

Low Emission Development Strategies in Agriculture. An Agriculture, Forestry, and Other Land Uses (AFOLU) Perspective

ALESSANDRO DE PINTO^a, MAN LI^a, AKIKO HARUNA^a, GLENN GRAHAM HYMAN^b, MARIO ANDRÉS LONDOÑO MARTINEZ^c, BERNARDO CREAMER^b, HO-YOUNG KWON^a, JHON BRAYAN VALENCIA GARCIA^b, JEIMAR TAPASCO^b and JESUS DAVID MARTINEZ^{b,*}

^a *International Food Policy Research Institute, USA*

^b *International Center for Tropical Agriculture, Colombia*

^c *Universidad de los Andes, Colombia*

Summary. — As countries experience economic growth and choose among available development pathways, they are in a favorable position to adopt natural resource use technologies and production practices that favor efficient use of inputs, healthy soils, and ecosystems. Current emphasis on increasing resilience to climate change and reducing agricultural greenhouse gasses (GHG) emissions strengthens the support for sustainable agricultural production. In fact, reducing losses in soil fertility, reclaiming degraded lands, and promoting synergistic interaction between crop production and forests are generally seen as good climate change policies. In order for decision-makers to develop long-term policies that address these issues, they must have tools at their disposal that evaluate trade-offs, opportunities, and repercussions of the options considered. In this paper, the authors combine and reconcile the output of three models widely accessible to the public to analyze the impacts of policies that target emission reduction in the agricultural sector. We present an application to Colombia which reveals the importance of considering the full scope of interactions among the various land uses. Results indicate that investments in increasing the efficiency and productivity of the livestock sector and reducing land allocated to pasture are preferable to policies that target deforestation alone or target a reduction of emissions in crop production. Investments in livestock productivity and land-carrying capacity would reduce deforestation and provide sufficient gains in carbon stock to offset greater emissions from increased crop production while generating higher revenues.
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Key words — climate change, land use change, low emission development, AFOLU

1. INTRODUCTION

Resource use in many developing countries, from crop production to deforestation is responsible for the bulk of greenhouse gasses (GHG) emissions, and there are instances in which the agricultural and forestry sectors can provide low-cost climate change mitigation opportunities (Golub *et al.*, 2013; Lubowski & Rose, 2013; Smith *et al.*, 2007). From a technical point of view, reducing expected increases in GHG emissions in agriculture requires the adoption of transformative approaches in the use of resources. Emphasis has been placed on methods that increase the efficiency in the use of fertilizers, water, and fossil fuels, as well as waste reduction. A growing body of literature analyzes the effects of alternative agricultural practices (Antle & Stoorvogel, 2008; Diagana, Antle, Stoorvogel, & Gray, 2007; Gilhespy *et al.*, 2014; Schneider & Smith, 2008; Smith *et al.*, 2013; Tenningkeit, Kahrl, Wolcke, & Newcombe, 2012; Tschakert, 2007). The livestock sector has also been the target of research on mitigation opportunities (Golub *et al.*, 2013; Li *et al.*, 2012; Schils, Olesen, del Prado, & Soussana, 2007), and the mitigation potential of forests, soil, and other biomass has been amply analyzed as well (Cacho, Marshall, & Milne, 2005; Lubowski & Rose, 2013; Makundi & Sathaye, 2004; Torres, Marchant, Lovett, Smart, & Tipper, 2010). However, from a policy-making perspective, the design of low emission development strategies is an example of multi-objective decision making in which policies target the reduction of GHG emissions while other goals such as increasing agricultural productivity and food security or attaining objectives such as export goals or

economic growth are preserved. It is also important to consider that all countries are part of a global economic system, and therefore it is critical that policies are devised with full recognition of the role of the international economic environment which, with its effects on commodity prices, can significantly affect the long-term viability and the budgetary implications of mitigation policies. The challenge at hand is to reconcile the limited spatial resolution of macro-level economic models that operate at a global or national level with models that function at a higher spatial resolution to properly account for changes in carbon stocks and GHG emissions. The

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number of analyses that confront this challenge is still small, but it is growing given the importance of the information that these studies can provide to policy makers. [Schneider and Smith \(2008\)](#) estimated mitigation potentials of U.S. agriculture with regionally disaggregated data and changes in welfare within the agricultural sector. [Golub *et al.* \(2013\)](#) examined the impact on food consumption and income of implementing mitigation policies at national and regional levels. [Rutten, van Dijk, van Rooij, and Hilderink \(2014\)](#) evaluated the effects of a series of climate change and economic growth scenarios on Vietnam's economy. [Dace, Muizniece, Blumberga, and Kaczala \(2015\)](#), used a system dynamic model to assess the effect of a group of policies on agricultural GHG emissions in Latvia. [Havlík *et al.* \(2014\)](#) estimated the effects of transitioning to a more efficient livestock production system on GHG mitigation and the economy, and [Lubowski and Rose \(2013\)](#) provided a review of a number of studies that model mitigation potentials of the Reducing Emissions from Deforestation and Forest Degradation (REDD) program along with conservation, sustainable management of forests, and enhancement of forest carbon stocks policies.

In this article we demonstrate that different models, all widely accessible to the public, can be brought together to help policy-makers in their evaluation of trade-offs, opportunities, and repercussions of alternative mitigation policies in the agricultural sector. While the focus of this work is on Colombia, the analytical framework can be applied to any country interested in exploring country-wide effects and the economic viability of climate change mitigation policies in agriculture. The approach is based on the use of public and widely accessible data and we believe that the flexibility and transparency of the approach proposed in this study can increase decision-makers' trust in the results. Naturally, additional data and targeted surveys can increase the accuracy of the results and the framework does not create barriers for the inclusion of additional input. Nonetheless, it is clear from our analysis that policy-makers need substantial support in their decision-making process as the range of options they face can be very diverse and the effects of their decisions have important, and sometimes unexpected repercussions. The effects of the policies we simulated cover the entire spectrum of potential outcomes. We found win-win policies (reducing land allocated to pasture increases profits and carbon stock and reduces GHG emissions), policies with tradeoffs (limiting deforestation in the Amazon increases carbon stock, decreases emissions, but reduces profits), and policies that could generate clearly inferior results (increasing the area allocated to oil palm cultivation beyond certain amounts reduces carbon stock, increases emissions, and reduces profits). Stakeholders, from government agencies to producer and consumers' organizations to farmers will benefit from policies devised with the support of solid evidence and the effects of which can be investigated and evaluated by all the parties affected.

2. GREENHOUSE GAS EMISSIONS IN COLOMBIA

In 2010, Colombia presented its second National Communication on Climate Change to the United Nations Framework Convention on Climate Change. The report contains data from the last National Greenhouse Gases Inventory carried out in 2004. Colombia contributes 0.37% (180,010 Gg) of the total worldwide emissions of GHG (49 Gt). Emissions are composed of 50% carbon dioxide (CO₂), 30% methane (CH₄), 19% nitrous oxide (N₂O), and the remaining 1% classified as chlorofluorocarbons (CFCs).

According to the last National Greenhouse Gases Inventory, agricultural activities emit 38% of total emissions, and land use, land use change, and forestry account for another 14%. Of the emissions resulting from agricultural activities, 48.5% are due to enteric fermentation, 47.5% from agricultural soil management, and 2% from emissions related to rice cultivation. Traditionally, Colombia has a large number of smallholder farmers and there is also a well-established culture of cattle ranching with both small and large livestock keepers. Urbanization and industrialization have been growing in Colombia, but agricultural and forestry activities are expected to grow and continue to claim a large share of emissions. Although the agriculture sector represents 7% of the gross national product, the sector employs 18% of the population ([CIA \(Central Intelligence Agency\), 2014](#)).

Colombia has developed plans and policies that address climate change mitigation identifying priority sectors with high GHG emission rates. A working group led by the Ministry of Environment and Sustainable Development (MADS) has selected target areas for low emissions development in the agriculture, forestry, and land use sectors. These include reducing emissions from deforestation and forest degradation, oil palm, livestock, forestry, and fertilizers. In December 2015, the government of Colombia presented its Intended Nationally Determined Contributions (INDCs) at the Conference of the Parties in Paris and this document includes contributions from the AFOLU sector.

According to official government statistics ([IAvH *et al.*, 2007](#); [IGAC, 2013](#)), 52% of Colombia's 115 million hectares is covered by natural forests, mostly within the Amazon basin but also forests along the Pacific coast and in the northern part of the country. Cultivated pastures and native savanna grasslands make up 26% of the land area. These lands are characterized by cattle grazing with low stocking rates and frequent natural and anthropogenic fires. Cropland is mostly concentrated in the intermountain valleys, making up about 4% of the land surface (see [Figure 1](#)).

In 2011, the Instituto Nacional de Hidrología Meteorología y Estudios Ambientales de Colombia (IDEAM) and MADS quantified national deforestation rates and trends ([Table 2.1](#)). The average annual deforestation rate over the entire period is some 238,000 hectares and the Amazon and Andes regions appear to be areas particularly at risk.

Prior to 2000, estimates of forest clearing suggested that two-thirds of this clearing was due to the pastureland encroaching into forest and one-third due to cropland expansion ([Etter, McAlpine, Wilson, Phinn, & Possingham, 2006](#)). A more recent analysis has suggested that 90% of forest clearing during 2005–10 was due to pastureland development ([Nepstad, Tepper, McCann, Stickler, & McGrath, 2013](#)).

Colombia is the fifth largest producer of palm oil and its production area is expected to increase. Official projections ([MADR \(Ministry of Agriculture & Rural Development\), 2011](#)) indicate that there will be little changes in cropland area over the coming decades, with the exception of oil palm. Oil palm is expected to increase substantially after 2016, due to its high demand for food products and biofuels. However, oil palm development mostly occurred on lands that were already cleared of their forests, a trend that according to some studies is expected to continue, at least partially ([Castiblanco, Etter, & Aide, 2013](#)). Pasturelands and livestock production may change substantially in the coming years. According to the Colombian Federation of Cattle Ranchers (Federación Colombiana de Ganaderos, FEDEGAN), the Colombian livestock inventory totals 23.5 million head of cattle and 39.2 million hectares of pasture. With less than one head of

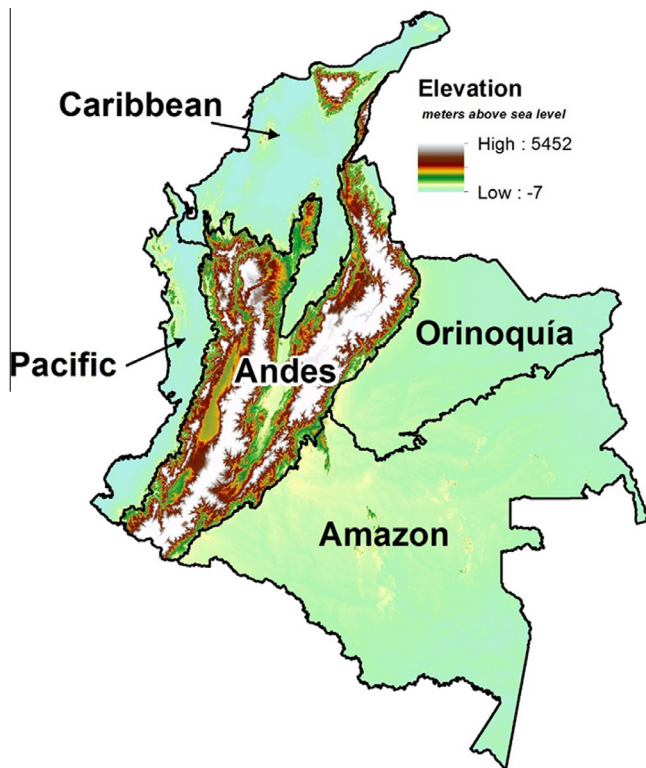


Figure 1. Main regions in Colombia.

cattle per hectare, livestock occupies 26% of the total land area of Colombia. The livestock area has expanded from 14.6 to 38 million hectares in the past 50 years, mostly at the expense of tropical forest (MADS (Ministry of Environment & Sustainable Development), 2012). As seen in Figure 2.2, the majority of pasture area is located in the eastern plains and Caribbean region. However, in terms of number of animals, the northwestern part of the Amazon region also appears to hold a significant share of pasture area.

3. MODELING FRAMEWORK

In order to evaluate the potential for GHG emission reductions and trade-offs of alternative mitigation policies, we combined and reconciled data and outputs of economic and biophysical models. This approach included the use of the following models:

- The International Model for Policy Analysis of Agricultural Commodities and Trade Model (IMPACT; Robinson *et al.*, 2015), a global partial equilibrium agriculture model that allows for policy and agricultural productivity investment simulations;
- A spatially explicit model of land use choices to determine the possible effects of future changes in the drivers of land use choices (Li, De Pinto, Ulimwengo, You, & Robertson, 2015); and
- DeNitrification–DeComposition crop model (DNDC; Li, 2007) that estimates spatially explicit profiles of GHG emissions from cropland with varying crop genetic productivity shifters, management systems, and climate scenarios.

This suite of models produces a series of country-specific results embedded in a framework consistent with global outcomes. Using the crop model, which incorporates the most updated knowledge on GHG emissions generated by crop production, it is possible to simulate the effects on GHG emissions of current and alternative agricultural management practices, when relevant (Figure 3.1). With the goal of making the results of our analysis as relevant as possible to policy-makers, we chose to work within a relatively short time horizon, approximately 20 years (from 2008 to 2030). The start year of 2008 was dictated by data availability on land use shares at the municipal level.

