

Default values were used for threshold flow accumulation and Borselli K, as per the SDR model. Values for subsurface critical length and maximum retention efficiency were also taken from default values suggested by (Sharp et al., 2020) in place of regional data. As with the SDR model, precise calibration of these was not required for the outputs sought.

Processing steps

The nutrient output raster file was the key output from the model, as it shows the load from each pixel of both nutrients that reach the stream. By comparing these results, it is possible to show the differences in water purification ES provision between scenarios. To show this, the business-as-usual scenario 2020 and all 2040 scenario files were again processed as above through the zonal statistics tool to show the percentage change between scenarios.

Annual water yield

The model

The Annual Water Yield (AWY) model from InVEST can be used to calculate the amount of water produced per watershed over a given landscape. It utilizes the Budyko curve approach (Budyko and Miller, 2014) and Fu-type equation (Yang et al., 2008) to make an estimation of water supply. This calculation involves two main categories of inputs, the first being dryness indices (evapotranspiration, precipitation) and the storage potential (soil depth, plant root depth, soil water storage, and seasonality) (Dennedy-Frank et al., 2016). Table SI 9 summarizes the data needed for the model. The model has been used in a variety of spatial contexts in order to evaluate the impact of land use change decisions on regional and national water availability, with a particular focus on agriculture and climate change (Leh et al., 2013; Sánchez-Canales et al., 2012).

Table SI 9. AWY data inputs

Data input	**Data type**	**Source(s)**
Precipitation	Raster	(Hijmans et al., 2005)
Reference evapotranspiration	Raster	(Trabucco and Zomer, 2009)
Depth to root restricting layer (soil depth used as proxy)	Raster	(Stoorvogel et al., 2016)
Plant available water content (PAWC) fraction	Raster	Estimated from literature review
LULC map	Raster	IEEM
Watersheds map	Vector	(Sistema de Informacion Ambiental de Colombia (SIAC), 2013)
Biophysical table	Comma separated file (csv)	Literature review
Z parameter	Integer	Estimated from literature review

Source: Authors' own elaboration.

Several parameters needed to be calculated using secondary sources where it was not directly available, including PAWC and the Z parameter. PAWC is estimated by subtracting the permanent wilting point from field capacity of a given soil type. In order to generate the PAWC raster file, a soil texture map was derived from available raster data on sand, clay and silt percentages according to UNCD/FAO soil texture classifications (e.g., visualized by Groenendyk et al., 2015). This map was then polygonised, and each class was assigned a PAWC based on the available literature on wilting points and field capacities of each soil texture (Elnesr, 2006) and finally converted back to a raster for input into the model.

The final biophysical parameter to be calculated was the Z(Zhang) parameter, which relates to the seasonality of other biophysical parameters. Z can be calculated by Z = ((ω – 1.25)*P / Available Water Content (AWC)), where ω represents the coefficient for water-energy partitioning assigned to the region estimated from literature (Xu et al., 2013), P is mean annual precipitation, and AWC is calculated by minimum soil depth and mean PAWC (Sharp et al., 2020). Minimum soil depth was derived from available data used for CLUE model runs, and mean PAWC was taken from the PAWC raster file. Following these calculations, the Z parameter was 45, reflecting a high level of seasonality. Overall, however, the InVEST equation for calculating AWL is generally not highly sensitive to the Z parameter [44].

For the depth-to-root-restricting-layer input, absolute root depth was used as a proxy in place of accurate data as suggested by Minga-León et al. (2018) and Sharp et al. (2020, AWY model documentation).

Processing steps

The water yield per pixel output was taken to show the differences between scenarios. Business as usual 2020 and all 2040 scenario results were processed as with other models to show the percentage difference between them using the zonal statistics tool.

InVEST model set-up

As mentioned above, all model runs were implemented using the InVEST python library as it was found to be considerably faster than using the InVEST software. Model run length varied per model, however on average:

- SDR model: ~8-10 minutes per scenario time step
- Carbon model: ~1 minute per scenario time step
- NDR model: ~10-15 minutes per scenario time step
- AWY model: ~8-10 minutes per scenario time step

Models were initially run using a simple for loop to iterate the process for all scenario time steps one after the other, while ultimately the Joblib library was used in order to run up to 5 scenarios concurrently using a pipeline, which reduced model runtime by up to 30%.

