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An Amazon Tipping Point: The Economic and Environmental Fallout

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Abstract
The Amazon biome, despite its resilience, is being pushed by unsustainable economic drivers towards an ecological tipping point where restoration to its previous state may no longer possible. This is the result of self-reinforcing interactions between deforestation, climate change and fire. In this paper, we develop scenarios that represent movement towards an Amazon tipping point and strategies to avert one. We assess the economic, natural capital and ecosystem services impacts of these scenarios using the Integrated Economic-Environmental Modeling (IEEM) Platform linked with high resolution spatial land use land cover change and ecosystem services modeling (IEEM+ESM). This paper's main contributions are developing: (i) a framework for evaluating strategies to avert an Amazon tipping point based on their relative costs, benefits and trade-offs, and; (ii) a first approximation of the economic, natural capital and ecosystem services impacts of movement towards an Amazon tipping point, and evidence to build the economic case for strategies to avert it. We find that a conservative estimate of the cumulative regional cost through 2050 of an Amazon tipping point would be US$256.6 billion in Gross Domestic Product. Policies that would contribute to averting a tipping point, including strongly reducing deforestation, investing in climate-adapted agriculture, and improving fire management, would generate approximately US$339.3 billion in additional wealth. From a public investment perspective, the returns to implementing strategies for averting a tipping point would be US$29.5 billion. Quantifying the costs, benefits and trade-offs of policies to avert a tipping point in a transparent and replicable manner can pave the way for evidence-based approaches to support policy action focusing on the design of regional strategies for the Amazon biome and catalyze global cooperation and financing to enable their implementation.

1.0 Introduction

There is a broad body of literature, extending back to at least 1991, outlining the mechanisms by which climate change, driven by the combination of deforestation and greenhouse gas accumulation in the atmosphere, could cause a significant portion of the Amazon biome to shift from broadleaf evergreen forests to drought-deciduous or degraded, savanna-like environments (Aragão et al., 2008; Malhi et al., 2009; Nobre et al., 1991). This paper evaluates the economic, natural capital and ecosystem service costs of continuing to move towards a tipping point in the Amazon, as well as the contribution of strategies to avert a one. In quantifying the impacts of movement towards a tipping point, our study focuses on continued deforestation and the climate risk to agricultural production stemming from increased water stress, increased intensity and frequency of droughts, and increased forest fires. Climate change and deforestation are changing the composition of Amazon forests (Esquivel-Muelbert et al., 2019) and affecting regional and local hydrological cycles, pushing the region toward drier conditions and leading to degradation of tropical forest ecosystems. The impacts of these phenomena are multi-scalar, with local, regional and global impacts (Lovejoy and Nobre, 2019).

Deforestation by itself can significantly reduce rainfall and lengthen the dry season by reducing the net energy and water vapor available for rainfall formation. The hydrological cycle of the Amazon depends on transpiration from the forest where as much as 75% of precipitation is returned to the air through evapotranspiration and once again recycled as precipitation. Deforestation and fire disrupt this cycle by reducing net surface radiation and evapotranspiration (Silvério et al., 2015), increasing rainfall runoff and land surface temperature, and ultimately decreasing rainfall (Butt et al., 2020; D'Almeida et al., 2007; Leite-Filho et al., 2020; Silvério et al., 2015; Wright et al., 2017). This has impacts for national and regional economies, particularly given heavy reliance on rainfed agriculture and South America's role as a primary exporter of agricultural commodities.

As the disruption of the hydrological cycle reduces moisture availability both for natural and cultivated plants, the regional ecosystems shift toward plant communities that are more drought tolerant and characteristic of a tropical savannah. This tendency towards savannization is evidenced in the eastern and south western Amazon. Savannization (Brando et al., 2019; Trumbore et al., 2015) is accelerated by climate change which is already reducing rainfall, increasing temperatures, increasing drought frequency and intensity, and increasing forest fires (Brando et al., 2020a; Lovejoy and Nobre, 2019; Nobre et al., 2016; Silvério et al., 2013). With more frequent anthropogenic fires, the likelihood of forest dieback increases considerably (Brando et al., 2014a).

Together the feedbacks between continued deforestation and climate could lead to a tipping point beyond which large areas of the Amazon no longer have sufficient rainfall to support broadleaf evergreen forests (Aragão et al., 2008; Malhi et al., 2009; Nepstad et al., 2007). Several studies have investigated the deforestation threshold that would cause a tipping point in the Amazon basin. Some authors view the tipping point to be imminent (Lovejoy and Nobre, 2019), while others have estimated that deforestation of 40% or more would push the Amazon past a tipping point (Nepstad et al., 2008; Sampaio et al., 2007; Walker et al., 2009). Therefore, the consensus is that at some amount of deforestation, a tipping point will be reached and that it will be reached earlier with greenhouse gas-driven climate change. Given this uncertainty, our study focuses on movement towards a tipping point and strategies that can delay and potentially avert one.

A tipping point for the Amazon would mean irreparable damage to the structure and function of this locally and globally important biome. This would include losses of biodiversity and critical material ecosystem services (IPBES, 2019) like agricultural production, forest product output and water supply, and; non-material ecosystem services including carbon storage, and nutrient and soil retention. With a reduction in natural capital stocks and ecosystem services which are the benefits people derive from nature (Daily, 1997), inter-generational wealth and well-being would be affected dramatically. This would be felt most acutely by indigenous populations that have for centuries sustained their livelihoods in harmony with the Amazon biome.

Over the last seven decades, the human occupation and the arc of deforestation in Brazil have been advancing, from the southern extent of the Amazon biome towards its center (Valentim, 2015; Valentim and Vosti, 2005). Over this period, close to 20% of the Amazon biome has been converted to other land uses (Smith et al., 2020) and at least 17% of the remaining forest has been disturbed since 1995 (Bullock et al. 2020). Economic growth, regional inequality and the environmental dynamics of rainforest frontiers are determinants of the intensity of migration flows in the region (Sathler et al., 2019; Schielein and Börner, 2018). The complex interactions between socio-economic and environmental systems that feedback and drive changes in land use in the Brazilian Amazon are at the center of the debate on sustainable development and are the focus of the attention of researchers, policy makers, businesses and civil society at local, national and international levels (Betts et al., 2008; Chambwera et al., 2014; Saatchi et al., 2012). Recent studies seek to associate environmental and socioeconomic variables at multiple scales as a more robust analytical strategy of the complex development processes of the Amazon biome (Cortner et al., 2019; Garrett et al., 2017; Meyfroidt et al., 2018).

Given the uncertainty in when a tipping point could be reached and the dire consequences of crossing one, strong sustainability dictates that urgent action is required to restore balance to the Amazon. Sustainable intensification of agriculture and cattle production systems in already deforested areas (Strassburg et al., 2014), and extensive economic reforestation of characteristically low productivity or abandoned pastures and fields are among the most promising measures (Lovejoy and Nobre, 2019). Adopted on a large landscape scale, these measures represent important innovation and nature-based solutions capable of effectively reconciling inclusive socioeconomic growth while reducing deforestation pressures and stabilizing not only the local hydrological system, but also contributing substantially to mitigate global climate change (Griscom et al., 2017). Other measures include enhancing conservation efforts, introducing more productive silvopastoral and agroforestry systems (Porro et al., 2012), strengthening forest-based livelihoods (Schmink, 2011), and developing strong local bioeconomies (Nobre and Nobre, 2018). While there is a growing literature on the potential ecological implications of an Amazon tipping point, the economic costs and trade-offs between strategies to avert a tipping point are not well understood.

This study fills this important gap by assessing the economic impacts of approaching an Amazon tipping point and strategies that can still be implemented to avert one. Our assessment goes beyond a conventional benefit-cost approach by developing and applying the Integrated Economic-Environmental Modeling (IEEM) Platform to countries of the region. We link IEEM with spatial Ecosystem Services Modeling (IEEM+ESM) to capture a broader set of impacts, from impacts on economies and society, to changes in the underpinning natural capital stocks and flows of ecosystem services (Banerjee et al., 2020a). We focus on the most economically important countries of the Amazon biome for which reliable economic and environmental data exists, namely Brazil, Peru, Colombia, Bolivia, and Ecuador.

In our modeling, we take a scenario analysis approach. We first develop a baseline projection of economic development and land use for the region from 2020 to 2050. This baseline reference scenario is an artificial modeling artifact developed to estimate the impacts of approaching an Amazon tipping point. To this reference scenario, we consider three main dimensions of a tipping point: (i) climate change impacts in inducing water stress; (ii) increasing frequency and intensity of drought, and; (iii) increasing fire. Upon this future trajectory for the region, which may be considered the business-as-usual scenario, we implement policy action aimed at averting a tipping point. This policy intervention begins with concerted regional efforts to strongly reduce deforestation over the next 10 years. There are various strategies through which this may be achieved which can include improved monitoring and enforcement of existing laws as well as by introducing more sustainable productive practices, such as: intensive cattle production systems based on mixed grass-legume pastures (Zu Ermgassen et al., 2018), integrated crop-livestock systems (Gil et al., 2018), establishing silvopastoral and agroforestry systems in already deforested and degraded areas (Porro et al., 2012), sustainable forest management systems, and payment for ecosystem services (Valentim, 2015). Experience in Brazil over the last 15 years has generated numerous lessons that can be applied in the region to slow deforestation (Ardila et al., 2021; Banerjee et al., 2009; Banerjee and Alavalapati, 2010). In addition to strongly reducing deforestation, the policy intervention scenario includes a reduction in anthropogenic fire and investment in climate adapted agricultural systems including irrigation.

We estimate the effect of our scenarios on standard economic indicators such as Gross Domestic Product (GDP), trade, income and employment, as well as robust indicators of economic development that include metrics of well-being and wealth (Arrow et al., 2004, 2012; Dasgupta, 2021; Dasgupta and Ehrlich, 2013; Polasky et al., 2015; Stiglitz et al., 2010, 2009). In addition, we estimate effects on natural capital stocks and ecosystem service supply, specifically: carbon storage, nutrient and sediment retention and water supply, as well as biodiversity which is the foundation of healthy and resilient ecosystem function. Estimates of the effects of our policy scenarios on economic indicators, natural capital stocks and ecosystem service supply are compared with the tipping point scenario to determine the net effect of a more sustainable vision for the Amazon.

The section that follows provides a brief overview of the IEEM+ESM methodological approach. Section 3 presents the key elements of the Amazon tipping point and policy scenarios. Section 4 provides a high-level overview of the results. Section 5 discusses some of the limitations and future directions for this line of research. Section 6 concludes the paper with key findings and policy implications. The paper includes Supplementary Information (SI) which provides a detailed description of the methods, the science underpinning our scenario design, and a more detailed view of the results, including additional country-level results.

2.0 Methods

2.1. Overview of the IEEM+ESM approach

The IEEM Platform is an economy-wide decision-making framework for evidence-based public policy and investment design (Banerjee et al., 2016; Banerjee et al., 2019b, 2019a). Linked with spatial ecosystem services modeling, IEEM+ESM (Banerjee et al., 2020; O. Banerjee et al., 2019a) is being used by multilateral institutions such as the Inter-American Development Bank and government institutions including Ministries of Finance and Central Banks in future-looking analysis of public policy and investment in Latin America and the Caribbean and beyond. IEEM+ESM models have been built for around 25 countries and have been applied to hundreds of questions of public policy and investment, including analysis of the complex challenges associated with the Sustainable Development Goals, the Paris Agreement and Green Growth Strategies.

The value-added of IEEM is: (i) its integration of detailed environmental information through the United Nations System of Environmental-Economic Accounting (SEEA) (United Nations et al., 2014) to represent the economy and the environment in a comprehensive and inter-connected way, all consistent with the System of National Accounts (European Commission et al., 2009); (ii) the indicators IEEM generates are those demanded by policy makers including GDP, employment and poverty, but also metrics of wealth, sustainability, natural capital stocks, and ecosystem services supply. Wealth metrics are necessary to inform policies aimed at sustainable economic development rather than once-off, short-run economic growth at the expense of a country's natural capital asset base (Dasgupta, 2021; Lange et al., 2018; Polasky et al., 2015; Stiglitz et al., 2010, 2009; UNEP, 2018), and; (iii) IEEM's environmental modeling modules capture the specific dynamics of natural capital-based sectors while IEEM's linkage with spatial ecosystem services modeling enables us to estimate impacts on the future flow of market and non-market ecosystem services.

At the core of IEEM is a dynamic computable general equilibrium (CGE) model. Black boxes no more, CGE models are among the most well-documented class of models in the literature which has developed over the last 4 decades, outlining the theory, methods, and strengths and limitations of the approach (Burfisher, 2017; Dervis et al., 1982; Dixon and Jorgenson, 2012; Kehoe, 2005; Shoven and Whalley, 1992). IEEM's mathematical structure is documented in (Banerjee and Cicowiez, 2020). The database for IEEM is an environmentally extended Social Accounting Matrix. The construction of an 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).

While IEEM may be used to estimate impacts on most material (IPBES, 2019) or provisioning ecosystem services (European Environment Agency, 2018; Haines-Young and Potschin, 2012), most of which have a market price, our linkage of IEEM with spatial ecosystem services modeling enables estimation of impacts on non-material or regulating ecosystem services that do not have a market price. The bridge between IEEM and ecosystem services modeling is made through the spatial allocation of IEEM-projected demand for land using a Land Use Land Cover (LULC) change model. With this model, we generate baseline and scenario-based LULC change maps which are used as inputs to the ecosystem services modeling.

We model Amazon tipping point and policy intervention impacts on carbon storage and erosion mitigation, water supply and water purification ecosystem services. In addition, we estimate a biodiversity index to examine scenario impacts on biodiversity which is the foundation of healthy functioning ecosystems and the services they provide. Economic results are estimated for the Amazon region as a whole, comprised of the five focal countries, and individually while changes in LULC and ecosystem services supply are calculated across a 1 km by 1 km spatial grid of the entire region.

2.2. IEEM models for Brazil, Bolivia, Colombia, Ecuador and Peru

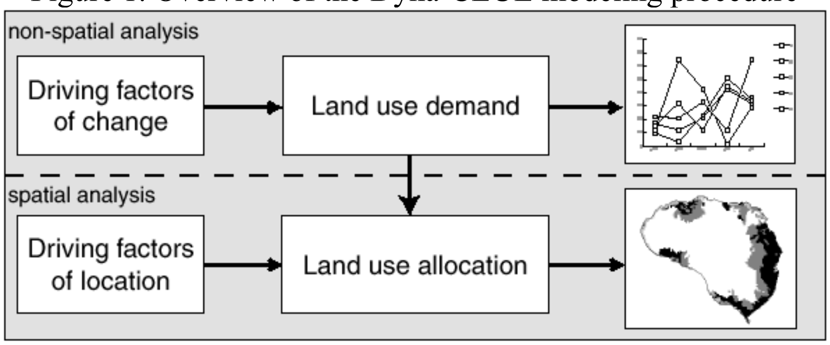
We constructed IEEM models for the 5 Amazon focal countries. The theoretical and mathematical structure of the IEEM modeling framework was developed with sufficient flexibility to account for country-specific features of most economies. For results that are comparable and consistent across countries and to enable the interpretation of the Amazon tipping point and policy scenarios, the theoretical structure of each IEEM model and model closures and rules are the same across countries. What differs between each IEEM model used in this exercise is the underpinning data which is based on each countries' System of National Accounts (European Commission et al., 2009) and their SEEA accounts where available.

IEEM model databases were constructed following the approach outlined in (Banerjee et al., 2019b). Colombia (DANE, 2017) and Brazil (ANA et al., 2018) are the only two of the five countries with SEEA accounts. The land-intensive sectors, namely crops, livestock, forest plantations and forests, were regionally disaggregated in each of the five IEEM models. The main data sources for this regionalization were LULC data sourced from agricultural census data and LULC maps; regional economic accounts, employment and labor supply data were also used to regionalize the crop, livestock, forest plantation and forest sectors. Regionalization of the IEEM models enables demand for land to be projected for each individual state or department for each country. This is important for enabling the LULC change and ecosystem services modeling that accurately reflects state/department-level demand for land. More details of the data used in model regionalization are provided in SI section 1.

2.3. Land use land cover change modeling

IEEM demand for land is spatially allocated across a 1 km by 1 km grid with the LULC change model which is used to generate baseline and scenario-based projected LULC maps. These maps are the main variable of change used in the ecosystem services modeling, with most other parameters held constant. We use the CLUE (Conversion of Land Use and its Effects; Verburg et al., 2008, 1999; Verburg and Overmars, 2009a) modeling framework to spatially allocate LULC change using empirically quantified relationships between land use and location factors, in combination with the dynamic modeling of competition between land use types. CLUE is among the most widely used spatial LULC change 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 LULC modeling (Veldkamp and Verburg, 2004; Verburg et al., 2002; Verburg and Overmars, 2009b).

Figure 1. Overview of the Dyna-CLUE modeling procedure

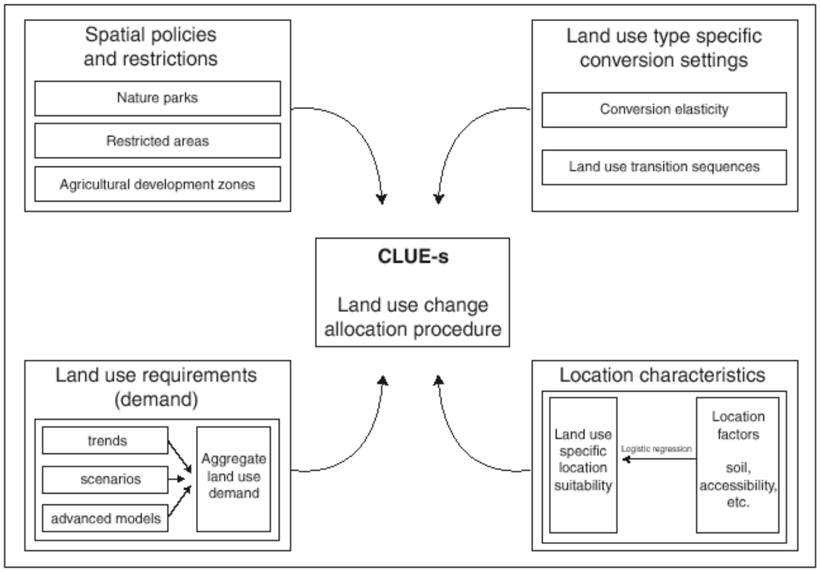


Source: Verburg et al. (2002).

The Dyna-CLUE model is sub-divided into two distinct modules: a non-spatial demand module and a spatially explicit allocation procedure (Figure 1). The non-spatial module calculates the area change for all land use types at the aggregate level and in this case is an input derived from IEEM. IEEM demand for land is spatially explicit at the level of the states/departments of the countries that share the Amazon and Cerrado biomes. Within the second module of Dyna-CLUE, these demands are translated into land use changes at different locations within the study region using a raster-based system.

Figure 2 provides an overview of the information required by 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 SI section 3. This section includes all variables used as location characteristics, their description as well as specific values used for each land use type.

Figure 2. Overview of the information flow in the Dyna-CLUE model.

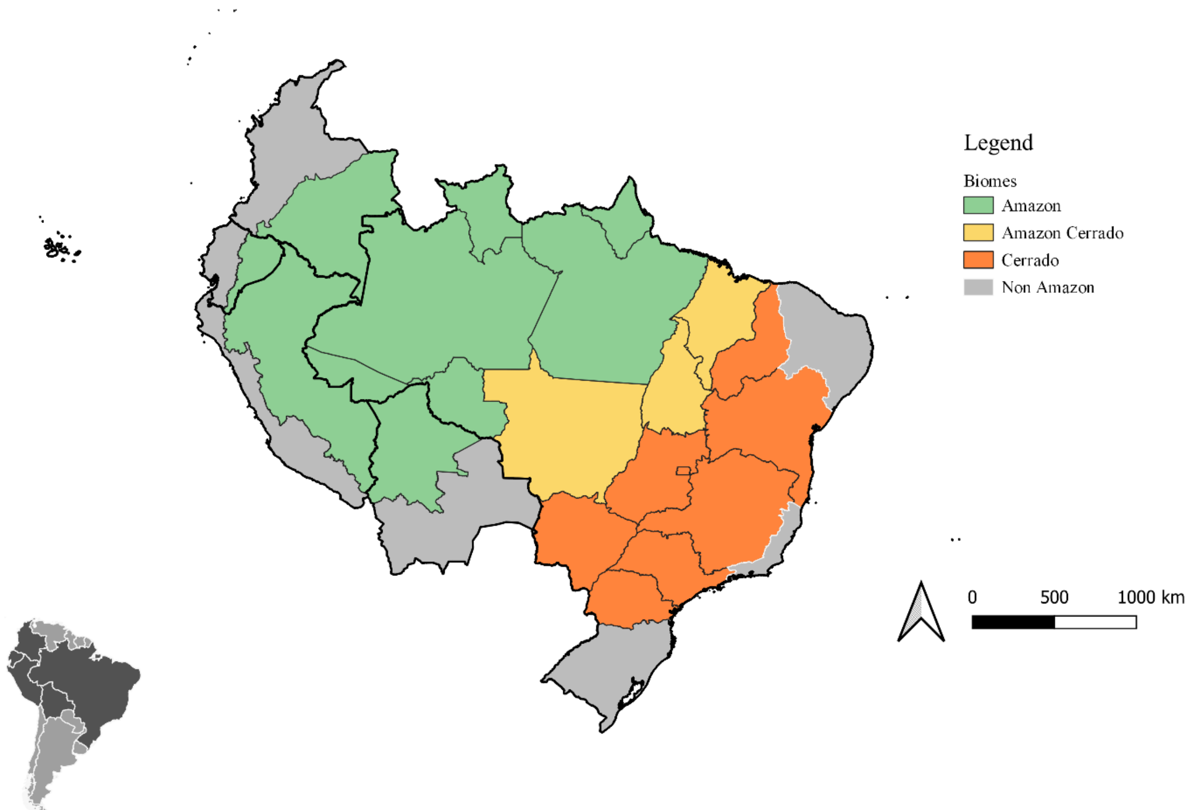


Source: (Verburg et al., 2002).

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 an annual basis, the area covered by the different land use types, which is a direct input to the allocation module. Annual demands for forest, forest plantation, cropland and grazing areas are generated 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, Dyna-CLUE calculates suitability maps for each land use type which reflect the probability of each land use class occurring for each pixel.

To apply the LULC model, several regions were identified by aggregating country states/departments that share the Amazon and Cerrado biomes. Figure 3 displays the states/departments selected, their country borders, and an overlay of the Amazon biome, Amazon Cerrado biome, the Cerrado biome, and an aggregation of non-Amazon/Cerrado biomes. Each state/department was run in Dyna-CLUE separately and then aggregated in post-processing.

Figure 3. Regional disaggregation indicating state/department, country and biome extents.



Source: Authors' own elaboration.

SI section 3 provides an overview of how annual bioclimatic spatial data was prepared to operationalize the scenarios in Dyna-CLUE. Also in SI section 3, we provide maps summarizing land use land cover change for each of the scenarios.

2.4. Ecosystem service modeling

The Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) suite of models (Sharp et al., 2020) was used to calculate scenario-based, spatially-explicit changes in ecosystem services supply. The InVEST models are open source, are very well documented and are the most widely used set of tools for ecosystem services modeling globally. InVEST combines LULC maps and biophysical information to calculate ecosystem services, with the option to add additional parameters to assist in ecosystem services valuation. In this paper, we parameterize and apply four ecosystem services models, namely: the sediment delivery ratio model used to calculate the

Revised Universal Soil Loss Equation; the carbon storage model used to calculate carbon storage and carbon sequestration potential; the annual water yield model to calculate water supply, and; the 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 ecosystem services models used and their inputs is documented in SI section 4.

In addition to the ecosystem services modeled, we also evaluated how scenarios impacted biodiversity by calculating composite Biodiversity Intactness Indices (Hudson et al., 2017; Newbold et al., 2016). The Biodiversity Intactness Index is a coefficient based on the average abundance of species originally present across undisturbed 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).

3.0. Baseline and scenario design

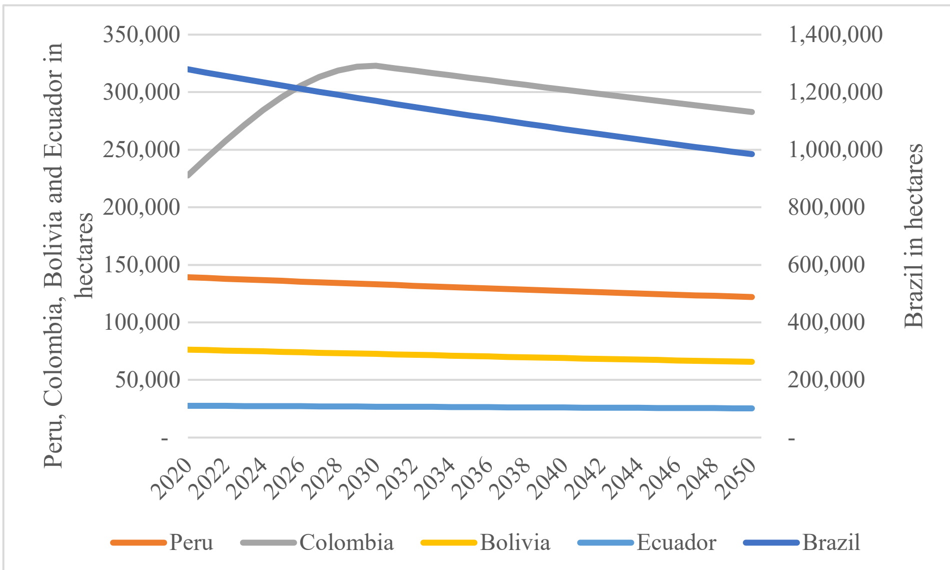
3.1. IEEM baseline

The baseline projection (BASE) in IEEM is the reference scenario. This baseline is an artificial modeling artifact developed for the sole purpose of enabling an estimation of the impacts of approaching a tipping point. Compared with this artificial reference scenario, we consider three main dimensions of an Amazon tipping point, namely climate change impacts in inducing water stress, increasing frequency and intensity of drought and increasing fire. In the BASE, IEEM models for each country are updated from their base year to the year 2020 based on observed trends of GDP and sectoral, population and labor force growth. For the period 2020 to 2050, GDP growth follows the projections from the latest IMF World Economic Outlook (IMF, 2019) while population growth rates are drawn from the United Nations' population projections (United Nations et al., 2019). GDP growth is exogenous in the BASE and imposed in IEEM by endogenously adjusting total factor productivity.

The BASE projection includes a projection of demand for crop, livestock, natural forest and forest plantation land, as well as a projection of deforestation which is based on historical trends. These

LULC trends are implemented in IEEM exogenously. The supply of agricultural land grows by the rate of deforestation. Figure 4 shows the BASE levels of deforestation across the five focal countries. Details specific to each IEEM country model including deforestation projections are provided in SI section 1.

Figure 4. Deforestation projections across Amazon focal countries in hectares. Note that Brazil's projection is read from the secondary y-axis.



Source: IEEM+ESM results.

In all scenarios other than BASE, GDP growth is endogenous and total factor productivity is exogenous. 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 as the overall economy. 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 BASE 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[1].

3.2. Amazon tipping point scenario

The following provides an overview of the three main components of the Amazon tipping point scenario. Detailed information on scenario design is presented in SI section 2.

YIELD: This scenario captures projected declines in agricultural productivity due to regional and global climate change. Tropical South America has already become warmer and drier, and these trends are expected to continue. To model the relationship between climate change and agricultural productivity, crop productivity specifically, we use historical crop yield data (1981-2017; (CONABIO, n.d.) combined with observed climate data from the 30-year period from 1981 to 2010, and future climate projections from 2020 to 2050. This approach enables the estimation of potential declines in agricultural productivity as regional climate becomes warmer and drier (IPCC, 2014). The input climate data used was monthly temperature and precipitation data based on 25 models from the Coupled Model Intercomparison Project 5 (CMIP5)[2].

We calculate the Maximum Cumulative Water Deficit (MCWD) for each year from 1981 to 2050 as a proxy for crop water demand. The MCWD is an index of dryness that integrates the effects of rainfall and temperature into a single variable. We calculate the MCWD following the methods described by Malhi et al. (2009) and adapted by Castanho et al. (2020). Our estimations with a

[1] Furthermore, in the BASE, 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.

[2] For more information on the Coupled Model Intercomparison Project, see: https://esgf-node.llnl.gov/projects/cmip5/

linear mixed model based on this historical data reveal a linear relationship between MCWD and crop yield. This relationship, projected to 2050, is implemented in IEEM as a crop productivity shock calibrated to the conditions of each state/department in our focal countries.

DRGHT: In this second component of the Amazon tipping point scenario, we simulate the expectation that extreme drought events will become more frequent and intense as climate changes. To quantify the increasing likelihood of extreme droughts and their potential effect on agricultural output in a drought year, we use the Standardized Precipitation-Evapotranspiration Index (SPEI) from 1981 to 2050 for each state/department of our focal countries. The SPEI is an index of drought severity that has been used widely to characterize the effects of droughts on agricultural yields (Beguería et al., 2014; Matiu et al., 2017).

In applying the SPEI to this analysis, we consider values lower than one standard deviation from the historical mean (less than -1.6) to represent an extreme drought that is likely to cause major crop losses. For the historical time series and projected SPEI values, we calculate the probability of drought occurring in any given year over our analytical period. To apply this in IEEM, a random draw is made for each year to determine if a drought will occur in that year; this approach is implemented for each department/state of the 5 focal countries. For example, if the probability of drought occurring is 5% on average in the Colombian state of Amazonas, the random draw will assign a drought year 5 times out of every 100 years. For every extreme drought year drawn, we estimate a 15% loss in crop productivity relative to the BASE. This magnitude of crop loss is based on Woetzel et al. (2020). While regional drying could also decrease livestock and pasture productivity by as much as 5% (Girardi and Deconto, 2008), our approach is conservative and only considers impacts on crop productivity.

FIR: Is the third and final component of the Amazon tipping point scenario and captures how climate change is expected to increase the frequency and intensity of fire. In the Amazon, fire is a novel disturbance and can rapidly degrade tropical forests that lack the adaptions needed to resist fire-related damage (Aragão et al., 2008). Combined with climate change, fire will be a key factor determining what kind of forests exist in the future and whether those forests can sustain critical ecosystem services over the long-term (Nobre et al. 2016).

This scenario relies on recent modeling and projections of burned area for a 192 million hectare region of the southern Amazon (Brando et al. 2020b). We combine these model outputs with future projections of forest flammability based on the MCWD and dry season length to estimate the vulnerability of Amazon forests to fire under future climate. These burned area estimates are implemented in IEEM as forest losses that go beyond the deforestation and land clearing use of fire which is accounted for in our BASE projection of deforestation.

Fire is only applied in those states/departments that exhibit a dry season length that is longer than the specified threshold of 3 months. For each year where the dry season length is greater than or equal to three months, we multiply the average percent burned area with the current standing forest stock for that state/department in that year. We assume that 0.5% of the area burned in a given year is converted to crops. The remaining burned area is left idle and unproductive. The spatial distribution of fire is determined through allocation rules in the LULC change modeling and its impacts on potential ecosystem services are accounted for in the ecosystem services modeling (Faria et al., 2017).

COMBI: This scenario represents all three components of the Amazon tipping point and is the joint implementation of YIELD, DRGHT and FIR.

3.3. Policy intervention

The policy intervention scenario is designed to avert an Amazon tipping point and is comprised of three main components that are described as follows:

NDEFOR: The first component of the policy intervention to avert an Amazon tipping point is the elimination of deforestation by 2030. In effect, this scenario could be interpreted as a policy of ***zero net deforestation***. The annual cost of this policy is estimated at US$5.5 billion and based on data from Stabile et al. (2020). This cost is distributed across countries based on their share of the Amazon biome (58.4% in Brazil, 12.8% in Peru, 7.7% in Bolivia, 7.1% in Colombia, and 1% in Ecuador) and is financed through international cooperation thus sharing the costs of eliminating this source of emissions given its global significance not only for climate change but also for biodiversity, natural capital and ecosystem services. In IEEM, any expenditure must be met with corresponding income. While different financing mechanisms may be applied, we have chosen this financing arrangement to focus on the multiple benefits of net zero deforestation including non-market benefits. Future analysis could consider various alternative financing mechanisms, including green bonds, the reallocation and more efficient use of existing resources, and taxes and transfers. Note that this scenario maintains the crop yield impacts of the YIELD and DRGHT scenarios.

The NDEFOR scenario reflects a consolidated government and civil society effort to monitor, enforce and effectively control deforestation across our 5 Amazon focal countries. Strongly reducing deforestation in the Amazon and Cerrado forests is the only near-term solution to mitigating regional climate change (see Costa et al. 2019). Native vegetation helps cool the land surface and triggers the onset of the rainy season, both of which are critical for rainfed agriculture. Forest clearing has a direct and immediate effect on the water and energy balance, resulting in regional warming and changes to the timing and availability of water in the system.

Forest clearing also has indirect effects including large-scale feedbacks to regional rainfall regimes (Spracklen et al., 2012; Spracklen and Garcia-Carreras, 2015; Staal et al., 2018) such as reductions in evapotranspiration, and changes to land-atmosphere feedbacks, which spur the onset of the rainy season (Costa et al., 2019; Yin et al., 2014) and reduce air dryness (Barkhordarian et al., 2019). Our implementation of this scenario in IEEM does not include these regional climate mitigation effects of eliminating deforestation and therefore the economic response to net zero deforestation are not fully captured and thus underestimated. Recent evidence that could support inclusion of these effects are provided in (Strand et al., 2018) and the feedbacks between deforestation and regional climate are increasingly well-documented and are an important part of the economic and ecological case for eliminating deforestation (Stabile et al., 2020).