(a) IMPACT model

IMPACT is a partial equilibrium agricultural model that uses a system of linear and nonlinear equations to approximate the underlying production and demand relationships of world agriculture (Robinson *et al.*, 2015). The model has a long record of applications and it has been employed in a wide range of analyses, from assessing the potential effects of climate change on global food production (Godfray & Robinson, 2015; Springmann *et al.*, 2016) to evaluating the global effects of biofuels production (Rosegrant, Zhu, Msangi, & Sulser, 2008). The world's food production and consumption is disaggregated into 159 countries and regional groupings with a further disaggregation in many regions to the river basin level and with the basic unit of analysis being the Food Production Unit (Figure 3.2). IMPACT models the global behavior of a competitive agricultural market for crops and livestock and is specified as a set of countries or regions, in which supply, demand, and prices for agricultural commodities are determined. Countries and regions are linked through trade so that the interactions among country-level production, consumption, and commodity prices are captured through net trade flows in global agricultural markets. Demand is a function of price, income, and population growth. Growth in crop production in each country is determined by crop prices

Table 2.1. Deforestation by regions

Period	Indicator	Natural region					Total
		Pacific	Orinoquía	Caribbean	Andes	Amazon	
1990–2000	Forest 1990 (Ha)	5,249,261	2,335,094	2,368,779	12,565,035	41,924,100	64,442,269
	Deforestation (Ha)	140,426	240,580	343,019	876,597	1,198,018	2,798,640
2000–05	Forest 2000 (Ha)	5,227,673	2,182,517	2,014,227	11,716,837	40,669,967	61,811,221
	Deforestation (Ha)	29,254	28,696	47,313	97,293	112,565	315,121
2005–2010	Forest 2005 (Ha)	5,035,400	2,123,340	1,807,073	11,151,591	40,096,203	60,213,607
	Deforestation (Ha)	110,744	46,534	200,090	435,450	398,985	1,191,803
Annual average deforestation		22,149	9,307	40,018	87,090	79,797	238,361

Source: IDEAM (Instituto Nacional de Hidrología Meteorología y Estudios Ambientales de Colombia) 2010.

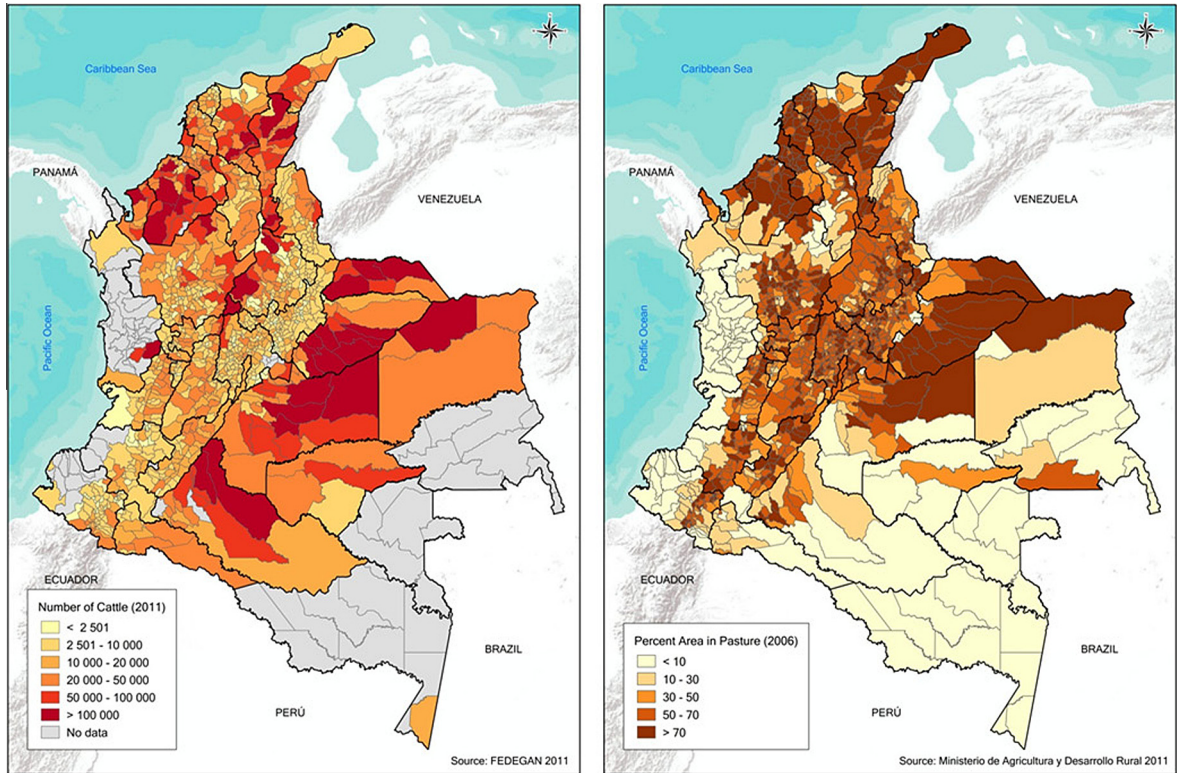


Figure 2.2. Number of cattle (left) and percent of pasture area (right) by municipality.. Source: FEDEGAN (2011) and MADR (Ministry of Agriculture & Rural Development) (2011).

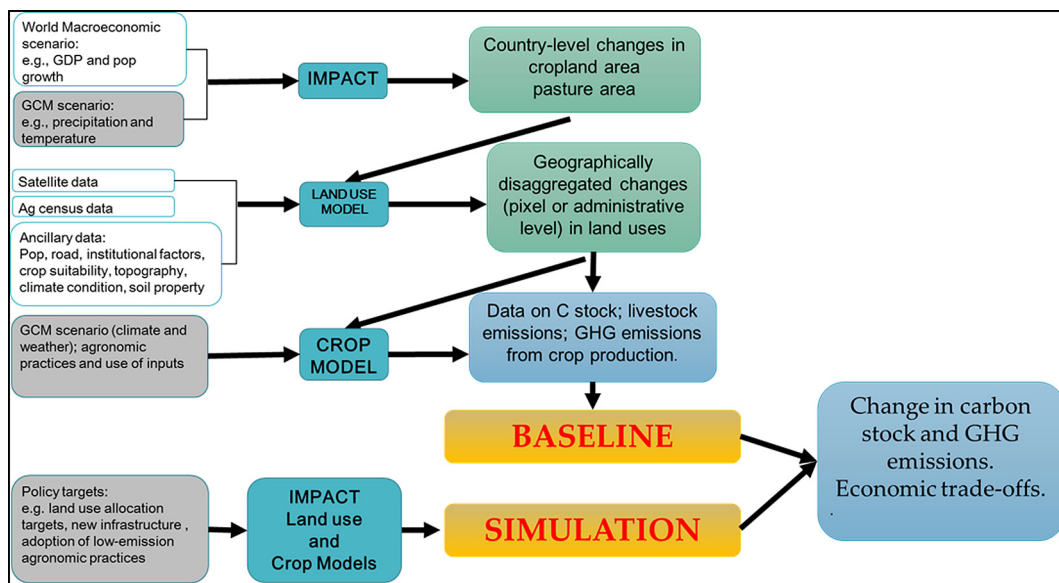


Figure 3.1. Workflow of the modeling approach.

and the rate of productivity growth from agricultural research and development, agricultural extension and education, markets, infrastructure, and irrigation. The model includes 64 commodities including all major cereals, soybeans, roots and tubers, meats, milk, eggs, oils, oilcakes and meals, vegetables, fruits, sugarcane and beets, and cotton.

IMPACT avails itself of the output from several other models. These include Global Circulation Models (GCM)¹ which simulate climate scenarios under global climate change; the Decision Support System for Agrotechnology Transfer (DSSAT) crop model suite which estimates yields with varying crop genetic productivity shifters and alternative management

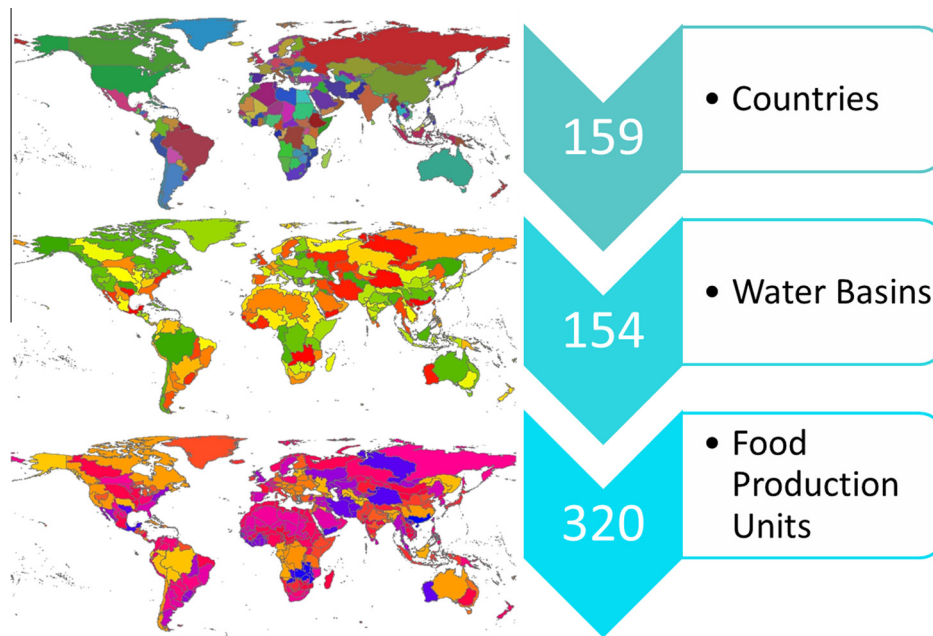


Figure 3.2. *IMPACT* global partitioning.. Source: *Robinson et al. (2015)*.

systems; the Spatial Production Allocation Model (SPAM) which provides an estimate of current area allocation to crop production and to management techniques such as rainfed/irrigated, and some *IMPACT* submodels such as the Water Simulation Model (IWSM) and the Global Hydrologic Model (IGHM).

IMPACT output is generally at a regional or national level. While this output provides information regarding changes in crop prices and in crop areas, it does not generate information with respect to the location of these changes and on the origin of new cropland. Given these limitations, it would be difficult to use the *IMPACT* model to quantify changes in carbon stock and GHG emissions from crop production. In order to do this, it is necessary to know the carbon content of the land uses that transitions in and out of production. Furthermore, GHG emissions from crop production are dependent on the characteristics of the land where farming takes place. It is therefore essential that the modeling output is sufficiently spatially disaggregated to account for the biophysical characteristics of each location.

(b) *Land use model*

In order to increase the spatial disaggregation of *IMPACT* output, we used an econometric model of land use choices. We followed the approach proposed by *Li et al. (2015)* based on a Maximum Likelihood method and employed a spatially explicit model which captures the main drivers of land use choice. The basic logic of the modeling approach is that the observed choices are the result of a utility-maximization process where each landholder will choose a land use that maximizes the stream of benefit deriving from the use of land. The econometric model, in this case a nested logit, attempts to explain the observed choices using a series of factors that are thought to influence the stream of benefits as explanatory variables. This class of models has been widely used in a variety of contexts (*Chomitz & Gray, 1996; De Pinto & Nelson, 2009; Nelson, De Pinto, Harris, & Stone, 2004; Nelson & Hellerstein, 1997* among many) and, given the characteristics of each location, it can be used to estimate the probability

for particular land use to be chosen. These probabilities are used to spatially allocate changes in cropland areas predicted by the *IMPACT* model.

As shown in *Figure 3.3*, the model structure consists of two levels of land use choices. The upper level estimates choices among large aggregation categories, such as cropland, pasture, forest, and other uses while the lower level estimates crop choices within a cropland. A detailed description of model specification and estimation method is provided in *Appendix 1*.

For the upper level model, we used a wide variety of biophysical and socioeconomic variables that influence land use choices, while for the lower level section we employed biophysical variables related to crop production as well as some economic variables such as crop prices and production costs which we considered to be key determinants of land allocation choices among crops (*Table 3.1*). To determine how land allocations will likely change in the year 2030, we used projections of commodity prices and the climate scenario MIROC General Circulation Model in combination with socioeconomic assumptions: AR5-SSP2 scenario (Shared Socioeconomic Pathway 2—middle of the road scenario).

(i) *Data for upper level model*

We used the Colombian government statistics to determine cropland and forest areas at the municipal level (*IGAC (Instituto Geografico Agustin Codazzi), 2013*) while for pastureland, we used data from the Instituto de Hidrología, Meteorología y Estudios Ambientales (*IAvH (Instituto de Investigación de Recursos Biológicos Alexander Von Humboldt) et al., 2007*). Based on these data, we classified the land use in four categories: cropland; forest; pasture; and other land uses which include shrub and secondary vegetation.

Population density data were gathered from the Gridded Population of the World, Version 3, with a spatial resolution of 30 arc-second (~1 km) (*CIESIN (Center for International Earth Science Information Network)/Columbia University/CIAT (Centro Internacional de Agricultura Tropical), 2005*). We used a lagged-population density value to mitigate endogeneity issues.