Assumptions and limitations of ES modeling

There are several limitations and assumptions that must be acknowledged relating to the ecosystem service models used. Generally speaking, biophysical parameters were calibrated to the regional context of Colombia as far as was possible from existing data. As discussed in this Supplementary Information section, often data was taken from other, similar regions, or averaged from other sources, in order to calibrate the biophysical parameters for each model. As a result, there is a relative degree of uncertainty about the precision of the results as they pertain specifically to Colombia. This was considered a sound approach for the purposes of this study, as the key output sought was a comparison between scenarios under different scenario circumstances. For these ends, it was enough to rely on empirical field data from similar regions, which maintained similar ratios across different LULC to ensure that a comparison between scenarios was possible. Absolute values are considered indicative only and cannot be relied upon directly.

Other assumptions include calibration of parameters specific to each model, for example threshold flow accumulation and other parameters for the SDR model, where default values given by InVEST documentation were used. Other input parameters were calculated from the best available research, such as the Z parameter for the AWY model, which was a composite of calculations of values collected from available literature, including the plant available water content. A full outline of how these values were calculated is given in Appendix A. Because each of these values were calculated indirectly, this may increase the uncertainty of results given. However, again, as these were only used as comparative values, the relative impact of that uncertainly on results derived is not considered to be high.

Supplementary Information 3
Raw outputs of ecosystem service models

Below is a summary of the raw outputs of each ES model in terms of absolute values, as well as comparisons to the initial 2014 scenario.

SDR Model

Soil loss by department in tons of soil per hectare.

Region	BASE 2014	BASE 2040	COMBI	HABITAT	PES	PES SPS	SPS
AMAZONAS	10,460	10,808	10,808	10,808	10,808	10,564	10,512
ANTIOQUIA	1,460,204	1,614,260	1,648,060	1,649,248	1,642,236	1,619,108	1,659,668
ARAUCA	76,220	90,608	91,372	90,828	88,160	90,204	93,332
ATLÁNTICO	7,068	7,044	7,048	7,028	7,040	6,932	7,024
BOGOTÁ, D.C.	79,540	78,824	78,824	78,824	78,824	78,288	78,864
BOLÍVAR	202,492	211,772	212,592	203,744	210,488	208,720	212,944
BOYACÁ	1,023,216	1,030,380	1,042,204	1,030,280	1,030,204	1,018,828	1,033,580
CALDAS	259,320	267,356	268,840	264,060	263,796	265,512	270,996
CAQUETÁ	303,180	494,428	487,856	491,712	490,468	477,628	492,568
CASANARE	136,028	152,756	152,044	152,056	151,760	150,588	153,708
CAUCA	841,244	866,444	867,168	853,240	876,632	863,116	869,636
CESAR	519,488	507,872	522,148	490,152	500,516	535,712	540,392
CHOCÓ	222,516	348,992	339,436	315,832	344,176	341,112	349,592
CÓRDOBA	116,016	137,756	137,016	144,348	135,972	136,260	146,232
CUNDINAMARCA	842,920	845,448	842,212	845,024	845,280	830,356	843,540
GUAINÍA	30,732	31,892	31,880	31,944	31,892	31,376	31,816
GUAVIARE	77,784	79,388	79,376	79,352	79,336	78,664	79,364
HUILA	559,088	581,028	581,480	580,364	580,332	572,280	581,776
LA GUAJIRA	308,132	308,060	303,428	295,732	307,732	299,144	303,728
MAGDALENA	256,612	247,208	243,288	236,568	241,428	244,148	246,480
META	333,340	430,868	427,440	425,520	423,212	415,288	432,484
NARIÑO	569,340	634,724	632,708	633,088	630,276	622,092	636,656
NORTE DE SANTANDER	743,392	830,192	821,696	822,816	821,264	809,360	834,192
PUTUMAYO	72,604	220,864	220,864	221,804	222,768	217,228	220,648
QUINDIO	57,072	58,500	58,124	31,508	58,028	56,912	58,304
RISARALDA	120,900	123,660	124,056	124,544	124,128	122,256	124,760
SANTANDER	830,520	871,036	869,880	865,204	867,536	851,888	871,900
SUCRE	16,004	15,520	15,932	15,932	15,928	15,676	15,936
TOLIMA	864,508	886,072	909,684	814,536	869,620	906,052	916,508
VALLE DEL CAUCA	427,568	439,248	437,936	440,160	438,544	431,604	438,256
VAUPÉS	69,992	70,356	70,468	70,496	70,464	69,504	70,380
VICHADA	86,640	86,636	86,604	86,616	86,620	82,796	86,536
Total	11,524,140	12,580,000	12,622,472	12,403,368	12,545,468	12,459,196	12,712,312
% change compared to BASE 2014		+8.39%	+8.70%	+7.09%	+8.14%	+7.50%	+9.35%