NDEFOR2: This scenario represents a more 'middle of the road' perspective with respect to deforestation and reduces deforestation to a lesser extent than in the previous scenario. In Brazil's Legal Amazon there are 212 Federal and State Sustainable Use Conservation Units (81.56 million hectares), in addition to 424 Indigenous Lands (115.34 million hectares), adding up to a total area of 196.4 million hectares, representing 74% of the Amazon territory with forest as the predominant land cover. The over 1.3 million indigenous and traditional inhabitants that live in these areas have immeasurable knowledge of biodiversity and depend on the sustainable use of natural capital for their socio-cultural and economic wellbeing. Some of these populations have a cultural reliance on slash and burn shifting agriculture for their food security, as they have done so over the last 12,000 years (Clement, 1999; Clement et al., 2015). As a result, even in the best environmental governance scenario, there will still be some level of deforestation taking place in the Amazon. This deforestation may also be compensated by secondary forest regeneration as result of the shifting practices of alternating a short agricultural cycle (3-5 years) with a long fallow cycle (20-30 years) to restore carbon and nutrient stock in the native vegetation and to restore soil fertility (Coomes et al., 2000; Valentim and Vosti, 2005; Vliet et al., 2013).

For this scenario, the reduction in deforestation was calculated based on one of the lowest levels of net change in forest cover reported for the Brazilian Amazon region over the last 15 years. This low level of net change was estimated based on Project MapBiomas data and was reported for 2009-2010, equivalent to 257,634.4 hectares (Project MapBiomas, 2020). This level of net change was implemented in IEEM as the target level of deforestation to be reached in the year 2050. The relationship between deforestation in 2009-2010 and deforestation in the year 2018 in Brazil is 8.95% (i.e., = 256,634 ha / 2,678,984 ha * 100). For other countries, we imposed a reduction that, in 2050, was equivalent to 8.95% of the value recorded in 2018. The costs of reducing deforestation were implemented in IEEM in the same way as in NDEFOR.

NFIR: The second component of the policy intervention scenario represents comprehensive efforts to control and prevent fires in the face of drier, more fire-prone climate conditions. We assume that effective implementation of fire management could prevent an additional 50-75% of the projected burned area (Brando et al. 2020b). Fire is one of the biggest drivers of forest degradation in the Amazon and is likely to increase as the regional climate becomes warmer and drier. Strongly reducing deforestation as captured through our NDEFOR scenario prevents build-up of ignition sources in the landscape and reduces the probability of fires used for land clearing escaping. To implement this scenario in IEEM, we imposed a gradual reduction of burned areas relative to the FIR scenario. The annual cost of improving fire management was estimated at

US$71.9 million and was distributed across countries based on their share of the Amazon biome. The cost of reducing fire was financed in IEEM through a combination of 50% international cooperation and a 50% increase in direct taxation in each of the focal countries.

This scenario simulates an aggressive fire management program operating on several fronts (Brando et al. 2020a). Elements of this programmatic approach include: (i) expanding the network of well-trained and equipped fire brigades to suppress accidental ignitions and illegal wildfires; (ii) developing climate-smart, fire-free land management systems to minimize fire ignition sources in the landscape; (iii) implementing command-and-control enforcement to stop deforestation and prevent escaped wildfires; (iv) improving fire early warning systems to help guide prevention and suppression efforts, and efficiently allocate resources months before the fire season starts, and; (v) investing in fire prevention to protect vulnerable areas through fire breaks; controlled burns to reduce fuel loads; and coordination with indigenous and traditional communities.

YIELD50: The third and final component of the policy intervention scenario simulates the introduction of climate-adapted crop varieties, targeted irrigation and other adaptation measures intended to enhance crop productivity under a future warmer and drier climate. These measures could mitigate up to 50% of projected productivity losses relative to the YIELD scenario in average years, though crops remain vulnerable to the extreme droughts simulated in the DRGHT scenario. The annual cost of implementing this scenario is US$1.3 billion and is distributed by country and state/department according to the relative size of each country's agricultural sector GDP. This investment is financed in each country through an increase in the stock of government domestic debt. This scenario also accounts for the expansion of irrigated agriculture, particularly in Brazil's Amazon and Cerrado region (Rattis et al., In review).

Farmers and ranchers are likely to adapt management practices to new climate and market conditions to mitigate crop productivity declines and crop losses. Adaptation strategies might include changing crop varieties (e.g. climate and drought-adapted varieties); shifting the timing and intensity of cultivation (e.g. switching from double- to single-cropping; planting later in the wet season); double cropping in the same area using varieties with shorter growing cycle (soy-corn, for example) (de Souza, 2019) or early planting of corn into existing planted soy crops

(Vasconcellos and Torres, 2020); no-tillage planting, currently used in 80% of the area cultivated with annual crops in Brazil and some other South American countries (Motter and de Almeida, 2015) to reduce soil erosion, nutrient leaching, conserve soil organic matter and soil moisture, and reduce greenhouse gas emissions from agriculture, and; experimenting with climate adapted agroforestry or crop rotation systems that are more resilient to climate change.

Irrigation is a key adaptation strategy and will likely increase in drier agricultural regions like Brazil’s Amazon-Cerrado region, where large swaths of cropland have already moved outside the optimal climate zone (Pousa et al., 2019; Rattis et al., In review). The National Water Agency of Brazil estimates that there are 76 million hectares of irrigable land in Brazil, but that figure includes areas without the logistical capacity to irrigate. Taking logistics and economic suitability into account, the National Water Agency projects that an additional 11.2 million hectares are effectively available for irrigation today, but realistically 3.14 million hectares could be installed by 2030. On average, central pivot irrigation has grown by 4% per year over the last 10 years (Fontenelle et al. 2019).

Following Brazilian government projections, we assume that irrigated area will reach approximately 10 million hectares by 2030 (an increase of 45%, relative to 2015) and reach 18 million hectares by 2050 (Ayrimoraes et al. 2017). While the expansion of irrigated agriculture upwards of 18 million hectares by 2050 is expected and would mitigate most climate-induced losses in agricultural productivity (Girardi and Deconto 2008), we adopt a more conservative approach and assume that interventions imposed in this scenario mitigate 50% of the crop productivity losses relative to the YIELD scenario. Also, we assumed no additional irrigation expansion beyond baseline projections for the other 4 Amazon countries because: (i) they are generally more buffered against the drying and warming trends that are already being observed in the Amazon and Cerrado regions of Brazil, and; (ii) information on potential expansion of irrigated agriculture as a climate adaptation strategy in these countries was relatively scarce, and what information was available suggested relatively small increases in irrigated agriculture relative to the projected increase in Brazil.

POL: The POL scenario is the consolidated policy response to averting an Amazon tipping point and is comprised of the joint implementation of NDEFOR, NFIR and YIELD50.

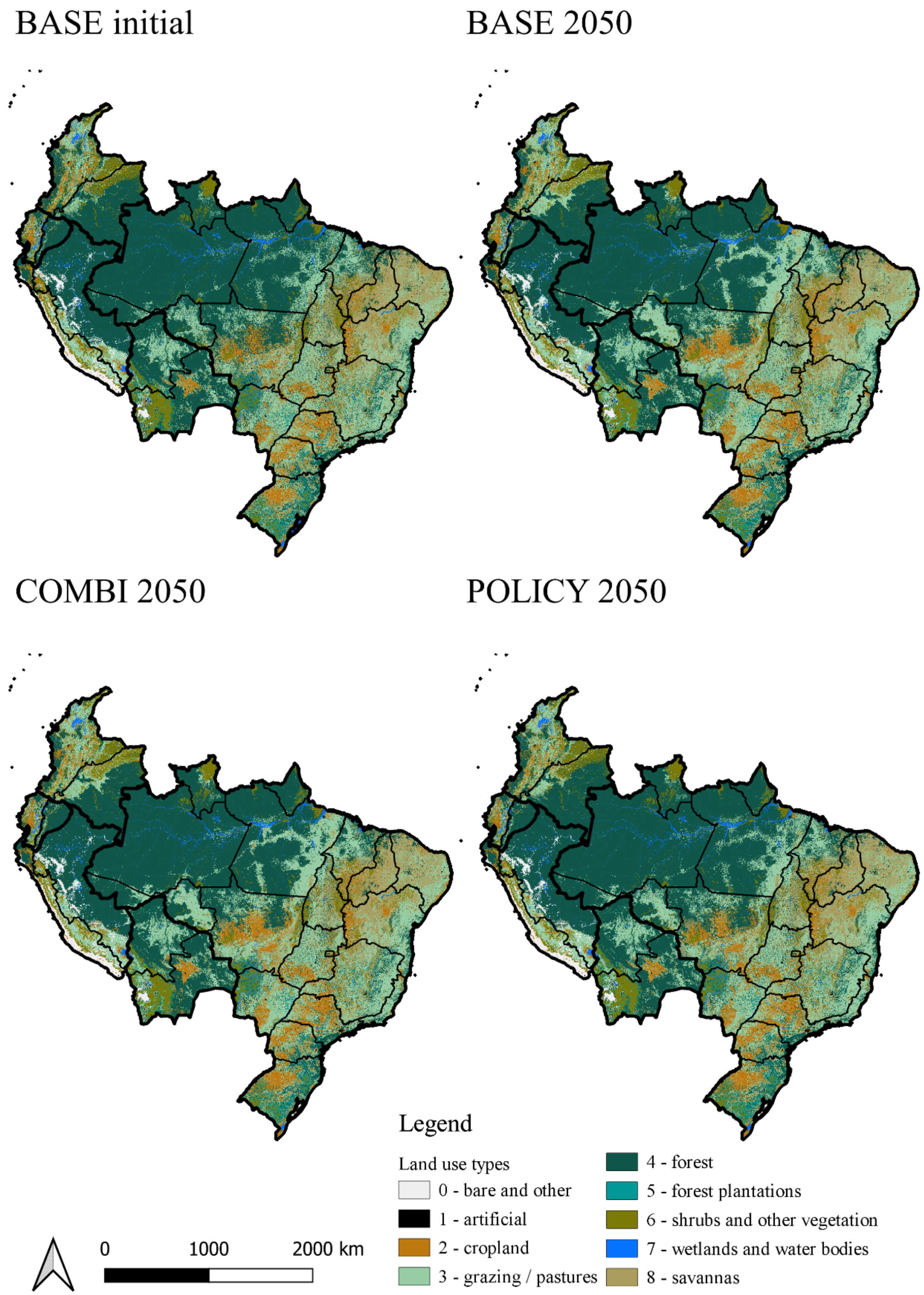
POL2: This scenario is the same as POL except that it includes the more conservative NDEFOR2 scenario together with NFIR and YIELD50.

4.0. Results
4.1. Land use land cover change impacts

The IEEM+ESM workflow begins with implementation of the BASE and Amazon tipping point scenarios in IEEM. IEEM results are used to drive change in LULC which then translates into impacts on ecosystem services supply. Given this workflow, our presentation of results begins with demand for land estimated with IEEM, how it is spatially distributed with the LULC change model, and then how this LULC change affects future ecosystem services supply. An overview of LULC in Figure 5 shows the region's original LULC and scenarios-based LULC in 2050. Note that for the presentation of LULC results, we focus on the tipping point scenario (COMBI) and the coordinated policy action scenario (POL). Enlarged versions on these maps can be found in SI section 3.

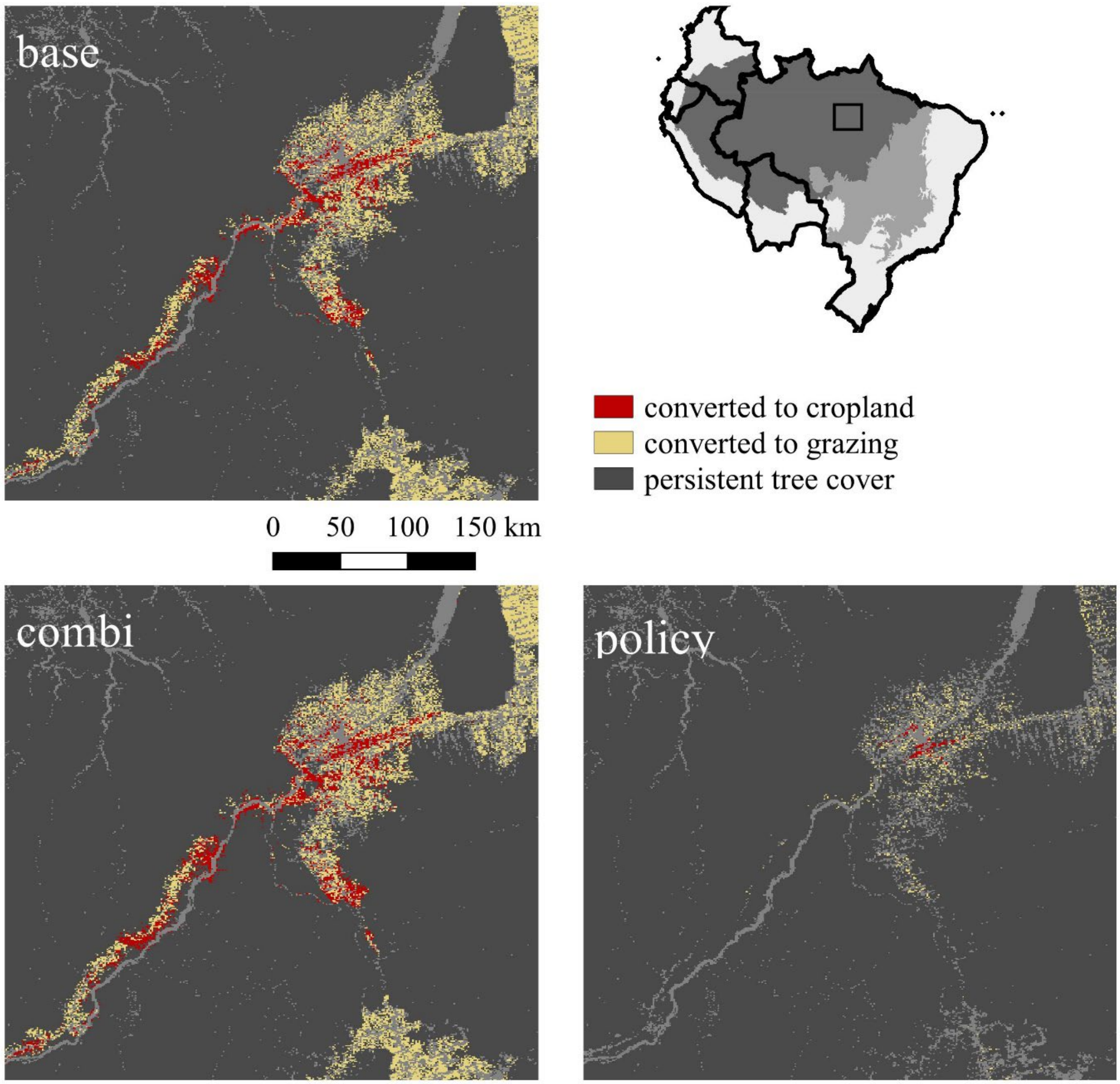
A close-up view of LULC in Brazil is shown in Figure 6 which illustrates the fine spatial detail of the modeling that is possible at a 1 km by 1 km spatial resolution. This figure identifies areas that were subject to change in the Amazon tipping point (COMBI) and the policy (POL) scenarios. LULC was modeled individually for the Amazon region's 26 different states/departments. The level of detail that results from such an analysis is uncommon when modeling LULC at a national scale and enables a detailed analysis of LULC change, which is the main driver of changes in future ecosystem service supply. This detailed analysis can also inform the spatial targeting of policies aimed to avert an Amazon tipping point.

Figure 5. Land use land cover change results for the BASE, Amazon tipping point and policy intervention scenarios.



Source: IEEM+ESM results.

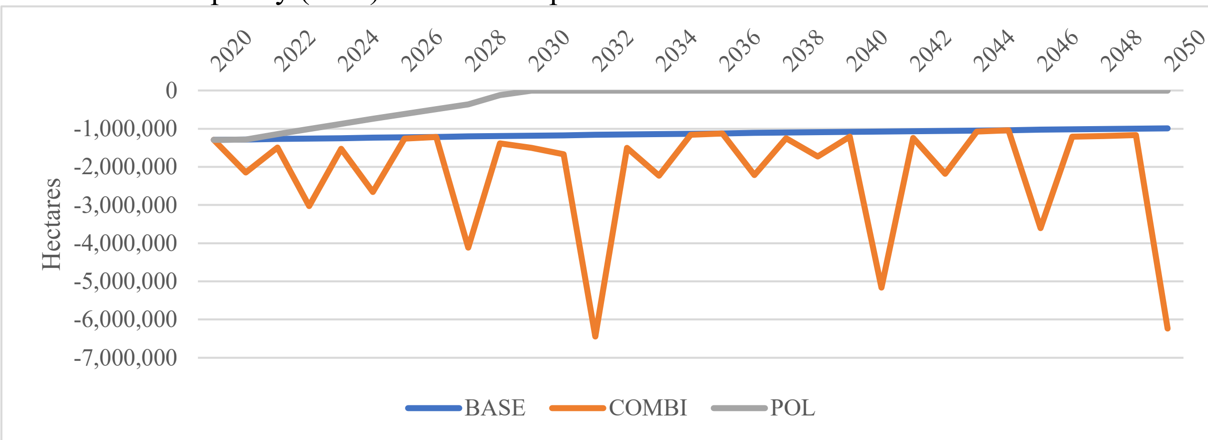
Figure 6. Close-up image of a region in the state of Pará, Brazil, illustrating the fine spatial resolution that was implemented across the case study countries.



Source: IEEM+ESM results.

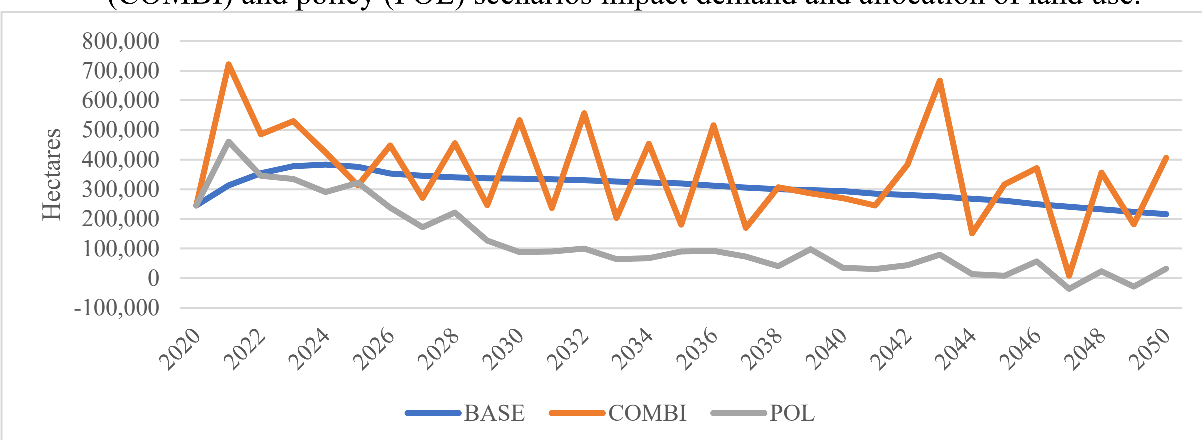
Figure 7, Figure 8 and Figure 9 show the potential annual change in deforestation and IEEM demand for crop and livestock land in Brazil to illustrate when and how scenario shocks translate into impacts on land use allocation in the LULC change modeling.

Figure 7. Annual change in deforestation in Brazil, illustrating how the tipping point (COMBI) and policy (POL) scenarios impact demand and allocation of land use.



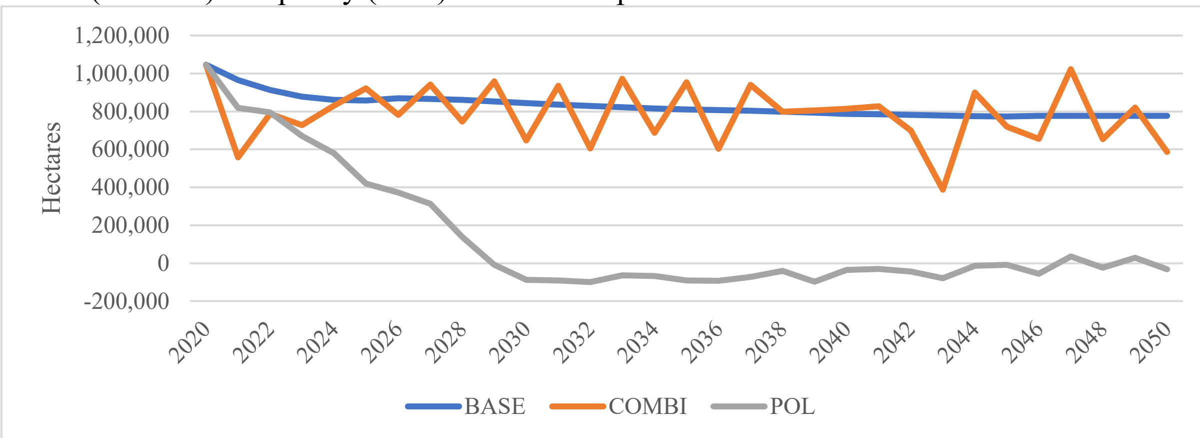
Source: IEEM+ESM results.

Figure 8. Annual change in demand for cropland in Brazil, illustrating how the tipping point (COMBI) and policy (POL) scenarios impact demand and allocation of land use.



Source: IEEM+ESM results.

Figure 9. Annual change in demand for livestock land in Brazil, illustrating how the tipping point (COMBI) and policy (POL) scenarios impact demand and allocation of land use.



Source: IEEM+ESM results.

4.2. Ecosystem services impacts

Figure 10, Figure 11, Figure 12, Figure 13, Figure 14 and Figure 15 present a collection of maps displaying potential changes in future ecosystem service supply in the Amazon tipping point (COMBI) and policy (POL) scenarios for all ecosystem services, as well as potential changes in the Biodiversity Intactness Index. While impacts on ecosystem services supply were estimated for all scenarios, we focus on the Amazon tipping point and policy intervention scenarios in the presentation of results. The differences in ecosystem services and biodiversity are calculated as the comparative magnitude of change between the Amazon tipping point (COMBI) and BASE scenario in 2050, and; the comparative magnitude of change between the policy intervention (POL) scenario and the tipping point scenario (COMBI) in 2050. These maps summarize impacts over states/departments and regions which were aggregated up from the original 1 km spatial resolution.

In terms of erosion mitigation ecosystem services, the tipping points scenario would have spatially diverse impacts across the region, with a loss of erosion mitigation services particularly acute across Bolivia (more than 25% loss), along the western slope of the Andes in Peru, and in the Colombian Amazon (5-25% loss). Paraná in Brazil would experience a more than 25% loss of erosion mitigation services, followed by Minas Gerais (5-25%), Pará, Roraima, Rondônia, and Acre (up to 5% loss of services). Colombia's non-Amazon region would experience a loss of up to 5% in erosion mitigation ecosystem services. Polices to avert a tipping point would have a drastic impact on improving ecosystem services supply, largely increasing ecosystem services flows by more than 50% across much of the region. Bolivia's Amazon region is an exception where a 25% loss of ecosystem services would be experienced.

Where carbon storage for climate mitigation is concerned, a tipping point would result in large losses of carbon capture in some of Brazil's northeastern states including Alagoas, Pernambuco, Paraíba, Rio Grande do Norte, and Ceará with a loss of more than 25%, while Piauí would experience a reduction of 5-25%. Rio Grande do Sul, Santa Catarina and Paraná would experience a loss of more than 25%. The Colombian and Ecuadorian Amazon would experience a loss of up to 5% along with the Bolivian Amazon, and the Brazilian states of Amazonas, Acre and Roraima. With the implementation of concerted policy action to avert a tipping point, carbon storage services would increase by more than 25% across most of the region.

Considering water quality, and focusing on nitrogen exports, reductions in water quality would be most acute in Bolivia's south and in Brazil's south eastern states of Minas Gerais, Sao Paulo and Paraná with a reduction of more than 25%. A 5 to 25% reduction in water quality would be found in the case of Peru's Andes and coast and the Brazilian states of Roraima, Amapá, Pará, Maranhão, Pará, Mato Grosso and Mato Gross del Sul. Policy intervention would have a strong impact in improving water quality equivalent to greater than 50% for much of the region. In the case of Minas Gerais, there would be an increase of over 25% and in Paraná, there would be a reduction in water quality of 5-25%.

Changes in water yield would be the most divergent compared with other ecosystem service results. Figure 10 shows that there would be a negative and generally higher magnitude of impact on water yield in the policy intervention scenario compared with the Amazon tipping point scenario. This is likely driven by the elimination of deforestation. Reforestation has been found to impact water yield in often conflicting ways, however, and has been shown to produce reductions in water yield in many studies (Filoso et al., 2017). This aligns with the structure of the InVEST water yield model (Sharp et al., 2020), as higher forest cover means there is a reduction in the water available for other uses.

Finally, with regard to biodiversity, the Colombian, Ecuadorian and Bolivian Amazon, would experience a reduction in biodiversity of up to 5% with respect to the BASE in 2050. The Brazilian states of Amazonas, Roraima, Pará, Mato Gross, Mato Grosso del Sul, Maranhão, Piaui and Bahía would experience a similar loss of biodiversity. The state of Minas Gerais and Goiás would experience a loss of 5 to 25% while Sao Paulo and Paraná would experience the greatest loss of more than 25%. Policy intervention to avert an Amazon tipping point would increase biodiversity almost across the entire region.

Figure 10. Comparison of the tipping point (COMBI) and policy (POL) scenarios with BASE in 2050 for annual water yield (AWY) as a percent change.

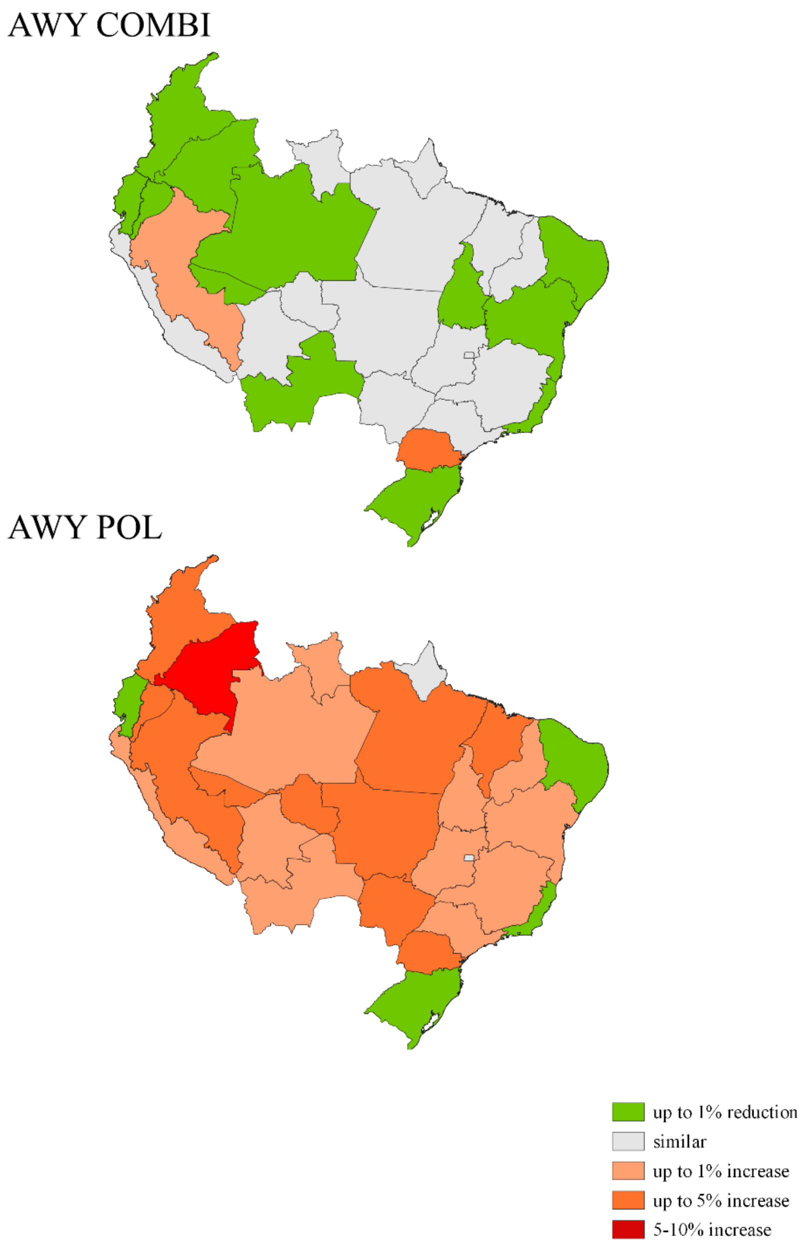
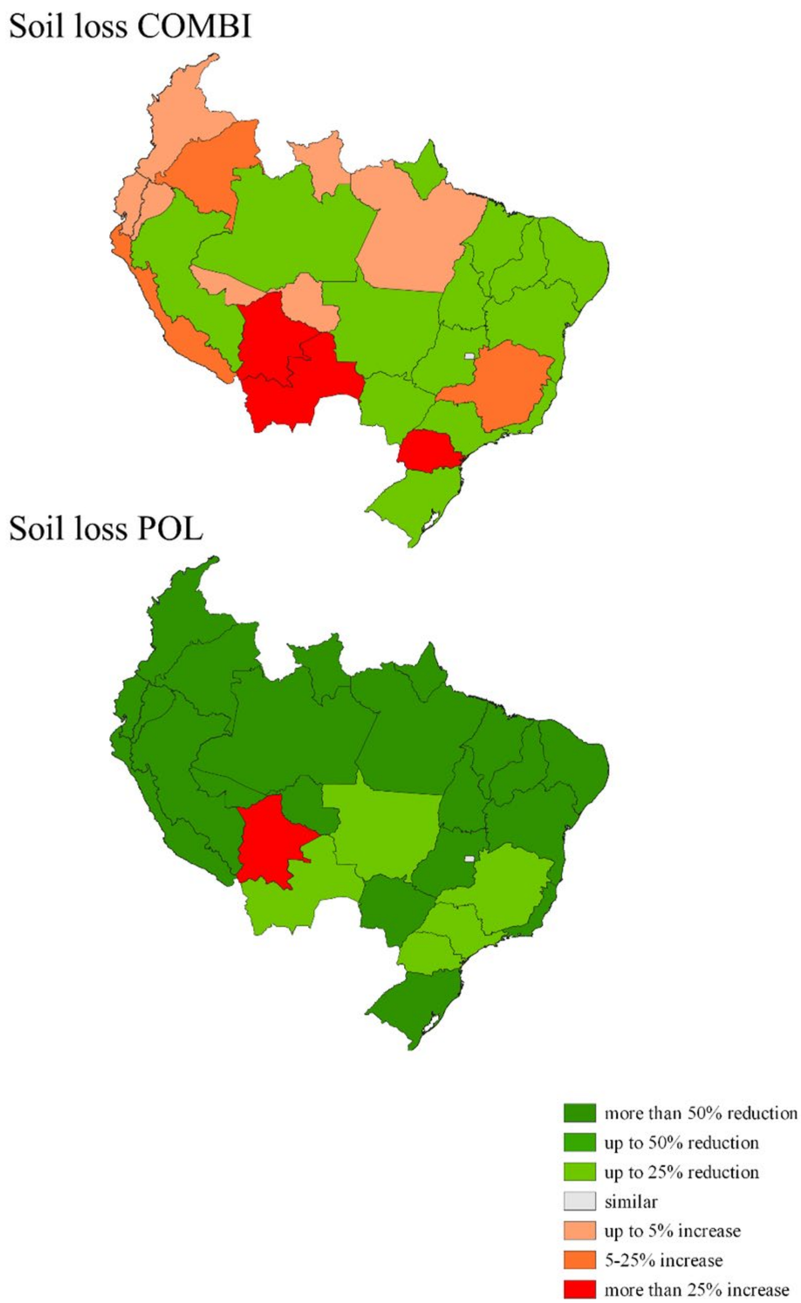
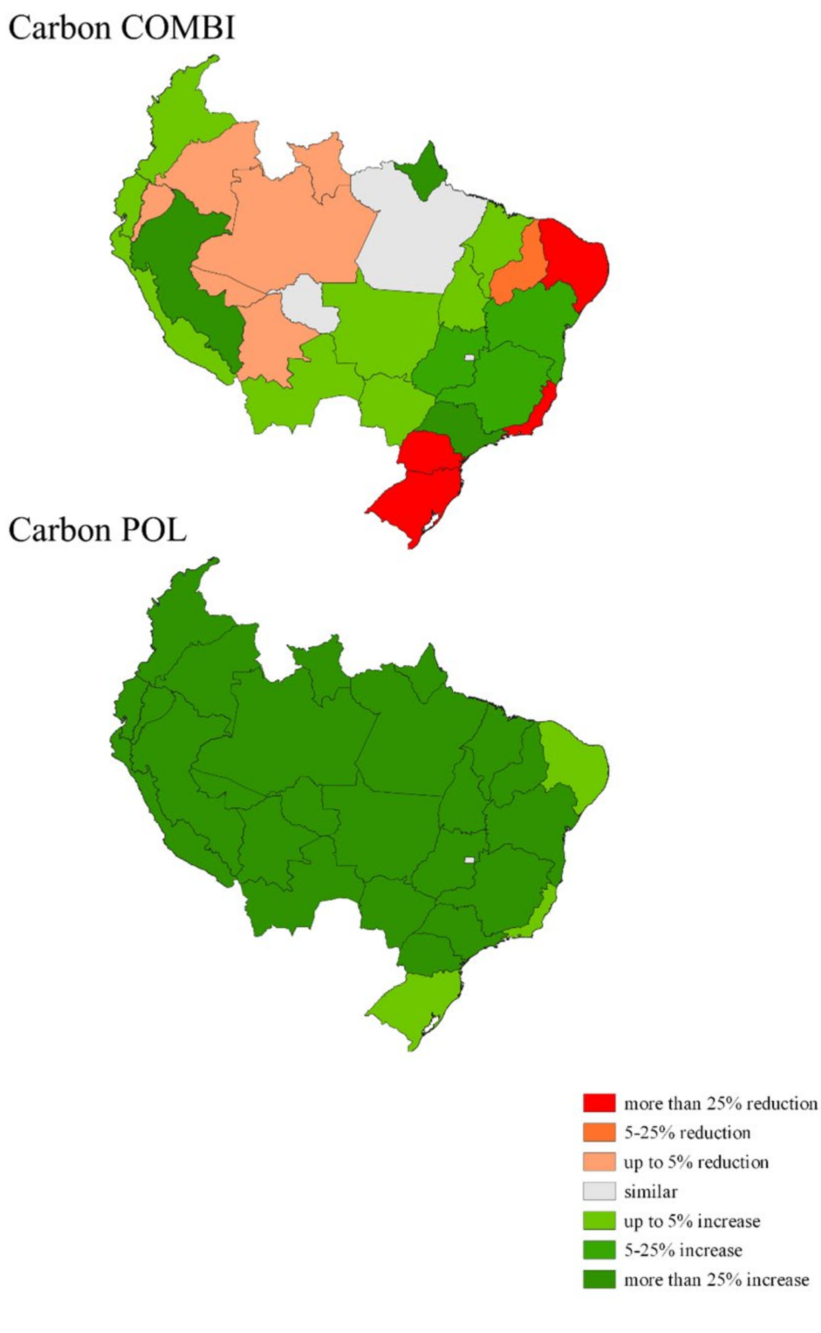


Figure 11. Comparison of the tipping point (COMBI) and policy (POL) scenarios with the BASE in 2050 for erosion mitigation ecosystem service as a percentage change.