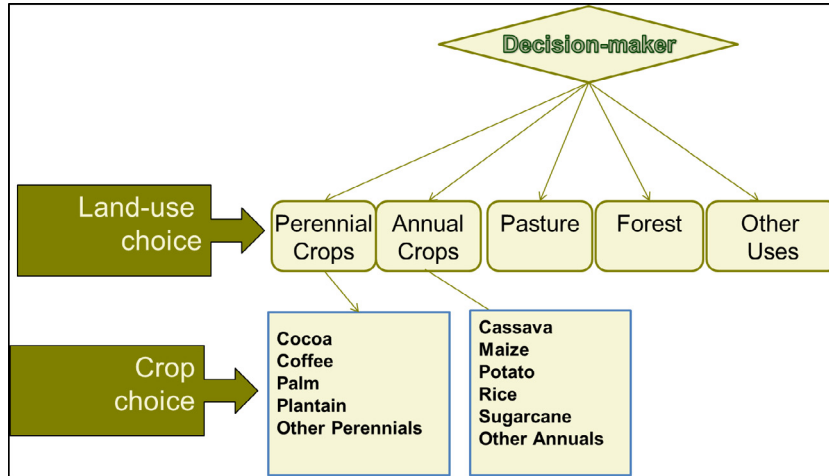


Figure 3.3. Structure of the land use model.

Table 3.1. Summary of the explanatory variables used for the land use model

Explanatory variables	
Lower level: Choice (dependent) variable: crop shares within municipal	Biophysical suitability by crop; commodity producer price by crop; production cost by crop; elevation; terrain slope; soil pH; annual precipitation; annual mean temperature.
Upper level: Choice (dependent) variable: land use shares within municipal	Price of meat and milk; timber price; production cost for livestock (cattle); population density; travel time to major cities; elevation; coefficient of variation of elevation; terrain slope; soil pH; annual precipitation; annual mean temperature; protected areas; indigenous reserves.

Note: A table with the descriptive statistics for the explanatory variable is provided in Appendix 1.

Data on market accessibility, measured by travel time to major cities (cities of 50,000 or more people in year 2000), were generated from a global map of accessibility with a resolution of 30 arc-second (Uchida and Nelson, 2010). Factors affecting the travel costs include transport network and environmental and political factors (see Nelson, 2000; Uchida and Nelson, 2010 for details).

Elevation and slope data were generated from a resampled Shuttle Radar Topography Mission (SRTM) digital elevation data with a 30 arc-second spatial resolution, produced by the U.S. National Aeronautics and Space Administration (NASA) and the U.S. National Geospatial-Intelligence Agency (NGA). The original SRTM data were available with a 90 m resolution. The original elevation data contain “no-data” observations where water or heavy shadow prevented the quantification of elevation. These observations were further processed by Jarvis, Reuter, Nelson, and Guevara (2008) to fill in the no-data voids.

Climate data, measured by mean precipitation and mean annual temperature, were generated from WorldClim (Hijmans & et al., 2005). Using MIROC Global Climate Model–AR5 SSP2, we applied rates of change to extrapolate the climate condition for the year 2030. Soil pH was collected from Harmonized World Soil Database (HWSD) (FAO/IIASA/ISRIC/ISS-CAS/JRC, 2012). Conservation practice and indigenous reserves were included as a dummy variable, extracted using Colombian government maps (SINAP (Sistema Nacional de Áreas Protegidas), 2012).

(ii) Data for lower level model

The lower level model combines local agricultural statistics with geo-referenced data. We used a dataset for cropland

physical area at municipality level (in total 1,121 municipalities for the year 2008 (MADR (Ministry of Agriculture & Rural Development), 2011). Based on these data, we identified the five major annual crops in terms of cultivated areas: cassava; maize; potato; rice; and sugarcane, and four major perennial crops: cacao; coffee; oil palm; and plantain.

Domestic commodity producer prices were collected from FAOSTAT for the year 2008. IMPACT projected rates of change for prices were utilized to extrapolate domestic commodity producer prices for the year 2030. The use of country-level commodity prices substantially reduces concerns about endogeneity between municipal crop choices and local producer prices. We assumed that domestic commodity producer prices can be observed at the major markets located in cities with populations greater than 50,000 and that farm-level producer prices move synchronously with domestic prices. With these assumptions, we estimated the spatially explicit prices, pp_{nj} , for each location and each crop using a distance decay function:

$$pp_{nj} = PP_j \times \exp(-access_n / \max_{\{n\}} access_n), \tag{1}$$

where PP_j represents the domestic producer price of commodity j and $access_n$ is travel time from each location n to its nearest major market.²

Data on biophysical suitability were derived from the global Agro-ecological Zones (GAEZ, v1.0) assessment (Fischer, Shah, van Velthuizen, & Nachtergaele, 2001), which was developed by the International Institute for Applied Systems Analysis (IIASA) and the Food and Agriculture Organization of the United Nations (FAO). Suitability data are available at a resolution of approximately 9 km at the equator. These data

were used as a proxy for the maximum attainable yield in Colombia.

(iii) *Crop model*

To estimate GHG emissions from crop production, we employed the biogeochemical model—DeNitrification and DeComposition (DNDC) (Li, Frolking, & Frolking, 1992)—along with coarse-resolution remote sensing data (5 arc-minute grids, approximately 10 km × 10 km) and information about local agricultural practices (Table 3.2). Carbon dioxide (CO₂), methane (CH₄), and nitrous oxide (N₂O) emitted from soil in cropland are all accounted for. Figure 3.4 illustrates key data required to run the DNDC model and Figure 3.5 shows the process followed for the computation of GHG emissions.

The processes embedded in DNDC have been intensively tested in numerous conditions of soils, of climate, and against observed GHG fluxes with results generally considered sufficiently accurate (Beheydt, Boeckx, Sluétel, Li, & van Cleemput, 2007; Cai *et al.*, 2003; Deng *et al.*, 2011; Giltrap, Li, & Sagar, 2010; Grote *et al.*, 2009; Li, 2007; Pathak, Li, & Wassmann, 2005; Werner, Butterbach-Bahl, Haas, Hickler, & Kiese, 2007).

We first identified cropland and mosaic cropland land use areas categorized by National Aeronautics and Space Administration’s Moderate Resolution Imaging Spectroradiometer (MODIS) and further divided them into a 5 arc-minute grid.

For each cell, we applied the DNDC model to estimate crop productivity and GHG emissions. To derive the crop and location-specific data required for simulations in DNDC, information about local cropping systems and nitrogen fertilization rates were obtained through interviews and literature review. Remote sensing data were used to characterize crop calendars (that is, planting and harvesting dates) (Sacks, Deryng, Foley, & Ramankutty, 2010) and soil physical and chemical properties (such as texture, soil organic C (SOC) content, pH, and bulk density) from HWSO (FAO/IIASA/ISRIC/ISS-CAS/JRC, 2012). To derive future weather series corresponding to the MIROC climatic scenario and ensure consistency with the IMPACT scenario, we used climatological data developed by the CGIAR Research Program on Climate Change, Agriculture and Food Security and the MarkSim weather generator accompanied by the data (www.ccafs-climate.org/pattern_scaling). Note that this is an essential step given that GHG emissions and changes in SOC vary with soil types and other location-specific biophysical determinants.

Finally, DNDC simulations were run to make forward projections of GHG emissions from four annual crops (maize, rice, cassava, and potato) and two perennial crops (plantain and oil palm) for the period 2008 to 2030. We assumed current crop management practices and input levels stay constant. Global warming potential (GWP) was computed using fluxes in GHG and changes in SOC content. In order to smooth

Table 3.2. *Dataset used for crop model*

Data	Spatial resolution	Source
Soil texture; soil C; pH; soil bulk density	30 arc sec grid	FAO/IIASA/ISRIC/ISS-CAS/JRC (2012)
Crop calendar	5 arc min grid	Sacks <i>et al.</i> (2010)
Inorganic N rate	Country level	FAO Fertistat (http://www.fao.org/ag/agp/fertistat/index_en.htm)
Tillage rate; residue incorporation rate; irrigation rate; rotation; potential yield (for sugarcane, cassava, potato, palm)	Country level	Agronet.gov.co, fedepapa.co, other local institutions
Precipitation and temperature	5 arc min grid	Marksim weather generator (www.ccafs-climate.org/pattern_scaling)

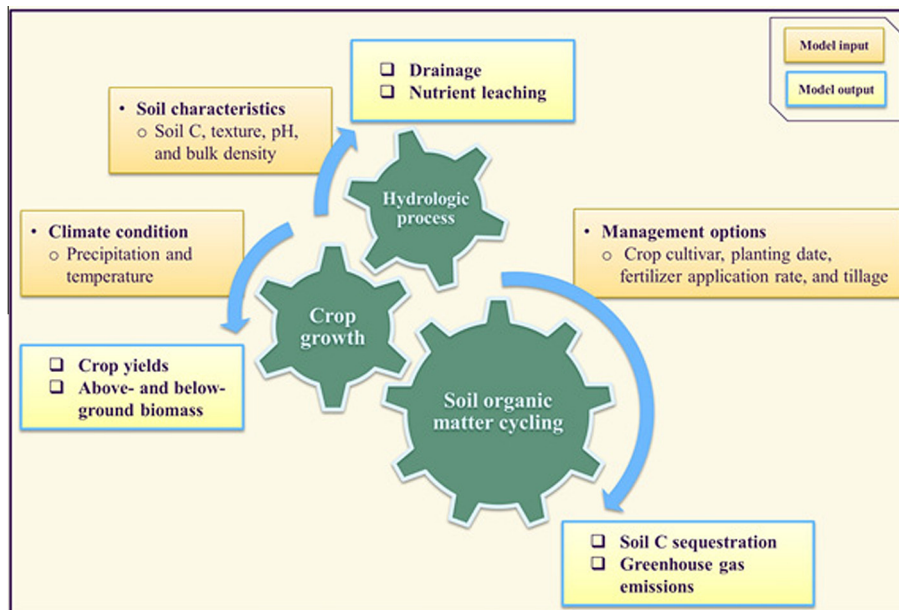


Figure 3.4. *Data requirement for the use of the DNDC model.*

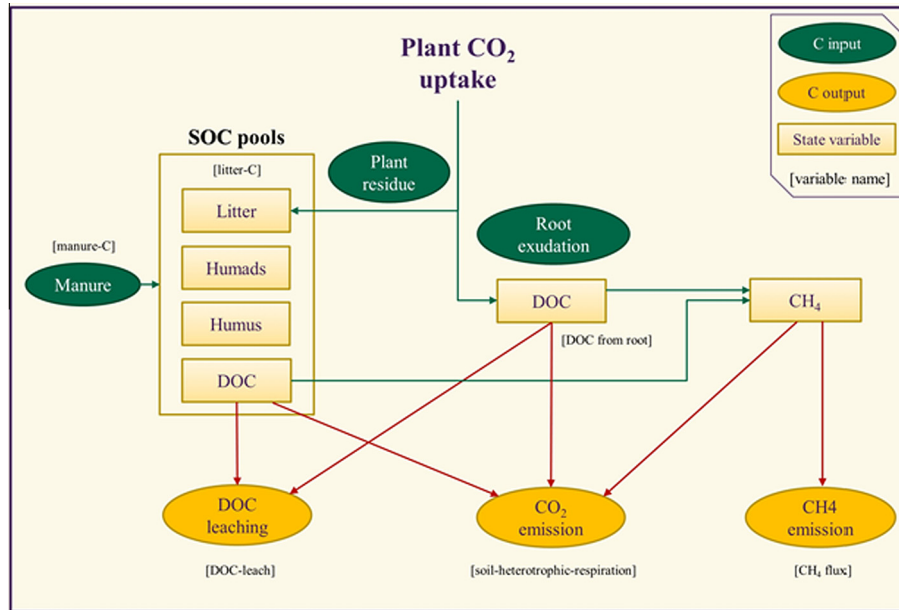


Figure 3.5. Simulation flow of GHG emissions in DNDC model.

out the effects of single weather event fluctuations such as a year with abnormal precipitation or temperatures we computed the average per-hectare GWP for each crop and for each pixel. Given that total emissions were computed by multiplying per-hectare emissions by crop area estimations, changes in total emission reflect only the effect of change in crop allocation decisions.

4. OTHER GHG EMISSIONS AND CARBON STOCK

For the crops that could not be modeled using DNDC (coffee, cacao, and sugarcane), we used emission factors available in the literature (De Figueiredo, Panosso, Romão, & La Scala, 2010; Hergoualc'h, Skiba, Harmand, & Hénault, 2008; Palm *et al.*, 2002). In addition to cropland emissions, we considered GHG emissions from land allocated to pasture such as methane emission from enteric fermentation and manure management, as well as N₂O emissions from manure left on the ground. To generate location-specific estimations, we used national statistics for GHG emissions from livestock (FAO (Food & Agriculture Organization of the United Nations), 2014) and IMPACT values for the country herd size to generate per-head emission estimates.³ Using total herd size and total hectares of pasture, we also estimated the stocking rate and therefore emissions per hectare of pasture. Due to lack of data on GHG emissions from standing forest (e.g., burning and decomposition) and other land uses, we disregard emissions from these sources. Above- and below-ground biomass as well as soil organic carbon (SOC) were the pools of carbon stocks estimated. Changes in stock are estimated in proportion to area changes at the municipality level for each land cover type (Figure 4.1). We assume that for uses other than cropland carbon stock does not change through time if land remains in the same land use.