Carbon model

Total carbon storage by department in megagrams.

Region	BASE 2014	BASE 2040	COMBI	HABITAT	PES	PES SPS	SPS
CAQUETÁ	1,789,370,486	1,422,929,637	1,445,352,942	1,417,072,150	1,443,579,502	1,442,937,577	1,422,326,172
CAUCA	456,575,689	436,341,527	437,448,379	447,406,253	436,064,894	435,611,916	436,490,458
PUTUMAYO	502,202,919	386,942,693	393,833,794	384,528,657	393,882,808	397,207,328	389,081,211
VALLE DEL CAUCA	274,205,190	265,619,608	267,334,027	265,052,354	265,836,301	266,169,834	267,113,272
GUAINÍA	1,716,870,210	1,699,813,060	1,700,773,103	1,699,666,679	1,700,749,370	1,700,736,215	1,700,390,464
VICHADA	1,477,612,985	1,441,431,002	1,442,920,711	1,440,651,807	1,443,275,341	1,444,018,975	1,440,810,303
CASANARE	391,169,578	366,947,436	368,422,356	366,730,259	368,275,243	368,062,841	367,193,763
AMAZONAS	2,732,149,122	2,719,616,567	2,720,375,357	2,719,638,930	2,722,200,247	2,721,387,401	2,720,016,772
VAUPÉS	1,299,754,894	1,285,096,112	1,285,773,345	1,284,826,850	1,285,871,660	1,286,016,767	1,284,888,562
GUAVIARE	1,261,627,308	1,071,906,405	1,083,874,537	1,071,297,698	1,087,358,200	1,089,323,543	1,072,288,895
CALDAS	55,863,202	51,854,314	51,737,020	51,390,867	51,873,069	51,860,024	51,762,211
QUINDIO	17,766,978	17,118,272	17,232,031	28,705,568	17,176,107	17,254,218	17,153,894
RISARALDA	43,624,787	41,945,985	41,866,414	41,536,717	41,719,898	41,956,832	41,686,878
ANTIOQUIA	686,373,715	515,005,175	519,188,815	514,874,601	522,948,569	521,272,426	508,334,779
CHOCÓ	1,030,465,191	935,180,158	943,078,340	954,745,553	939,958,725	939,008,251	934,628,437
NARIÑO	509,912,684	460,649,308	463,553,614	460,444,183	463,317,273	464,157,841	461,584,028
CÓRDOBA	176,517,702	155,170,097	158,330,755	155,656,743	156,701,429	158,582,706	156,261,921
BOLÍVAR	250,704,985	211,678,279	213,754,336	223,953,019	215,226,331	214,207,384	211,793,705
CESAR	130,858,060	122,829,402	123,352,490	135,679,784	123,339,205	124,005,996	122,943,859
LA GUAJIRA	141,082,553	134,462,308	134,889,334	147,477,451	135,083,058	134,769,027	134,492,598
MAGDALENA	142,069,263	130,686,959	132,205,076	143,225,557	132,101,211	132,958,935	132,406,627
SUCRE	37,299,652	34,850,206	34,293,861	47,144,300	34,380,728	34,289,845	34,089,676
ARAUCA	224,212,242	190,522,177	191,060,982	189,877,261	192,702,879	192,174,317	189,421,580
BOYACÁ	208,039,860	201,008,825	202,505,763	200,774,042	201,197,180	202,556,822	201,082,785
CUNDINAMARCA	160,031,250	157,156,124	156,337,553	156,853,632	157,143,372	156,293,270	156,553,642
NORTE DE SANTANDER	276,481,575	198,968,195	207,073,576	202,105,322	206,382,745	207,366,124	200,606,482
BOGOTÁ, D.C.	8,994,353	8,699,200	8,699,200	8,699,200	8,699,200	8,699,200	8,692,038
META	1,154,133,708	897,231,247	912,549,864	896,813,485	915,341,780	916,143,681	897,110,744
HUILA	188,346,392	183,187,721	183,519,365	183,000,132	183,467,545	183,503,922	183,320,111
SANTANDER	234,666,636	193,654,420	196,348,234	193,865,329	196,559,702	198,134,070	194,228,987
TOLIMA	217,297,645	211,600,412	212,521,668	221,188,040	210,738,822	211,695,574	211,586,099
ATLÁNTICO	17,391,788	16,970,956	17,030,377	29,871,726	16,919,705	17,027,642	16,945,500
TOTAL	17,813,672,602	16,167,073,784	16,267,237,217	16,284,754,146	16,270,072,099	16,279,390,503	16,167,286,452
% changes compared to BASE 2014		-10.18%	-9.51%	-9.39%	-9.49%	-9.42%	-10.18%