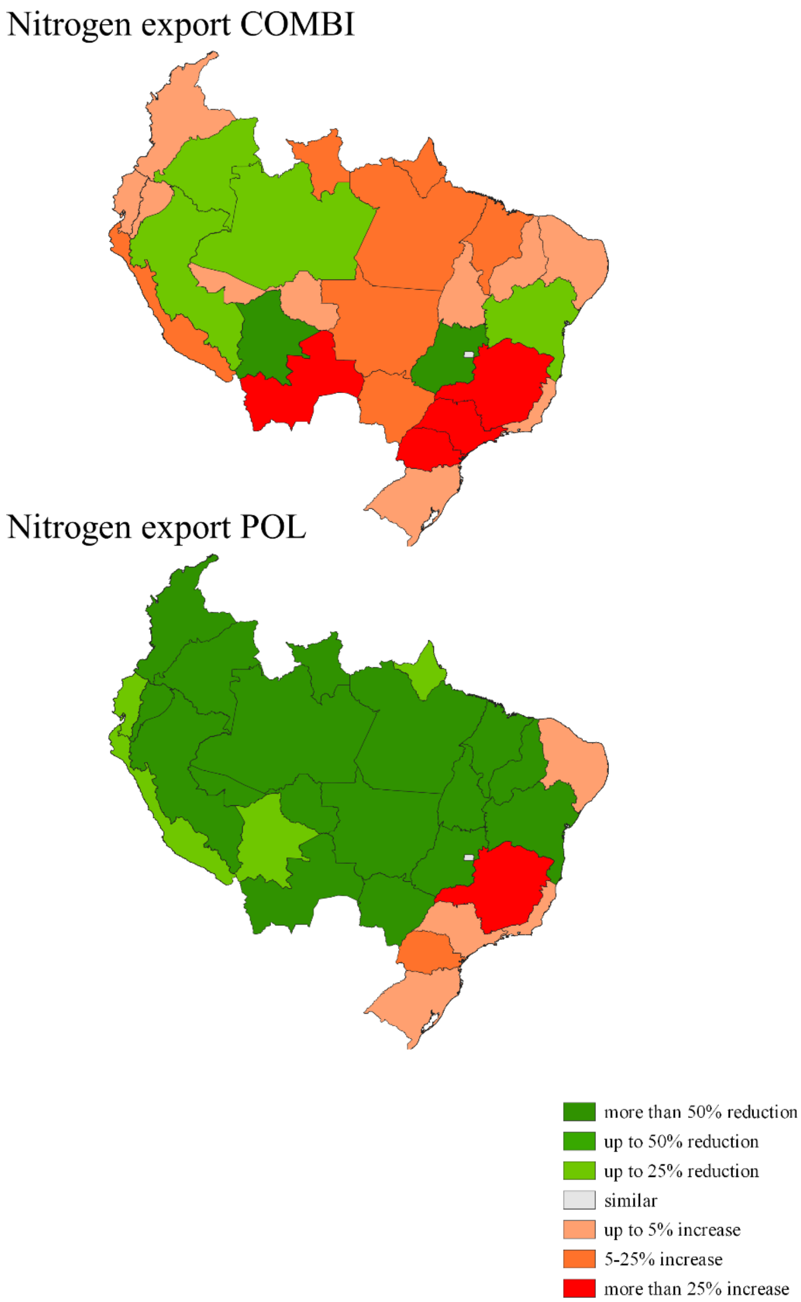
Source: IEEM+ESM results.

Figure 12. Comparison of the tipping point (COMBI) and policy (POL) scenarios with the BASE in 2050 for carbon storage ecosystem services as a percentage change.



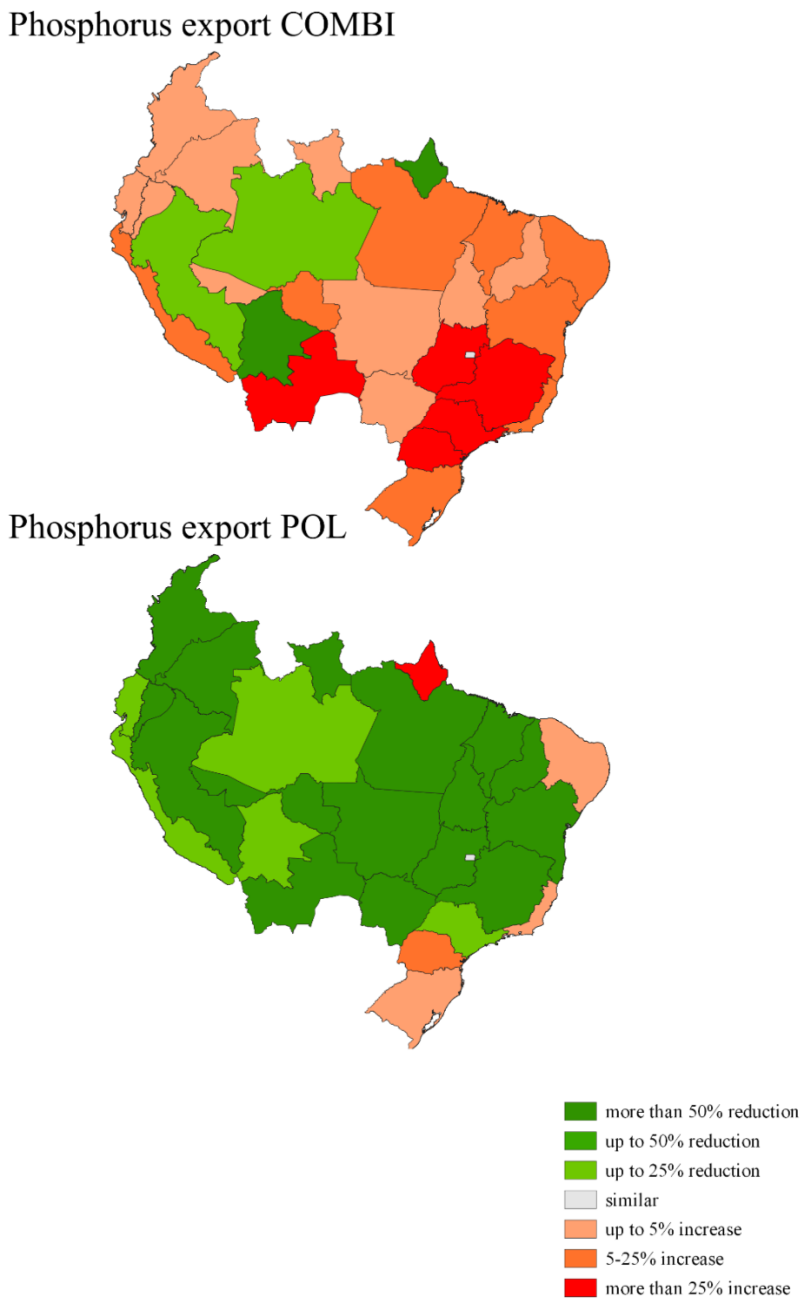
Source: IEEM+ESM results.

Figure 13. Comparison of the tipping point (COMBI) and policy (POL) scenarios with the BASE in 2050 for water quality (nitrogen retention) ecosystem services as a percentage change.



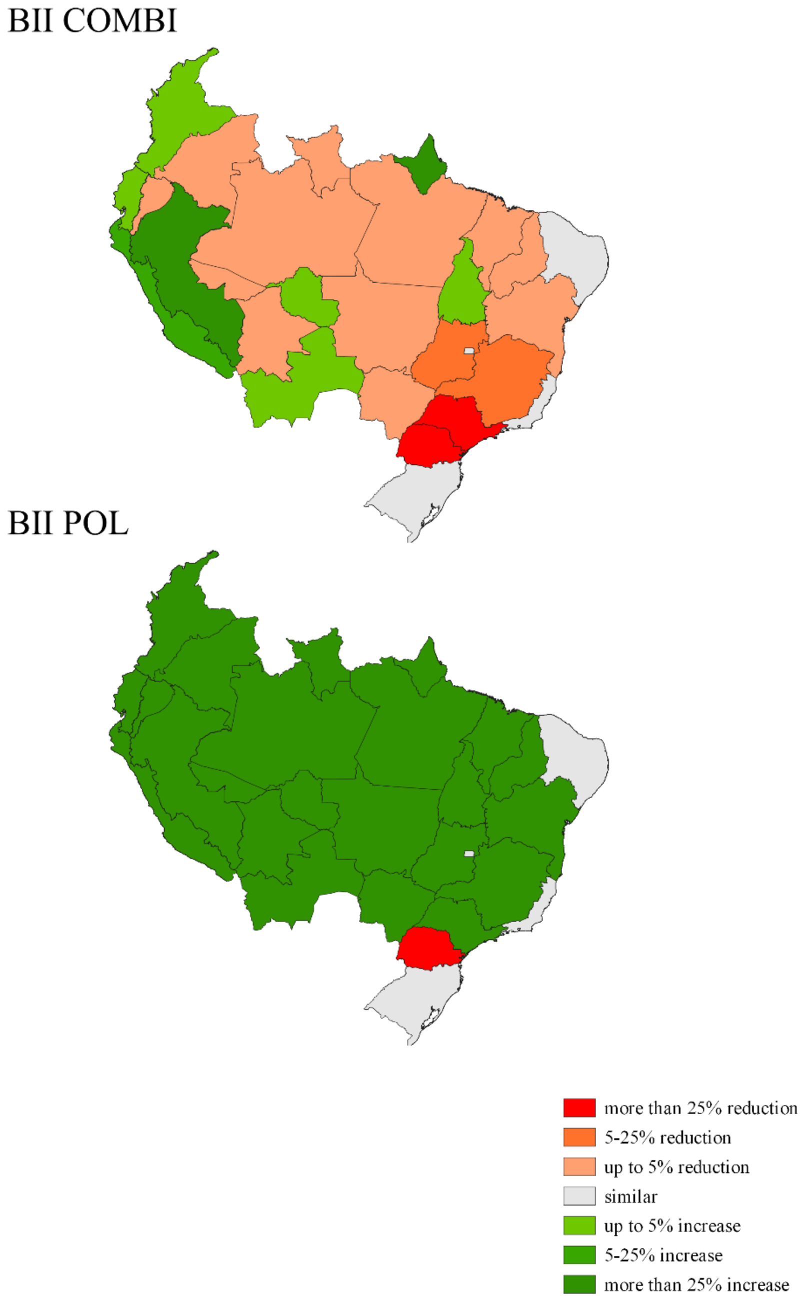
Source: IEEM+ESM results.

Figure 14. Comparison of the tipping point (COMBI) and policy (POL) scenarios with the BASE in 2050 for water quality (phosphorus retention) ecosystem services as a percentage change.



Source: IEEM+ESM results.

Figure 15. Comparison of the tipping point (COMBI) and policy (POL) scenarios with the BASE in 2050 for the Biodiversity Intactness Index as a percentage change. Note the small, grey square region in the state of Goiás is the Brasilia Federal District and was excluded from the analysis.



Source: IEEM+ESM results.

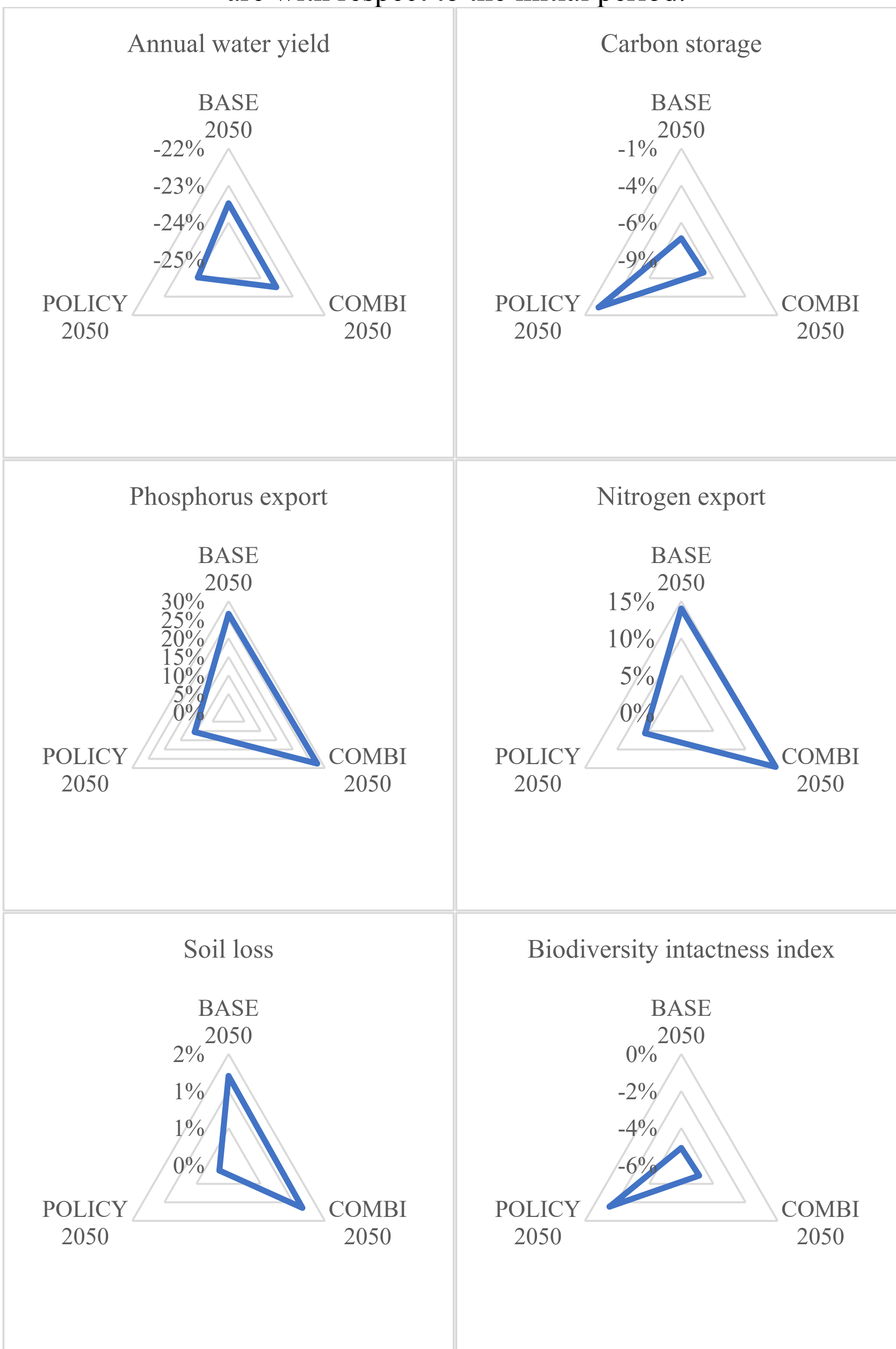
Several drivers of change between scenarios and ecosystem services can be highlighted that relate both to the functioning of the ecosystem service models themselves, as well as changes in biophysical and bioclimatic inputs. For example, the soil loss results from erosion mitigation ecosystem services model are highly sensitive to the cover-management (C-factor) assigned to different land use types (Hamel et al., 2017). The C-factor accounts for the effect of plants, soil, biomass, and other physical characteristics, in mitigating erosion. Forests have the highest potential to mitigate soil loss while cropland and livestock areas have comparatively higher C-factor values and therefore higher erosion potential. As a result, continued deforestation trends in the BASE and Amazon tipping point scenarios explain the strong reduction in erosion mitigation ecosystem services with the conversion of forest to livestock and crop area. Similar trends in the carbon storage results are explained in the same way, as forested areas have the highest potential for carbon storage. Strongly reducing deforestation is therefore fundamental to reversing both these trends.

With regard to water quality and water supply ecosystem services models, several inputs help explain the negative changes in the BASE and Amazon tipping point scenarios in 2050, as well as their relative improvement in the policy intervention scenario. Generally, forested areas have lower nitrogen and phosphorus loads and higher nutrient retention potentials compared to crop and livestock areas, and thus deforestation tends to have a negative impact on nutrient retention and water quality. In addition, bioclimatic inputs, specifically precipitation and plant evapotranspiration are strongly influenced by climate change over our analytical period to the year 2050. Precipitation plays a key role in nutrient retention as increased rainfall in areas of lower nutrient retention potential can intensify nutrient run-off and thus reduce water quality (Salata et al., 2017).

As described in SI section 4, precipitation on average is projected to increase in the peripheral areas of the study region, which contributes to explaining why this periphery shows lower water quality and nutrient retention potential. A similar conclusion may be drawn for reductions in water yield in peripheral regions, with changes in plant evapotranspiration, another key input to the water yield ecosystem services mode. Our future climate models show increases in plant evapotranspiration, primarily in the central (Brazilian/Colombian) Amazon region, with less change in peripheral regions. Higher plant evapotranspiration indicates a higher potential for soil dryness and a greater depth at which soil moisture dissipates. Reductions in precipitation and plant evapotranspiration combined tend to reinforce reductions in overall water yield that arise from the elimination of deforestation as discussed above (Redhead et al., 2016).

Figure 16 provides a regional summary of the ecosystem services results discussed, showing the percent difference in ecosystem services supply with respect to the initial period for the BASE, Amazon tipping point and policy intervention scenarios. The figure shows that most ecosystem services and biodiversity impacts would be reduced significantly with policy intervention. The exception to this would be annual water yield, for reasons described previously. The most severe reductions in ecosystem service provision in the Amazon tipping point scenario would be found for water quality, as phosphorus and nitrogen exports would increase by up to 20% and 15%, respectively. Following this, overall carbon storage would fall by about 8% in the tipping point scenario, compared to a less than 1% reduction in the policy intervention scenario. Results would be similar for biodiversity. The smallest overall impacts would be found for soil erosion mitigation services and water supply. These results highlight the importance of analyzing results on both a regional and sub-regional level as overall, regional trends may otherwise mask severe sub-regional impacts that are not uniformly distributed, as is the case illustrated here with soil erosion mitigation ecosystem services.

Figure 16. Summary of scenario performance, considering the BASE, tipping point (COMBI) and policy (POL) scenarios, with respect to future ecosystem services supply. Percentage change are with respect to the initial period.



Source: IEEM+ESM results.

4.3. Economic impacts

Table 1 presents the cumulative scenario impacts on GDP and wealth as differences from the BASE and the components of the tipping point and policy scenarios. The impact of climate change on reducing yields would pose the greatest losses across countries, with increasing drought also important but to a lesser degree. Fire impacts would not register prominently in terms of GDP impacts, but would register more so in terms of wealth due to the loss of healthy standing forest stock. GDP impacts would vary by scenario and country. For example, while the impact of climate change on yields would be felt more severely in Brazil and then Bolivia and Ecuador, the drought impact would be felt more acutely in Brazil, followed by Colombia, Bolivia and Peru. Variability across scenarios and countries would also hold true in the case of wealth.

The cumulative GDP impact of an Amazon tipping point in Brazil would be on the order of US$184.1 billion, followed by US$35.3 billion, US$17.6 billion, US$11.4 billion, and US$8.2 billion in Colombia, Bolivia, Ecuador, and Peru, respectively. The impact of a tipping point on wealth would be smaller, but still important, with a US$55.2 billion in lost wealth in Brazil, followed by US$16.9 billion, US$5.4 billion, US$3.98 billion, US$2.3 billion and US$1.7 billion in Colombia, Bolivia, Ecuador and Peru.

Table 1. Cumulative impacts on GDP and Genuine Savings as difference from BASE scenario in millions of USD.

Indicator	Country	YIELD	DRGHT	FIR	COMBI	NDEFOR	NDEFOR2	YIELD50	NFIR	POL	POL2
GDP											
	Brazil	-146,800	-33,515	30	-184,121	-191,209	-188,426	-73,928	-129	-81,245	-77,290
	Peru	-7,107	-1,064	4	-8,200	-9,168	-9,017	-4,104	-35	-5,117	-4,640
	Colombia	-26,656	-8,430	13	-35,266	-47,158	-44,998	-19,096	-142	-31,177	-27,878
	Bolivia	-16,271	-1,678	-49	-17,610	-20,238	-21,629	-10,421	-254	-14,555	-13,128
	Ecuador	-11,408	-30	18	-11,420	-19,746	-15,118	-8,410	-17	-16,775	-12,040
Genuine Savings											
	Brazil	-42,922	-9,880	-743	-55,207	123,561	24,069	-15,886	113	162,804	64,404
	Peru	-1,218	-184	-318	-1,729	19,233	11,314	252	1	20,952	13,278
	Colombia	-12,040	-3,773	-809	-16,868	87,660	66,401	-5,893	-166	98,165	77,715
	Bolivia	-4,685	-441	-36	-5,413	6,769	5,240	-2,042	6	10,062	9,334
	Ecuador	-2,044	-5	-291	-2,337	45,515	28,170	-463	-52	47,311	29,943

Source: IEEM+ESM results.

Through the lens of GDP, policies to avert a tipping point, including net zero deforestation, would mitigate some of these economic impacts, by more than half in the case of Brazil with a US$81.2 billion loss to GDP, a US$31.2 billion loss in Colombia, a US$16.8 billion loss in Ecuador, US$14.6 billion in Bolivia, and US$5.1 billion in Peru (POL scenario). POL2 which includes a strong reduction in deforestation, would also mitigate some of the negative economic impacts, with GDP losses on the order of US$$77.3 billion in Brazil, US$27.9 billion in Colombia, US$13.1 billion in Bolivia, US$12.0 in Ecuador and US$4.6 in Peru. Strategies to avert a tipping point, including net zero deforestation, would generate positive gains for inter-generational wealth; the impact of a policy of net zero deforestation is particularly strong. For Brazil, averting a tipping point with net zero deforestation (POL scenario) would mean an additional US$162.8 billion in wealth, followed by US$98.2 billion in Colombia, US$47.3 billion in Ecuador,, US$20.95 billion in Peru and US$10.1 billion in Bolivia. Policies to avert a tipping point that include the strong reduction in deforestation would be more modest in terms of inter-generational wealth gains. This scenario would result in an increase in wealth of US$64.4 billion in Brazil, US$77.7 billion in Colombia, US$29.9 billion in Ecuador, US$13.3 billion in Peru and US$9.3 billion in Bolivia

Specific interventions to expand climate adapted agriculture and irrigation would contribute to mitigating agricultural productivity losses and the reduction in wealth, particularly through household savings, but only in the case of Peru would these interventions be sufficient to generate a positive wealth impact (Table 1). Improved fire management would generate wealth gains in the case of Brazil, Colombia, Peru and Bolivia which is a function of the increased stock of standing forest. Improved fire management would be insufficient, however in the case of Ecuador, with the albeit small reduction in available agricultural land outweighing the positive impact of increased standing forest stock.

In interpreting impacts across countries, the costs of the different policy interventions in each country provide some insights. The cost of reducing deforestation and fire is proportional to each country's share of the Amazon biome (Table 3). The cost of implementing climate adapted agriculture and irrigation was distributed across the five focal countries based on their share of total agricultural GDP. As a share of base year GDP, averting a tipping point would be most costly for Bolivia, with the cumulative cost representing 39.2% of base year GDP. Policy interventions for Peru would represent 11.7% of base year GDP, followed by Brazil (6.4%), Colombia (6.3%), and Ecuador (4.3%). The cost of eliminating deforestation and reducing fire in Brazil would be 7.6 times higher than in Bolivia. However, Brazil's GDP is 51 times larger than Bolivia's GDP.

How the strategies to avert a tipping point are financed in IEEM is also important for interpreting the results. In the case of improved fire management, for example, 50% of the investment cost is financed through household income tax with the other 50% financed through foreign borrowing. Increased income tax has implications for household savings which has a direct impact on wealth. Implementing climate adapted agriculture is financed fully in IEEM through an increase in the stock of domestic debt. The policy of net zero deforestation is fully financed in IEEM by external grants. With various financing mechanisms possible for each of the scenarios and with important implications for the results, these alternative financing mechanisms will be explored in subsequent analysis.

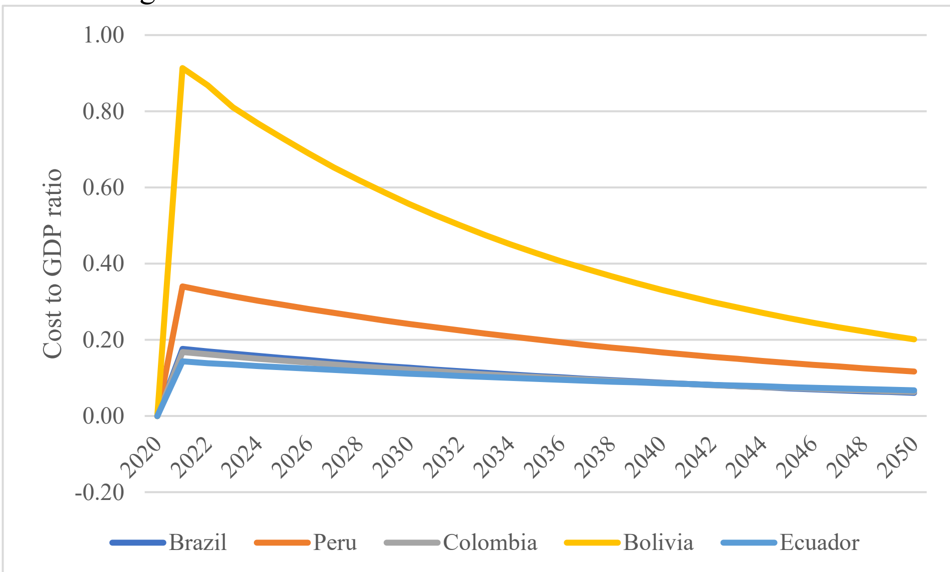
Table 2. Cumulative investment costs as a share of base year GDP in percent.

	Brazil	Peru	Colombia	Bolivia	Ecuador
Share of Amazon (% of total biome)	58	13	7	8	1
Country GDP in base year (millions of USD)	$1,892,584	$215,516	$289,667	$37,111	$100,397
Cumulative cost as a percent of base year GDP in percent					
NDEFOR	5.0	9.5	4.1	35.0	1.5
NDEFOR2	4.6	8.6	3.7	31.8	1.4
YIELD50	1.3	2.0	2.2	3.8	2.8
NFIR	0.1	0.1	0.1	0.5	0.0
POL	6.4	11.7	6.3	39.2	4.3
POL2	6.0	10.8	5.9	36.1	4.2

Source: IEEM+ESM results; shares of Amazon biome derived from Coca-Castro et al. (2013).

Another important consideration in interpreting the results is the trajectory of the cost of the interventions relative to each counties' GDP. Figure 17 shows how the costs of the intervention strategies are distributed through time. This distribution of costs shows a large initial cost to GDP ratio which is indicative of high start-up costs of the intervention strategies. These large up-front investments involve large government expenditures relative to GDP, which due to a stronger Keynesian effect in the earlier periods, the interventions offset some of the initial difference between GDP in the BASE compared with GDP in the policy intervention scenario.

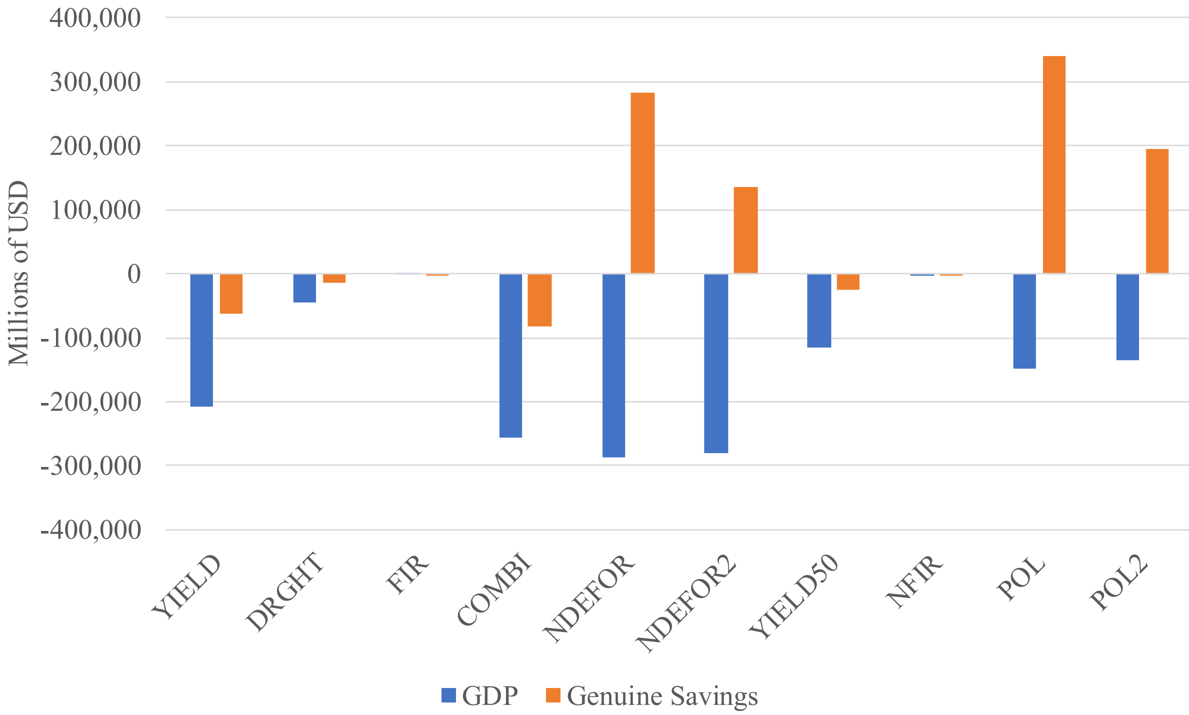
Figure 17. Cost to GDP ratio for Amazon focal countries.



Source: IEEM+ESM results.

Figure 18 shows the cumulative impact of each scenario on GDP and wealth for the Amazon region as a whole. Reaching an Amazon tipping point would result in a GDP loss of over US$256.6 billion. Policies to avert a tipping point (POL) would mitigate some of this GDP loss, particularly through investment in climate adapted agriculture, though there would still be a US$148.9 billion impact on regional GDP nonetheless. Where deforestation is strongly reduced (POL2), the GDP impact would be US$135.0 billion. While GDP does not value standing forests, wealth does. We find that the outlook completely changes from the perspective of wealth. A policy of net zero deforestation across the region, along with policies to adapt agriculture to climate change and reduce fire (POL) would generate an additional US$339.3 billion in wealth. Where deforestation is strongly reduced (POL2), the policy intervention would generate less wealth, on the order of US$195.0 billion. Indeed, the evidence that GDP versus Genuine Savings, our metric of wealth, provides for the design and implementation of policies for the region are in stark contrast and has been demonstrated in our previous work (Banerjee et al., 2021).

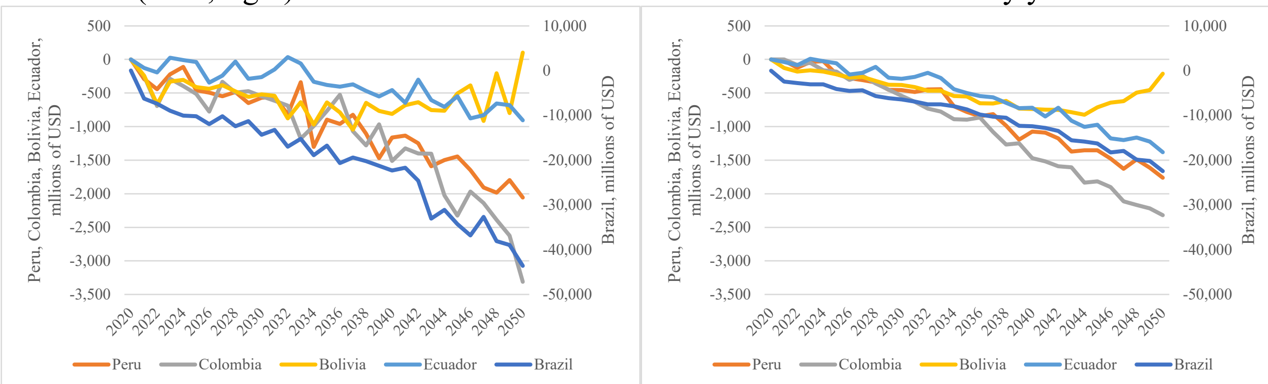
Figure 18. Cumulative regional impacts on GDP and Genuine wealth as difference from the BASE in millions of USD.