For the categories of forest; grassland; and other land uses, we used a spatial above-ground biomass dataset (Anaya, Chuvieco, & Palacios-Orueta, 2009; Saatchi *et al.*, 2011) to calculate average biomass for each land use and for each

municipality. According to the country's land cover map (IAvH (Instituto de Investigación de Recursos Biológicos Alexander Von Humboldt) *et al.*, 2007), nearly 50% of "other land uses" category in Colombia consists of shrub and secondary vegetation. Biomass for this land cover category is also taken into account. For the estimation of below-ground biomass, root-shoot ratio for each land cover type is adopted from the available literature (IPCC, 2006; Saatchi *et al.*, 2011). For major perennial crops, we used biomass figures from Dossa, Fernandes, Reid, & Ezui, 2007; Henson, Ruiz, & Romero, 2012; Koskela, Nygren, Berninger, & Luukkanen, 2000. The municipal average SOC per land use type was elaborated using a global SOC dataset (Hiederer & Köchy, 2011), land cover map (IAvH (Instituto de Investigación de Recursos Biológicos Alexander Von Humboldt) *et al.*, 2007), and soil type map (Niels, 2010). Average SOC is calculated by extracting existing combinations of soil type and land cover in each municipality and weighing each combination according to the corresponding area size within the municipality. Table 4.1 provides an overview of all carbon pools and GHG fluxes accounted for in the study.

5. ECONOMIC TRADE-OFFS, BASELINE, AND ALTERNATIVE SCENARIOS

Policies that aim at reducing emissions can generate trade-offs by reducing or increasing area allocated to crops, pasture, or forests or by affecting yields or production costs. Due to lack of data, we did not consider possible changes in input usage and we only account for changes in profits caused by projected changes in yields, prices, and land allocations. Forest economy was not included due to lack of data. Yields and producer prices from national statistics (FAO (Food & Agriculture Organization of the United Nations), 2014) are used for the year 2008 while growth rates for yields and prices from the IMPACT model are used for year 2030.

Figure 5.1 summarizes the methodology used to compare alternative policy scenarios with the baseline. The modeling

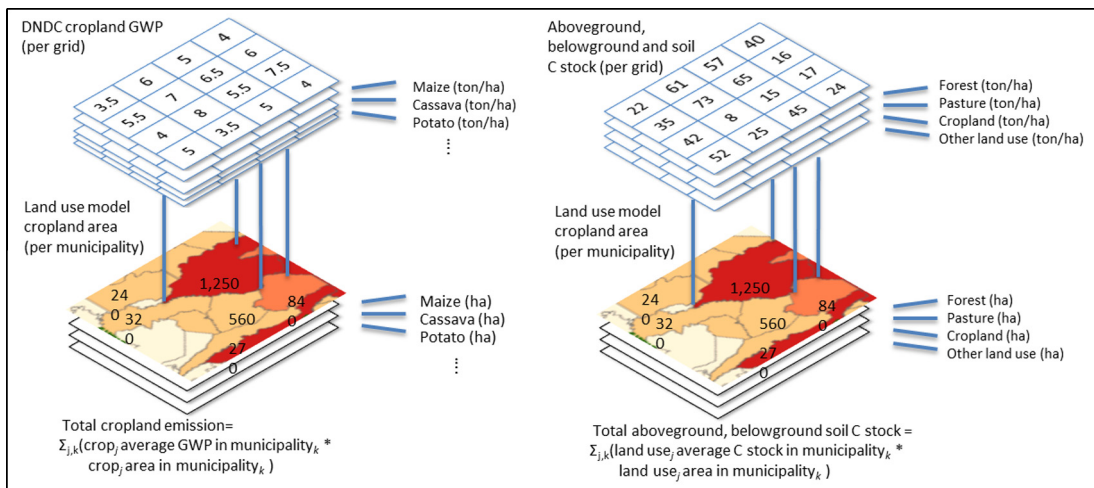


Figure 4.1. Calculation of carbon pools and GHG fluxes.

Table 4.1. Carbon pools and GHG fluxes by land use category

Land use category	Carbon pools			GHG fluxes		
	Aboveground carbon stock	Below-ground carbon stock	Soil organic carbon	CO ₂	N ₂ O	CH ₄
Cropland	YES ^a	YES ^a	YES	YES	YES	YES
Pasture ^c	YES	YES	YES		YES	YES
Forest	YES	YES	YES			
Other land uses	YES ^b	YES ^b	YES			

^a Figures are only for perennial crops.

^b Figures are only for areas with shrub and secondary vegetation.

^c Emissions consider enteric fermentation and manure management.

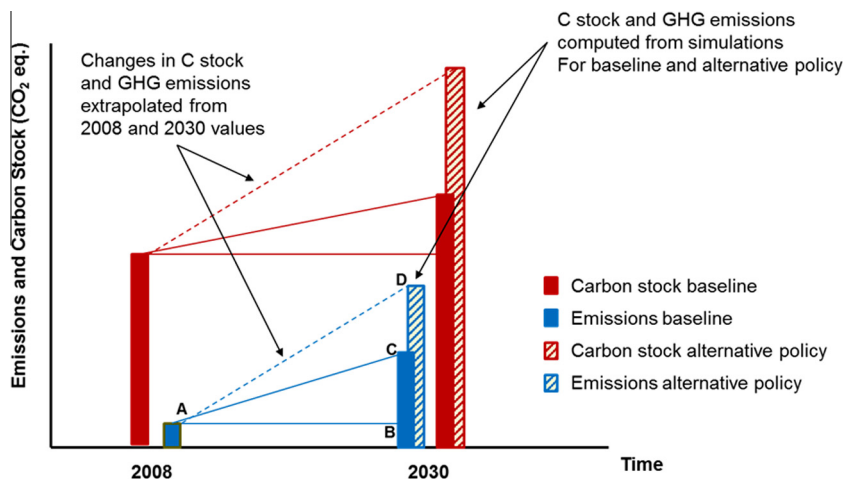


Figure 5.1. Computation of changes in GHG emissions and carbon stock for baseline and alternative policy scenarios.

framework we used for the analysis of low emission development strategies generated estimations and projections for the base year (2008) and the end-period (2030). Therefore, the annual rates of change had to be extrapolated from the starting and ending values. The annual rate of change is essential to compute the total amount of GHG emissions generated under a particular scenario.

The stylized example provided in Figure 5.1 is a case where both GHG emission and carbon stock increase in 2030 compared to 2008. Total change in emissions is obtained by accounting for the yearly changes throughout the time period considered (area triangle ABC). Similarly, the computation of changes in GHG emissions from implementing a particular policy is obtained by measuring the area of triangle ACD. Note

that the effect of each policy is computed against the changes in emissions and carbon stock projected for the baseline.

For the baseline, we assumed that all field activities and agronomic practices stay constant, and therefore our computation of GHG emissions is based only on changes in land use due to changes in commodity prices and other underlying assumptions in IMPACT regarding changes in GDP, population growth, and climatic conditions.

Carbon stocks present in the soil and above- and below-ground biomass in each land use were also assumed constant, thus carbon stock accounting also was based only on land use change. Changes in profits were similarly computed as cumulative effects over the 21 years under consideration.

6. BASELINE RESULTS

IMPACT model results, reported in [Table 6.1](#), indicate that global market forces determine significant increases in area for oil palm, plantain, and sugar cane (7%, 7%, and 25% respectively). These results are dependent on assumed population and GDP growth in Colombia (1.1% per year and 4% per year respectively during the period 2008-2030) but also on assumed global population and GDP growth (1.15% and 3.1%, respectively), technology growth, and changes in diets. For a comprehensive review of how the IMPACT model functions, including IMPACT development over time and an explanation for possible differences among published results, we refer the reader to a more detailed analysis available in [Robinson et al., 2015](#) and for comparison of IMPACT results with other global models to [Nelson et al., 2014](#).

These changes in crop areas were used as an input in the land use model. The land use model was used to spatially allocate changes in cropland projected by IMPACT and to determine how these changes affect carbon stock, GHG fluxes, and profits. The technical details on how the projected changes were used in the land use model are provided in [Appendix 1](#). Given that we relied on the land use model for the spatial allocation of the changes in areas, it was important to evaluate how correctly the model predicts land use choices. We found that the model performed well in predicting most land uses (see [Appendix 1](#) for a detailed assessment). As far as the upper level is concerned, the highest and lowest discrepancies were for pasture, whose share was over-predicted by 4.6% and forest which was under-predicted by 5.7%. Regarding the

lower level component, the model tended to overestimate the share of perennial and annual croplands by a total of 16% and 34%, respectively. We considered this level of accuracy sufficient for the model to capture the effects of the main drivers of land use and that the parameter estimates can be used to make projections regarding future land use choices. In order to further evaluate the robustness of our econometric model, we compared different specifications (two alternatives are explored [Appendix 1](#)). We noted differences in land share predictions but very little difference in the transitions from one use to the other when policy simulations are performed. A change in these transitions could significantly alter the results, but no significant changes are noted.

[Table 6.2](#) reports the results for the upper level of the land use model and shows how changes in agricultural product prices are projected to affect large land use categories. The most significant change is in forested area: a decrease of 4 million hectares, which is an average loss of some 190,000 hectares per year. Most of the change is caused by an increase in pastureland, 3.6 million hectares, and in lower amounts by growth in perennial and annual crop areas.

[Figure 6.1](#) depicts the location of deforestation and pasture expansion at the municipality level. Observing the Amazon region, it appears that pastureland expansion corresponds with the areas where deforestation occurs. A very similar pattern is apparent in the Andes region.

Cropland (the sum of annual and perennial cropland) is projected to increase by a total of 500,000 hectares. [Figure 6.2](#) shows projected change for two of the crops with the largest growth in area. Most of the growth for these two crops occurs outside the Amazon region and appears concentrated in the Andes and Caribbean regions. Among the annual crops considered, sugarcane shows the greatest projected change in area with a gain of 87,000 hectares. Rice and maize areas are projected to increase by some 36,000, and 26,000 hectares respectively. Area allocated to perennial crops is also projected to increase. For example, coffee, oil palm, and plantain areas increase by 12,000, 28,000, and 32,000 hectares respectively.

Projected changes in land use translate into changes in carbon stocks, and these are reported in [Table 6.3](#). The model results show a net decrease in carbon stock, a total of 599 Tg C. This large reduction in the stock of carbon is due mostly to the decrease in forested area.

[Table 6.4](#) reports the estimated changes in GHG emissions from cropland and pastureland. By far, the greatest change

Table 6.1. IMPACT projected changes in prices and areas for crop and livestock commodities, 2008–30

Crop	Projected change in price	Area 2008 (1,000 ha)	Area 2030 (1,000 ha)	Change 2008–30 (1,000 ha)	Change (%)
Cacao	24%	183	189	6	3%
Coffee	30%	812	824	12	1%
Oil Palm	85%	377	405	28	7%
Plantain	34%	473	505	32	7%
Other perennial	31%	181	243	62	34%
Cassava	38%	261	275	14	5%
Maize	39%	835	861	26	3%
Potato	26%	191	201	10	5%
Rice	24%	745	781	36	5%
Sugarcane	107%	346	433	87	25%
Other annual	19%	164	166	2	1%
Cow meat	23%	–	–	–	–
Cow milk	16%	–	–	–	–
Pasture	–	36,157	39,724	3,567	10%

Source: IMPACT 3.1.1.

Table 6.2. *Predicted land use change, 2008–30*

Land use category	2008 area (Mha)	2030 area (Mha)	Change 2008–30 (Mha)	Change (%)
Perennial crops	2.0	2.2	0.2	10
Annual crops	2.5	2.7	0.2	8
Pasture	36.2	39.7	3.5	10
Forest	55.8	51.7	−4.1	−7
Other land uses	17.9	18.1	0.2	1
Total	114.4	114.4		

Note: Both 2008 and 2030 figures are model predictions.