AWY model

Annual water production per department in billions of cubic meters.

Region	BASE 2014	BASE 2040	COMBI	HABITAT	PES	PES SPS	SPS
AMAZONAS	214	214	214	214	214	214	214
ANTIOQUIA	128	128	128	128	128	128	128
ARAUCA	32	32	32	32	32	32	32
ATLÁNTICO	1	1	1	1	1	1	1
BOGOTÁ, D.C.	1	1	1	1	1	1	1
BOLÍVAR	34	34	34	34	34	34	34
BOYACÁ	27	27	27	27	27	27	27
CALDAS	27	27	27	27	27	27	27
CAQUETÁ	11	11	11	11	11	11	11
CASANARE	160	160	160	160	160	160	160
CAUCA	76	76	76	76	76	76	76
CESAR	63	63	63	63	63	63	63
CHOCÓ	18	18	18	18	18	18	18
CÓRDOBA	192	193	193	193	193	193	193
CUNDINAMARCA	28	28	28	28	28	28	28
GUAINÍA	162	162	162	162	162	162	162
GUAVIARE	93	93	93	93	93	93	93
HUILA	18	18	18	18	18	18	18
LA GUAJIRA	5	5	5	5	5	5	5
MAGDALENA	13	13	13	13	13	13	13
META	141	141	141	141	141	141	141
NARIÑO	67	67	67	67	67	67	67
NORTE DE SANTANDER	26	27	27	27	27	27	27
PUTUMAYO	61	61	61	61	61	61	61
QUINDIO	2	2	2	2	2	2	2
RISARALDA	5	5	5	5	5	5	5
SANTANDER	40	40	40	40	40	40	40
SUCRE	8	8	8	8	8	8	8
TOLIMA	26	26	26	26	26	26	26
VALLE DEL CAUCA	38	38	38	38	38	38	38
VAUPÉS	114	114	114	114	114	114	114
VICHADA	172	172	172	172	172	172	172
TOTAL	2002	2004	2004	2004	2004	2004	2004
% changes compared to BASE 2014		+0.14%	+0.13%	+0.14%	+0.13%	+0.13%	+0.14%

NDR model for nitrogen

Total nitrogen export that eventually reaches the stream by department in kilograms.