Source: IEEM+ESM results.

The GDP trajectory by country, as a difference from business-as-usual, is strongly influenced by the climate change projections and derived indicators used to estimate agricultural productivity and fire-related shocks throughout the analytical period. Figure 19 shows the trajectory of GDP as the difference from BASE for the tipping point scenario on the left. On the right, Figure 19 shows the GDP trajectory for the policy intervention scenario (POL) as the difference from the tipping point scenario. Note that impacts for Brazil are read from the secondary y-axis due to the relatively large impacts compared with other Amazon countries. The cumulative impacts presented in Table 1 and discussed above provide a useful overview summary. What is interesting to note from this figure is the irregularity of impacts through time where some years would register markedly worse impacts than others. In the case of Bolivia, policies to avert a tipping point, when considered from the perspective of GDP, would appear to gain traction nearing the end of the analytical period.

Figure 19. GDP trajectory for the tipping point (COMBI, left) and policy intervention scenario (POL, right) in millions of USD. Note: Brazil is shown on secondary y-axis.



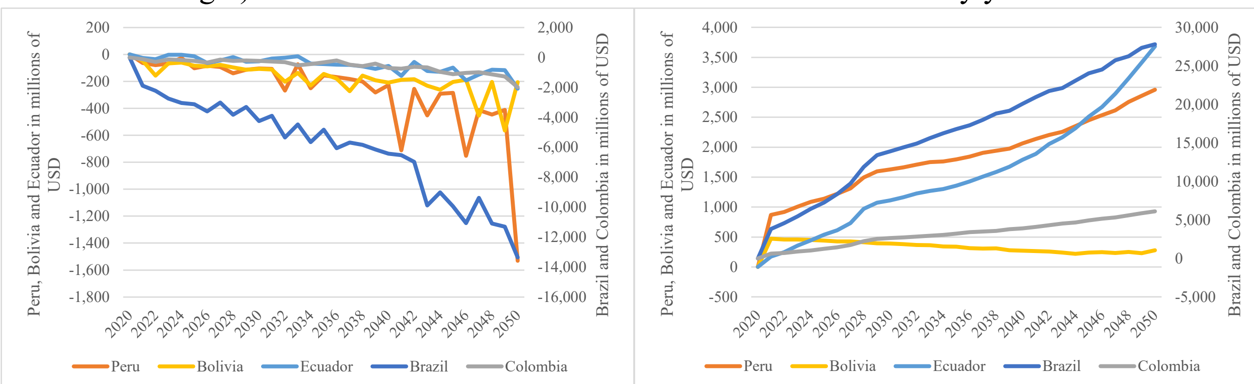
Source: IEEM+ESM results.

Figure 20 shows the trajectory of wealth as a difference from BASE for the tipping point and the policy intervention (POL) scenarios as a difference from the tipping point scenario. What we can observe from the tipping point figure on the left is that Brazil's path would follow a relatively steep decline throughout the analytical period. Peru would suffer a rather precipitous drop in wealth at the end of the period which is due to a fire that destroys a large tract of forest. This important loss of natural capital stocks would go undetected from the perspective of GDP. Where policies are implemented to avert a tipping point, we would see smoother upward trends for most countries while Bolivia would experience a boost to wealth in the initial years with a tendency toward the BASE levels of wealth in later years.

The smoother trend in the policy scenario compared with the tipping point scenario is explained by the gradual implementation of the yield improvement shock. Note that the yield improvement is relative to the tipping point scenario. Explaining Bolivia's response to the policy scenario, recall the large cost of averting a tipping point relative to the size of Bolivia's GDP (Table 3). In addition, the unit rent used to value the loss of standing forest is comparatively smaller in Bolivia compared with that of other countries. This has impacts on the magnitude of the value of the natural capital stock component of our wealth indicator. Note that unit rent is directly derived from the System of National Accounts and land cover and land use data from each country.

Furthermore, how the policy intervention is financed has very important impacts on the results. In averting a tipping point, the investment costs are imposed in IEEM as a decreasing share of GDP, 50% of which are financed through direct taxation. Taking Bolivia as an example, we see that in the final years of the policy intervention, the required increase in direct taxation to finance the investment would be lower and thus there would be an increase in household disposable income, savings, and investment.

Figure 20. Wealth trajectory as difference from BASE for the tipping point (COMBI, left) and the policy intervention (POL) scenario as a difference from the tipping point scenario (COMBI, right) in millions of USD. Note: Brazil is shown on secondary y-axis.



Source: IEEM+ESM results.

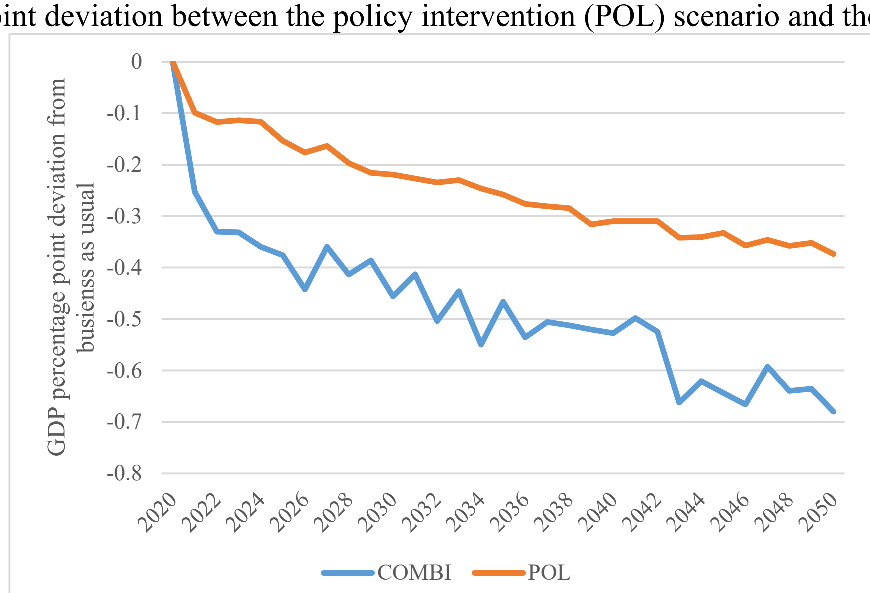
Figure 21 shows the trajectory of regional GDP and wealth as a difference from the BASE for the Amazon tipping point (COMBI) and as a difference from the tipping point scenario in the case of the policy intervention (POL) scenarios. Some of the irregularity evident in country-level impacts would be averaged out. The trend from the perspective of GDP would, however, still be downward for both the Amazon tipping point and the policy intervention scenario. The good news is that wealth for the region would increase steadily with decisive policy action through the elimination of deforestation, the implementation of climate adapted agriculture and improved fire management.

Figure 21. GDP (left) and Genuine Savings (right) trajectory for COMBI and POL in millions of USD.

Source: IEEM+ESM results.

Another form of viewing regional GDP impacts is as a percentage point difference from the BASE as shown in Figure 22. Here we find that by 2050, reaching an Amazon tipping point would result in GDP that was 0.68 percentage points less than the levels registered in the BASE in 2050. Where concerted policy action (POL) would intervene to avert a tipping point, GDP in 2050 would be 0.37 percentage points below the BASE. Of course, the potential cumulative GDP impact is important to keep in mind for both the tipping point and policy scenarios as shown in Figure 18.

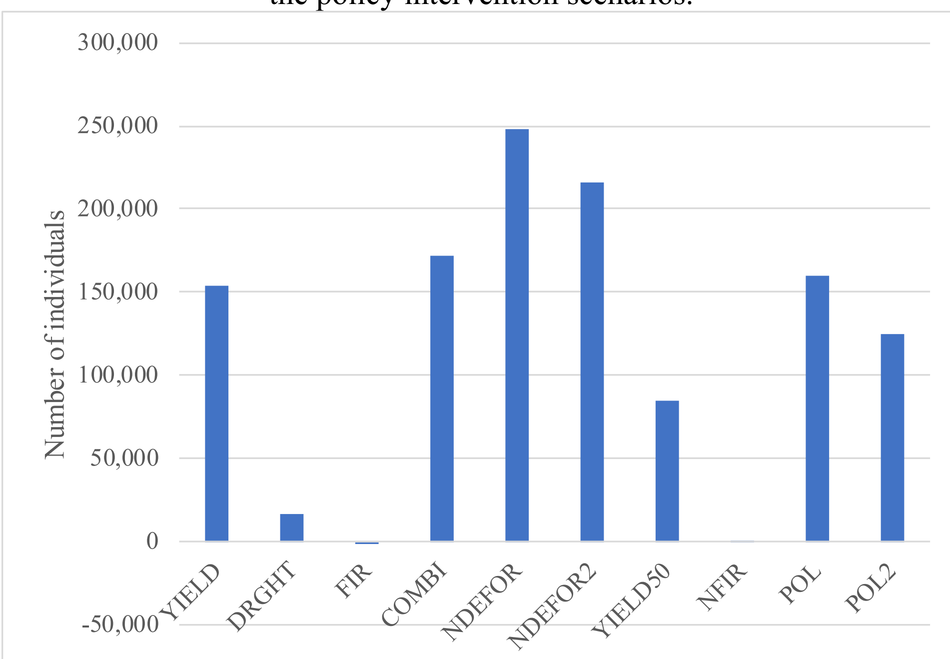
Figure 22. Regional GDP percentage point deviation between the tipping point and the BASE; percentage point deviation between the policy intervention (POL) scenario and the tipping point.



Source: IEEM+ESM results.

A distinct advantage of the IEEM Platform is the ability to estimate poverty and distributional impacts of scenarios as shown in Figure 23. Clearly the climate change impacts on agricultural productivity of an Amazon tipping point would push the greatest number of people into poverty, by over 153 thousand more people than in the BASE. Overall, the tipping point means that at least 171 thousand more people would be living in poverty across the region. While the policy intervention (POL) scenario mitigates some of the increased poverty, poverty would still increase by 159.6 thousand when compared with the tipping point scenario and by 125.3 thousand with a policy intervention that strongly reduces deforestation (POL2). This result is important in signaling the need for complementary policies to mitigate poverty impacts that could arise with policy interventions that could have important impacts on land use dynamics across the Amazon, particularly those that affect small holder subsistence farmers. Enhancing property rights, developing a strong bioeconomy, greater provision of agricultural extension and other services, and payment for ecosystem services are examples of complementary policies.

Figure 23. Number of individuals below the poverty line as difference from the BASE in the case of the tipping point scenarios, and; as a difference from the tipping point scenario in the case of the policy intervention scenarios.



Source: IEEM+ESM results.

Calculating the Net Present Value (NPV) in a benefit-cost analytical framework is a standard approach to assessing the economic viability of public policies 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. Table 4 presents NPV based on equivalent variation by country and scenario. Equivalent variation is interpreted as 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., 2019b).

Brazil, with the greatest investment required to avert an Amazon tipping point (POL), would present a negative NPV of US$31.9 billion viewed through the lens of a conventional benefit-cost analysis; the NPV of other countries would be much less, about 6% of the NPV of Brazil in the case of Colombia for example. Where we consider changes in natural capital stocks and environmental quality, strategies to avert a tipping point (POL) would generate an NPV of US$17.8 billion for Brazil, US$7.7 in the case of Colombia, US$3.4 billion in Ecuador and US$2.4 billion in Peru. The NPV of Bolivia would remain negative (US$1.7 billion) with the implementation of strategies to avert a tipping point.

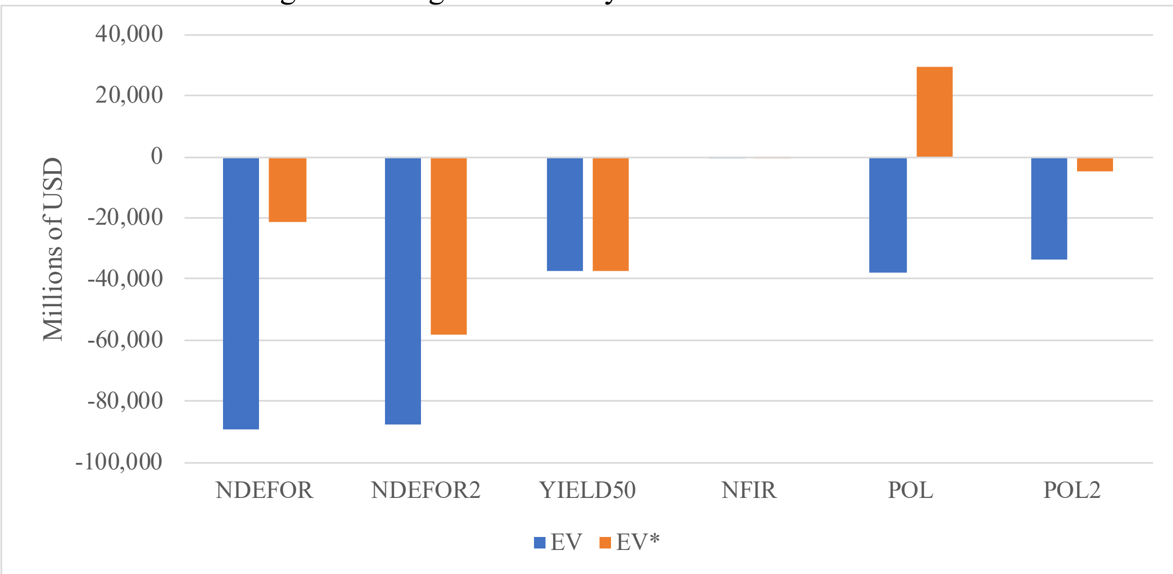
Table 3. Net Present Value based on equivalent variation (EV, left) and adjusted equivalent variation (EV*, right) by country and scenario in millions of USD.

	EV						EV*					
	NDEFOR	NDEFOR2	YIELD50	NFIR	POL	POL2	NDEFOR	NDEFOR2	YIELD50	NFIR	POL	POL2
Brazil	-78,478	-77,305	-32,344	-102	-31,865	-28,937	-28,823	-58,718	-32,172	-148	17,770	-10,456
Peru	-2,426	-2,418	-1,612	-25	-1,443	-1,040	1,389	-856	-1,614	-59	2,372	523
Colombia	-3,451	-3,341	-1,388	-9	-1,876	-1,586	5,993	3,797	-1,345	-18	7,565	5,542
Bolivia	-3,157	-3,135	-1,317	-29	-1,679	-1,345	-3,143	-3,129	-1,317	-29	-1,665	-1,338
Ecuador	-1,536	-1,205	-752	-1	-1,194	-832	3,099	829	-756	-6	3,431	1,182
Total	-89,048	-87,404	-37,413	-167	-38,057	-33,739	-21,485	-58,075	-37,204	-260	29,473	-4,546

Source: IEEM+ESM results.

Figure 24 presents the regional NPV by scenario in millions of USD. The investment in averting economic and ecological disaster in the Amazon (POL), when viewed from a conventional benefit-cost analytical perspective, would result in negative economic returns of US$38 billion. Where we consider the value of changes in natural capital stocks and environmental quality, strategies to avert a tipping point (POL) would generate positive returns on the order of US$29.6 billion, indicating a sound investment in the region's future.

Figure 24. Regional NPV by scenario in millions of USD.



Source: IEEM+ESM results.

4.4. Economic transmission pathways

Before closing our results section, it is useful to consider in more detail some of the main transmission pathways that drive the IEEM results presented in the previous section. All results generated by IEEM are entirely explainable within the consistent structure of the model and the assumptions and input parameters used. The Amazon tipping point and the policy intervention scenarios include two drivers of agricultural productivity impacts; the first is the average climate change effect which is isolated in the YIELD scenario and the second is the increasing frequency and intensity of drought which is isolated in the DRGHT scenario.

Figure 25 outlines the transmission pathways of agricultural productivity shocks in these two scenarios. These two drivers, the average climate effect and increasing frequency and intensity of drought, reduce agricultural productivity and output, and with increased scarcity, agricultural output prices tend to rise. As a result, food processing costs increase and the quantity of processed food output declines. To compensate for reduced productivity, agricultural factor use increases which competes with non-agricultural factor use, thus reducing the latter. This puts a downward pressure on wages, increases unemployment and reduces household income. With reduced income, households consume less, save less and as a result, investment also declines. The combined impact of reduced output both of agricultural products and processed food, and the reduction in household income, savings and investment, negatively impacts GDP growth rates as we have seen in the YIELD and DROUGHT scenarios presented in Table 1.

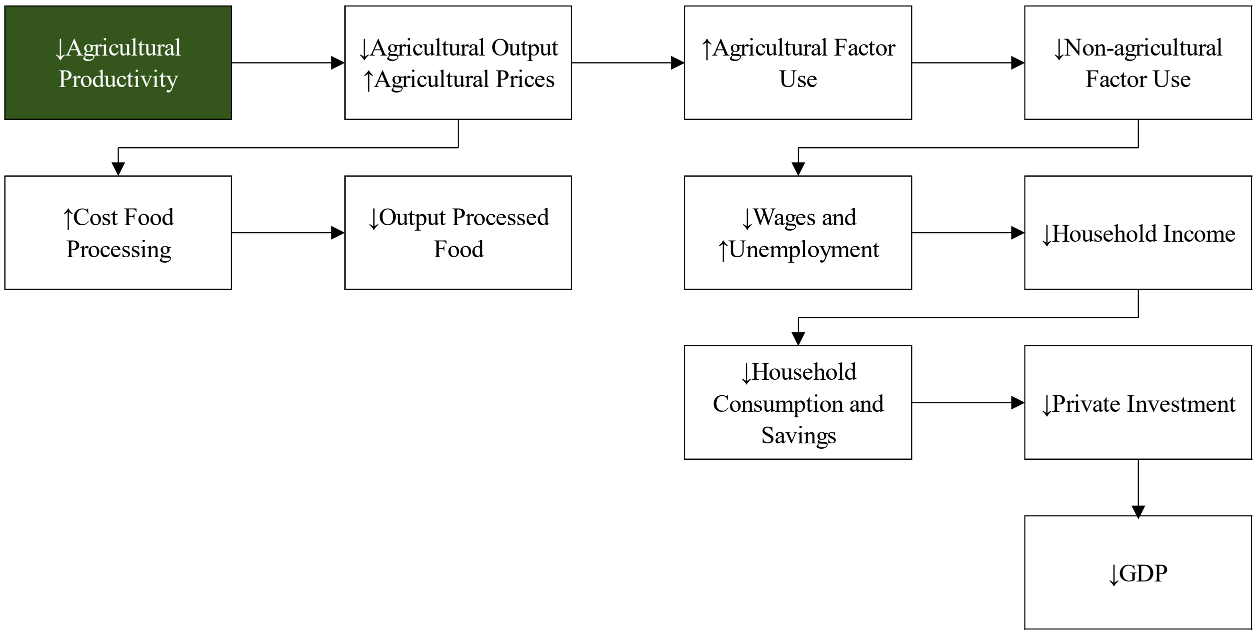
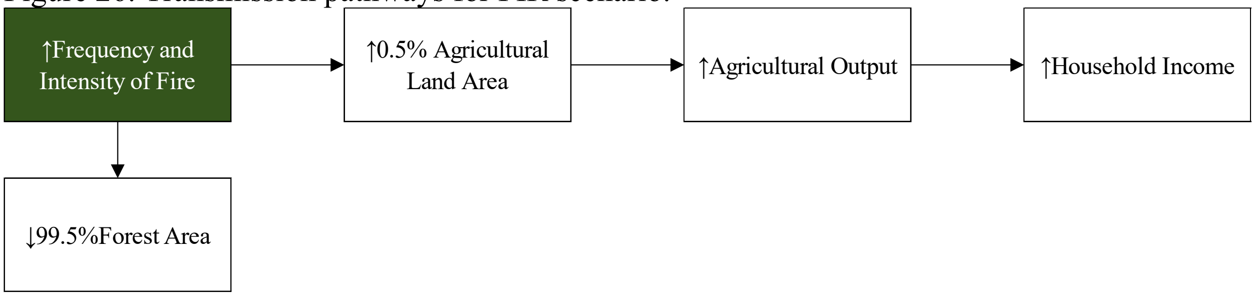


Figure 25. Transmission pathways for YIELD and DROUGHT scenarios.
Source: Authors' own elaboration.

Figure 26 presents the economic transmission pathway for the FIR scenario. In this scenario, with an increase in the frequency and intensity of fire, we assume that a very small area of the total burned (0.5%) is converted to agricultural areas[3]. This increase in the land available for agriculture makes it possible to produce more agricultural output which has a positive impact on household income and thus on savings and investment, which all have a positive impact on GDP growth. On the other hand, fire reduces the standing forest stock which factors in negatively in our calculation of wealth and the net present value of policy interventions.

[3] Note that most fire used in deforestation and land clearing is captured in our BASE projection of deforestation.

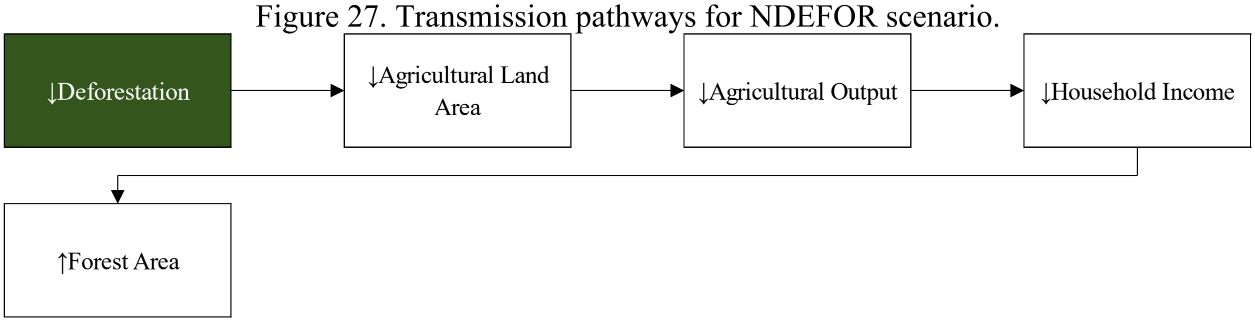
Figure 26. Transmission pathways for FIR scenario.



Source: Authors' own elaboration.

Figure 27 shows the transmission pathways of the NDEFOR scenario. Net zero deforestation would have important impacts on the economies of the region, reducing the agricultural land available and as a result, agricultural output. This pushes the income of households downward, which reduces savings and investment. Note that depending on factor ownership and unemployment, the poor can be disproportionately affected by such drastic changes in land use dynamics. Reductions in income and savings slow GDP growth. As with the FIR scenario, this scenario preserves the standing stock of forest which has important positive implications for wealth and net present value.

Figure 27. Transmission pathways for NDEFOR scenario.



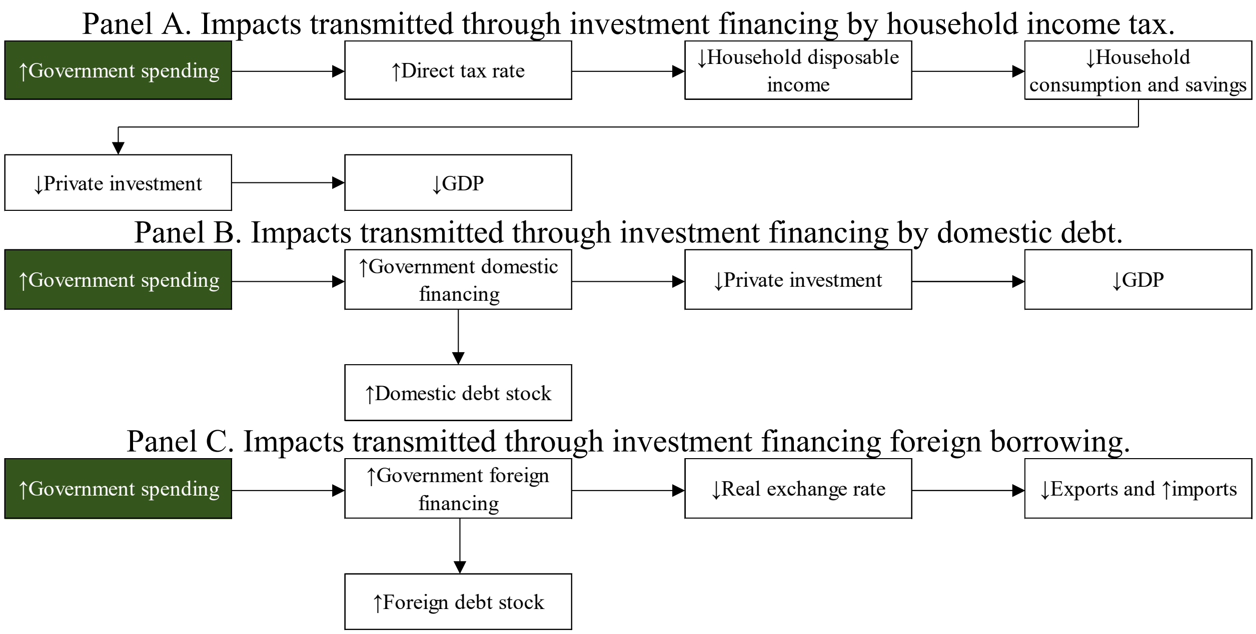
Source: Authors' own elaboration.

The way in which the investment costs are financed in IEEM (and in the real world) has a strong impact on the results presented; Figure 28 outlines the main transmission pathways for the financing options used in this analysis. Beginning with investment financed through direct taxation in IEEM (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. Fifty percent of NFIR in IEEM is financed through direct taxation.

Where investments are financed in IEEM through domestic debt (Panel B), the increase in government spending is achieved through the government taking on additional domestic debt which in turn lowers the level of private investment. The reduction in the level of private investment can have lasting impacts on GDP. The YIELD50 scenario in IEEM is financed fully through an increase in the stock of domestic debt.

Finally, where increased government spending is financed in IEEM through foreign borrowing, the foreign debt stock increases and the real exchange rate appreciates. This exchange rate appreciation can place downward pressure on exports rendering them less competitive, though through a more powerful local currency, imports may increase as a result. NDEFOR is fully financed in IEEM through foreign borrowing; clearly, adjusting this assumption would have important impacts on the results. Fifty percent of the NFIR scenario in IEEM is financed through foreign borrowing.

Figure 28. Transmission pathways for investment financing options.



Source: Authors’ own elaboration.

5.0. Limitations and future research directions

There are various limitations and caveats to note in the interpretation of the results of this study. First, our policy intervention scenarios include a net zero deforestation scenario and a scenario in which deforestation is strongly reduced. There are many views on what may be realistic and optimal from a political, social and environmental perspective in the short and medium term, across our five focal countries. What our results show is that where deforestation generates new land for agricultural production, GDP impacts would be negative. From the perspective of wealth, however, the enhancement of natural capital stocks and ecosystem service flows that arise from reducing deforestation can more than compensate for these negative impacts as demonstrated in Table 1. Our choice of scenarios representing net zero deforestation and a strong reduction in deforestation may be viewed as imposing measures reflecting a strong sustainability policy stance on the one hand, and a more balanced view on the other, which takes into greater consideration short-run costs and adjustment factors which are non-trivial as shown in Figure 23. With the IEEM+ESM framework now developed for the five focal countries, subsequent work could explore this question in more detail on a country-by-country basis, also taking into account within-country diversity of conditions.

The IEEM+ESM framework enables the spatial and temporal targeting of policies to reduce deforestation. In this study, the LULC change modeling was used to determine what areas were deforested and in what sequence. This spatial assignment of deforestation was based on the suitability analysis described in section 2.3; in this approach, the areas most suitable for crop and livestock production were identified based on regression analysis of multiple biophysical and socioeconomic variables. Those areas most suitable for these activities were deforested first. There are of course other ways in which the reduction of deforestation could be spatially targeted. This could include additional criteria not currently captured in this study, for example, spatial variation in the cost of reducing deforestation or the identification of particularly high conservation value forests, among others. Indeed, the ecosystem service analysis presented in section 4.2 could be used to target areas that were identified as especially productive in the provision of specific ecosystem services.

In a whole of economy model such as IEEM, all expenditure must be met by an equivalent source of income. Figure 28 provides an overview of the main financing options in IEEM and their transmission pathways, which include financing derived from changes in household income tax, domestic debt, and foreign borrowing and foreign. For each of our policy intervention scenarios which include investments, we have made assumptions on the possible financing mechanisms, for example, in the case of improved fire management, 50% of the investment cost is financed through household income tax with the other 50% financed through foreign borrowing. In the case of reducing deforestation, our policy intervention scenario finances these measures through a foreign grant. Of course, alternative assumptions are possible, which could be evaluated in future work, including innovative financing mechanisms such as green bonds and habitat banking, among others.

As we have discussed, continued deforestation and fire in the Amazon region is affecting regional hydrological cycles with discernable localized impacts including the reduction of rainfall and lengthening of the dry season. Our implementation of the policy intervention scenarios in IEEM, which include net zero deforestation and strongly reducing deforestation, does not capture these potential climate mitigation effects. Our improved agricultural productivity (YIELD) scenario includes gains achieved by implementing climate adapted agriculture and irrigation; including the climate mitigation effects of reducing deforestation could further enhance these gains, and therefore our results underestimate the potential benefits of reducing deforestation. Recent work by Strand et al. (2018) provides a basis for how some of these climate mitigation benefits could be included (Strand et al., 2018).

In assessing the impacts of movement towards a tipping point, our study focuses on how continued deforestation and climate change could affect some provisioning ecosystem services such as food, fiber and water, as well as specific regulating ecosystem services, namely water quality, erosion mitigation services and carbon sequestration. These ecosystem services were chosen as the focus given their relatively high potential to affect economic outcomes and the availability of tools and data to model them. There are, however, various other ecosystem services that could be impacted by continued deforestation and climate change, including numerous provisioning ecosystem services such as: the production of genetic material, and hydro and wave/tidal power; regulating services such as stopping landslides, regulating air quality, water flows, wind and fire, pollination, habitat, and pest control, and finally; cultural services including recreation, tourism and education (European Environment Agency, 2018). Work currently underway is examining the feasibility of incorporating these additional services into the tipping point analysis.

There are a number of uncertainties related to the ecosystem services modeling conducted in this study, which in general are characteristic of other ecosystem service modeling efforts. The ecosystem service models used in this study are uncalibrated due to a lack of data reliable field data across our five focal countries. For example, calibration of the water quality modeling, specifically the nitrogen and phosphorous export modeling, would require data from a national water quality monitoring program including stream gauges with adequate coverage within and across our five focal countries (Banerjee et al., 2020b). While there is less certainty around absolute values resulting from this ecosystem services modeling, our presentation of results focuses on relative changes between the tipping point and policy intervention scenarios where the direction of effect and approximate relative magnitudes provides useful and actionable information from a policy making perspective.

Finally, various simplifying assumptions were required with regard to the cost of policy interventions. While many experts agree on the importance of reducing deforestation, implementing climate adapted agriculture, and improving fire management, there is a great deal of uncertainty around the costs of implementing these measures across our five focal countries. In building on this study, we are working on generating better estimates of costs for these critical intervention measures. Policy makers require this information in order to assess costs, benefits and trade-offs involved in preparing national budgets and plans to invest in a more sustainable vision for the Amazon region.

6.0. Discussion and conclusions

We evaluated the economic and environmental impacts of reaching a tipping point in the Amazon and key strategies to avert it with the IEEM Platform linked with spatial LULC change and ecosystem services modeling. The best science available shows that we are at the precipice of an Amazon tipping point due to the self-reinforcing interactions between climate change, deforestation and fire. We operationalize the tipping point concept as being comprised of continued high levels of deforestation across Amazon focal countries, average climate change impacts on temperature and precipitation, and increasing frequency and intensity of both drought and fire. These different dimensions of a tipping point, in the way we have modeled them, interact with regional economies primarily through direct impacts on agricultural productivity and the land market. Both lower productivity and land availability have implications for output and prices. With economy-wide implications, no economic sectors are spared the impacts, which would translate into reduced economic growth and wealth, and higher levels of poverty across the region. Impacts on natural capital stocks and future flows of ecosystem services would be severe.

Coordinated action by Amazon countries would contribute to mitigating the negative economic and environmental fall-out of a tipping point. Key strategies to avert disaster should include drastically reducing levels of deforestation across the region, improving the management of fire and implementing climate-adapted agricultural strategies. We find that since economic and environmental damage has gone unchecked for decades and the necessary measures to avert a tipping point would require some time to be implemented and take effect, there would still be some economic hardship involved in the short-run, as economies invest and adjust to new realities. The changes to land use dynamics would be significant, and those households that sustain their livelihoods through employment and/or ownership of land and natural capital would be affected. Complementary policies may be required to support those that would be disproportionately affected, especially those with less capacity to adapt on their own. Nonetheless, our results show that strong action taken now could avert disaster and in fact contribute to building wealth for current and future generations.

The impacts on natural capital and future ecosystem services flows would also be wealth and biodiversity-enhancing. With the implementation of strategies to avert a tipping point, future ecosystem services supply would improve greatly. Soil erosion mitigation services for example would improve by more than 50% in most regions. Carbon storage would increase almost across all countries by more than 25%. Water quality also generally would improve across the region with 50% less nutrient exports. Biodiversity would improve with a greater than 25% increase in most but a few sub-regions.