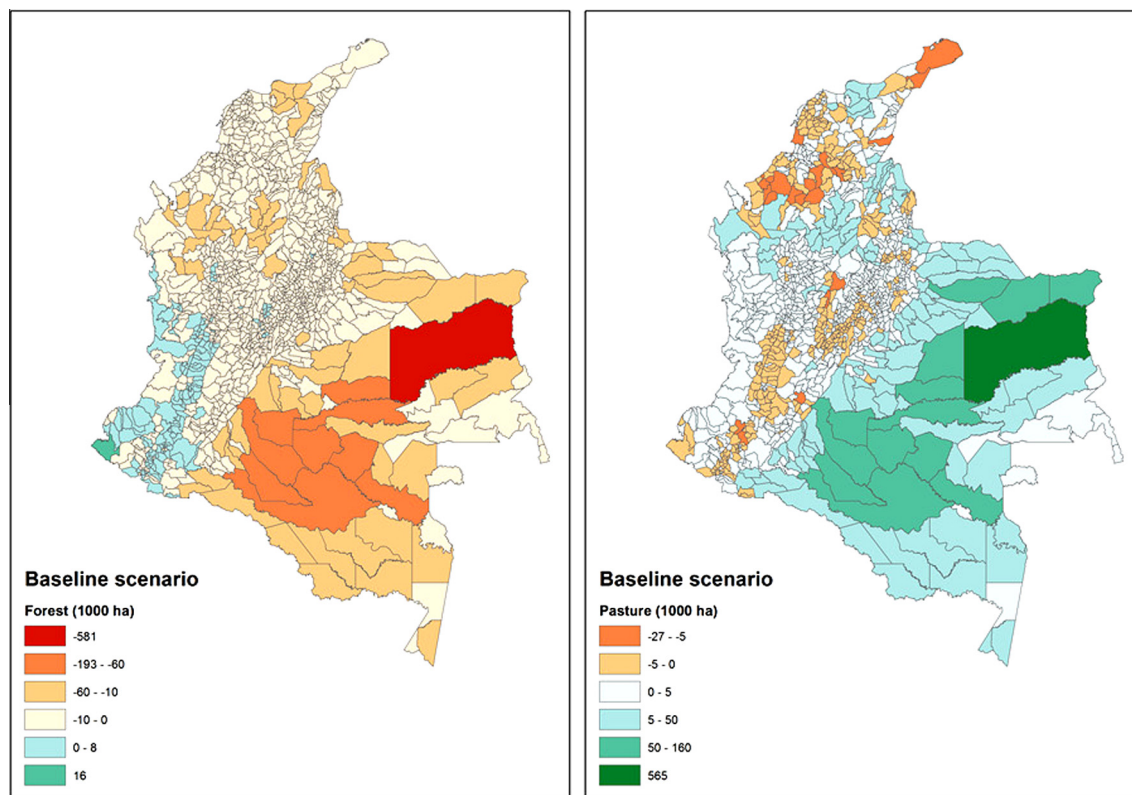


Figure 6.1. *Projected changes in forest and pasture areas at municipality level, 2008–30.*

in emissions is connected to pastureland expansion and rice production. The next significant increase in GHG emissions comes from oil palm and plantain cultivation. This is projected to generate an average yearly increase in emissions equivalent to 12 Tg of CO₂ eq. Note that these changes are driven completely by changes in land use, and we assumed that land management practices, as well as livestock management practices remain unchanged for the entire period considered.

7. POLICY SIMULATIONS

Colombian public and private sectors are actively involved in finding viable strategies for reducing emissions from the agriculture sector and from land use change. A series of meetings were held with the objective of soliciting opinions and ideas on high-priority objectives from government officials, private-sector representatives, producers' organizations, and researchers. Our goal was to internalize in our simulations

the interests and priorities of a wide range of stakeholders interested or involved in the design of low emission strategies. Given that some of the policy targets identified were clearly aspirational, we simulated two stages of accomplishment, (1) scenario in which the target is fully met and (2) scenario in which only half of the target is achieved. It is essential to note that the policies were evaluated with respect to the baseline which represents our best prediction of what the landscape and emissions will be in 2030.

For all scenarios, we evaluated the effects on carbon stock and GHG emissions and the impact on profits. Computing the impact on profits was particularly challenging given the lack of data on production costs. However, we believe that even limited insights into these effects can provide important information to policymakers who need to decide which policies are best to pursue. In order to accomplish this, data needed to be compiled from multiple sources. We used the change in commodity prices projected by IMPACT (Table 6.1) to compute changes in revenues. Data on production costs

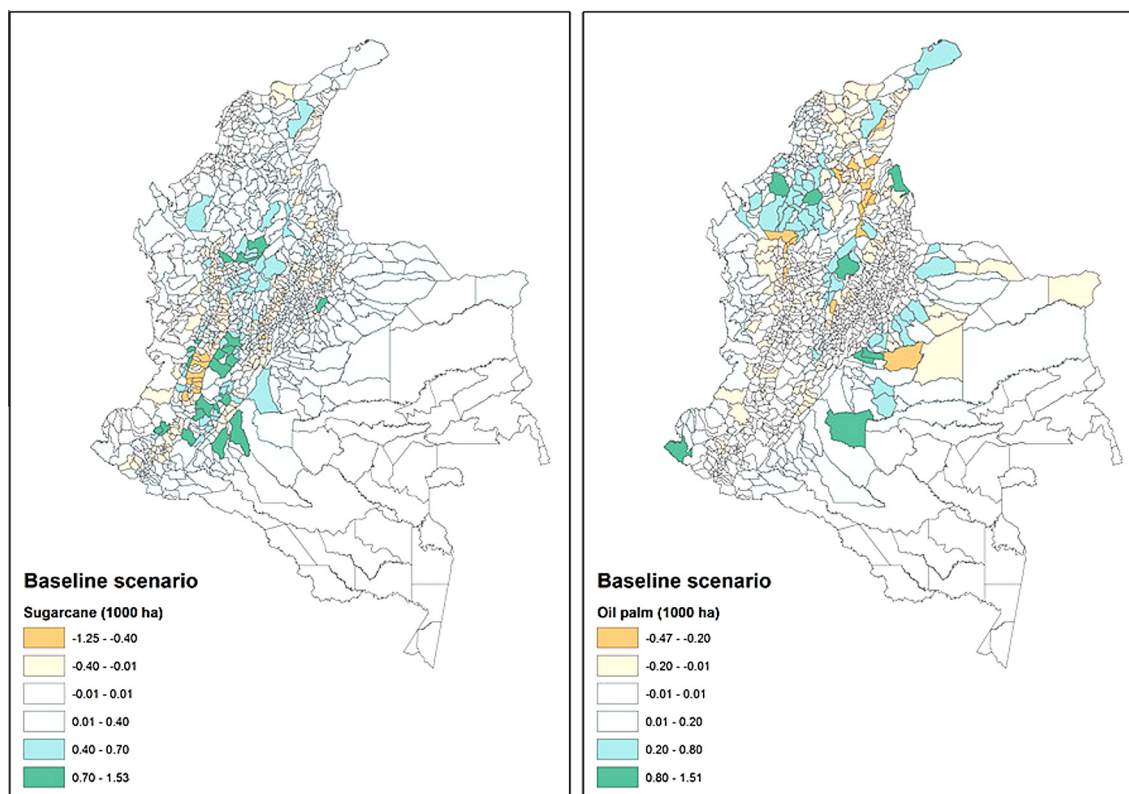


Figure 6.2. Projected changes in sugarcane and oil palm area at municipality level, 2008–30.

Table 6.3. Change in carbon stocks by land use, 2008–30

Land use category	Soil organic carbon 2008 (Tg C)	Above- and below-ground biomass 2008 (Tg C)	Total carbon stock 2008 (Tg C)	Soil organic carbon 2030 (Tg C)	Above- and below-ground biomass 2030 (Tg C)	Total carbon stock 2030 (Tg C)	Net change in carbon stock (Tg C)
Cropland	555	77	632	596	83	679	47
Pasture	4,190	327	4,517	4,604	359	4,963	446
Forest	6,012	9,369	15,381	5,576	8,690	14,266	-1,115
Other land uses	1,986	584	2,570	2,005	590	2,595	25
Total	12,743	10,358	23,101	12,780	9,721	22,501	-600

Table 6.4. GHG emissions in cropland and pasture, 2008–30

Crops	Change in area 2008–30 (1,000 ha)	Average per ha GHG emission in 2008 (Mg ha ⁻¹ yr ⁻¹)	Average per ha GHG emission in 2030 (Mg ha ⁻¹ yr ⁻¹)	Cumulative GHG emission 2008–30 (Tg CO ₂ eq)
Pasture	3,567	1.1	1.1	40.2
Perennial crop				
Cacao	6	0.1 ^a	0.1 ^a	0.4
Coffee	12	0.7 ^a	0.7 ^a	12.6
Oil Palm	28	4.0	3.8	32.8
Plantain	32	3.5	3.0	35.9
Other perennial	62	-	-	-
Annual crop				
Cassava	14	2.0	1.9	11.2
Maize	26	1.7	1.8	30.3
Potato	10	3.5	3.6	14.4
Rice	36	7.2	7.2	115.3
Sugarcane	87	1.7 ^a	1.7 ^a	13.8
Other annual	2	-	-	-

^a Indicates values derived from existing literature.

Table 7.1. *Production costs by crop and region*

Region	Cocoa ^a (\$ ha ⁻¹)	Coffee ^b (\$ ha ⁻¹)	Oil palm ^c (\$ ha ⁻¹)	Plantain ^d (\$ ha ⁻¹)	Other Perennials ^e (\$ ha ⁻¹)	Cassava ^e (\$ ha ⁻¹)	Maize ^f (\$ ha ⁻¹)	Potato ^e (\$ ha ⁻¹)	Rice ^g (\$ ha ⁻¹)	Sugar Cane ^e (\$ ha ⁻¹)	Other Annual ^e (\$ ha ⁻¹)
Carribe	2,101	2,106	2,063	1,103	1,843	870	415	2,373	532	1,429	606
Andena	2,577	1,906	2,158	1,772	2,103	1,402	450	2,743	1,141	1,429	998
Amazon	2,189	1,979	1,811	1,943	1,980	1,136	634	2,383	901	1,429	890
Orinoquia	2,189	1,979	1,529	2,954	2,162	1,136	813	2,383	1,029	1,429	993
Pacific	2,101	1,924	1,492	1,943	1,865	1,136	858	2,031	901	1,429	965

^a Ministerio de Agricultura, Colombia.

^b Corporación Colombiana de Investigación Agropecuaria.

^c Fedepalma, Colombia. USAID.

^d Colombia, Programa MIDAS.

^e Departamento Nacional de Planeación.

^f Industria y Comercio Superintendencia.

^g Fedearroz, Colombia.

related to crop production (Table 7.1) are available relatively well disaggregated by region.⁴ Unfortunately, key costs associated with other policy simulations are much more uncertain. Costs related to improving the quality of pasture were derived from a single study on the issue (Martínez, 2009) and from direct communications with the cattle producers' association (FEDEGAN). Costs of preventing deforestation were extracted from current studies on Nationally Appropriate Mitigation Actions and projects in the Amazon that aim at the valorization of local production compatible with standing forest.⁵ The data obtained, however accurate and sound, represent very limited experiences. Therefore, results will have to be revisited as more data become available.

(a) Pasture

The Colombian livestock sector association, Federación Colombiana de Ganaderos (FEDEGAN), proposed a strategy called "Plan Estratégico de la Ganadería 2019 (PEGA)", which calls for the national cattle herd to reach 48 million heads while reducing pasture area to 24 million hectares (equivalent to a reduction of more than 10-million-hectare in pastureland) by 2019 (FEDEGAN (Federación Colombiana de Ganaderos), 2006). The Ministry of Agriculture, meanwhile, proposes reducing land allocated to pasture to a total of 13 million hectares. FEDEGAN proposes to return the land to natural vegetation by promoting reforestation and silvopastoral systems (FEDEGAN (Federación Colombiana de Ganaderos), 2006). We simulated the effects of a reduction in pastureland of 10 million hectares, as well as a "middle of the road" scenario in which only 5 million hectares are removed from pasture. It is unclear how this objective would be met and what incentives would be put in place to reduce the area. It is only with a certain degree of speculation that the costs associated with achieving this goal can be assessed. The impact on profits of reaching these policy targets was evaluated by assuming that the stocking rate is increased on a portion of pastureland so that the total number of cattle in 2030 remains the same as the one projected in the baseline. On this area, stocking rate was assumed to increase to an average of 0.95 heads per hectare from the current value of 0.64 heads per hectare. This is assumed to be achieved with an improvement of pasture quality and rational use of land. The cost of this type of intervention was estimated to be between \$400 and \$800 per hectare (Caicedo, Escobar, & Tapasco, 2016; FEDEGAN, 2006; Martínez, 2009). We used a mid-point value of \$600 per hectare in our simulations. The area on which improved pasture would have to be implemented is about 3.1 million hectare for the "middle of the road" scenario and 4.3 million hectares to achieve the full target.

(b) Forestry

Prevention of deforestation in the Amazon forest is considered a critical objective for climate change mitigation as well as biodiversity and cultural conservation. Deforestation occurs in other areas besides the Amazon forest according to historical data (Table 2.1) and to our projections (Figure 6.1); however, given its importance, the government puts an emphasis on the Amazon forest. The Colombian Low Carbon Development Strategy proposed by the government has a goal of a complete halt to deforestation in the Amazon region, while lowering the rate of deforestation in the rest of the country.

We simulated two scenarios: a complete stop to deforestation in the Amazon forest and a reduction of deforestation by half. The costs associated with achieving these targets are very uncertain. We relied on data from current studies on Nationally Appropriate Mitigation Actions and projects in the Amazon that aim at halting deforestation (Caicedo *et al.*, 2016). According to their calculations, the costs per hectare vary between \$1,600 and \$2,000. We used a mid-point value of \$1,800 per hectare in our simulations.

(c) Oil palm cultivation

The Colombian government is planning to incentivize the cultivation of strategic crops. The list of strategic crops includes oil palm, sugarcane, and soybeans, the expansion of which has been driven by both biofuel and dietary demands. The expectation is that the majority of the area expansion would occur on pastureland which is widely considered underutilized land. We simulated two policy objectives, (1) an expansion in area allocated to oil palm cultivation by a total of 1.5 million hectares⁶ and (2) a scenario in which 50% of this goal is achieved.