Region	BASE 2014	BASE 2040	COMBI	HABITAT	PES	PES SPS	SPS
AMAZONAS	6,109,676	6,457,235	6,468,770	6,454,954	6,391,579	6,425,328	6,458,306
ANTIOQUIA	36,800,633	39,239,376	38,749,157	39,241,299	39,231,468	39,118,249	39,323,715
ARAUCA	1,754,939	1,969,806	1,960,735	1,956,966	1,921,587	1,952,971	1,979,626
ATLÁNTICO	542,787	532,750	540,205	501,877	536,055	536,593	535,531
BOGOTÁ, D.C.	418,569	415,380	414,781	415,380	415,380	414,912	414,005
BOLÍVAR	6,615,514	7,007,100	7,039,962	6,736,571	6,993,441	7,019,707	7,076,140
BOYACÁ	12,255,641	12,205,987	12,116,069	12,193,499	12,203,336	12,211,757	12,344,157
CALDAS	5,540,677	5,490,769	5,508,240	5,435,560	5,484,119	5,505,021	5,568,600
CAQUETÁ	9,483,163	11,143,650	11,116,433	11,119,293	11,093,793	11,119,687	11,184,416
CASANARE	5,710,466	5,846,485	5,826,268	5,772,851	5,836,752	5,868,507	5,871,087
CAUCA	22,571,414	22,854,035	22,820,494	22,499,385	22,811,425	22,944,516	22,852,448
CESAR	4,283,963	4,309,287	4,300,742	4,155,181	4,246,616	4,407,635	4,433,166
CHOCÓ	18,333,820	20,883,940	20,360,838	20,575,160	20,747,196	20,721,480	20,649,500
CÓRDOBA	6,127,965	6,477,562	6,490,223	6,542,994	6,450,457	6,506,120	6,606,108
CUNDINAMARCA	14,150,117	14,270,537	14,089,803	14,255,266	14,262,872	14,071,264	14,095,773
GUAINÍA	4,198,711	4,523,857	4,513,970	4,526,555	4,517,649	4,506,574	4,521,288
GUAVIARE	3,855,988	4,513,003	4,461,913	4,458,220	4,426,156	4,448,666	4,513,234
HUILA	9,570,646	9,699,526	9,732,734	9,637,800	9,677,515	9,681,120	9,726,801
LA GUAJIRA	1,528,433	1,556,588	1,552,200	1,459,000	1,551,867	1,542,630	1,556,377
MAGDALENA	3,689,834	3,399,630	3,386,266	3,235,484	3,347,813	3,383,072	3,407,862
META	16,343,936	18,549,228	18,459,413	18,439,996	18,369,363	18,370,350	18,563,876
NARIÑO	18,265,363	19,152,712	19,105,082	19,094,810	19,089,327	19,068,755	19,151,287
NORTE DE SANTANDER	11,668,965	12,541,518	12,401,487	12,457,849	12,659,406	12,342,081	12,600,930
PUTUMAYO	7,094,197	7,870,222	7,928,392	7,902,088	8,010,971	7,937,219	7,959,544
QUINDIO	2,260,099	2,143,519	2,181,154	1,517,159	2,160,602	2,145,369	2,184,345
RISARALDA	2,938,504	2,967,803	2,960,415	2,947,955	2,954,839	2,964,991	2,969,655
SANTANDER	16,683,599	16,885,983	16,860,903	16,688,482	16,838,965	16,759,679	16,887,763
SUCRE	2,043,650	2,031,822	2,030,735	1,881,847	2,024,735	2,028,260	2,032,029
TOLIMA	14,314,381	14,593,483	14,645,367	13,182,408	14,380,704	14,749,572	14,793,948
VALLE DEL CAUCA	10,146,876	10,170,523	10,138,262	10,033,586	10,021,744	10,071,156	10,138,954
VAUPÉS	4,097,109	4,489,571	4,498,589	4,495,048	4,458,564	4,479,056	4,508,707
VICHADA	3,703,115	3,804,039	3,799,968	3,802,089	3,796,106	3,794,841	3,810,458
Total	283,102,750	297,996,924	296,459,571	293,616,611	296,912,401	297,097,139	298,719,637
% changes compared to BASE 2014		+5.00%	+4.51%	+3.58%	+4.65%	+4.71%	+5.23%

NDR model for phosphorus

Total phosphorus export that eventually reaches the stream by department in kilgorams.