The economic impacts of an Amazon tipping point and policies to avert it would vary by country. In our results, this is primarily attributed to the importance of agriculture to each country's economy and its share of the Amazon biome. It is no surprise that the cumulative GDP impact of a tipping point would be the greatest in Brazil, on the order of US$184.1 billion. The next greatest impact would be under 20% of that of Brazil's and would be felt in Colombia (US$US35.3 billion), followed by Bolivia, Ecuador, and Peru.

In terms of wealth, country variability is again largely explained by the importance of agriculture to the country's economy and its share of the Amazon biome, but also by the returns to forest land which vary country to country. For example, the implementation of strategies to avert a tipping point in the Brazilian Amazon, including net zero deforestation, would generate an additional US$162.8 billion in wealth. Colombia would follow with a US$98.2 billion increase in wealth, followed by Peru, Ecuador and Bolivia. While the implementation of policies to avert environmental disaster in the Amazon would show short-term costs which is reflected by our measure of income flows (i.e. GDP), that these same policies would enhance inter-generational wealth makes a strong case for coordinated policy action if commitments to sustainable development (goals) are indeed prioritized above short-term gains.

Note that in this analysis, we primarily consider how a tipping point interacts with the economy through agricultural productivity and the land market. Clearly, there are many more interactions that could be considered, such as health impacts, implications of increased water scarcity, among others. As such, we consider the estimates we have presented to be highly conservative and indicative of a lower bound in terms of the negative consequences of moving towards an Amazon tipping point.

In terms of the trajectory of impacts of an Amazon tipping point, we find the impacts on both GDP and wealth would be quite volatile on an annual basis, with some years differing markedly from others. What drives this variability is climate change and the resulting variability in temperature and precipitation which are captured in the indicators used to calibrate the agricultural productivity shocks in IEEM. The implementation of fire is based on dry season length and projections of areas burned, both of which are driven by climate change and climate variability. Where strategies to avert a tipping point are implemented, this volatility is reduced somewhat due to the more gradual implementation of policies to reduce deforestation, manage fire and implement climate adapted agriculture.

What are the overall impacts for the region? We find that reaching an Amazon tipping point would generate a cumulative GDP loss of over US$256.6 billion. Policies to avert a tipping point including zero net deforestation would mitigate some of this GDP loss, resulting in a cumulative loss of US$148.9 billion by 2050, nonetheless. From the perspective of wealth, also on a regional basis, the panorama changes and there is some hope for leaving a prosperous future for the generations to come. Policies for zero net deforestation, climate adapted agricultural practices and improved fire management would generate an additional US$339.3 billion dollars in intergenerational wealth. Again, averting an Amazon tipping point and generating wealth for future generations would imply some short-run costs, which would include increased poverty, on the order of 159.6 thousand individuals falling into poverty in the short-run. This potential short-run negative impact signals the need for spatially targeted, complementary policies, such as payment for ecosystem services, the development of a strong bioeconomy, strengthened property rights and greater provision of agricultural extension services, among others.

Finally, how a strategy to avert an Amazon tipping point would be financed is of critical importance. The question of who will pay cannot be ignored. While we have shown that averting a tipping point would generate long-term sustainability and wealth, there would be clear costs to bear in the short run. Analysis with IEEM demands that assumptions are made about how every line of action is financed; every dollar spent in IEEM must be a dollar earned. While it is beyond the scope of this paper to discuss how costs should be distributed between regions within a country, between countries, and among the global community, what we have done is layout plainly the costs of doing nothing, compared with the costs and benefits of coordinated and decisive action. Indeed, a compelling business case is presented: our benefit-cost net present value analysis shows that when we consider the value of natural capital, investing in averting a tipping point, including zero net deforestation, would provide a return of US$29.5 billion, and that return is generated even when applying what is considered to be the high rate of discount of 12% applied by some multi-lateral development banks, such as the Inter-American Development Bank.

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References

ANA, IBGE, SRHQ, 2018. Contas Economicas Ambientais da Agua no Brasil 2013-2015. Agencia Nacional de Aguas, Instituto Brasileiro de Estadistica and Secretaria de Recursos Hidricos e Qualidade Ambiental, Brasilia.

Andela, N., Morton, D.C., Giglio, L., Chen, Y., Werf, G.R. van der, Kasibhatla, P.S., DeFries, R.S., Collatz, G.J., Hantson, S., Kloster, S., Bachelet, D., Forrest, M., Lasslop, G., Li, F., Mangeon, S., Melton, J.R., Yue, C., Randerson, J.T., 2017. A human-driven decline in global burned area. Science 356, 1356–1362. https://doi.org/10.1126/science.aal4108

Aragão, L.E.O.C., Malhi, Y., Barbier, N., Lima, A., Shimabukuro, Y., Anderson, L., Saatchi, S., 2008. Interactions between rainfall, deforestation and fires during recent years in the Brazilian Amazonia. Philosophical Transactions of the Royal Society B: Biological Sciences 363, 1779–1785. https://doi.org/10.1098/rstb.2007.0026

Ardila, J., Arieria, J., Bauch, S.C., Bezerra, T., Blackman, A., David, O., Finegan, B., Nascimento, N., Nepstad, D., Nobre, C.A., Rajão, R., Robalino, J., Sohngen, B., Stickler, C., Vargas, R., Warren, M., 2021. Latin American and Caribbean Forests in the 2020s: Trends, Challenges, and Opportunities. Inter-American Development Bank. https://doi.org/10.18235/0003019

Arrow, K., Dasgupta, P., Goulder, L., Daily, G., Ehrlich, P., Heal, G., Levin, S., Mäler, K.-G., Schneider, S., Starrett, D., Walker, B., 2004. Are We Consuming Too Much? Journal of Economic Perspectives 18, 147–172. https://doi.org/10.1257/0895330042162377

Arrow, K.J., Dasgupta, P., Goulder, L.H., Mumford, K.J., Oleson, K., 2012. Sustainability and the measurement of wealth. Environment and Development Economics 17, 317–353. https://doi.org/10.1017/S1355770X12000137

Assis, L.F., Ferreira, K.R., Vinhas, L., Maurano, L., Almeida, C., Carvalho, A., Rodrigues, J., Maciel, A., Camargo, C., 2019. TerraBrasilis: A Spatial Data Analytics Infrastructure for Large-Scale Thematic Mapping. ISPRS International Journal of Geo-Information 8, 513. https://doi.org/10.3390/ijgi8110513

Ayrimoraes, S., Fontenelle, T.H., Vilella, W.M. d. C., 2017. Atlas Irrigação: Uso da Água na Agricultura Irrigada. Agencia Nacional de Águas; Embrapa, Brasilia.

Banerjee, O., Alavalapati, J., 2010. Illicit exploitation of natural resources: The forest concessions in Brazil. Journal of Policy Modeling 32, 488–504. https://doi.org/10.1016/j.jpolmod.2010.06.001

Banerjee, Onil, Bagstad, K.J., Cicowiez, M., Dudek, S., Horridge, M., Alavalapati, J.R.R., Masozera, M., Rukundo, E., Rutebuka, E., 2020a. Economic, land use, and ecosystem services impacts of Rwanda's Green Growth Strategy: An application of the IEEM+ESM platform. Science of The Total Environment 729, 138779. https://doi.org/10.1016/j.scitotenv.2020.138779

Banerjee, O., Cicowiez, M., 2020. The Integrated Economic-Environmental Modeling (IEEM) Platform, IEEM Platform Technical Guides: IEEM Mathematical Statement, IDB Technical Note No. 01842. Inter-American Development Bank, Washington DC.

Banerjee, O., Cicowiez, M., 2019. The Integrated Economic-Environmental Modeling Platform (IEEM), IEEM Platform Technical Guides: User Guide, IDB Technical Note No. 01843. Inter-American Development Bank, Washington DC.

Banerjee, O., Cicowiez, M., Dudek, S., 2019a. The IEEM+ESM Approach: An Application to the SDGs in Guatemala. Presented at the SEEA Forum of Experts on Experimental Ecosystem Accounting, United Nations, Glen Cove.

Banerjee, Onil, Cicowiez, M., Horridge, M., Vargas, R., 2019a. Evaluating synergies and trade-offs in achieving the SDGs of zero hunger and clean water and sanitation: An application of the IEEM Platform to Guatemala. Ecological Economics 161, 280–291. https://doi.org/10.1016/j.ecolecon.2019.04.003

Banerjee, O., Cicowiez, M., Horridge, M., Vargas, R., 2016. A Conceptual Framework for Integrated Economic–Environmental Modeling. The Journal of Environment & Development 25, 276–305. https://doi.org/10.1177/1070496516658753

Banerjee, O, Cicowiez, M., Malek, Z., Verburg, P.H., Vargas, R., Goodwin, S., 2020. The Value of Biodiversity in Economic Decision Making: Applying the IEEM+ESM Approach to Conservation Strategies in Colombia (Inter-American Development Bank Working Paper). Inter-American Development Bank, Washington D.C.

Banerjee, O., Cicowiez, M., Moreda, A., 2019b. Evaluating the Economic Viability of Public Investments in Tourism. Journal of Benefit-Cost Analysis 32, 1–30.

Banerjee, Onil, Cicowiez, M., Vargas, R., Horridge, M., 2019b. The SEEA-Based Integrated Economic-Environmental Modelling Framework: An Illustration with Guatemala's Forest and Fuelwood Sector. Environmental and Resource Economics 1–20. https://doi.org/10.1007/s10640-017-0205-9

Banerjee, O., Cicowiez, M., Vargas, R., Horridge, M., 2019c. Construction of an Extended Environmental and Economic Social Accounting Matrix from a Practitioner's Perspective, IDB Technical Note No. IDB-TN-01793. Inter-American Development Bank, Washington DC.

Banerjee, O., Cicowiez, M., Vargas, R., Obst, C., Cala, J.R., Alvarez-Espinosa, A.C., Melo, S., Riveros, L., Romero, G., Meneses, D.S., 2021. Gross domestic product alone provides misleading policy guidance for post-conflict land use trajectories in Colombia. Ecological Economics 182, 106929. https://doi.org/10.1016/j.ecolecon.2020.106929

Banerjee, O., Macpherson, A.J., Alavalapati, J., 2009. Toward a policy of sustainable forest management in Brazil: a historical analysis. Journal of Environment & Development 18, 130–153. https://doi.org/10.1177/1070496509333567

Barkhordarian, A., Saatchi, S.S., Behrangi, A., Loikith, P.C., Mechoso, C.R., 2019. A recent systematic increase in vapor pressure deficit over tropical South America. EGU General Assembly Conference Abstracts 10876.

BCE, 2020a. Cuentas Nacionales Regionales: Cuentas Provinciales Serie 2007-2018 Cuadros. Banco Central del Ecuador, Guayaquil.

BCE, 2020b. Cuentas Nacionales Anuales: Cuentas Económicas Integradas (CEI) 2007-2018. Banco Central del Ecuador, Guayaquil.

Beguería, S., Vicente-Serrano, S.M., Reig, F., Latorre, B., 2014. Standardized precipitation evapotranspiration index (SPEI) revisited: parameter fitting, evapotranspiration models, tools, datasets and drought monitoring. International Journal of Climatology 34, 3001–3023. https://doi.org/10.1002/joc.3887

Betts, R., Sanderson, M., Woodward, S., 2008. Effects of large-scale Amazon forest degradation on climate and air quality through fluxes of carbon dioxide, water, energy, mineral dust and isoprene. Philosophical Transactions of the Royal Society B: Biological Sciences 363, 1873–1880. https://doi.org/10.1098/rstb.2007.0027

Blanchflower, D.G., Oswald, A.J., 2005. The Wage Curve Reloaded. National Bureau of Economic Research, NBER Working Paper 11338.
Brando, P., Macedo, M., Silvério, D., Rattis, L., Paolucci, L., Alencar, A., Coe, M., Amorim, C., 2020. Amazon wildfires: Scenes from a foreseeable disaster. Flora 268, 151609. https://doi.org/10.1016/j.flora.2020.151609
Brando, P.M., Balch, J.K., Nepstad, D.C., Morton, D.C., Putz, F.E., Coe, M.T., Silvério, D., Macedo, M.N., Davidson, E.A., Nóbrega, C.C., Alencar, A., Soares-Filho, B.S., 2014a. Abrupt increases in Amazonian tree mortality due to drought–fire interactions. Proceedings of the National Academy of Sciences 111, 6347–6352. https://doi.org/10.1073/pnas.1305499111
Brando, P.M., Balch, J.K., Nepstad, D.C., Morton, D.C., Putz, F.E., Coe, M.T., Silvério, D., Macedo, M.N., Davidson, E.A., Nóbrega, C.C., Alencar, A., Soares-Filho, B.S., 2014b. Abrupt increases in Amazonian tree mortality due to drought–fire interactions. Proceedings of the National Academy of Sciences 111, 6347–6352. https://doi.org/10.1073/pnas.1305499111
Brando, P.M., Paolucci, L., Ummenhofer, C.C., Ordway, E.M., Hartmann, H., Cattau, M.E., Rattis, L., Medjibe, V., Coe, M.T., Balch, J., 2019. Droughts, Wildfires, and Forest Carbon Cycling: A Pantropical Synthesis. Annual Review of Earth and Planetary Sciences 47, 555–581. https://doi.org/10.1146/annurev-earth-082517-010235
Brando, P.M., Soares-Filho, B., Rodrigues, L., Assunção, A., Morton, D., Tuchschneider, D., Fernandes, E.C.M., Macedo, M.N., Oliveira, U., Coe, M.T., 2020a. The gathering firestorm in southern Amazonia. Science Advances 6, eaay1632. https://doi.org/10.1126/sciadv.aay1632
Brando, P.M., Soares-Filho, B., Rodrigues, L., Assunção, A., Morton, D., Tuchschneider, D., Fernandes, E.C.M., Macedo, M.N., Oliveira, U., Coe, M.T., 2020b. The gathering firestorm in southern Amazonia. Science Advances 6, eaay1632. https://doi.org/10.1126/sciadv.aay1632
Burfisher, M.E., 2017. Introduction to Computable General Equilibrium Models. Cambridge University Press, Cambridge. https://doi.org/10.1017/CBO9780511975004
Butt, E.W., Conibear, L., Reddington, C.L., Darbyshire, E., Morgan, W.T., Coe, H., Artaxo, P., Brito, J., Knote, C., Spracklen, D.V., 2020. Large air quality and human health impacts due to Amazon forest and vegetation fires. Environ. Res. Commun. 2, 095001. https://doi.org/10.1088/2515-7620/abb0db
Castanho, A.D.A., Coe, M.T., Brando, P., Macedo, M., Baccini, A., Walker, W., Andrade, E.M., 2020. Potential shifts in the aboveground biomass and physiognomy of a seasonally dry tropical forest in a changing climate. Environmental Research Letters 15, 034053. https://doi.org/10.1088/1748-9326/ab7394
Chambwera, M., Heal, G., Dubeux, C., Hallegatte, S., Leclerc, L., Markandya, A., McCarl, B.A., Mechler, R., Neumann, J.E., 2014. Economics of Adaptation, in: Economics of Adaptation. Cambridge University Press, Cambridge and New York, pp. 945–977.
Clement, C.R., 1999. 1942 and the Loss of Amazonian Crop Genetic Resources. I. The Relation between Domestication and Human Population Decline. Economic Botany 53, 188–202.
Clement, C.R., Denevan, W.M., Heckenberger, M.J., Junqueira, A.B., Neves, E.G., Teixeira, W.G., Woods, W.I., 2015. The domestication of Amazonia before European conquest. Proceedings of the Royal Society B: Biological Sciences 282, 20150813. https://doi.org/10.1098/rspb.2015.0813

Coca-Castro, A., Reymondin, L., Bellfield, H., Hyman, G., 2013. Land Use Status and Trends in Amazonia: A report for the Amazonia Security Agenda Project, Report for Global Canopy Programme and International Center for Tropical Agriculture as part of the Amazonia Security Agenda project. International Center for Tropical Agriculture and the Global Canopy Programme.

CONAB, 2019. Soy and maize harvest time series. Companhia Nacional do Abastecimiento.

CONABIO, n.d. Soy and maize harvest time series [WWW Document]. URL http://www.conab.gov.br. (accessed 3.12.20).

Coomes, O.T., Grimard, F., Burt, G.J., 2000. Tropical forests and shifting cultivation: secondary forest fallow dynamics among traditional farmers of the Peruvian Amazon. Ecological Economics 32, 109–124. https://doi.org/10.1016/S0921-8009(99)00066-X

Cortner, O., Garrett, R.D., Valentim, J.F., Ferreira, J., Niles, M.T., Reis, J., Gil, J., 2019. Perceptions of integrated crop-livestock systems for sustainable intensification in the Brazilian Amazon. Land Use Policy 82, 841–853. https://doi.org/10.1016/j.landusepol.2019.01.006

Costa, M.H., Fleck, L.C., Cohn, A.S., Abrahão, G.M., Brando, P.M., Coe, M.T., Fu, R., Lawrence, D., Pires, G.F., Pousa, R., Soares-Filho, B.S., 2019. Climate risks to Amazon agriculture suggest a rationale to conserve local ecosystems. Frontiers in Ecology and the Environment 17, 584–590. https://doi.org/10.1002/fee.2124

Daily, G.C. (Ed.), 1997. Nature’s Services: Societal Dependence on Natural Ecosystems. Island Press, Washington, D.C.

D’Almeida, C., Vörösmarty, C.J., Hurtt, G.C., Marengo, J.A., Dingman, S.L., Keim, B.D., 2007. The effects of deforestation on the hydrological cycle in Amazonia: a review on scale and resolution. Int. J. Climatol. 27, 633–647. https://doi.org/10.1002/joc.1475

DANE, 2018. Cuentas Económicas Integradas - CEI. Departamento Administrativo Nacional de Estadística, Bogotá.

DANE, 2017. Las Cuentas Ambientales y Economicos en Colombia, Grupo de Indicadores y Cuentas Ambientales. Dirección Nacional de Estadística, Bogota.

DANE, 2016. Tercer Censo Nacional Agropecuario. Departamento Administrativo Nacional de Estadistica, Bogota.

DANE, 2015a. Cuentas nacionales anuales - Base 2015. Departamento Administrativo Nacional de Estadística, Bogotá.

DANE, 2015b. Gran Encuesta Integrada de Hogares (GEIH). Departamento Administrativo Nacional de Estadística, Bogotá.

Dasgupta, P., 2021. The Economics of Biodiversity: The Dasgupta Review. HM Treasury, London.

Dasgupta, P.S., Ehrlich, P.R., 2013. Pervasive Externalities at the Population, Consumption, and Environment Nexus. Science 340, 324–328. https://doi.org/10.1126/science.1224664

de Oliveira, A.S., Rajão, R.G., Soares Filho, B.S., Oliveira, U., Santos, L.R.S., Assunção, A.C., van der Hoff, R., Rodrigues, H.O., Ribeiro, S.M.C., Merry, F., de Lima, L.S., 2019. Economic losses to sustainable timber production by fire in the Brazilian Amazon. The Geographical Journal 185, 55–67. https://doi.org/10.1111/geoj.12276

de Souza, L.M.B., 2019. Assessment of Future Climate Risk in Double Cropping Agricultural Systems for Brazil. Universidade Federal de Vicosa, Vicosa.

Dervis, K., de Melo, J., Robinson, S., 1982. General Equilibrium Models for Development Policy. Cambridge University Press, Cambridge.

Dixon, P., Jorgenson, D.W. (Eds.), 2012. Handbook of Computable General Equilibrium Modeling, 1st ed. Elsevier, Oxford.

Esquivel-Muelbert, A., Baker, T.R., Dexter, K.G., Lewis, S.L., Brienen, R.J.W., Feldpausch, T.R., Lloyd, J., Monteagudo-Mendoza, A., Arroyo, L., Álvarez-Dávila, E., Higuchi, N., Marimon, B.S., Marimon-Junior, B.H., Silveira, M., Vilanova, E., Gloor, E., Malhi, Y., Chave, J., Barlow, J., Bonal, D., Davila Cardozo, N., Erwin, T., Fauset, S., Hérault, B., Laurance, S., Poorter, L., Qie, L., Stahl, C., Sullivan, M.J.P., ter Steege, H., Vos, V.A., Zuidema, P.A., Almeida, E., Almeida de Oliveira, E., Andrade, A., Vieira, S.A., Aragão, L., Araujo-Murakami, A., Arets, E., Aymard C, G.A., Baraloto, C., Camargo, P.B., Barroso, J.G., Bongers, F., Boot, R., Camargo, J.L., Castro, W., Chama Moscoso, V., Comiskey, J., Cornejo Valverde, F., Lola da Costa, A.C., del Aguila Pasquel, J., Di Fiore, A., Fernanda Duque, L., Elias, F., Engel, J., Flores Llampazo, G., Galbraith, D., Herrera Fernández, R., Honorio Coronado, E., Hubau, W., Jimenez-Rojas, E., Lima, A.J.N., Umetsu, R.K., Laurance, W., Lopez-Gonzalez, G., Lovejoy, T., Aurelio Melo Cruz, O., Morandi, P.S., Neill, D., Núñez Vargas, P., Pallqui Camacho, N.C., Parada Gutierrez, A., Pardo, G., Peacock, J., Peña-Claros, M., Peñuela-Mora, M.C., Petronelli, P., Pickavance, G.C., Pitman, N., Prieto, A., Quesada, C., Ramírez-Angulo, H., Réjou-Méchain, M., Restrepo Correa, Z., Roopsind, A., Rudas, A., Salomão, R., Silva, N., Silva Espejo, J., Singh, J., Stropp, J., Terborgh, J., Thomas, R., Toledo, M., Torres-Lezama, A., Valenzuela Gamarra, L., van de Meer, P.J., van der Heijden, G., van der Hout, P., Vasquez Martinez, R., Vela, C., Vieira, I.C.G., Phillips, O.L., 2019. Compositional response of Amazon forests to climate change. Global Change Biology 25, 39–56. https://doi.org/10.1111/gcb.14413

European Commission, International Monetary Fund, Organisation for Economic Cooperation and Development, United Nations, Bank, W., 2009. System of National Accounts 2008. EC, IMF, OECD, UN, WB.

European Environment Agency, 2018. The Common International Classification of Ecosystem Services (CICES: Towards A Common Classification of Ecosystem Services [WWW Document]. URL https://cices.eu/ (accessed 1.1.18).

Faria, B.L.D., Brando, P.M., Macedo, M.N., Panday, P.K., Soares-Filho, B.S., Coe, M.T., 2017. Current and future patterns of fire-induced forest degradation in Amazonia. Environ. Res. Lett. 12, 095005. https://doi.org/10.1088/1748-9326/aa69ce

Filoso, S., Bezerra, M.O., Weiss, K.C.B., Palmer, M.A., 2017. Impacts of forest restoration on water yield: A systematic review. PLoS ONE 12, e0183210. https://doi.org/10.1371/journal.pone.0183210

Fonseca-Morello, T., Ramos, R., Steil, L., Parry, L., Barlow, J., Markusson, N., Ferreira, A., Fonseca-Morello, T., Ramos, R., Steil, L., Parry, L., Barlow, J., Markusson, N., Ferreira, A., 2017. FIRES IN BRAZILIAN AMAZON: WHY DOES POLICY HAVE A LIMITED IMPACT? Ambiente & Sociedade 20, 19–38. https://doi.org/10.1590/1809-4422asoc0232r1v2042017

Fontenelle, T., Ferreira, D., Guimaraes, D., Landau, E., 2017. Levantamento da agricultura irrigada por pivôs centrais no Brasil. Agencia Nacional de Aguas, Embrapa Milho e Sorgo., Brasilia.

Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., Husak, G., Rowland, J., Harrison, L., Hoell, A., Michaelsen, J., 2015. The climate hazards infrared precipitation with stations—a new environmental record for monitoring extremes. Scientific Data 2, 150066. https://doi.org/10.1038/sdata.2015.66

Garrett, R., Gardner, T., Morello, T., Marchand, S., Barlow, J., Ezzine de Blas, D., Ferreira, J., Lees, A., Parry, L., 2017. Explaining the persistence of low income and environmentally degrading land uses in the Brazilian Amazon. Ecology and Society 22. https://doi.org/10.5751/ES-09364-220327

GDAL/OGR contributors, 2020. GDAL/OGR Geospatial Data Abstraction software Library. Open Source Geospatial Foundation.

GFW, 2020a. Location of tree cover loss in Bolivia. Global Forest Watch, World Resources Institute, Washington, D.C.

GFW, 2020b. Location of tree cover loss in Ecuador. Global Forest Watch, World Resources Institute, Washington, D.C.

Giglio, L., Schroeder, W., Justice, C.O., 2016. The collection 6 MODIS active fire detection algorithm and fire products. Remote Sensing of Environment 178, 31–41. https://doi.org/10.1016/j.rse.2016.02.054

Gil, J.D.B., Garrett, R.D., Rotz, A., Daioglou, V., Valentim, J., Pires, G.F., Costa, M.H., Lopes, L., Reis, J.C., 2018. Tradeoffs in the quest for climate smart agricultural intensification in Mato Grosso, Brazil. Environmental Research Letters 13, 064025. https://doi.org/10.1088/1748-9326/aac4d1

Gillies, S., and others, 2013. Rasterio: geospatial raster I/O for {Python} programmers. Mapbox.

Girardi, G., Deconto, J.G., 2008. Aquecimento global ea nova geografia da produção agrícola no Brasil. EMBRAPA, Brasilia.

Griscom, B.W., Adams, J., Ellis, P.W., Houghton, R.A., Lomax, G., Miteva, D.A., Schlesinger, W.H., Shoch, D., Siikamäki, J.V., Smith, P., Woodbury, P., Zganjar, C., Blackman, A., Campari, J., Conant, R.T., Delgado, C., Elias, P., Gopalakrishna, T., Hamsik, M.R., Herrero, M., Kiesecker, J., Landis, E., Laestadius, L., Leavitt, S.M., Minnemeyer, S., Polasky, S., Potapov, P., Putz, F.E., Sanderman, J., Silvius, M., Wollenberg, E., Fargione, J., 2017. Natural climate solutions. Proceedings of the National Academy of Sciences 114, 11645–11650. https://doi.org/10.1073/pnas.1710465114

Haines-Young, R., Potschin, M., 2012. Common International Classification of Ecosystem Services (CICES): Consultation on Version 4, August-December 2012. EEA Frameork Contract No. EEA/IEA/09/003.

Hamel, P., Falinski, K., Sharp, R., Auerbach, D.A., Sánchez-Canales, M., Dennedy-Frank, P.J., 2017. Sediment delivery modeling in practice: Comparing the effects of watershed characteristics and data resolution across hydroclimatic regions. Science of The Total Environment 580, 1381–1388. https://doi.org/10.1016/j.scitotenv.2016.12.103

Hansen, M.C., Potapov, P.V., Moore, R., Hancher, M., Turubanova, S.A., Tyukavina, A., Thau, D., Stehman, S.V., Goetz, S.J., Loveland, T.R., Kommareddy, A., Egorov, A., Chini, L., Justice, C.O., Townshend, J.R.G., 2013. High-Resolution Global Maps of 21st-Century Forest Cover Change. Science 342, 850–853. https://doi.org/10.1126/science.1244693

Harris, I., Jones, P.D., Osborn, T.J., Lister, D.H., 2014. Updated high-resolution grids of monthly climatic observations – the CRU TS3.10 Dataset. International Journal of Climatology 34, 623–642. https://doi.org/10.1002/joc.3711

Hijmans, R.J., Cameron, S.E., Parra, J.L., Jones, P.G., Jarvis, A., 2005. Very high resolution interpolated climate surfaces for global land areas. Int. J. Climatol. 25, 1965–1978. https://doi.org/10.1002/joc.1276

Hudson, L.N., Newbold, T., Contu, S., Hill, S.L.L., Lysenko, I., Palma, A.D., Phillips, H.R.P., Alhusseini, T.I., Bedford, F.E., Bennett, D.J., Booth, H., Burton, V.J., Chng, C.W.T., Choimes, A., Correia, D.L.P., Day, J., Echeverría-Londoño, S., Emerson, S.R., Gao, D., Garon, M., Harrison, M.L.K., Ingram, D.J., Jung, M., Kemp, V., Kirkpatrick, L., Martin, C.D., Pan, Y., Pask-Hale, G.D., Pynegar, E.L., Robinson, A.N., Sanchez-Ortiz, K., Senior, R.A., Simmons, B.I., White, H.J., Zhang, H., Aben, J., Abrahamczyk, S., Adum, G.B., Aguilar-Barquero, V., Aizen, M.A., Albertos, B., Alcala, E.L., Alguacil, M. del M., Alignier, A., Ancrenaz, M., Andersen, A.N., Arbeláez-Cortés, E., Armbrecht, I., Arroyo-Rodríguez, V., Aumann, T., Axmacher, J.C., Azhar, B., Azpiroz, A.B., Baeten, L., Bakayoko, A., Báldi, A., Banks, J.E., Baral, S.K., Barlow, J., Barratt, B.I.P., Barrico, L., Bartolommei, P., Barton, D.M., Basset, Y., Batáry, P., Bates, A.J., Baur, B., Bayne, E.M., Beja, P., Benedick, S., Berg, Å., Bernard, H., Berry, N.J., Bhatt, D., Bicknell, J.E., Bihn, J.H., Blake, R.J., Bobo, K.S., Bóçon, R., Boekhout, T., Böhning-Gaese, K., Bonham, K.J., Borges, P.A.V., Borges, S.H., Boutin, C., Bouyer, J., Bragagnolo, C., Brandt, J.S., Brearley, F.Q., Brito, I., Bros, V., Brunet, J., Buczkowski, G., Buddle, C.M., Bugter, R., Buscardo, E., Buse, J., Cabra-García, J., Cáceres, N.C., Cagle, N.L., Calviño-Cancela, M., Cameron, S.A., Cancello, E.M., Caparrós, R., Cardoso, P., Carpenter, D., Carrijo, T.F., Carvalho, A.L., Cassano, C.R., Castro, H., Castro-Luna, A.A., Rolando, C.B., Cerezo, A., Chapman, K.A., Chauvat, M., Christensen, M., Clarke, F.M., Cleary, D.F.R., Colombo, G., Connop, S.P., Craig, M.D., Cruz-López, L., Cunningham, S.A., D’Aniello, B., D’Cruze, N., Silva, P.G. da, Dallimer, M., Danquah, E., Darvill, B., Dauber, J., Davis, A.L.V., Dawson, J., Sassi, C. de, Thoisy, B. de, Deheuvels, O., Dejean, A., Devineau, J.-L., Diekötter, T., Dolia, J.V., Domínguez, E., Dominguez-Haydar, Y., Dorn, S., Draper, I., Dreber, N., Dumont, B., Dures, S.G., Dynesius, M., Edenius, L., Eggleton, P., Eigenbrod, F., Elek, Z., Entling, M.H., Esler, K.J., Lima, R.F. de, Faruk, A., Farwig, N., Fayle, T.M., Felicioli, A., Felton, A.M., Fensham, R.J., Fernandez, I.C., Ferreira, C.C., Ficetola, G.F., Fiera, C., Filgueiras, B.K.C., Fırıncıoğlu, H.K., Flaspohler, D., Floren, A., Fonte, S.J., Fournier, A., Fowler, R.E., Franzén, M., Fraser, L.H., Fredriksson, G.M., Freire, G.B., Frizzo, T.L.M., Fukuda, D., Furlani, D., Gaigher, R., Ganzhorn, J.U., García, K.P., Garcia-R, J.C., Garden, J.G., Garilleti, R., Ge, B.-M., Gendreau-Berthiaume, B., Gerard, P.J., Gheler-Costa, C., Gilbert, B., Giordani, P., Giordano, S., Golodets, C., Gomes, L.G.L., Gould, R.K., Goulson, D., Gove, A.D., Granjon, L., Grass, I., Gray, C.L., Grogan, J., Gu, W., Guardiola, M., Gunawardene, N.R., Gutierrez, A.G., Gutiérrez-Lamus, D.L., Haarmeyer, D.H., Hanley, M.E., Hanson, T., Hashim, N.R., Hassan, S.N., Hatfield, R.G., Hawes, J.E., Hayward, M.W., Hébert, C., Helden, A.J., Henden, J.-A., Henschel, P., Hernández, L., Herrera, J.P., Herrmann, F., Herzog, F., Higuera-Diaz, D., Hilje, B., Höfer, H., Hoffmann, A., Horgan, F.G., Hornung, E., Horváth, R., Hylander, K., Isaacs-Cubides, P., Ishida, H., Ishitani, M., Jacobs, C.T., Jaramillo, V.J., Jauker, B., Hernández, F.J., Johnson, M.F., Jolli, V., Jonsell, M., Juliani, S.N., Jung, T.S., Kapoor, V., Kappes, H., Kati, V., Katovai, E., Kellner, K., Kessler, M., Kirby, K.R., Kittle, A.M., Knight, M.E., Knop, E., Kohler, F., Koivula, M., Kolb, A., Kone, M., Kőrösi, Á., Krauss, J., Kumar, A., Kumar, R., Kurz, D.J., Kutt, A.S., Lachat, T., Lantschner, V., Lara, F., Lasky, J.R., Latta, S.C., Laurance, W.F., Lavelle, P., Féon, V.L., LeBuhn, G., Légaré, J.-P., Lehouck, V., Lencinas, M.V., Lentini, P.E., Letcher, S.G., Li, Q., Litchwark, S.A., Littlewood, N.A., Liu, Y., Lo-Man-Hung, N., López-Quintero, C.A., Louhaichi, M., Lövei, G.L., Lucas-Borja, M.E., Luja, V.H., Luskin, M.S., G, M.C.M., Maeto, K., Magura, T., Mallari, N.A., Malone, L.A., Malonza, P.K., Malumbres-Olarte, J., Mandujano, S., Måren, I.E., Marin-Spiotta, E., Marsh, C.J., Marshall, E.J.P., Martínez, E., Pastur, G.M., Mateos, D.M., Mayfield, M.M., Mazimpaka, V., McCarthy, J.L., McCarthy, K.P., McFrederick, Q.S., McNamara, S., Medina, N.G., Medina, R., Mena, J.L., Mico, E., Mikusinski, G., Milder, J.C., Miller, J.R., Miranda-Esquivel, D.R., Moir, M.L., Morales, C.L., Muchane, M.N., Muchane, M., Mudri-Stojnic, S., Munira, A.N., Muoñz-Alonso, A., Munyekenye, B.F., Naidoo, R., Naithani, A., Nakagawa, M., Nakamura, A., Nakashima, Y., Naoe, S., Nates-Parra, G., Gutierrez, D.A.N., Navarro-Iriarte, L., Ndang'ang'a, P.K., Neuschulz, E.L., Ngai, J.T., Nicolas, V., Nilsson, S.G., Noreika, N., Norfolk, O., Noriega, J.A., Norton, D.A., Nöske, N.M., Nowakowski, A.J., Numa, C., O'Dea, N., O'Farrell, P.J., Oduro, W., Oertli, S., Ofori-Boateng, C., Oke, C.O., Oostra, V., Osgathorpe, L.M., Otavo, S.E., Page, N.V., Paritsis, J., Parra-H, A., Parry, L., Pe'er, G., Pearman, P.B., Pelegrin, N., Pélissier, R., Peres, C.A., Peri, P.L., Persson, A.S., Petanidou, T., Peters, M.K., Pethiyagoda, R.S., Phalan, B., Philips, T.K., Pillsbury, F.C., Pincheira-Ulbrich, J., Pineda, E., Pino, J., Pizarro-Araya, J., Plumptre, A.J., Poggio, S.L., Politi, N., Pons, P., Poveda, K., Power, E.F., Presley, S.J., Proença, V., Quaranta, M., Quintero, C., Rader, R., Ramesh, B.R., Ramirez-Pinilla, M.P., Ranganathan, J., Rasmussen, C., Redpath-Downing, N.A., Reid, J.L., Reis, Y.T., Benayas, J.M.R., Rey-Velasco, J.C., Reynolds, C., Ribeiro, D.B., Richards, M.H., Richardson, B.A., Richardson, M.J., Ríos, R.M., Robinson, R., Robles, C.A., Römbke, J., Romero-Duque, L.P., Rös, M., Rosselli, L., Rossiter, S.J., Roth, D.S., Roulston, T.H., Rousseau, L., Rubio, A.V., Ruel, J.-C., Sadler, J.P., Sáfián, S., Saldaña-Vázquez, R.A., Sam, K., Samnegård, U., Santana, J., Santos, X., Savage, J., Schellhorn, N.A., Schilthuizen, M., Schmiedel, U., Schmitt, C.B., Schon, N.L., Schüepp, C., Schumann, K., Schweiger, O., Scott, D.M., Scott, K.A., Sedlock, J.L., Seefeldt, S.S., Shahabuddin, G., Shannon, G., Sheil, D., Sheldon, F.H., Shochat, E., Siebert, S.J., Silva, F.A.B., Simonetti, J.A., Slade, E.M., Smith, J., Smith-Pardo, A.H., Sodhi, N.S., Somarriba, E.J., Sosa, R.A., Quiroga, G.S., St-Laurent, M.-H., Starzomski, B.M., Stefanescu, C., Steffan-Dewenter, I., Stouffer, P.C., Stout, J.C., Strauch, A.M., Struebig, M.J., Su, Z., Suarez-Rubio, M., Sugiura, S., Summerville, K.S., Sung, Y.-H., Sutrisno, H., Svenning, J.-C., Teder, T., Threlfall, C.G., Tiitsaar, A., Todd, J.H., Tonietto, R.K., Torre, I., Tóthmérész, B., Tscharntke, T., Turner, E.C., Tylianakis, J.M., Uehara-Prado, M., Urbina-Cardona, N., Vallan, D., Vanbergen, A.J., Vasconcelos, H.L., Vassilev, K., Verboven, H.A.F., Verdasca, M.J., Verdú, J.R., Vergara, C.H., Vergara, P.M., Verhulst, J., Virgilio, M., Vu, L.V., Waite, E.M., Walker, T.R., Wang, H.-F., Wang, Y., Watling, J.I., Weller, B., Wells, K., Westphal, C., Wiafe, E.D., Williams, C.D., Willig, M.R., Woinarski, J.C.Z., Wolf, J.H.D., Wolters, V., Woodcock, B.A., Wu, J., Wunderle, J.M., Yamaura, Y., Yoshikura, S., Yu, D.W., Zaitsev, A.S., Zeidler, J., Zou, F., Collen, B., Ewers, R.M., Mace, G.M., Purves, D.W., Scharlemann, J.P.W., Purvis, A., 2017. The database of the PREDICTS (Projecting Responses of Ecological Diversity In Changing Terrestrial Systems) project. Ecology and Evolution 7, 145–188. https://doi.org/10.1002/ece3.2579