At the time of the consultations with stakeholders, there was no consensus on what instruments would be used to achieve the desired goals. We therefore simulated all the scenarios by altering the benefits deriving from the targeted land use in comparison to alternative uses in the land use model. In essence, we treated the policy instrument as an unobserved factor specific to the targeted land use and assumed that this policy instrument acts homogeneously across all municipalities. We added this factor to the net benefit equation of the targeted land use (Eqn. (2), Appendix 1) to reach a desired number of hectares allocated to that particular land use.

Table 7.2 shows the changes in land use induced by the implementation of these objectives. Table 7.3 shows the effects on carbon stock, GHG emissions, and profits from agricultural production.

Table 7.2. Land use change under alternative policy scenarios

Crop	Policy targets partially met						Policy targets fully met					
	Pasture reduction		Reduce deforestation		Oil Palm expansion		Pasture reduction		Zero deforestation		Oil Palm expansion	
	Area 2030 (1,000 ha)	Difference from baseline 2030 (1,000 ha)	Area 2030 (1,000 ha)	Difference from baseline 2030 (1,000 ha)	Area 2030 (1,000 ha)	Difference from baseline 2030 (1,000 ha)	Area 2030 (1,000 ha)	Difference from baseline 2030 (1,000 ha)	Area 2030 (1,000 ha)	Difference from baseline 2030 (1,000 ha)	Area 2030 (1,000 ha)	Difference from baseline 2030 (1,000 ha)
Perennial crop	<i>2,407</i>	<i>240</i>	<i>2,161</i>	<i>-5</i>	<i>2,238</i>	<i>72</i>	<i>2,667</i>	<i>501</i>	<i>2,156</i>	<i>-10</i>	<i>2,629</i>	<i>463</i>
Cacao	208	20	188	-1	149	-40	229	40	188	-1	92	-97
Coffee	910	86	823	-1	775	-50	1,001	177	822	-3	666	-158
Oil Palm	458	53	404	-1	750	345	518	113	403	-2	1,500	1,095
Plantain	559	54	503	-2	391	-114	616	111	502	-3	266	-239
Other crops	272	29	242	-1	173	-70	303	60	242	-1	104	-139
Annual crop	<i>3,057</i>	<i>340</i>	<i>2,707</i>	<i>-9</i>	<i>2,702</i>	<i>-14</i>	<i>3,438</i>	<i>722</i>	<i>2,699</i>	<i>-18</i>	<i>2,668</i>	<i>-49</i>
Cassava	310	36	273	-2	273	-2	351	76	271	-3	268	-6
Maize	969	108	858	-3	856	-5	1,090	229	854	-7	845	-16
Potato	226	25	201	0	201	0	252	51	201	0	201	0
Rice	890	109	778	-3	775	-7	1,015	234	775	-6	760	-21
Sugarcane	476	44	432	0	432	-1	522	90	432	-1	429	-4
Other crops	185	20	165	0	165	0	207	41	165	0	164	-1
Pasture	<i>34,724</i>	<i>-5,000</i>	<i>38,828</i>	<i>-896</i>	<i>39,599</i>	<i>-125</i>	<i>29,724</i>	<i>-10,000</i>	<i>37,933</i>	<i>-1,792</i>	<i>39,302</i>	<i>-422</i>
Forests	<i>53,996</i>	<i>2,252</i>	<i>52,947</i>	<i>1,203</i>	<i>51,761</i>	<i>17</i>	<i>56,237</i>	<i>4,493</i>	<i>54,151</i>	<i>2,407</i>	<i>51,737</i>	<i>-7</i>
Other land uses	<i>20,257</i>	<i>2,167</i>	<i>17,796</i>	<i>-294</i>	<i>18,140</i>	<i>51</i>	<i>22,374</i>	<i>4,284</i>	<i>17,502</i>	<i>-587</i>	<i>18,105</i>	<i>15</i>
Total	<i>114,440</i>	<i>-</i>	<i>114,440</i>	<i>-</i>	<i>114,440</i>	<i>-</i>	<i>114,440</i>	<i>-</i>	<i>114,440</i>	<i>-</i>	<i>114,440</i>	<i>-</i>

Italics indicate total values for the main land use categories.

Table 7.3. Summary of predicted total changes in carbon stock (C stock), GHG emissions, and profits, 2008–30

		Change in C stock (Tg C)	Total change in GHG emission (Tg CO ₂ eq)	Total change in profits (US\$ billion)
Reduce pasture by 5 million hectares	Cropland	80	16.8	2.0
	Livestock	-625	-56.7	-1.8
	Forest	621	-	-
	Other	311	-	-
	Total	387	-39.9	0.2
Reduce pasture by 10 million hectares	Cropland	168	35.0	4.0
	Livestock	-1,249	-116.0	-2.6
	Forest	1,239	-	-
	Other	614	-	-
	Total	772	-81.0	1.4
Reduce deforestation in the Amazon by 50%	Cropland	-2	-0.4	0.0
	Livestock	-112	-9.9	-0.3
	Forest	332	-	-0.5
	Other	-42	-	-
	Total	176	-10.3	-0.8
Reduce deforestation in the Amazon by 100%	Cropland	-4	-0.8	0.0
	Livestock	-224	-20.0	-0.7
	Forest	664	-	-1.0
	Other	-84	-	-
	Total	352	-20.8	-1.7
Increase area allocated to oil palm by 750,000 hectares	Cropland	10	7.5	-0.6
	Livestock	-16	-1.4	0.0
	Forest	5	-	-
	Other	7	-	-
	Total	6	6.1	-0.6
Increase area allocated to oil palm by 1.5 million hectares	Cropland	35	23.1	-1.3
	Livestock	-43	-4.7	-0.1
	Forest	-2	-	-
	Other	2	-	-
	Total	-8	18.4	-1.4

Note: Effects on profits are expressed in 2008 money and discounted using a yearly discount rate of 8% (A sensitivity analysis to the value of the discount rate was carried out and revealed that qualitatively the outcome of each policy simulation remained unchanged. One exception is the “reduction of pastureland by 5 million hectares” policy target. With a greater discount, the additional profits generated by the increased crop production would not offset the costs of improving pasture productivity, which are mostly upfront costs. A discount rate of 12% would generate a loss in profits of \$0.3 billion causing a tradeoff between reduction in GHG gasses and profits. The implicit cost of abating one ton of CO₂ eq would still be very low: \$0.30. Of course, increasing the discount rate high enough would cause the 10-million-hectares-reduction policy to generate tradeoffs. A discount rate of 18% would reduce the profit gains of this policy to zero.)

(d) *Policy target 1: reduction in area allocated to pasture*

Results of the policy simulations should be interpreted as assessing the changes in land use brought about by a policy that limits expansion and reduces pasture area by a total 10 million hectares compared to the baseline. Baseline results predicted a 3.6-million-hectare expansion to a total of 39.7 million hectares of pastureland, equivalent to a 10% growth during the period 2008–30. As it can be observed in Table 7.2, the effects of a 10-million-hectare reduction in pasture area would cause a growth in cropland (1.2 million hectares), forest (4.5 million hectares), and other land uses (4.2 million hectares). These changes correspond to an estimated increase in carbon stock of some 772 Tg C (Table 7.3). GHG emissions are also affected. Emissions from pastureland and the associated livestock are expected to decrease while emissions from crop production are expected to rise. The net effect would be a reduction of some 81 Tg CO₂ eq. Given our assumptions on how the reduction of pastureland was achieved, reaching this objective would lead to a reduction in profits from cattle raising compared to the baseline, which is estimated to be about \$2.6 billion over the 21 years considered. However, the \$4-billion increase in profits deriving from cropland expansion is expected to compensate for the loss and generate

a net gain of some \$1.4 billion. Of course, higher costs of implementing pasture improvements would change the outcome. A cost of \$721 per hectare would reduce the profit gains to zero and costs higher than that would generate a tradeoff between economic gains and reduction of emissions. The intermediate scenario, 50% achievement of the policy goal, also returns the double benefit of a reduction of emissions and economic gains. Carbon stock is projected to increase by 387 Tg C while in total GHG emissions are reduced by a total of 39.9 Tg CO₂ eq. The expected net change in profits is estimated at \$0.2 billion.

(e) *Policy target 2: reduction in the rate of deforestation in the Amazon forest*

Results for the baseline scenario indicate a decrease in forested area of 4 million hectares during the period 2008–30, equivalent to an annual average loss of some 190,000 hectares. Results also indicate that the loss in carbon stock due to deforestation would be substantial: a total of 1,116 Tg of carbon. The implementation of a policy that stops deforestation in the Amazon would result in an additional 2.4 million hectares of forest compared to the baseline (Table 7.2). However, this would be at the expense of land that would

otherwise transition into pasture and into crop production. The implementation of this policy would result in 1.8 million hectares of pastureland less than the baseline. Considered all together, the changes in land use lead to 352 Tg C of net increase in carbon stock and a total reduction in GHG emissions quantified to be about 21 Tg CO₂ eq. The avoided expansion of pasture and cropland into the forest results in a total loss of \$1.7 billion in profits (Table 7.3). These losses are caused by costs incurred in protecting the forest, costs related to improving pasture quality to increase the stocking rate, and forgone crop production.⁷ The scenario in which we simulate an intermediate achievement of the policy goal (deforestation reduced by half) returns similar trade-offs between mitigation and economic returns. The increase in carbon stock, which amounts to 176 Tg C, and the 10 Tg CO₂eq reduction in cropland and pasture emissions come at the expense of profits which are reduced by about \$0.8 billion. Clearly, this policy generates significant tradeoffs which is not surprising given that it prevents the expansion of land uses that have a direct economic return into forests. However, the gains in carbon stock and reduction of emissions are also significant. In fact, the cost per ton of GHG abated is about \$4.8 per Mg C (\$1.3 Mg CO₂ eq). This is a relatively low cost considering that, despite that estimates for the social cost of carbon vary wildly and might be biased upward (Havranek, Irova, Janda, & Zilberman, 2015), surveys and meta-analyses find values that are in the order of \$43 Mg C (Yohe et al., 2007). Off course, these results are dependent on the recorded costs of preventing deforestation. The greater the costs, the greater the tradeoffs, and in turn the greater the cost of a ton of GHG abated. For example, an increase in the cost of preventing deforestation by 50% would result in a cost per ton of GHG abated of \$6.3 per Mg C.

(f) Policy target 3: increase the area allocated to the cultivation of oil palm

The baseline scenario projects a growth in area allocated to oil palm cultivation of about 28,000 hectares by 2030. In order to reach the policy target of 1.5 million hectares, land allocated to oil palm has to increase by more than 1 million hectares. Our simulation reveals that this policy could have significant unintended consequences if not implemented

judiciously. Model results (Table 7.2) indicate that the expansion of oil palm production occurs at the expense of area allocated to perennial crops causing decreases in plantain area (239,000 hectares), coffee area (158,000 hectares), cacao area (97,000 hectares), and other perennials (139,000 hectares). Similarly, annual crops are negatively affected and total area allocated to them is reduced by a total of 49,000 hectares. Changes in land use result in a decrease in carbon stock of 8 Tg C and an increase in GHG emission of 18.4 Tg CO₂ eq. It is important to note that this policy objective comes with heavy economic costs. This is because, against conventional wisdom, the expansion of oil palm cultivation only partially occurs on pastureland. The net effect of this expansion is a loss in profits equivalent to \$1.4 billion for the period 2008–30.

The intermediate-goal scenario (50% of the policy goal) shows an important difference. While GHG emissions increase and profits decrease, carbon stock increases by 6 Tg C. These results indicate that there might be a role in low emission development for oil palm production but that policymakers ought to be careful to the extent of area expansion and vigilant to the land uses that might be displaced by oil palm production. A higher profit margin in palm production could potentially change results and produce a win-win outcome when area expansion is not too large. However, according to our calculations profits would have to double for this policy (additional 750,000 hectares) to achieve a “win-win” status.