Region	BASE 2014	BASE 2040	COMBI	HABITAT	PES	PES SPS	SPS
AMAZONAS	132,196	182,359	183,636	182,018	173,453	176,577	181,965
ANTIOQUIA	6,068,393	7,203,656	7,137,703	7,177,120	7,167,921	7,143,697	7,208,317
ARAUCA	198,403	223,132	222,772	219,997	215,216	221,555	223,916
ATLÁNTICO	101,752	101,277	101,657	78,447	102,185	101,700	100,222
BOGOTÁ, D.C.	83,401	84,711	84,713	84,711	84,711	84,731	84,551
BOLÍVAR	1,050,618	1,220,139	1,221,678	1,128,981	1,221,156	1,218,463	1,234,393
BOYACÁ	2,235,130	2,284,505	2,315,001	2,285,545	2,283,927	2,279,330	2,304,341
CALDAS	824,072	896,908	902,531	894,303	896,267	895,666	906,503
CAQUETÁ	894,368	1,237,035	1,221,902	1,216,779	1,220,994	1,221,280	1,242,136
CASANARE	798,612	815,267	811,785	803,139	813,915	818,686	818,645
CAUCA	3,622,470	3,873,835	3,870,844	3,738,101	3,838,689	3,898,090	3,879,576
CESAR	654,157	792,951	707,514	743,552	804,773	704,505	713,651
CHOCÓ	2,006,731	2,450,223	2,360,979	2,413,705	2,422,481	2,426,638	2,413,764
CÓRDOBA	1,046,201	1,196,405	1,191,964	1,172,055	1,187,290	1,191,147	1,196,579
CUNDINAMARCA	2,449,044	2,519,499	2,499,736	2,519,235	2,518,136	2,496,718	2,501,597
GUAINÍA	95,909	139,596	138,597	139,659	138,914	137,777	139,376
GUAVIARE	224,112	290,055	285,211	280,718	278,722	282,231	291,042
HUILA	1,709,707	1,776,196	1,779,960	1,765,858	1,769,731	1,772,912	1,783,708
LA GUAJIRA	279,822	294,912	298,580	263,307	292,347	298,659	298,389
MAGDALENA	542,811	552,696	554,152	498,625	548,745	543,905	550,031
META	2,093,867	2,800,120	2,766,837	2,782,456	2,747,431	2,748,353	2,804,163
NARIÑO	2,723,512	2,994,025	2,976,806	2,983,315	2,973,181	2,970,284	2,996,681
NORTE DE SANTANDER	1,916,849	2,288,804	2,213,325	2,244,014	2,302,658	2,199,783	2,271,149
PUTUMAYO	975,303	1,291,368	1,311,206	1,307,250	1,331,419	1,306,950	1,316,112
QUINDIO	351,767	365,039	366,555	208,431	365,690	363,894	366,529
RISARALDA	498,624	526,246	527,797	524,487	526,452	528,006	529,916
SANTANDER	2,761,445	3,072,704	3,060,265	3,029,132	3,054,033	3,032,209	3,073,580
SUCRE	345,194	365,261	367,077	286,864	364,826	366,156	369,147
TOLIMA	2,203,423	2,364,602	2,393,844	2,203,372	2,307,197	2,387,891	2,398,161
VALLE DEL CAUCA	1,644,797	1,767,817	1,763,246	1,757,157	1,756,890	1,761,267	1,764,704
VAUPÉS	210,448	262,437	261,567	263,557	258,546	258,807	262,957
VICHADA	178,731	198,009	197,724	197,824	196,321	196,361	200,018
Total	40,921,871	46,431,789	46,097,161	45,393,714	46,164,216	46,034,227	46,425,820
% changes compared to BASE 2014		+11.87%	+11.23%	+9.85%	+11.36%	+11.11%	+11.86%