IBGE, 2017a. Sistema de Contas Nacionais - Tabelas de Recursos e Usos 2017. Instituto Brasileiro de Geografía e Estatística, Brasilia.

IBGE, 2017b. Sistema de Contas Nacionais - Contas econômicas integradas 2017. Instituto Brasileiro de Geografía e Estatística, Brasilia.

IBGE, 2017c. Sistema de Contas Regionais. Instituto Brasileiro de Geografía e Estatística, Brasilia.

IBGE, 2016. Monitoramento da Cobertura e Uso da Terra 2010-2016.
ICA, 2019. Censo Pecuario Nacional Año 2019. Instituto Colombiano Agropecuario, Bogota.
IDEAM, 2020a. Programa de Monitoreo y Seguimiento de los bosques y Áreas de Aptitud Forestal [WWW Document]. URL http://www.ideam.gov.co/web/bosques/deforestacion-colombia
IDEAM, 2020b. Programa de Monitoreo y Seguimiento de los bosques y Áreas de Aptitud Forestal [WWW Document]. URL http://www.ideam.gov.co/web/bosques/deforestacion-colombia
IDEAM, 2012. Mapa de Uso y Cobertura de la Tierra de Colombia 2012.
IMF, 2019. Global Manufacturing Downturn, Rising Trade Barriers. International Monetary Funds, Washington, D.C.
INE, 2019. Producto Interno Bruto Departamental 1989-2019. Instituto Nacional de Estadísticas, La Paz.
INE, 2018. Encuesta de Hogares 2018. Instituto Nacional de Estadística, La Paz.
INE, 2014. Cuadro de Cuentas Económicas Integradas. Instituto Nacional de Estadísticas, La Paz.
INEC, 2017. Encuesta de Superficie y Producción Agropecuaria Contínua 2017. Instituto Nacional de Estadística y Censos, Guayaquil.
INEI, 2018a. Distribución funcional del presupuesto inicial de gastos del sector público. Instituto Nacional de Estadística e Informática, Lima.
INEI, 2018b. Balanza de Pagos, por años. Instituto Nacional de Estadística e Informática, Lima.
INEI, 2018c. Oferta y Demanda Global 1950-2018 (Valores a precios constantes de 2007). Instituto Nacional de Estadística e Informática, Lima.
INEI, 2012. IV Censo Nacional Agropecuario 2012. Instituto Nacional de Estadística e Informática, Lima.
INPE, 2020. Terrabrasilis – Geographic Data Platform. URL http://terrabrasilis.dpi.inpe.br/en/home-page/ (accessed 5.30.20).
IPBES, 2019. Summary for Policymakers in the Global Assessment Report on Biodiversity and Ecosystem Services of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services. Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services, Bonn.
IPCC, 2014. Climate change 2014: synthesis report. Contribution of Working Groups I, II, and III to the fifth assessment report of the Intergovernmental Panel on Climate Change., Geneva, Switzerland. Intergovernmental Panel on Climate Change, Geneva.
Kehoe, T.J., 2005. An Evaluation of the Performance of Applied General Equilibrium Models of the Impact of NAFTA, in: T.J. Kehoe, T.N.S. and J.W. (Ed.), Frontiers in Applied General Equilibrium Modeling: Essays in Honor of Herbert Scarf. Cambridge University Press, Cambridge, pp. 341–377.
Lange, G.-M., Wodon, Q., Carey, K. (Eds.), 2018. The Changing Wealth of Nations 2018: Building a Sustainable Future. World Bank, Washington DC.
Leite-Filho, A.T., Costa, M.H., Fu, R., 2020. The southern Amazon rainy season: The role of deforestation and its interactions with large-scale mechanisms. International Journal of Climatology 40, 2328–2341. https://doi.org/10.1002/joc.6335
Lovejoy, T.E., Nobre, C., 2019. Amazon tipping point: Last chance for action. Science Advances 5, eaba2949. https://doi.org/10.1126/sciadv.aba2949
MacDonald, A.J., Mordecai, E.A., 2019. Amazon deforestation drives malaria transmission, and malaria burden reduces forest clearing. PNAS 116, 22212–22218. https://doi.org/10.1073/pnas.1905315116

MADR, 2019. Evaluaciones Agropecuarias Municipales. Ministerio de Agricultura y Desarrollo Rural, Bogota.

MAGAP, MAE, 2015. Protocolo Metodológico para la Elaboración del Mapa de Cobertura y Uso de la Tierra del Ecuador Continental 2013-2014, Escala 1:100.000, Proyecto "Mapa de Cobertura y Uso de la Tierra del Ecuador Continental 2013-2014, Escala 1:100.000." Ministerio de Agricultura, Ganadería, Acuacultura y Pesca (MAGAP); Ministerio del Ambiente, Guayaquil.

MAGAP, MAE, GEF, PNUD, 2014. Mapa de Uso y Cobertura de la Tierra del Ecuador Continental 2013-2014.

Malhi, Y., Aragão, L.E.O.C., Galbraith, D., Huntingford, C., Fisher, R., Zelazowski, P., Sitch, S., McSweeney, C., Meir, P., 2009. Exploring the likelihood and mechanism of a climate-change-induced dieback of the Amazon rainforest. PNAS 106, 20610–20615. https://doi.org/10.1073/pnas.0804619106

Matiu, M., Ankerst, D.P., Menzel, A., 2017. Interactions between temperature and drought in global and regional crop yield variability during 1961-2014. PLOS ONE 12, e0178339. https://doi.org/10.1371/journal.pone.0178339

Meyfroidt, P., Roy Chowdhury, R., de Bremond, A., Ellis, E.C., Erb, K.-H., Filatova, T., Garrett, R.D., Grove, J.M., Heinimann, A., Kuemmerle, T., Kull, C.A., Lambin, E.F., Landon, Y., le Polain de Waroux, Y., Messerli, P., Müller, D., Nielsen, J.Ø., Peterson, G.D., Rodriguez García, V., Schlüter, M., Turner, B.L., Verburg, P.H., 2018. Middle-range theories of land system change. Global Environmental Change 53, 52–67. https://doi.org/10.1016/j.gloenvcha.2018.08.006

MINAM, 2020. Pérdida de la Superficie de Bosques. Sistema Nacional de Información Ambiental (SINIA).

MINAM, 2015. Mapa Nacional de Cobertura Vegetal.

Ministerio del Ambiente, 2020. Portal Regional SINIA [WWW Document]. URL https://sinia.minam.gob.pe/informacion/analisis (accessed 5.30.20).

Motter, P., de Almeida, H.G., 2015. Plantio Direto: A Tecnologia que Revolucionou a Agricultura Brasileira.

Muhammad, A., Seale, J.L., Meade, B., Regmi, A., 2011. International Evidence on Food Consumption Patterns: An Update Using 2005 International Comparison Program Data, United States Department of Agriculture Economic Research Service Technical Bulletin Number 1929. United States Department of Agriculture, Washington DC.

Nelson, E., Mendoza, G., Regetz, J., Polasky, S., Tallis, H., Cameron, Dr., Chan, K.M., Daily, G.C., Goldstein, J., Kareiva, P.M., Lonsdorf, E., Naidoo, R., Ricketts, T.H., Shaw, Mr., 2009. Modeling multiple ecosystem services, biodiversity conservation, commodity production, and tradeoffs at landscape scales. Frontiers in Ecology and the Environment 7, 4–11. https://doi.org/10.1890/080023

Nepstad, D.C., Stickler, C.M., Filho, B.S.-, Merry, F., 2008. Interactions among Amazon land use, forests and climate: prospects for a near-term forest tipping point. Philosophical Transactions of the Royal Society B: Biological Sciences 363, 1737–1746. https://doi.org/10.1098/rstb.2007.0036

Nepstad, D.C., Tohver, I.M., Ray, D., Moutinho, P., Cardinot, G., 2007. Mortality of Large Trees and Lianas Following Experimental Drought in an Amazon Forest. Ecology 88, 2259–2269. https://doi.org/10.1890/06-1046.1

Newbold, T., Hudson, L.N., Arnell, A.P., Contu, S., De Palma, A., Ferrier, S., Hill, S.L.L., Hoskins, A.J., Lysenko, I., Phillips, H.R.P., Burton, V.J., Chng, C.W.T., Emerson, S., Gao, D., Pask-Hale, G., Hutton, J., Jung, M., Sanchez-Ortiz, K., Simmons, B.I., Whitmee, S., Zhang, H., Scharlemann, J.P.W., Purvis, A., 2016. Has land use pushed terrestrial biodiversity beyond the planetary boundary? A global assessment. Science 353, 288. https://doi.org/10.1126/science.aaf2201

Nobre, C.A., Sampaio, G., Borma, L.S., Castilla-Rubio, J.C., Silva, J.S., Cardoso, M., 2016. Land-use and climate change risks in the Amazon and the need of a novel sustainable development paradigm. Proceedings of the National Academy of Sciences 113, 10759–10768. https://doi.org/10.1073/pnas.1605516113

Nobre, C.A., Sellers, P.J., Shukla, J., 1991. Amazonian Deforestation and Regional Climate Change. Journal of Climate 4, 957–988. https://doi.org/10.1175/1520-0442(1991)004<0957:ADARCC>2.0.CO;2

Nobre, I., Nobre, C.A., 2018. The Amazonia Third Way Initiative: The Role of Technology to Unveil the Potential of a Novel Tropical Biodiversity-Based Economy. Land Use - Assessing the Past, Envisioning the Future. https://doi.org/10.5772/intechopen.80413

Polasky, S., Bryant, B., Hawthorne, P., Johnson, J., Keeler, B., Pennington, D., 2015. Inclusive Wealth as a Metric of Sustainable Development. Annual Review of Environment & Resources 40, 445–466. https://doi.org/10.1146/annurev-environ-101813-013253

Porro, R., Miller, R.P., Tito, M.R., Donovan, J.A., Vivan, J.L., Trancoso, R., Van Kanten, R.F., 2012. Agroforestry in the Amazon Region: A Pathway for Balancing Conservation and Development | SpringerLink, in: Agroforestry- The Future of Global Land Use. Springer, Dordrecht, Dordrecht.

Pousa, R., Costa, M.H., Pimenta, F.M., Fontes, V.C., Brito, V.F.A. de, Castro, M., 2019. Climate Change and Intense Irrigation Growth in Western Bahia, Brazil: The Urgent Need for Hydroclimatic Monitoring. Water 11, 933. https://doi.org/10.3390/w11050933

Project MapBiomas, 2020. Collection 4.1 of Brazilian Land Cover & Use Map Series [WWW Document]. URL (accessed 5.1.20).

R Core Team, 2020. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria.

Rattis, L., Brando, P., Macedo, M., Spera, S., Castanho, A., Marques, E.Q., Queiroz, N., Silverio, D., Coe, M., In Review. When will Brazil reach a climatic limit to rainfed agriculture? Nature.

Rattis, L., Brando, P.M., Macedo, M., Spera, S., Castanho, A., Marques, E.Q., Queiroz, N., Silverio, D., Coe, M., In review. When will Brazil reach a climatic limit to rainfed agriculture. Nature Climate Change.

Redhead, J.W., Stratford, C., Sharps, K., Jones, L., Ziv, G., Clarke, D., Oliver, T.H., Bullock, J.M., 2016. Empirical validation of the InVEST water yield ecosystem service model at a national scale. Science of The Total Environment 569–570, 1418–1426. https://doi.org/10.1016/j.scitotenv.2016.06.227

Saatchi, S., Asefi-Najafabady, S., Malhi, Y., Aragão, L.E.O.C., Anderson, L.O., Myneni, R.B., Nemani, R., 2012. Persistent effects of a severe drought on Amazonian forest canopy. Proc Natl Acad Sci USA 201204651. https://doi.org/10.1073/pnas.1204651110

Sadoulet, E., de Janvry, A., 1995. Quantitative Development Policy Analysis. The Johns Hopkins University Press, Baltimore.

Salata, S., Garnero, G., Barbieri, C., Giaimo, C., 2017. The Integration of Ecosystem Services in Planning: An Evaluation of the Nutrient Retention Model Using InVEST Software. Land 6, 48. https://doi.org/10.3390/land6030048

Sampaio, G., Nobre, C., Costa, M.H., Satyamurty, P., Soares-Filho, B.S., Cardoso, M., 2007. Regional climate change over eastern Amazonia caused by pasture and soybean cropland expansion. Geophysical Research Letters 34. https://doi.org/10.1029/2007GL030612

Sathler, D., Adamo, S., Lima, E.E.C., Macedo, D.R., de Sherbinin, A., Kim-Blanco, P., 2019. Assessing the regional context of migration in the Brazilian Amazon through spatial regression modeling. Applied Geography 109, 102042. https://doi.org/10.1016/j.apgeog.2019.102042

Schielein, J., Börner, J., 2018. Recent transformations of land-use and land-cover dynamics across different deforestation frontiers in the Brazilian Amazon. Land Use Policy 76, 81–94. https://doi.org/10.1016/j.landusepol.2018.04.052

Schmink, M., 2011. FOREST CITIZENS: Changing Life Conditions and Social Identities in the Land of the Rubber Tappers. Latin American Research Review 46, 141–158.

Sharp, R., Tallis, H., Ricketts, T., Guerry, A., Wood, S., Chaplin-Kramer, R., Nelson, E., Ennaanay, D., Wolny, S., Olwero, N., Vigerstol, K., et al., 2020. InVEST 3.8.1 User's Guide.

Shoven, J., Whalley, J., 1992. Applying general equilibrium. Cambridge University Press, Cambridge.

Silvério, D.V., Brando, P.M., Balch, J.K., Putz, F.E., Nepstad, D.C., Oliveira-Santos, C., Bustamante, M.M.C., 2013. Testing the Amazon savannization hypothesis: fire effects on invasion of a neotropical forest by native cerrado and exotic pasture grasses. Philosophical Transactions of the Royal Society B: Biological Sciences 368, 20120427. https://doi.org/10.1098/rstb.2012.0427

Silvério, D.V., Brando, P.M., Macedo, M.N., Beck, P.S.A., Bustamante, M., Coe, M.T., 2015. Agricultural expansion dominates climate changes in southeastern Amazonia: the overlooked non-GHG forcing. Environmental Research Letters 10, 104015. https://doi.org/10.1088/1748-9326/10/10/104015

Smith, C.C., Espírito-Santo, F.D.B., Healey, J.R., Young, P.J., Lennox, G.D., Ferreira, J., Barlow, J., 2020. Secondary forests offset less than 10% of deforestation-mediated carbon emissions in the Brazilian Amazon. Global Change Biology 26, 7006–7020. https://doi.org/10.1111/gcb.15352

Spracklen, D.V., Arnold, S.R., Taylor, C.M., 2012. Observations of increased tropical rainfall preceded by air passage over forests. Nature 489, 282–285. https://doi.org/10.1038/nature11390

Spracklen, D.V., Garcia-Carreras, L., 2015. The impact of Amazonian deforestation on Amazon basin rainfall. Geophysical Research Letters 42, 9546–9552. https://doi.org/10.1002/2015GL066063

Staal, A., Tuinenburg, O.A., Bosmans, J.H.C., Holmgren, M., van Nes, E.H., Scheffer, M., Zemp, D.C., Dekker, S.C., 2018. Forest-rainfall cascades buffer against drought across the Amazon. Nature Climate Change 8, 539–543. https://doi.org/10.1038/s41558-018-0177-y

Stabile, M.C.C., Guimarães, A.L., Silva, D.S., Ribeiro, V., Macedo, M.N., Coe, M.T., Pinto, E., Moutinho, P., Alencar, A., 2020. Solving Brazil's land use puzzle: Increasing production and slowing Amazon deforestation. Land Use Policy 91, 104362. https://doi.org/10.1016/j.landusepol.2019.104362

Stiglitz, J.E., Sen, A., Fitoussi, J., 2009. Report by the Commission on the Measurement of Economic Performance and Social Progress.
Stiglitz, J.E., Sen, A.K., Fitoussi, J.P., 2010. Mis-Measuring Our Lives: Why GDP Doesn't Add Up. New Press, New York.
Strand, J., Soares-Filho, B., Costa, M.H., Oliveira, U., Ribeiro, S.C., Pires, G.F., Oliveira, A., Rajão, R., May, P., van der Hoff, R., Siikamäki, J., da Motta, R.S., Toman, M., 2018. Spatially explicit valuation of the Brazilian Amazon Forest's Ecosystem Services. Nature Sustainability 1, 657–664. https://doi.org/10.1038/s41893-018-0175-0
Strassburg, B.B.N., Latawiec, A.E., Barioni, L.G., Nobre, C.A., da Silva, V.P., Valentim, J.F., Vianna, M., Assad, E.D., 2014. When enough should be enough: Improving the use of current agricultural lands could meet production demands and spare natural habitats in Brazil. Global Environmental Change 28, 84–97. https://doi.org/10.1016/j.gloenvcha.2014.06.001
Taylor, J.E., Dyer, G.A., Yúnez-Naude, A., 2012. Disaggregated Rural Economywide Models for Policy Analysis. World Development 33, 1671–1688. https://doi.org/10.1016/j.worlddev.2005.05.003
Thornthwaite, C.W., Mather, J.R., 1955. Instructions and tables for computing potential evapotranspiration and the water balance [WWW Document]. World Vegetable Center. URL https://worldveg.tind.io/record/3826 (accessed 7.13.20).
Trumbore, S., Brando, P., Hartmann, H., 2015. Forest health and global change. Science 349, 814. https://doi.org/10.1126/science.aac6759
Trustees of the Natural History Museum, London, n.d. The PREDICTS project [WWW Document]. PREDICTS. URL https://www.predicts.org.uk/ (accessed 5.24.20).
UNEP, 2018. Inclusive Wealth Report 2018. United Nations Environment Programme, Geneva.
United Nations, Department of Economic and Social Affairs, Population Division, 2019. World population prospects Highlights, 2019 revision Highlights, 2019 revision.
United Nations, European Commission, Food and Agriculture Organization, International Monetary Fund, Organisation for Economic Cooperation and Development, The World Bank, 2014. System of Environmental Economic Accounting 2012- Central Framework. UN, New York.
UTNIT, 2010. Mapa de Cobertura y Uso Actual de la Tierra Bolivia 2010.
Valentim, J.F., 2015. Environmental governance and technological innovations for sustainable development in the Amazon. University Press of Florida, Gainesville, pp. 219–240.
Valentim, J.F., Vosti, S.A., 2005. The Western Brazilian Amazon, in: Slash-and-Burn Agriculture: The Search for Alternatives. Columbia University Press, New York, pp. 265–290.
Vasconcellos, J.H., Torres, M., 2020. Sistema Antecipe diminui riscos de plantio para milho safrinha.
Veldkamp, A., Verburg, P.H., 2004. Modelling land use change and environmental impact. Journal of Environmental Management, Modelling land use change and environmental impact 72, 1–3. https://doi.org/10.1016/j.jenvman.2004.04.004
Verburg, P.H., de Koning, G.H.J., Kok, K., Veldkamp, A., Bouma, J., 1999. A spatial explicit allocation procedure for modelling the pattern of land use change based upon actual land use. Ecological Modelling 116, 45–61. https://doi.org/10.1016/S0304-3800(98)00156-2
Verburg, P.H., Eickhout, B., van Meijl, H., 2008. A multi-scale, multi-model approach for analyzing the future dynamics of European land use. The Annals of Regional Science 42, 57–77. https://doi.org/10.1007/s00168-007-0136-4

Verburg, P.H., Overmars, K.P., 2009a. Combining top-down and bottom-up dynamics in land use modeling: exploring the future of abandoned farmlands in Europe with the Dyna-CLUE model. Landscape Ecology 24, 1167. https://doi.org/10.1007/s10980-009-9355-7

Verburg, P.H., Overmars, K.P., 2009b. Combining top-down and bottom-up dynamics in land use modeling: exploring the future of abandoned farmlands in Europe with the Dyna-CLUE model. Landscape Ecol 24, 1167–1181. https://doi.org/10.1007/s10980-009-9355-7

Verburg, P.H., Soepboer, W., Veldkamp, A., Limpiada, R., Espaldon, V., Mastura, S.S.A., 2002. Modeling the Spatial Dynamics of Regional Land Use: The CLUE-S Model. Environmental Management 30, 391–405. https://doi.org/10.1007/s00267-002-2630-x

Vliet, N. van, Adams, C., Vieira, I.C.G., Mertz, O., 2013. "Slash and Burn" and "Shifting" Cultivation Systems in Forest Agriculture Frontiers from the Brazilian Amazon. Society & Natural Resources 26, 1454–1467. https://doi.org/10.1080/08941920.2013.820813

Walker, R., Moore, N.J., Arima, E., Perz, S., Simmons, C., Caldas, M., Vergara, D., Bohrer, C., 2009. Protecting the Amazon with protected areas. PNAS 106, 10582–10586. https://doi.org/10.1073/pnas.0806059106

WHRC, 2020. Amazon Dry Season Length from 1961-2100. Woods Hole Research Center, Falmouth, MA.

Woetzel, J., Pinner, D., Samandari, H., Engel, H., Krishnan, M., Boland, B., Powis, C., 2020. Climate risk and response: Physical hazards and socioeconomic impacts. MGI Report, January, MGI Report. McKinsey Global Institute, New York.

Wright, J.S., Fu, R., Worden, J.R., Chakraborty, S., Clinton, N.E., Risi, C., Sun, Y., Yin, L., 2017. Rainforest-initiated wet season onset over the southern Amazon. PNAS 114, 8481–8486. https://doi.org/10.1073/pnas.1621516114

Yin, L., Fu, R., Zhang, Y.-F., Arias, P.A., Fernando, D.N., Li, W., Fernandes, K., Bowerman, A.R., 2014. What controls the interannual variation of the wet season onsets over the Amazon? Journal of Geophysical Research (Atmospheres) 119, 2314–2328. https://doi.org/10.1002/2013JD021349

Zu Ermgassen, E.K.H.J., Alcântara, M.P. de, Balmford, A., Barioni, L., Neto, F.B., Bettarello, M.M.F., Brito, G.D., Carrero, G.C., Florence, E.D.A.S., Garcia, E., Gonçalves, E.T., Da Luz, C.T., Mallman, G.M., Strassburg, B.B.N., Valentim, J.F., Latawiec, A., 2018. Results from On-The-Ground Efforts to Promote Sustainable Cattle Ranching in the Brazilian Amazon. Sustainability 10, 1301. https://doi.org/10.3390/su10041301

Supplementary Information 1

IEEM database and calibration

IEEM elasticities

In this study, we focus on structural differences between our Amazon focal countries of Brazil, Peru, Colombia, Bolivia and Ecuador. Consequently, we assume the same elasticities for all countries. In other words, the four IEEM applications only differ in the structural parameters calibrated based on the respective social accounting matrix of each country. In all cases, the values for elasticities are the most reliable estimates available from the literature and are as follows: (i) the elasticities of substitution among factors are in the 0.2-0.95 range, and lower for natural resource activities such as agriculture (0.25) and mining (0.2) (Hertel et al. 2012); (ii) trade-related elasticities are in the 2 to 0.9 range for the substitution between imports and domestic purchases and transformation between exports and domestic sales, respectively (Sadoulet and de Janvry, 1995); (iii) the expenditure elasticities for household consumption demand are in the range 0.6-1.4 (Muhammad et al., 2011), and; (iv) the wage curve unemployment elasticity is -0.5 (Blanchflower and Oswald, 2005).

Brazil

The base year for Brazil's SAM is 2014 and was built based on the Supply and Use (SUT) tables and Integrated Economic Accounts from Brazil's System of National Accounts (SNA) developed by the Instituto Brasileiro de Geografia e Estatistica (IBGE) (IBGE, 2017a, 2017b). The regionalization of crops, livestock and forestry output was conducted using IBGE regional accounts data for each of Brazil's 26 states (IBGE, 2017c). The number of hectares of crops and livestock by state was sourced from the Land Use Land Cover (LULC) map (IBGE, 2016). Natural forest and forest plantation data was sourced from (Project MapBiomas, 2020). Note that for the states of Ceará, Pernambuco, and Rio Grande do Norte, there is no land used in forestry. The number of workers by activity was part of the SUT publication (IBGE, 2017a).

The baseline area in 2015 and the projection for crop, livestock, forest and forest plantations was estimated as follows. For all countries in this study, total land in IEEM is fixed. The baseline (BASE) deforestation projections for all countries are based on historical trends. In the case of Brazil, these trends are derived from (INPE, 2020; Project MapBiomas, 2020). For all countries, the area of forest plantations grows at the same rate as the population which is a conservative assumption. Deforestation increases the availability of cleared land for crop and livestock activities. The distribution of deforested land between crops and livestock is endogenous.

For all countries, for the period 2020 to 2050, we draw on projections from the latest International Monetary Fund's World Economic Outlook to impose GDP growth rates (IMF, 2019). In the BASE projection, GDP growth is exogenous and imposed by endogenously adjusting total factor productivity. In all policy scenarios, however, 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. For all countries, unless otherwise indicated, population projections were obtained from the United Nations Department of Economic and Social Affairs, Population

Division (United Nations et al., 2019). 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 Computable General Equilibrium (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 BASE 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[4].

For all countries, among the government-related payments, tax rates are fixed at BASE-year values. Fixed GDP shares at base-year values are imposed for the other payments: (i) government demand for (alternatively, government provision of) government services; (ii) transfers from government to households; and (ii) domestic financing of the government. For non-government payments, BASE-year GDP shares are similarly imposed over time for transfers from the rest of the world to households, foreign direct investment, non-government net foreign financing, and factor income to/from abroad.

Peru

The base year for Peru's SAM is 2017 and was constructed based on the SUT and Integrated Economic Accounts from the SNA from the Instituto Nacional de Estadística e Informática (INEI) combined with balance of payments and fiscal data from other official sources (INEI, 2018a, 2018b, 2018c). Deforestation projections are based on official sources from (Ministerio del Ambiente, 2020). The regionalization of crops and livestock output for each of Peru's 24 Departments was conducted using the 2012 Agricultural Census (INEI, 2012). The number of hectares in crops, livestock, and forestry is drawn from LULC map data by department (MINAM, 2015). The regionalization of forestry was conducted using LULC data (MINAM, 2015). The number of workers by activity was derived from the SUT publication (INEI, 2018c).

Colombia

The base year for Colombia's SAM is 2014 and was constructed based on SUT and Integrated Economic Accounts from the SNA (DANE, 2015a, 2018). Crop land use and output was regionalized according to Colombia's 32 Departments based on data 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). Forest plantations and natural forest areas are regionally disaggregated based on data from IDEAM

[4] Furthermore, In the BASE, 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.

(IDEAM, 2020a) and account for 179,225 ha and 58,518,031 ha of the national territory, respectively. This area of forest plantations and natural forest are computed from the base land use land cover map for Colombia (IDEAM, 2012). The number of workers by activity is from a nationally representative household survey (DANE, 2015b). The LULC base map used was from (IDEAM, 2012). Population projections were obtained from Colombia's National Administrative Department of Statistics.

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, 2020b). 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 2050.

Bolivia

The base year for Bolivia's SAM is 2014 and was built using the SUT and Integrated Economic Accounts from the SNA (INE, 2014). Deforestation projections are based (GFW, 2020a).The regionalization of crops, livestock, and forestry output according to Bolivia's 9 Departments was conducted using regional accounts from Bolivia (INE, 2019). The number of hectares in crops, livestock and forestry is drawn from LULC data by department (UTNIT, 2010). Bolivia's deforestation projections are based on historical data from Global Forest Watch data (GFW, 2020a). The number of workers by activity was calculated using data from the Bolivian household survey *Encuesta de Hogares* (INE, 2018).

Ecuador

The base year for Ecuador's SAM is 2015 and was constructed based on the SUT and Integrated Economic Accounts from Ecuador's SNA data from the Central Bank of Ecuador (BCE, 2020a, 2020b). The SAM regionalization of crops, livestock, and forestry output was conducted using the Central Bank's regional accounts data at the provincial level for the country's 24 Provinces (BCE, 2020a). The number of hectares in crops and livestock by province was sourced from the Encuesta de Superficie y Producción Agropecuaria Continua 2017 (INEC, 2017). The forest area was sourced from Ecuador's Land Use Land Cover (LULC) map, Mapa de Uso y Cobertura de la Tierra del Ecuador Continental 2013-2014 (MAGAP et al., 2014, p. 2014; MAGAP and MAE, 2015). Labor force participation was obtained from the SUT tables (BCE, 2020c). Ecuador's deforestation projections are based on historical data from Global Forest Watch data (GFW, 2020b).