8. DISCUSSION AND CONCLUSIONS

Results reveal the importance of considering the full scope of interactions and changes in the various land uses when planning for GHG reduction policies. As other studies have noted (Burney, Davis, & Lobell, 2010; Gockowski & Sonwa, 2011; Li et al., 2015), the fate of forests matters considerably given that their carbon stock overwhelms potential changes in GHG emissions generated by crop production. Our results indicate that one additional hectare allocated to agriculture increases GHG emissions on average by some 2.5 Mg CO₂ eq per year while one hectare of forest lost in the Amazon results in a loss of carbon stock (above- and below-ground biomass) equivalent to some 367 Mg CO₂ eq. Shifts in land uses determined by changes in area allocated to agricultural

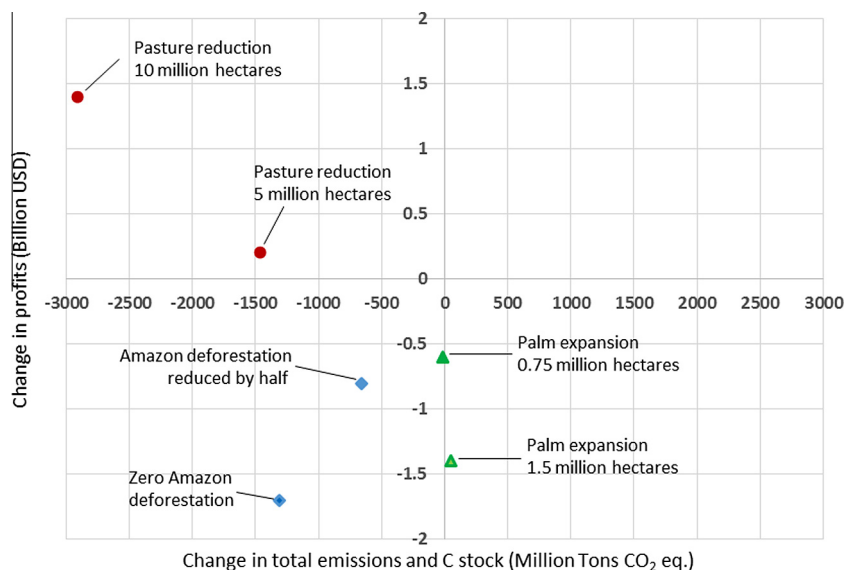


Figure 7.1. Trade-off between profits and GHG emission reduction.

production can have a great effect on the existing carbon stock and these might be of greater importance than the possible changes in GHG emission from crop cultivation. To provide some perspective on the possible contribution of mitigation activities in crop production, we simulated a hypothetical reduction of GHG emissions by 50% across all crops. By the end of 2030, this would generate a total reduction of about 130 Tg CO₂ eq. Our results for the baseline scenario project a total loss of carbon stock equivalent to 2,198 Tg CO₂ eq. Therefore, even a drastic reduction in GHG emissions represents only about 6% of the change in carbon stock induced by land use transitions. This is not to say that reduction of emissions in crop production is not important. Reduction in emissions is generally obtained through an increase in efficiency and as such it represents an important goal. However, results indicate that it is paramount to consider the totality of interactions among the different land uses. [Figure 7.1](#) provides a visual representation of the tradeoffs between profits and GHG emissions across the policies simulated. For comparison purposes, we express changes in carbon stock in CO₂ eq and add them to changes in GHG gasses. This allows us to compare overall performances for the period under consideration. Of course, one needs to keep in mind that changes in carbon stock are a one-time event while changes in emissions are yearly recurrences. “Win-win” policies are those represented in the upper left quadrant of the graph (decreased GHG emissions and increased profits). The policy that targets a reduction of land allocated to pasture performs better than all others and returns significant mitigation and economic gains. It is particularly important to note that, even though reducing pasture in our simulation is equivalent to increasing costs of production to improve carrying capacity, the increment in profits from other agricultural products offsets the loss and generates a net gain. At the same time, it is clear that halting the expansion of pastureland is key to reducing deforestation and loss of carbon stock. The policy that targets deforestation in the Amazon forest is a typical example of a policy that generates trade-offs. The significant gains in terms of carbon stock and reduction in GHG emissions generate projected losses in profits of about \$1.7 billion. Expressed in dollars per ton of GHG abated, these results indicate costs of about \$1.5 per Mg CO₂ eq. However, even if these costs are not prohibitive, this policy ranks relatively low compared to reducing pastureland: the gain in carbon stock is about one-half of what would be achieved with the pasture reduction policy and profits are reduced. This is because a policy

that targets pasture prevents deforestation over the entirety of the country and it induces a more efficient use of land. Therefore, the choice between the two policies becomes an issue of political feasibility and implementation challenges.

Plans that promote an increase in land allocated to oil palm cultivation need to be considered with extreme caution and investigated further. Model results suggest that the past trend of oil palm cultivation taking over underproductive pastureland might not continue into the future. Area expansion beyond certain levels could lead to a detrimental reduction in land allocated to other perennial crops. This is not necessarily because oil palm cultivation replaces, for example, coffee, but because a rather complex chain of land use transitions initiated by oil palm expansion takes place. The model indicates that other important factors besides economic profit might underlie the decision of keeping land in pasture and these might impede the desired land use transition. This suggests that additional research on this issue is warranted and that particular attention should be given to the instruments and incentives that need to be put in place to achieve the desired outcome.

Some additional general considerations can be made. Given the complexity of low emission development strategies, modeling approaches, frameworks, and tools should be adaptable, open, and transparent. Modeling frameworks should be adaptable so that policy makers can explore the consequences of using different data sets and incorporate new information as it becomes available. Modeling frameworks and tools should be open to the inclusion of inputs from different models so that the robustness of the results can be assessed. In the case presented in this article, we have chosen models with which the authors were most familiar. Each one of the models chosen comes with its own set of strengths and weaknesses. For example, the use of a partial equilibrium model like IMPACT limits the scope of the analysis to the agricultural sector, and the use of a parametric model to determine land use choices cannot incorporate land uses that are not already present in the area at the time of the analysis. These limitations become more or less severe according to the specific situation and country analyzed. However, the advantage of the approach proposed is that each one of the models does have alternatives and researchers have the option to replace them or integrate them with other models. We believe that this level of transparency and openness is essential to generate trust in the results among end users.

NOTES

1. IMPACT generates scenarios based on four different Global Circulation Models (GCMs): Hadley, IP SL, MIROC, and GFDL. We work with IMPACT results that use MIROC GCM. While the choice of MIROC is arbitrary, the average difference among IMPACT projections for crop areas and prices for the year 2030 for Colombia using the four GCMs is rather low, about 0.5% (with some larger differences for oil palm and cocoa areas using GFDL: 3% and 2% respectively). MIROC seems to provide a “middle of the road” scenario for Colombia and for the year 2030. It should be noted that while the use of alternative GCMs returns different rates of growth for the prices of the considered agricultural commodities, changes in areas for Colombia are not significantly different across the different GCMs.

2. The specification of distance decay function is arbitrary, but the authors tested other specifications in previous work ([Li et al., 2015](#); [De Pinto & Nelson, 2009](#)) and found this particular one to have some

desirable properties. Specifically, in Eqn. (1) producer price decays at a moderate speed (the spatially explicit price is between $0.368PP_j$ and PP_j), and the price is never zero which corresponds to a subsistence value at all locations.

3. The herd size is computed using IMPACT model’s output on number of slaughtered animals and by assuming a constant ratio of slaughtered animal and herd size.

4. We make the simplifying assumption that the ratio revenue-cost remains constant through time.

5. The Redd Early Mover (REM) Programme active in the Colombian Amazon uses a cost per ton of CO₂ eq reduced by about \$0.8. The average mitigation per hectare is considered to be about 378 tons CO₂ eq. This generates an approximate costs of about \$302 per hectare.

6. The government plans indicate a goal of over three million hectares of oil palm plantations by 2020. However, as other authors have indicated (Castiblanco *et al.*, 2013) it is highly unlikely that this goal will be met. Our IMPACT simulations also indicated that if such an increase in production were to be achieved, world prices would be depressed by about five percent, which makes the goal difficult to attain.

7. It is assumed that primary forest does not generate a revenue stream. Although this is not likely true in all cases, lack of data prevents us from accounting for the contribution of forest products to the overall economy.

8. We choose municipal as the unit of analysis in order to keep the units of upper and lower level models consistent. We apply the coefficient of variation of elevation to control potential heterogeneity within a municipal.

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APPENDIX 1

Conceptual framework of the land use model

Consider how a decision-maker allocates land use in a municipal,⁸ indexed by n ; $n = 1, \dots, N$. Suppose the decision-maker is a risk-neutral landowner; s/he chooses land uses to maximize the present discounted value of the stream of the expected net benefits from the land. The land grid could be allocated to K alternative major uses, indexed by k ; $k = 1, \dots, K$. Among these uses, perennial cropland and annual cropland are two nests of crop, within which the decision maker is allowed to select different crops, indexed by j ; $j = 1, \dots, J_K$. Our data for Colombia include four major perennial crops (cacao, coffee, oil palm, plantain) and five major annual crops (maize, potato, rice, sugarcane, cassava); the remaining crops are lumped into other perennial crops and other annual crops, respectively. Under these simplifying assumptions, the steady-state decision rule that emerges from

Table 10.1. *Summary statistics: lower level model*

	Crop	Unit	N	Min	Max	Mean	STD
Price by crop	Cacao	US \$/kg	1120	1.4057	2.1733	2.1180	0.0861
	Coffee		1120	1.1414	1.7647	1.7198	0.0699
	Palm		1120	0.4734	0.7319	0.7133	0.0290
	Plantain		1120	0.2155	0.3331	0.3247	0.0132
	Othr_perennials		1120	0.2309	0.3570	0.3479	0.0141
	Cassava		1120	0.1378	0.2131	0.2076	0.0084
	Maize		1120	0.1984	0.3067	0.2989	0.0121
	Potato		1120	0.1214	0.1878	0.1830	0.0074
	Rice		1120	0.2001	0.3093	0.3015	0.0122
	Sugarcane		1120	0.0173	0.0268	0.0261	0.0011
	Othr_annuals		1120	0.5257	0.8128	0.7921	0.0322
Production cost by crop	Cacao	Million COP/ha	1120	7.0031	8.5909	8.1235	0.7016
	Coffee		1120	6.3541	7.0185	6.5028	0.2587
	Palm		1120	4.9742	7.1940	6.9251	0.5828
	Plantain		1120	3.6763	9.8456	5.6645	1.2012
	Othr_perennials		1120	5.6850	6.4786	6.2684	0.3018
	Cassava		1120	2.8991	4.6735	4.2299	0.7047
	Maize		1120	1.3837	2.8610	1.5988	0.3573
	Potato		1120	6.7701	9.1446	8.7244	0.6600
	Rice		1120	1.7749	3.8029	3.3360	0.7901
	Sugarcane		1120	4.7644	4.7644	4.7644	0.0000
	Othr_annuals		1120	0.8637	7.4355	1.7311	1.6260
Biophysical suitability by crop	Cacao	0–1	1120	0.0000	0.9969	0.2284	0.2548
	Coffee		1120	0.0000	0.9738	0.3667	0.2543
	Palm		1120	0.0000	1.0000	0.1589	0.2756
	Plantain		1120	0.0000	0.9442	0.3019	0.2719
	Othr_perennials		1120	0.0000	0.8510	0.2169	0.1905
	Cassava		1120	0.0000	0.9455	0.3765	0.3123
	Maize		1120	0.0000	0.9513	0.3136	0.2224
	Potato		1120	0.0000	0.9321	0.1599	0.2048
	Rice		1120	0.0000	1.0000	0.3798	0.3264
	Sugarcane		1120	0.0000	0.9900	0.3106	0.2604
	Othr_annuals		1120	0.0000	1.7468	0.6057	0.3720
Other explanatory variables	Elev	1000 m	1120	0.0032	3.7336	1.3248	0.9953
	Slope_l	Proportion	1120	0.0084	0.8046	0.2166	0.1862
	Slope_m	Proportion	1120	0.0311	0.9793	0.5356	0.2046
	Slope_h	Proportion	1120	0.0311	0.9999	0.8338	0.2366
	Soilph		1120	0.9380	7.6794	3.8496	1.5338
	Rain2010	1000 mm	1120	0.3751	8.0898	2.0661	1.0404
	Temp2010	1 degree	1120	5.8861	28.5597	20.7905	5.5052

the related dynamic optimization problem is to put a land parcel to the use generating the greatest present discounted value of net benefit (Lubowski, Plantinga, & Stavins 2006). That is, allocate a parcel of land to use j if

$$U_{nkj} > U_{nk'j'}, \forall k' \text{ and } j \neq j' \text{ if } k = k' \quad (1)$$

where U_{nkj} is the one-period expected net benefit from allocating land parcel to use j ($j \in k$). The potential value of U_{nkj} depends on attributes of the parcel, such as land quality, weather conditions, locational characteristics, and economic conditions in the surrounding area, as well as attributes associated with alternative choices, such as price and yield (see Tables 10.1 and 10.2).

A standard practice in the land use modeling literature is to decompose U_{nkj} into a deterministic component \bar{U}_{nkj} and a random error term ε_{nkj} . \bar{U}_{nkj} represents the expected average net benefit from allocating land use in a grid; ε_{nkj} represents the deviation from the average net benefit and is often assumed to follow a normal, logit, or type-I extreme value distribution. We further decompose \bar{U}_{nkj} into two deterministic components:

$$\bar{U}_{nkj} = X_{nk} + Y_{nkj}. \quad (2)$$

X_{nk} depends on variables that describe the nest k ; it differs over nests but not over alternatives within each nest. Y_{nkj} depends on variables that describe nested use j ($j \in k$); it varies over choices within the nest.

Under the assumption analogous to the nested logit model about ε_{nkj} , for example, that ε_{nkj} is correlated within nest k but uncorrelated across nests, the probability of grid n allocated to alternative j ($j \in k$) can be derived as a product of two multinomial logit probabilities (McFadden 1977; Train 2003):

$$P_{nk} = \frac{\exp(X_{nk} + \lambda_k I_{nk})}{\sum_{k'=1}^K \exp(X_{nk'} + \lambda_{k'} I_{nk'})}, \quad (3)$$

and

$$P_{nkj|k} = \frac{\exp(Y_{nkj}/\lambda_k)}{\sum_{j' \in k} \exp(Y_{nkj'}/\lambda_k)}, \quad (4)$$

where the parameter λ_k is a measure of the degree of independence in ε_{nkj} among the alternatives in each nest and $I_{nk} = \ln(\sum_{j' \in k} \exp(Y_{nkj'}/\lambda_k))$, often called inclusive value of nest k . A higher value of λ_k implies less correlation and $\lambda_k = 1$ indicates complete independence.