Supplementary Information 2
Detailed Description of Scenario Design

Amazon Tipping Point Scenario Components

1. Baseline deforestation: BASE scenario.

We estimated baseline deforestation rates using the best available annual estimates of deforestation for each focal country. Data for Brazil came from the National Space Agency (INPE), which publishes annual deforestation data summarized at the state level for the Cerrado and Amazon biomes (Assis et al., 2019; INPE, 2020) and the MapBiomas Project (Project MapBiomas, 2020). Data for Peru came from official sources from the Ministry of the Environment, which publishes annual data on forest loss by Department (MINAM, 2020). Data for Colombia was obtained from the National Institute of Hydrology, Meteorology, and Environmental Studies (IDEAM, 2012). Data for Bolivia and Ecuador were based on World Resources Institute's Global Forest Watch program (GFW, 2020a, 2020b). To implement the BASE scenario, we first calculated the rate of deforestation as a proportion of remaining forests for each state. We then took the average rate of deforestation for the last decade in the data record and assumed that future deforestation would follow the same annual BASEtrend.

2. Climate change impacts on agriculture: YIELD and DRGHT scenarios.

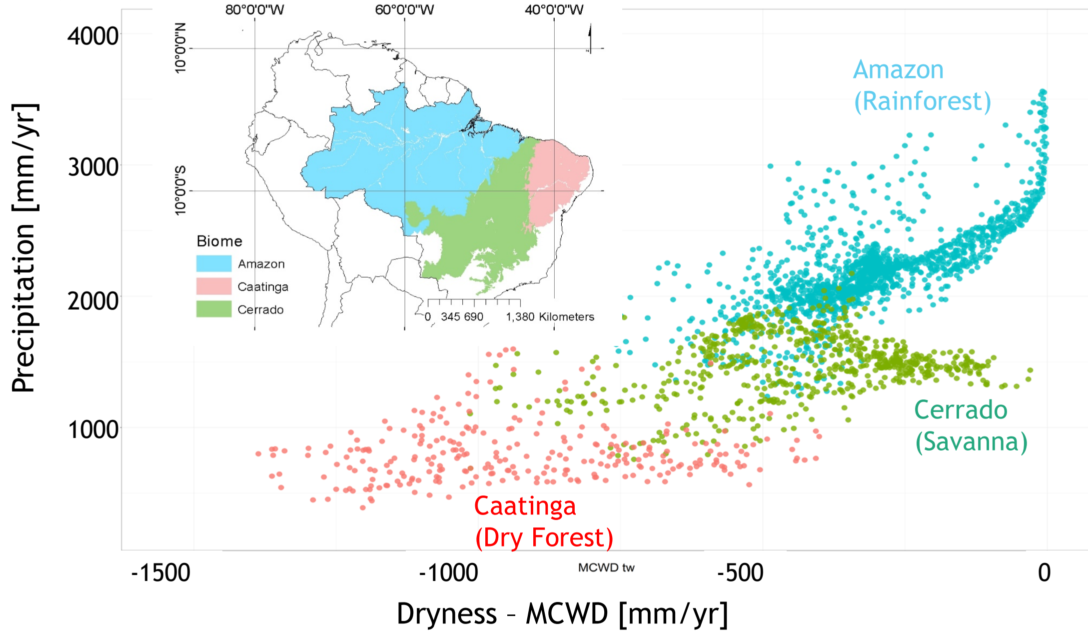
To quantify the impacts of crop failures as climate becomes less favorable for agriculture, we developed statistical models to relate historic variability in crop productivity to existing gradients in climate (spatial variability) and periodic shocks to the system during extreme droughts. We obtained soybean and late-season maize yields from the National Food Supply Company of Brazil (CONAB), which provides state-level averages of crop yield from 1981-2017 (CONAB, 2019). This is the longest time series available for the study area and includes the Brazilian states of Mato Grosso, Goiás, Maranhão, Tocantins, Piauí, Bahia, and the Federal District of Brasília which comprises a large agricultural region that has already experienced climate-induced crop losses.

To quantify regional changes in temperature and dryness, we applied the climate space concept, which uses the rainfall and the Maximum Cumulative Water Deficit (MCWD, an index of dryness) to delineate the climate envelope which in this case is the range of precipitation and temperature that is most suitable for agricultural production. Malhi et al. (2009) used this approach to delineate the climatic envelope that defines biomes. Castanho et al. (2020) adapted the approach to quantify the effect of future climate change on vegetation distribution and biomass in dryland ecosystems.

We adapted the approach to quantify changes in the climate space for agriculture. We used a generalized linear model in the R statistical package (R Core Team, 2020) to relate historic yields to the Maximum Cumulative Water Deficit and the Standardized Precipitation Evapotranspiration Index. The resulting statistical models allowed us to make hypothetical yield projections under mean future climate conditions. This allowed us to quantify the upper and lower bounds of expected crop losses as a percentage of baseline yield for each state, without explicitly modeling the sensitivity of specific crops. These results were the basis of our YIELD scenario shocks implemented in IEEM. To simulate drought impacts on agriculture in the DRGHT scenario, and in addition to yield losses due to changes in the average climatic conditions and the Maximum Cumulative Water Deficit (captured in the YIELD scenario), we assumed a 15% loss in yield during extreme drought events, which are expected to become more frequent in the future (Woetzel et al., 2020).

Figure SI 3). Rattis et al. (In Review) found that from 1980-2019, regional warming and drying pushed 37% of current agricultural lands in the Amazon and Cerrado region out of the optimum climate space for agricultural productivity. This shift in climate space is projected to reach 64% by 2030 and 94% by 2060 (Rattis et al., In Review).

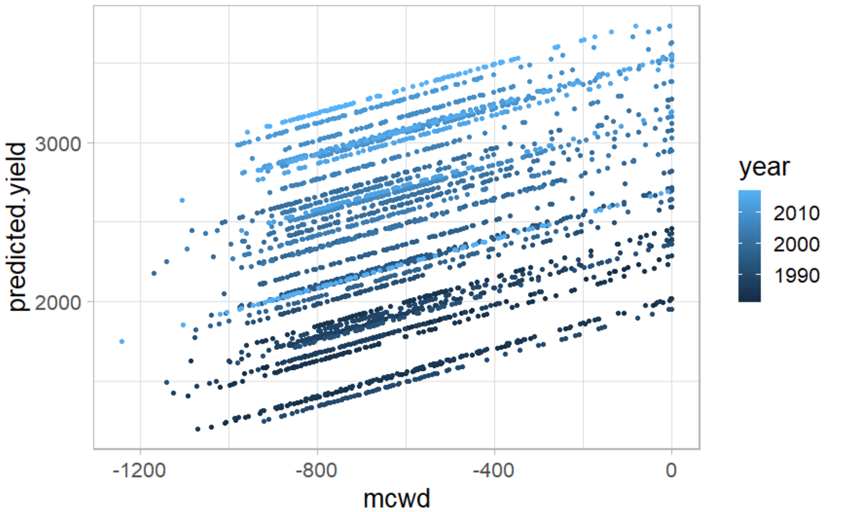
Figure SI 1. Bioclimatic zones for Caatinga, Cerrado, and Amazon rainforest, averaged for the 30-year period 1950–1979. Biome locations are shown in the inset map (upper left). Climate space is defined by annual precipitation and potential maximum cumulative water deficit (Malhi et al., 2009). Points are 0.5° grid cells from CRU (Harris et al., 2014).



Source: Adapted from Castanho et al. (2020).

To calculate the Maximum Cumulative Water Deficit, we used monthly temperature and precipitation from CMIP5 as described in the main text (Castanho et al., 2020; Malhi et al., 2009). Potential Evapotranspiration, required to calculate monthly climatological water deficit, was based on the Thornthwaite equation (Thornthwaite and Mather, 1955). We considered the 30-year period from 1981-2010 as our climatic baseline and calculated Maximum Cumulative Water Deficit for the (bias-corrected) time series from 1981-2100. Our estimations with a linear mixed model based on this historical data reveal a linear relationship between Maximum Cumulative Water deficit and crop yield. Specifically, for every 100-millimeter decrease in Maximum Cumulative Water Deficit, there is a decline of 76.5 kg/ha in soybean and 236 kg/ha in late season corn relative to the baseline Figure SI 2.

Figure SI 2. Historical relationship between crop yields and Mean Cumulative Water Deficit, from 1990 to 2020.



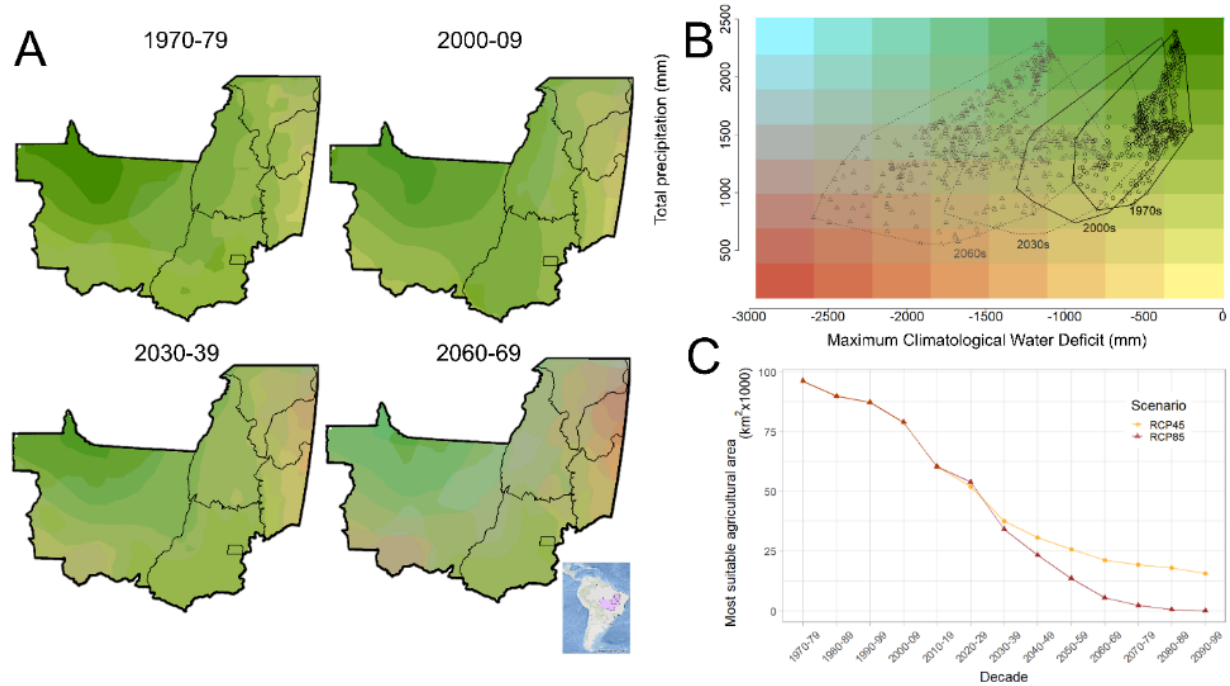
Source: Climate data used to calculate Mean Cumulative Water Deficit came CRU (Harris et al., 2014) and yield data came from CONAB (2019).

To implement the agricultural productivity shock in IEEM in the YIELD scenario, we modify total factor productivity for all crops in the relevant regions by applying the average of change in corn and soy productivities. To test the sensitivity of results to variations in the productivity shock, we also calculated a lower and upper bound where the lower bound (YIELD_LO) applies changes to corn productivity to all crops and the upper bound (YIELD_HI) applies change in soy productivity to all crops.

Using a similar approach to calculating Maximum Cumulative Water Deficit, we calculated the Standardized Precipitation Evapotranspiration Index (SPEI) – a standard metric used to monitor droughts (Beguería et al., 2014). We estimated the historic and future frequency of extreme events based on a threshold of one standard deviation of the Standardized Precipitation Evapotranspiration Index. A negative value indicates an extreme dry year, while a positive value indicates an extreme wet year. All climate variables were summarized by state/department for each of our Amazon focal country.

We used a generalized linear model in the R statistical package (R Core Team, 2020) to relate historic yields to the Maximum Cumulative Water Deficit and the Standardized Precipitation Evapotranspiration Index. The resulting statistical models allowed us to make hypothetical yield projections under mean future climate conditions. This allowed us to quantify the upper and lower bounds of expected crop losses as a percentage of baseline yield for each state, without explicitly modeling the sensitivity of specific crops. These results were the basis of our YIELD scenario shocks implemented in IEEM. To simulate drought impacts on agriculture in the DRGHT scenario, and in addition to yield losses due to changes in the average climatic conditions and the Maximum Cumulative Water Deficit (captured in the YIELD scenario), we assumed a 15% loss in yield during extreme drought events, which are expected to become more frequent in the future (Woetzel et al., 2020).

Figure SI 3. Mean climate space of the Amazon-Cerrado region over four decades. The historical climate space was defined using observed data (Harris et al., 2014). The future climate space was based on the mean of 35 models from CMIP5. Panel A on the left if the climate space distribution. Colors correspond to specific combinations of precipitation and Maximum Cumulative Water Deficit from Panel B. Panel B on the top right is a scatterplot of all cropland as a function of their location in the climate space. Each point corresponds to one pixel on the maps in Panel A. Black and purple convex hulls mathematically delimit the climate space occupied by current croplands for each decade. Panel C on the bottom right shows the total decadal mean cropland area (km^2) falling within the optimum climate space, as defined by 1970s climate (black convex hull in Panel B).

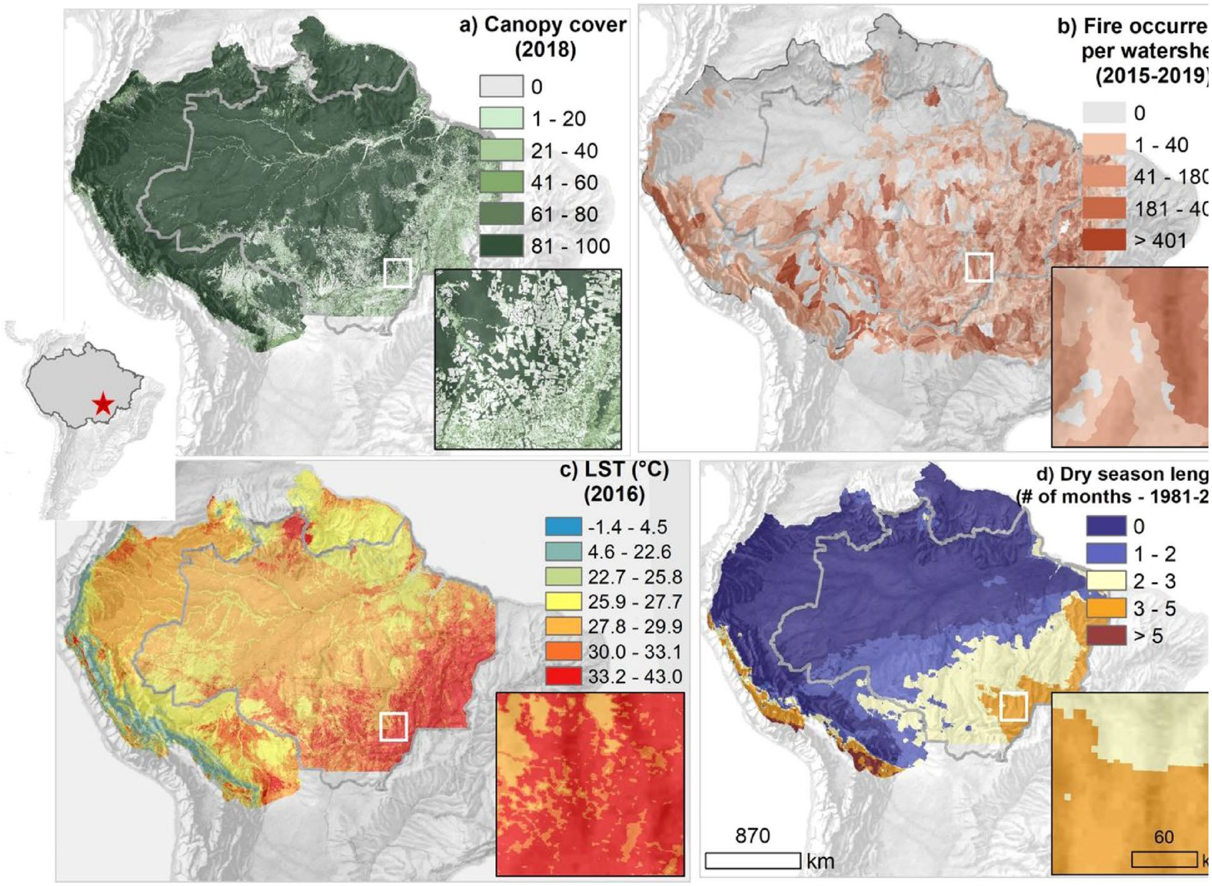


Source: Figure reproduced from Rattis et al. In Review.

3. Deforestation-climate-fire interactions: FIR scenario.

To implement the FIR scenario in IEEM, we used previously published model outputs to quantify the interactions between deforestation, climate change and fire in the driest region of the southern Amazon which is comprised of about 192 million hectares and is where most fires occur (Brando et al. 2020b). We used dry-season length as a spatial mask in a Geographic Information System (GIS) to distinguish between flammable and non-flammable forests (Figure SI 4). To account for the effect of climate change on dry season length, we used data from the Amazon Climate Source, a data platform that synthesizes information on observed historical climate (Harris et al., 2014) and modeled future climate (Taylor et al., 2012) in the Amazon (WHRC, 2020). We assume that Amazon forest areas with a dry season length of greater than or equal to 3 months are eligible to burn.

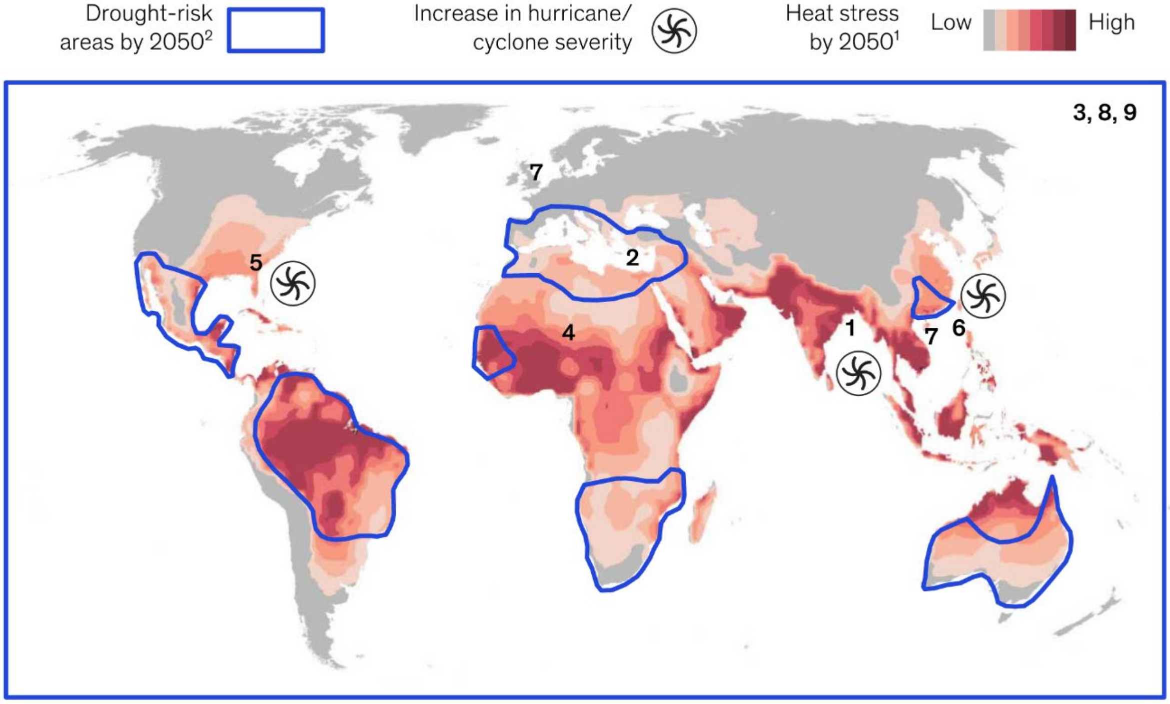
Figure SI 4. Land cover, climate, and fire occurrence across the Amazon forest biome. (a) Percent tree cover (Hansen et al., 2013). (b) Active fire occurrence from MOD14A1 (Giglio et al., 2016). (c) Land surface temperature (from MOD11A2; Wan et al. 2015). (d) Mean dry-season length from 1981-2019 calculated from CHIRPS (Funk et al., 2015).



Source: (P. M. Brando et al., 2020b).

For the FIR scenario and all other scenarios, we assume that future climate will follow the high-emissions scenario outlined by the Intergovernmental Panel on Climate Change (IPCC, 2014). This scenario, referred to as a Representative Concentration Pathway (RCP), assumes that atmospheric greenhouse gases will accumulate at the current rate of emissions, causing a climate forcing of 8.5 Watts per square meter.

Figure SI 5. Global drought risk and heat stress by 2050. The Amazon-Cerrado region stands out as a hotspot of future climate risk.

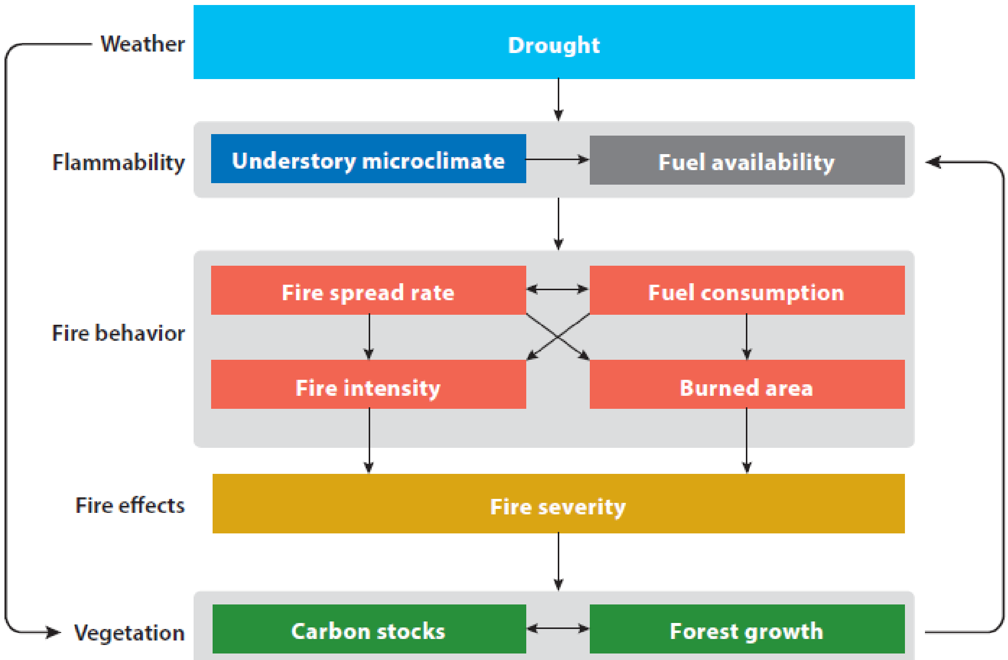


[1]Heat stress measured in wet-bulb temperatures.
[2]Drought risk defined based on % of month in drought according to Palmer Drought Severity index (PDSI).

Source: Figure reproduced from Woetzel et al. (2020).

Although medium- and low-emission scenarios exist, we focus on RCP8.5 because it most closely represents the pathway we are currently on. Moreover, the lag time in the climate system means that the three scenarios do not differ substantially until after 2050. Under RCP8.5, dry season length is projected to increase from the first period (2016-2039) to the second (2040-2069). As a result, several states/departments that are not eligible to burn in the early period of our analysis become eligible to burn after 2039 (Figure SI 5 and Figure SI 6). Figure SI 6 describes how drought-mediated wildfires impact tropical forests. Droughts can affect vegetation directly through physiological responses that reduce carbon stocks and forest growth; they affect flammability which in turn affects fire behavior and impacts. The outcome of these interactions is more severe fires, lower carbon stocks and reduced productivity. These interactions can also result in positive feedbacks through increasing fuel loads and dryness, and consequently fire severity.

Figure SI 6. Schematic diagram showing how drought-mediated wildfires impact tropical forests. Droughts can affect vegetation directly through physiological responses that reduce carbon stocks and forest growth (green). They also affect vegetation by increasing forest flammability (blue), and altering fire behavior (red) and fire effects (yellow). The result is more severe fires, lower carbon stocks, and reduced productivity. This fire pathway may cause a positive feedback, further increasing fuel loads and dryness, and consequently fire severity.



Source: Figure reproduced from Brando et al. (2019).

We assume that deforestation follows baseline (BASE) trends in this and all components of the Amazon tipping point (COMBI) scenario. For each climate period, we assumed that all states/departments of our focal countries with a dry season length greater than or equal to 3 months were eligible to burn. Using the annual model outputs from Brando et al. (2020b), we multiplied the percent burned area expected for that year by the remaining forest area which is tracked in IEEM to estimate the annual burned area in each state. For each "flammable" Amazon state, we then spatially allocated the burned area in the land use land cover change modeling.

Note that we modeled these deforestation-climate-fire interactions only in the Amazon forest biome. Because Amazon forests have not burned historically, they are not fire-adapted and are particularly vulnerable to changing fire regimes. Once they become flammable, fire occurrence in these forests can lead to abrupt ecosystem change (Brando et al., 2014b). In contrast, savanna ecosystems are fire-adapted and have very different historic fire regimes (Andela et al., 2017). State-of-the-art fire modeling for the southern Amazon allows us to consider the joint effects of climate, ignition sources, and deforestation on burned area in the Amazon.

Components of the Policy Intervention Scenario

1. Zero Deforestation: NDEFOR scenario.

To implement the NDEFOR intervention, we reduced deforestation after 2020, reaching zero deforestation by 2030 Figure 8. One positive feedback of slowing deforestation is a reduction in the number of wildfires that escape into primary Amazon forests. These fires can degrade forest ecosystems and eventually cause them to change to another stable state or become so degraded that they are eventually converted to other uses. To account for this, we assumed that the burned area in flammable parts of the Amazon decreased by 50% in NDEFOR (P. M. Brando et al., 2020b).

Co-benefits of avoiding deforestation include reduced disease transmission (MacDonald and Mordecai, 2019), improved air quality, climate mitigation (Costa et al., 2019; Wright et al., 2017), and biodiversity conservation. All of these impacts could have positive impacts on the economy and human well-being. For example, the climate regulation effect of stopping deforestation would have a positive impact on agricultural productivity by modulating regional rainfall and temperature regimes relative to the baseline and Amazon tipping point scenarios. The economic benefits of reducing deforestation are captured in IEEM through changes in the total stock of forestland. These benefits are taken into account in the calculation of some but not all economic indicators. Some of the non-market benefits are quantified in the ecosystem service modeling.

We recognize that the cost of implementing zero-deforestation policies, including monitoring and enforcement, could be substantial. Our preliminary estimate of the investments required is based on a recent study outlining a strategy to stop deforestation and increase agricultural production on already cleared lands in Brazil. Achieving this would require an estimated investment of US$53 billion through to the year 2030. Some of this cost could be offset by enhanced monitoring and enforcement of forest policy and related laws, which would increase the collection of fines (Banerjee and Alavalapati 2010). There is also a potentially large net return on these investments, estimated at US$68 billion over the same period (Stabile et al., 2020), but more research is needed to constrain these estimates.

3. Fire Prevention: NFIR scenario.

To implement the fire management (NFIR) scenario in IEEM, we relied on the same key datasets as in FIR (P. M. Brando et al., 2020b; WHRC, 2020). To implement NFIR, we assume that comprehensive fire prevention and suppression efforts can mitigate an additional 60-75% of the burned area, above and beyond the reduction achieved through the NDEFOR scenario

Investments in preventing wildfires would have a number of ecosystem service and human health co-benefits. It may also have economic benefits by preventing loss of life, infrastructure, and forest resources. For example, high-intensity fires (e.g. FIR) have been shown to cause losses in timber production value of up to 10% in intact forest areas, while low-intensity fires (e.g. NDEF) could cause losses of up to 5% (de Oliveira et al., 2019). Effective fire suppression would prevent these losses. Substantially reducing the burned area would require significant investments in all aspects of fire control and prevention, including:

- *Expanding the network of well-trained and equipped fire brigades*. These brigades can help suppress accidental ignitions and illegal wildfires. This strategy receives nearly all of the federal funding available today but remains extremely under-resourced. The Amazon Fund's PrevFogo program, for example, allocated ~US$6.3 million over five years to prevent forest fires, but effectively covers only 3.2% of the Brazilian Legal Amazon (P. Brando et al., 2020; Fonseca-Morello et al., 2017).

- *Developing fire-free land management systems*. Under a changing climate, fire should be eliminated as a strategy for clearing land except in very limited cases. While some research has been done into fire-safe agroforestry systems and 'ecological pastures' silvopastoral systems, very little research has been devoted to developing these systems for operational use (Fonseca-Morello et al., 2017).
- *Command-and-control enforcement of illegal fire activity.* This requires investments to enforce laws geared towards preventing wildfires and illegal deforestation (P. Brando et al., 2020; P. M. Brando et al., 2020b).
- *Improving fire early warning systems.* This includes weather forecast systems and fire behavior models that can help guide fire prevention and suppression efforts and efficiently allocate resources months before the fire season starts deforestation (P. Brando et al., 2020; P. M. Brando et al., 2020b).
- *Investing in Fire Prevention.* In addition to the above, fire management agencies need to consider fire prevention and control strategies in highly vulnerable areas. Among other things, this might include building fire breaks and conducting controlled burns to reduce fuel loads, especially in drought years when mega-fires are more probable.

Implementing these strategies across all Amazon countries would require some ramp-up time. The main firefighting program in Brazil today (PrevFogo) focuses primarily on the first aspect of NFIR, establishing fire brigades to suppress wildfires. Implementing NFIR would require expanding such activities from its current coverage of approximately 3.2% of the Brazilian Amazon (Fonseca-Morello et al., 2017) to 100% of the most flammable areas across the biome. It would also require reallocation of resources towards fire prevention and preparedness rather than fighting fires reactively. Extrapolating from the current budget of PrevFogo, the cost of expanding fire-fighting efforts would be upwards of US$42 million per year. This first-order estimate is likely very conservative, but further work is needed to develop a more realistic estimate. For comparison, the United States Federal Government spent US$2 billion on fire suppression in 2016 alone.

These costs should be weighed against the substantial cost of doing nothing, including damage to infrastructure, human health, and reduced ecosystem services and degraded natural capital among others. Over the near term, the largest impacts of fire would be on biodiversity and ecosystem service provision. Potential economic impacts might include: substantial costs in terms of human health (e.g. respiratory issues from prolonged exposure to smoke), damage to infrastructure, impacts on rural livelihoods (e.g. production of non-timber forest products and subsistence agriculture), timber production, and forest plantations, and possible impacts on large-scale agricultural production (e.g. via feedbacks on regional climate, pollination services). On the other hand, the costs of fire management and prevention, especially in remote areas, are large.

3. Agricultural adaptation to climate change: YIELD50 scenario.

To implement the climate adaptation scenario, we relied on the same future projections of Maximum Cumulative Water Deficit and the Standardized Precipitation Evapotranspiration Index which was calculated by state/department in developing the YIELD and DRGHT scenarios. We assume that all countries will attempt a mix of adaptation strategies to buffer their agricultural output to changing climate, and that these interventions could mitigate approximately 50% of the productivity losses projected in average years in our Amazon tipping point (YIELD and COMBI) scenarios. Extreme drought events based on the Standardized Precipitation Evapotranspiration Index would still cause major crop losses as in DRGHT. This scenario also assumes large-scale expansion of irrigation in Brazil, given ongoing policy incentives and research to expand this adaptation strategy in the country's driest agricultural regions (Ayrimoraes et al., 2017; Fontenelle et al., 2017). By comparison, the extent of irrigated area in our other focal countries is considered relatively small and was not considered in this analysis.

Farmers and ranchers are likely to adapt management practices to new climate and market conditions to mitigate crop losses. Adaptation strategies that could be considered include implementing drought-adapted varieties; shifting the timing and intensity of cultivation, including switching from double- to single-cropping and planting later in the wet season, and; implementing agroforestry or crop rotation systems that are more resilient to climate change. Increasing irrigation is another key adaptation strategy that will likely increase in drier agricultural regions like Brazil's Amazon-Cerrado where large swaths of croplands have already moved outside the optimal climate zone (Pousa et al., 2019; Rattis et al., In Review).

As of 2015, irrigation in Brazil spanned several categories: central pivot (20%, 1.4 million ha); inundated rice (22%, 1.54 million ha); sugar cane (29.5%, 2.07 million ha); and other corps (28.6%, 2 million ha). To approximate potential expansion of irrigation in the region, we followed projections from Brazil's National Water Agency (ANA), which estimate 45% growth in irrigated area from 2015 to 2030 and further expansion of approximately 4% per year until 2050 regions regions (Ayrimoraes et al., 2017; Fontenelle et al., 2017). Areas with a Maximum Cumulative Water Deficit less than or equal to -600 were considered ineligible for irrigation because they are likely not dry enough to warrant the initial investment. We selected this threshold based on comparison of plots of the Maximum Cumulative Water Deficit for existing irrigated and non-irrigated areas over time.

Before 2030, irrigation is expected to expand only to regions where it is already prevalent, that is, areas where there is sufficient energy and water infrastructure available. After 2030, expansion into new areas is possible with additional investments in energy and water infrastructure. Based on Brazil's National Water Agency projections, we assume an expansion of 11.2 million hectares as states enter a drier climate. The overall impact of this scenario captured in IEEM is a 50% mitigation of the yield losses projected in our Amazon tipping point scenario (YIELD and COMBI). This is a conservative estimate. Some studies suggest that irrigation can lead to two-fold increases (or more) in productivity relative to non-irrigated areas.