Eqn. (3) defines marginal probability of choosing any alternative in nest k and Eqn. (4) defines conditional probability of choosing alternative j given that any alternative in nest k is chosen. We refer to the marginal probability as an upper level model and to the conditional probability as a lower level model, reflecting their relative positions in the hierarchy structure. In Eqn. (4), λ_k is treated as a scale parameter that scales coefficient parameters implicitly defined in Y_{nkj} . For those nests where there are no alternative choices inside, the conditional probability given in (4) equals 1 and the inclusive value is reduced to $I_{nk} = Y_{nkj}/\lambda_k$. Insert I_{nk} into (3) and λ_k will be canceled. Probabilities (3) and (4) are fundamental equations in the nested logit model.

Land use model specification

The average expected net benefits from allocating every grid n to nest k , X_{nk} , is specified as $X_{nk} = x_n \beta_k$, where x_n is a vector of location-specific variables describing population density, market accessibility, conservation practice, topography, soil pH level, and weather conditions; β_k is vector of coefficients on x_n . Within any nest k , the average expected net benefits from allocating each location n to alternative j , Y_{nkj} , is specified as $Y_{nkj} = y_{nj} \gamma_{kj}$, where y_{nj} is a vector of crop-specific variables, including the crop prices, production costs, land suitability, topography, soil pH level, and weather conditions, and an inertia variable (a lagged crop share) that captures land use conversion costs; γ_{kj} is a vector of coefficient parameters specific to crop.

Note that if the choice-specific variables perfectly captured the average expected net revenues for each crop at the level of the individual grid, then γ_{kj} should simply reflect the marginal net benefit and would not be expected to differ over crops. We allow this parameter varying across crops in our specification because both crop-specific variables are originally measured at relatively coarse resolutions and hence cannot perfectly capture the average expected net benefits for each

Table 10.2. Summary statistics: upper level model

	Crop		N	Min	Max	Mean	STD
Lagged land use share (explanatory variable)	Perennials	Proportion	1120	0.0000	0.0949	0.0244	0.0210
	Annuals		1120	0.0000	0.2974	0.0371	0.0372
	Pasture		1120	0.0000	0.9733	0.2497	0.2455
	Forest		1120	0.0000	0.9971	0.2540	0.2232
	Others		1120	0.0029	0.9479	0.4348	0.1756
Other explanatory variables	Production cost for pastureland	Million COP/tonne	1120	1.367	2.0910	1.7021	0.2034
	Pop. Density	1000 people/ha	1120	0	7.3498	0.1381	0.4761
	Access	1000 minutes	1120	0.0024	6.0203	0.3720	0.6302
	Elevation	1000 m	1120	0.0032	3.7336	1.3248	0.9953
	Elevation_cv		1120	0.0018	2.2420	0.3850	0.3425
	Slope	Proportion	1120	0.0084	0.8046	0.2166	0.1862
	Soil ph		1120	0.9380	7.6794	3.8496	1.5338
	Rain	1000 mm	1120	0.3751	8.0898	2.0661	1.0404
	Temp	1 degree	1120	5.8861	28.5597	20.7905	5.5052
	Park	Proportion	1120	0.0000	0.8635	0.0304	0.1002
	Afrodese	Proportion	1120	0.0000	0.9920	0.0281	0.1397
	Meat	US \$/kg	1120	1.8269	2.8246	2.7528	0.1118
	Timber	1000 USD/ha	1120	0.0040	0.8513	0.2239	0.2788

crop at each location. To eliminate λ_k from the lower level model, we introduce $\tilde{\gamma}_{kj}$ by dividing γ_{kj} by λ_k such that $\tilde{\gamma}_{kj} = \gamma_{kj}/\lambda_k$. This scaling facilitates the estimation.

We estimate the model in a “bottom-up” sequential fashion, starting from the estimation of the lower level model and using the estimated coefficients to calculate the inclusive values, which enter the upper level model as explanatory variables. This approach exploits the fact that the choice probabilities can be decomposed into marginal and conditional probabilities that are logit functions.

Crop allocation based on IMPACT baseline projection

Assumption:

- (1) The growth rate of crop area between the base year and the projected year is consistent with that generated from IMPACT baseline projection.
- (2) The specification of the nested land use model is correct; the parameter estimates of the land use model are consistent.

Allocating projected crop area based on the nested land use model

Let n be municipal index, j be crop index, and t be time period index. At the base year $t = 0$, share of crop j can be expressed as

$$H_{nj0} \equiv (1 + \varepsilon_{nj0})P_{nj0}, \tag{5}$$

where P_{nj0} is the estimated crop probability from land use model and ε_{nj0} is the error between the agricultural census (H) and the land use model estimation (P). Rearranging Eqn. (9), we have

$$\varepsilon_{nj0} \equiv \frac{H_{nj0}}{P_{nj0}} - 1. \tag{6}$$

Hence, for any n , the adjusted share of crop j is

$$\tilde{P}_{ij0} \equiv H_{nj0} \tag{7}$$

Let’s now turn to the projected year $t = 1$. Let g_j be the growth rate of crop area between time 0 and 1, derived from IMPACT baseline projection. Then the area of crop j at time 1 can be extrapolated as

$$H_{nj1} \equiv (1 + g_j)H_{nj0}, \tag{8}$$

and

$$H_{nj1} \equiv (1 + \varepsilon_{nj1})P_{nj1}. \tag{9}$$

Rearranging Eqn. (13), we have

$$\varepsilon_{nj1} \equiv \frac{H_{nj1}}{P_{nj1}} - 1 = \frac{(1 + g_j)H_{nj0}}{P_{nj1}} - 1. \tag{10}$$

For any municipal, the adjusted share of crop j at time 1 is

$$\tilde{P}_{nj1} \equiv (1 + \varepsilon_{nj1})P_{nj1} = \frac{(1 + g_j)H_{nj0}}{P_{nj1}} \times P_{nj1} = (1 + g_j)H_{nj0} \tag{11}$$

Table 10.3. Assessment of the predictive power of the upper level model

Land	Observed		Predicted		Deviation from the observed area		Deviation from the observed shares	
	Mha	Share	Mha	Share	Mha	Percent	Mean	Median
Perennial cropland	1.7	5%	2.0	5%	0.28	16.1%	0%	2%
Annual cropland	1.9	6%	2.5	6%	0.61	31.4%	0%	1%
Pasture	34.6	43%	36.2	43%	1.59	4.6%	0%	0%
Forests	59.1	21%	55.8	21%	-3.34	-5.7%	0%	2%
Other land uses	17.1	26%	17.9	26%	0.87	5.1%	0%	0%

Source: Authors.

Table 10.4. Assessment of the predictive power of the lower level model

Crop	Observed		Predicted		Deviation from the observed area		Deviation from the observed shares	
	1000 Ha	Percent	1000 Ha	Percent	1000 Ha	Percent	Mean	Median
<i>Perennial crop</i>								
Cacao	115	6%	183	7%	68.4	59.7%	1%	2%
Coffee	770	41%	812	44%	42.1	5.5%	3%	1%
Palm	262	6%	377	16%	114.5	43.6%	9%	1%
Plantain	437	26%	473	23%	35.9	8.2%	-4%	5%
Other perennial crops	160	20%	181	10%	21.3	13.3%	-10%	2%
<i>Annual crop</i>								
Cassava	183	12%	261	8%	77.4	42.3%	-4%	1%
Maize	592	34%	835	30%	243.0	41.0%	-4%	1%
Potato	150	11%	191	13%	40.7	27.1%	1%	0%
Rice	505	10%	745	16%	239.8	47.5%	7%	3%
Sugarcane	371	20%	346	23%	-25.7	-6.9%	4%	3%
Other annual crops	137	14%	164	10%	27.1	19.8%	-4%	1%

Source: Authors.

Table 10.5. *Robustness check of land use prediction in thousand hectares for the year 2008*

	Observed area (1)	Spatial price: exponential decay		Flat price		Spatial price: linear decay	
		Area (2)	Deviation from (1) (3)	Area (4)	Deviation from (1) (5)	Area (6)	Deviation from (1) (7)
<i>Perennial crop</i>	1744	2026	16%	1355	-22%	2024	16%
Cacao	115	183	60%	126	10%	158	38%
Coffee	770	812	5%	537	-30%	859	12%
Palm	262	377	44%	248	-5%	375	43%
Plantain	437	473	8%	321	-27%	453	4%
Other crops	160	181	13%	123	-23%	179	12%
<i>Annual crop</i>	1939	2541	31%	2325	20%	2544	31%
Cassava	183	261	42%	238	30%	257	40%
Maize	592	835	41%	765	29%	837	41%
Potato	150	191	27%	171	14%	191	27%
Rice	505	745	47%	681	35%	751	49%
Sugarcane	371	346	-7%	319	-14%	346	-7%
Other crops	137	164	20%	152	11%	161	18%
<i>Pasture</i>	34568	36157	5%	37560	9%	36160	5%
<i>Forests</i>	59134	55790	-6%	55273	-7%	55790	-6%
<i>Other lands</i>	17054	17925	5%	17926	5%	17923	5%
<i>Total</i>	114440	114440	-	114440	-	114440	-

Source: Authors.

Table 10.6. *Robustness check of land use projection in thousand hectares for the year 2030*

	Spatial price: exponential decay		Flat price		Spatial price: linear decay	
	Area (1)	Area (2)	Area (2)	Deviation from (1) (3)	Area (4)	Deviation from (1) (5)
<i>Perennial crop</i>	2166	1449	1449	-33%	2161	-0.3%
Cacao	189	130	130	-31%	163	-13%
Coffee	824	545	545	-34%	872	5.7%
Palm	405	266	266	-34%	403	-0.5%
Plantain	505	343	343	-32%	483	-4.3%
Other crops	243	165	165	-32%	239	-1.5%
<i>Annual crop</i>	2716	2486	2486	-8%	2719	0.1%
Cassava	275	251	251	-9%	270	-1.5%
Maize	861	789	789	-8%	863	0.3%
Potato	201	180	180	-11%	202	0.2%
Rice	781	714	714	-9%	788	0.8%
Sugarcane	433	400	400	-8%	433	-0.02%
Other crops	166	153	153	-8%	163	-1.5%
<i>Pasture</i>	39724	41252	41252	3.8%	39715	-0.02%
<i>Forests</i>	51744	51150	51150	-1.1%	51759	0.03%
<i>Other lands</i>	18090	18103	18103	0.07%	18087	-0.01%
<i>Total</i>	114440	114440	114440	-	114440	-

Source: Authors.

Therefore, changes in crop share at municipal can be derived as

$$\tilde{P}_{ij1} - \tilde{P}_{ij0} = (1 + g_j)H_{nj0} - H_{nj0} = g_j H_{nj0} \quad (12)$$

Land use model performance assessment

Tables 10.3 and 10.4 present an assessment of the predictive power of the upper and lower levels of the land use model,

respectively. In each table, columns 1 and 2 correspond to the observed land use derived from the data sample; columns 3 and 4 correspond to the predicted land use estimated from the land use model; columns 5 and 6 present the discrepancies by subtracting entries in columns 1 and 2 from entries in columns 3 and 4. We find that the model performs well in predicting most land uses. As far as the upper level is concerned, the model provides generally accurate in-sample predictions. The highest and lowest discrepancies, expressed in percentage

terms, are -0.2% for perennial cropland and -2.3% for forests. Regarding the lower level component, the model tends to overestimate perennial and annual croplands by a total of 0.2% and 0.4% , respectively. These discrepancies arise mainly from overestimating areas allocated to oil palm, cacao, maize, and rice. Even so, the predicted errors of these four crops in terms of percentage are in a reasonable range, from 2.3% to 3.2% . The model performs well in the prediction of the remaining crops in terms of both magnitude and percentage.

Robustness check of the specification of spatially explicit price in the land use model

The major assumption made in the land use model is the functional form of spatially explicit prices with exponential decay assumed in Eqn. (1) on page 11. As a robustness check, we considered two alternative specifications—original country-level “flat prices” and spatial prices with linear decay. With the specification of flat prices, all prices are equal across the country; with the specification of linear decay, prices decline more sharply than the specification of exponential decay as the distance from major markets located in cities increases.

We compared the prediction accuracy of the three models, presenting the results in Table 10.5, Appendix 1. A comparison between the flat-price and the spatial-price specifications indicates (1) both specifications tend to under-predict forested area and over-predict the area of annual cropland, pastureland, and other lands; (2) the models with spatial-price specifications generate smaller prediction errors in both pasture and forestland, two dominant land types in Colombia; (3) the models with flat-price and the spatial-price specifications generate prediction errors in perennial cropland in opposite directions, but the prediction errors generated by the spatial price models are smaller. The balance of evidence, and log-likelihood ratio, suggests the spatial-price specifications perform better than the flat-price specification.

We also compared the projected areas of land use among the three models for the end-period year (2030), presenting the results in Table 10.6. The comparison indicates that the two spatial-price models yield similar results. Given the fact that the exponential distance decay function allows crop prices to decay at a moderate speed and ensures a positive value at every location, this paper uses the functional form of exponential decay for the analysis.

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