The adoption of climate adaptation strategies would require substantial investments in research into climate adapted production strategies, water management, drought-adapted crop varieties, and irrigation expansion and efficiency. Such investments could have substantial benefits to the economy by preventing breadbasket failures and losses in agricultural incomes. They could also have important impacts on human well-being by improving food security and nutrition. On the other hand, strategies like irrigation will greatly increase water use (including increased evaporation from reservoir surfaces as the region becomes drier) and energy demand, taxing an already fragile energy grid that depends on hydroelectric power. Water and energy conflicts may arise if irrigation is a big part of the adaptation strategy (e.g. Pousa et al., 2019), but we assume sufficient water availability to sustain the projected irrigation expansion until 2050.

Reports from the International Food Policy Research Institute and the World Bank estimate that Latin America would require annual investments (in 2000 USD) on the order of US$30-31 million to expand irrigation infrastructure; US$128-129 million to improve irrigation efficiency; and US$392-426 million for agricultural research to counteract the effects of climate change on nutrition (Nelson et al., 2009). We based our initial cost estimates on these reports, although further research is needed to update and improve these estimates for the focal countries in this study.

Supplementary Information 3

Land Use Land Cover Change Modeling

Climate data preparation for use in land use land cover change modeling

The operationalization of the Amazon tipping point scenario in CLUE required the creation of annual bioclimatic spatial data. This included yearly average temperature, evapo-transpiration (PET) as well as average precipitation raster layers. This data was created using modelled future climate data provided by WorldClim (Hijmans et al., 2005). For annual temperature, evapotranspiration and precipitation, data from 1970-2000 was used as the basis for current climatic, or BASE conditions, compared to future climate data averaged between 2040 and 2060 to approximate data for the year 2050. In order to account for uncertainly in modelling future climate in 2050, seventeen future Coupled Model Intercomparison Project 5 (CMIP5)[5] simulations for the year range 2040 to 2060 were averaged to produce the final 2050 bioclimatic map files. The details of these models can be found in the Supplementary Information 4.

To then create annual files, equation 1 was used to approximate an annual rate of change in a Geographic Information System.

$$Rate\ of\ change = \left(\frac{end\ value}{beginning\ value}\right)^{\frac{1}{n}} - 1 \qquad \text{equation 1}$$

Where:

- end value was the final averaged 2050 raster modelled as described above;
- beginning value was the previously obtained 2020 raster, and;
- n = 30.

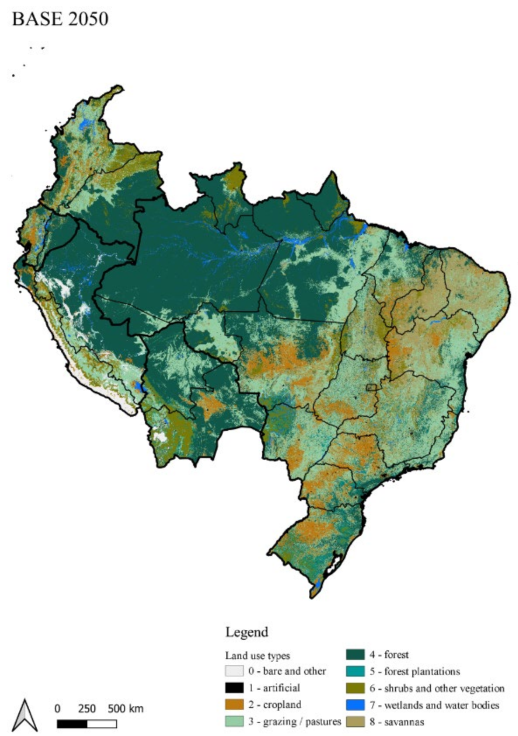
This rate of change was then multiplied by the base 2020 file for each bioclimatic variable, and then iterated 30 times using the python (3.7) rasterio and GDAL libraries to produce maps displaying the compound changes over the period 2020 to 2050 (GDAL/OGR contributors, 2020; Gillies et al., 2013).

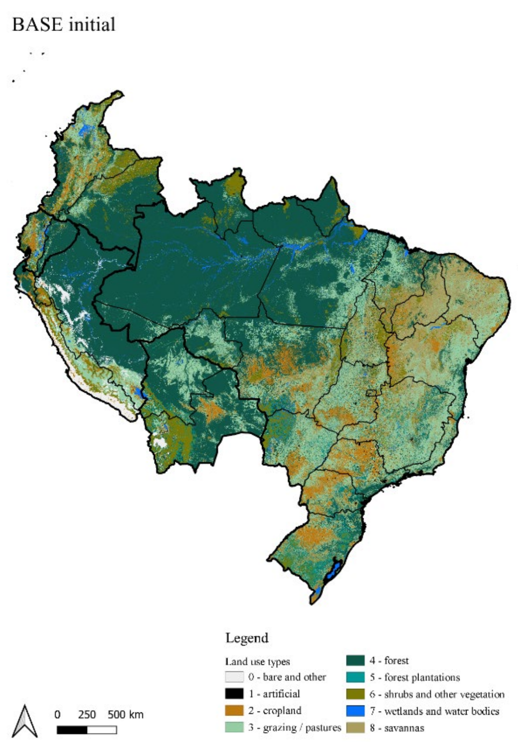
Note that this bioclimatic spatial data was also applied in calculating future ecosystem services supply, in order to consider the cumulative impacts of bioclimatic shocks over time. These effects are both direct and indirect. Specifically, the raster files created using the above method for modelling future climate changes (equation 1) are used as direct inputs for water supply as well as nutrient and soil delivery ratio models in InVEST for the final 2050 model runs. This was undertaken to account for changes in climate between the initial time period and 2050. Indirect impacts arise since these modelled bioclimatic inputs were used to generate the LULCC projections and maps.

[5] For more information on the Coupled Model Intercomparison Project, see: https://esgf-node.llnl.gov/projects/cmip5/

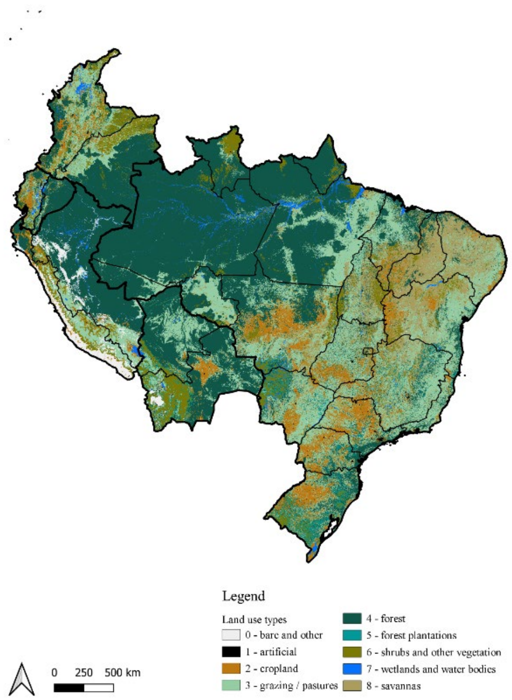
Land Use Land Cover Change maps by scenario.

The following are enlarged LULC maps by scenario.

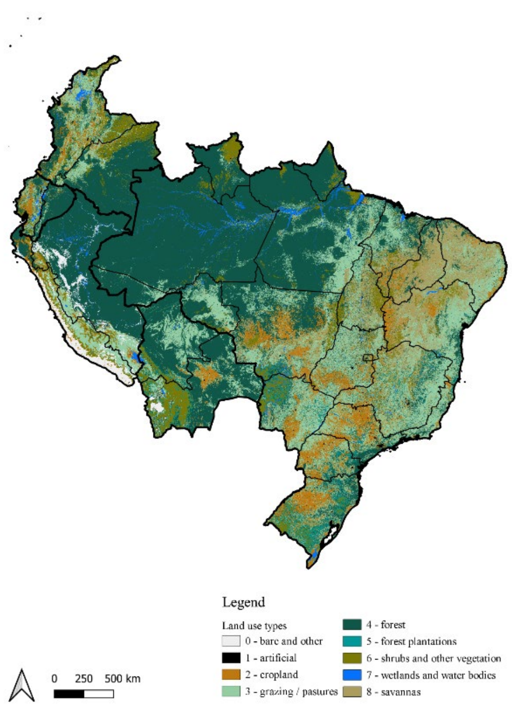




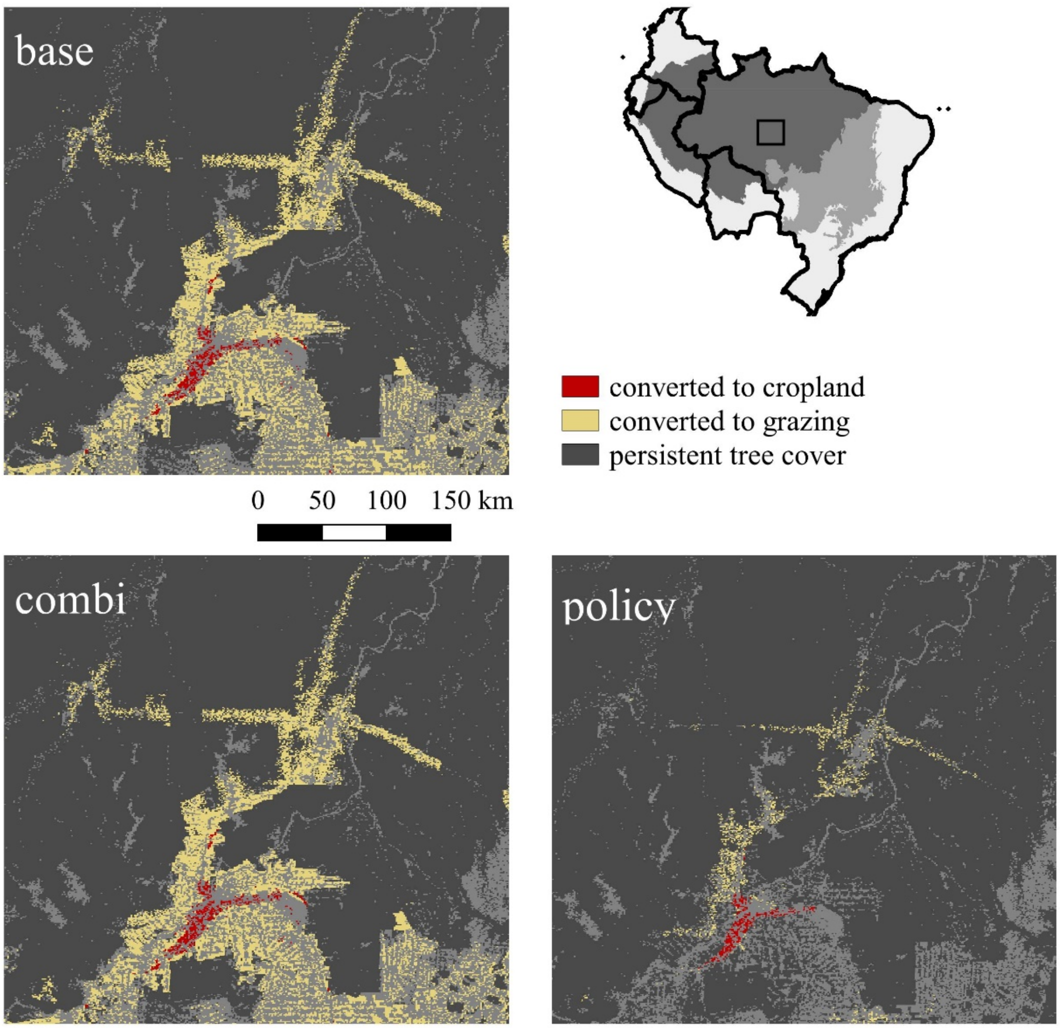
COMBI 2050

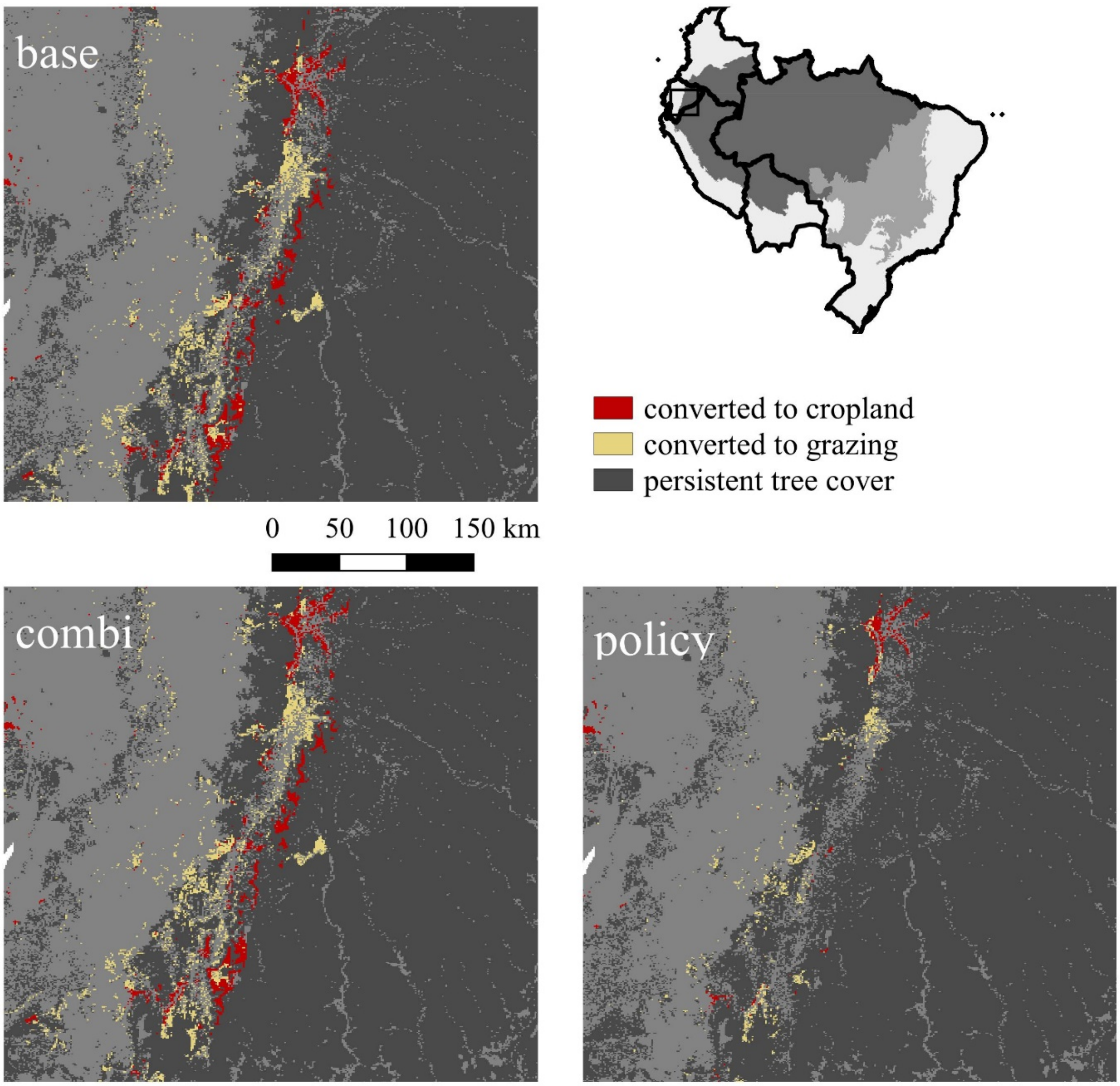


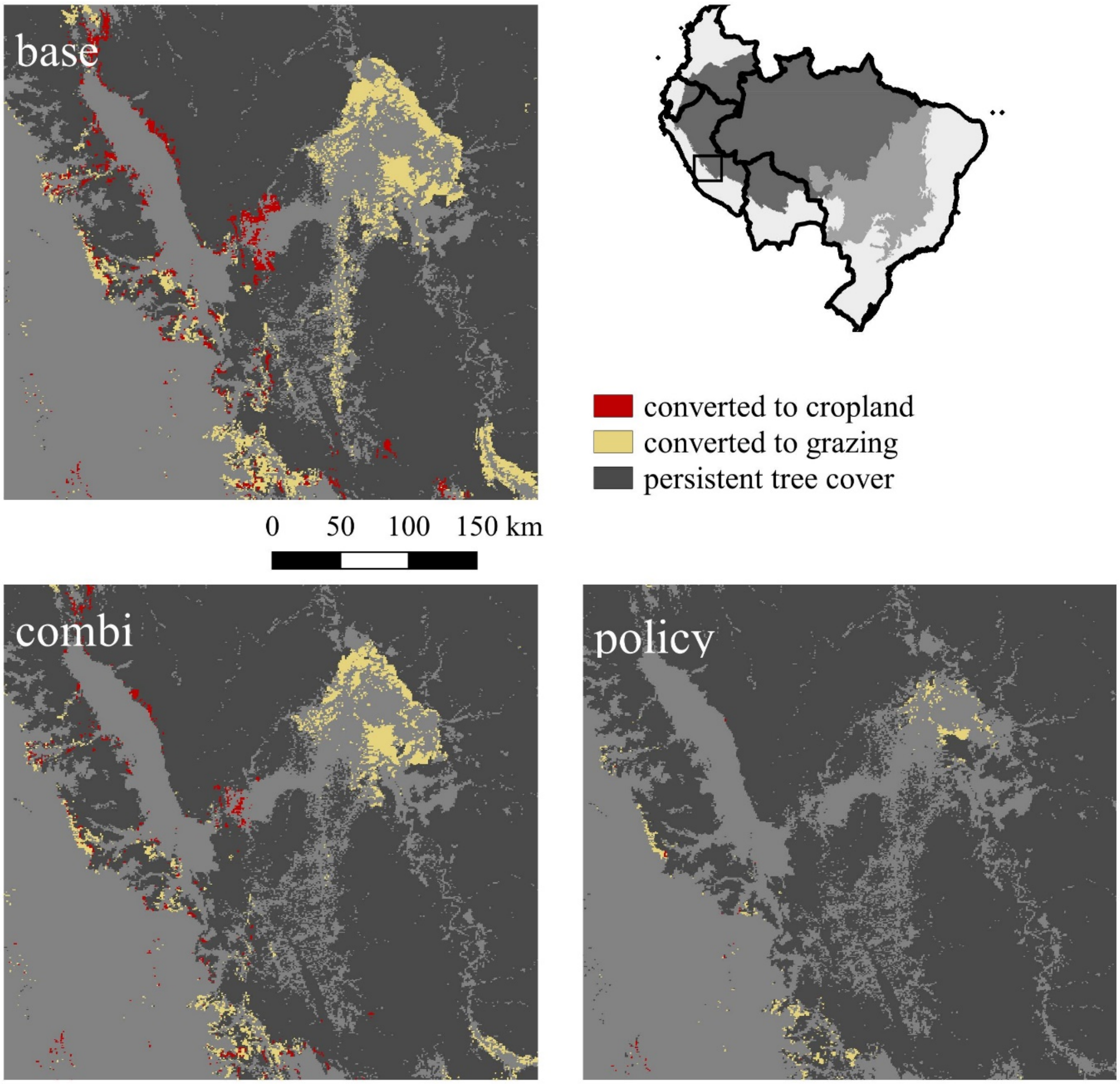
POLICY 2050

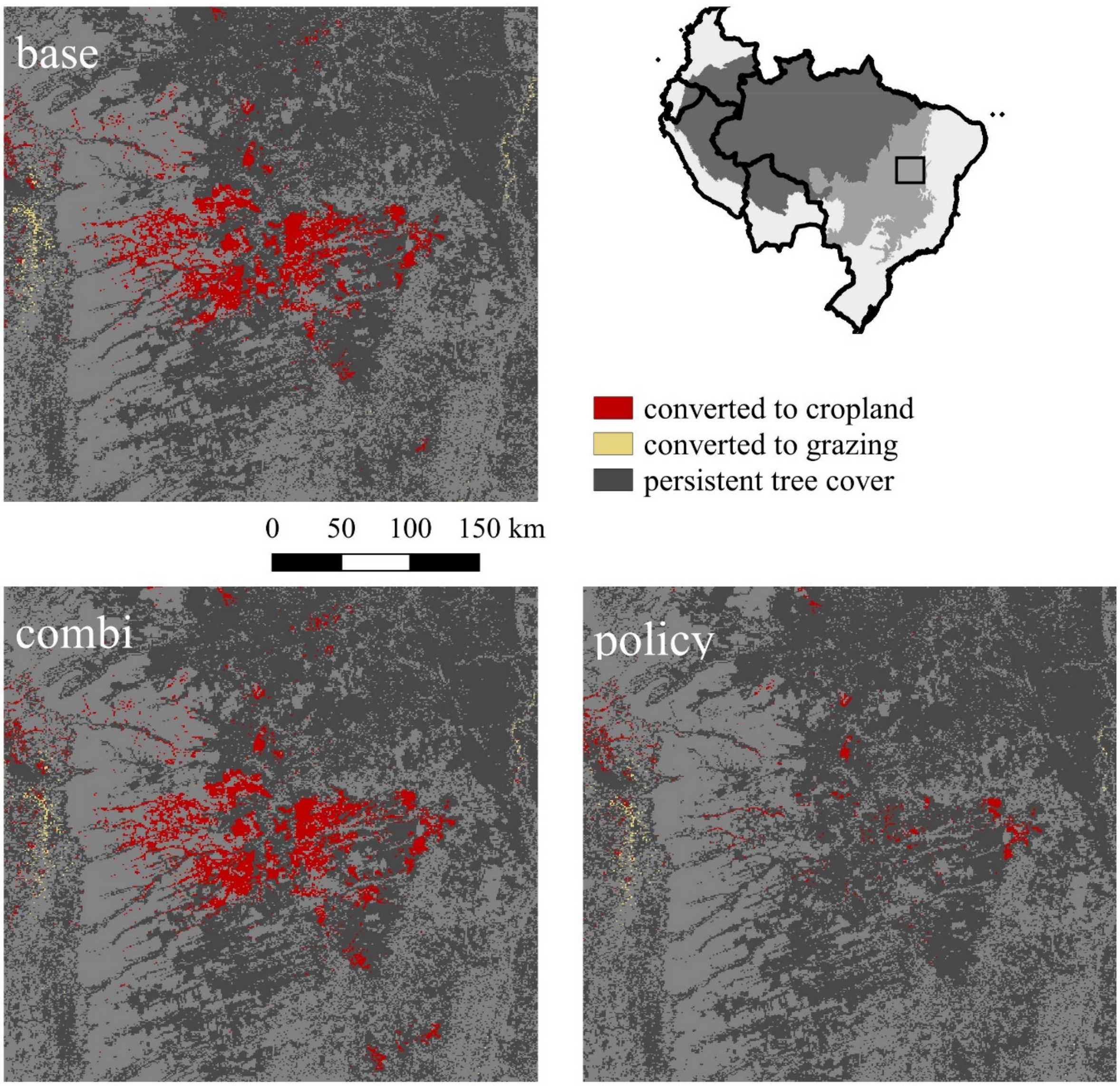


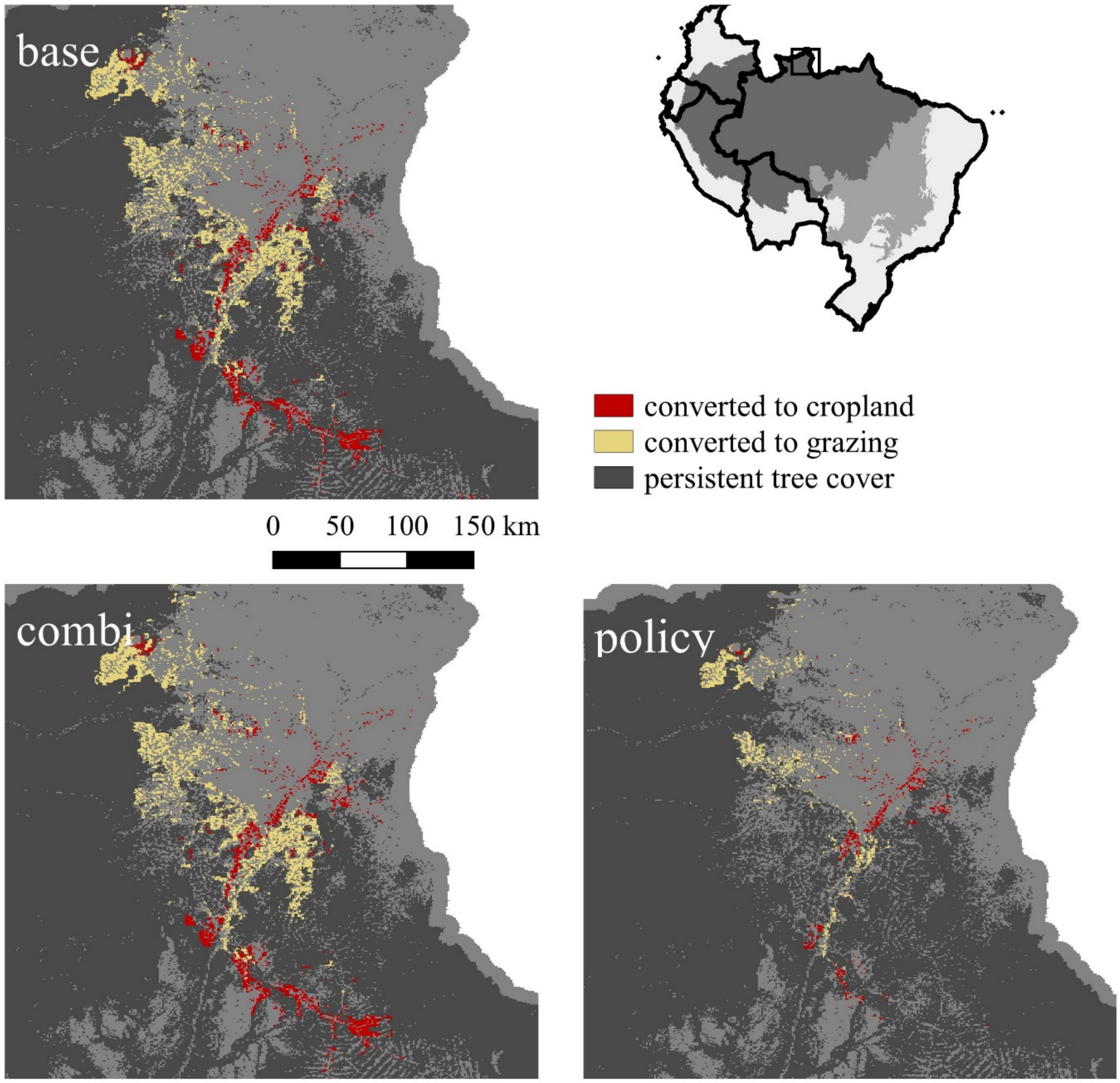
The maps below zoom in on some of the areas experiencing the greatest change in the Amazon tipping point and policy scenarios.




base
converted to cropland
converted to grazing
persistent tree cover
0 50 100 150 km
combi
policy


base
converted to cropland
converted to grazing
persistent tree cover
0 50 100 150 km
combi
policy


base
converted to cropland
converted to grazing
persistent tree cover
0 50 100 150 km
combi
policy


base
converted to cropland
converted to grazing
persistent tree cover
0 50 100 150 km
combi
policy

Supplementary Information 4
Ecosystem Services Modeling

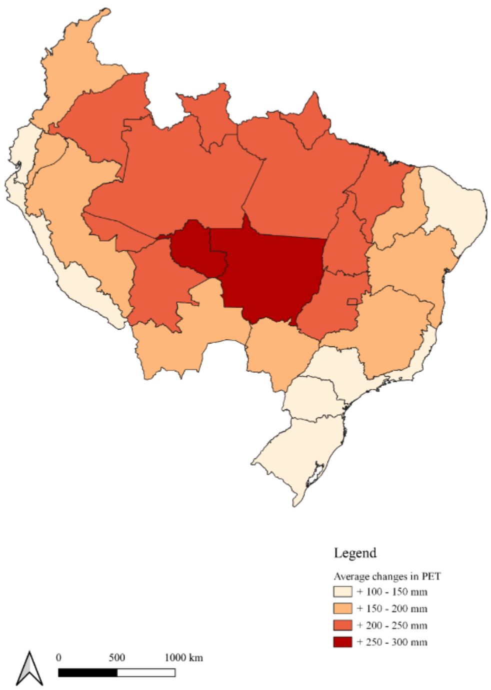
Table SI 1 presents the models used for the calculations of future potential evapotranspiration, precipitation and temperature.

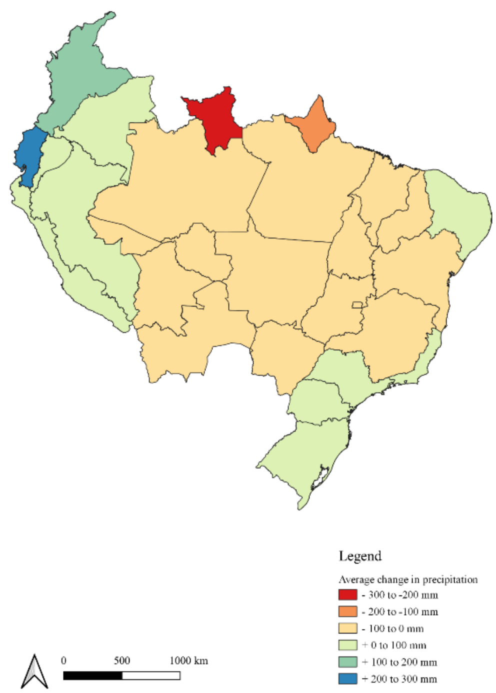
Table SI 1. Bioclimatic models averaged for calculation of future PET, precipitation, and temperature.

Model	Institution
ACCESS1-0	Commonwealth Scientific and Industrial Research Organisation (CSIRO) and Bureau of Meteorology, Australia
bcc-csm1-1	Beijing Climate Center, China Meteorological Administration
CCSM4	National Center for Atmospheric Research, USA
CNRM-CM5	Centre National de Recherches Météorologiques / Centre Européen de Recherche et Formation Avances en Calcul Scientifique, France
GFDL-CM3	NOAA, Geophysical Fluid Dynamics Laboratory, USA
GISS-E2-R	NASA Goddard Institute for Space Studies, USA
HadGEM2-AO	National Institute of Meteorological Research / Korea Meteorological Administration
HadGEM2-CC	Met Office Hadley Centre, UK
HadGEM2-ES	Met Office Hadley Centre / Instituto Nacional de Pesquisas Espaciais)
INM-CM4	Institute for Numerical Mathematics, Russia
IPSL-CM5A-LR	Institut Pierre-Simon Laplace, France
MIROC-ESM-CHEM	Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), and National Institute for Environmental Studies
MIROC-ESM	Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), and National Institute for Environmental Studies
MIROC5	Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology
MPI-ESM-LR	Max Planck Institute for Meteorology (MPI-M), Germany
MRI-CGCM3	Meteorological Research Institute, Japan
NorESM1-M	Norwegian Climate Centre

Source: as indicated in table.

The maps below show regional changes in bioclimatic variables (yearly PET, yearly precipitation and yearly average temperature) over time (initial to 2050) used as inputs for InVEST models. Evapotranspiration, or PET, is a measure of the depth of which moisture is removed from soil as a result of climatic processes. An increase in the depth of PET indicates an increase in soil dryness. Precipitation refers to yearly average rainfall, where red areas on the below map indicate a decrease in rainfall, while areas of green and blue shades mean areas receive higher average rainfall. The final map shows increases in temperature in degrees, averaged across each regional analyzed.




Legend
Average change in precipitation
- 300 to -200 mm
- 200 to -100 mm
- 100 to 0 mm
+ 0 to 100 mm
+ 100 to 200 mm
+ 200 to 300 mm
0
500
1000 km

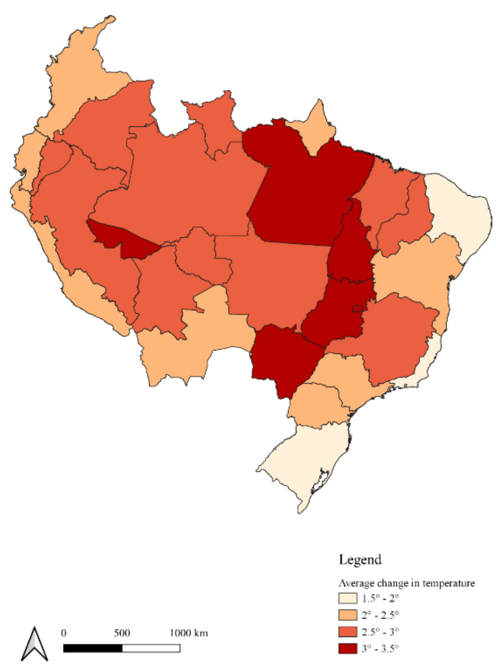

Legend
Average change in temperature
1.5° - 2°
2° - 2.5°
2.5° - 3°
3° - 3.5°
0
500
1000 km

Table SI 2, Table SI 3, Table SI 4 and Table SI 5 present ecosystem service modeling results for each ecosystem service and scenario aggregated according to biome.

Table SI 2. Annual water yield results aggregated to biome level in cubic meters of water yield.

Biome	BASE 2020	BASE 2050	COMBI 2050	POLICY 2050
Amazon Cerrado	651,343,746,051	384,329,992,511	384,259,015,999	380,354,226,455
Cerrado	369,957,880,976	260,736,882,637	260,578,588,102	260,267,414,082
Non-Amazon	884,926,024,086	947,283,044,647	947,262,016,391	944,681,823,132
Amazon	4,244,726,764,651	3,327,098,677,633	3,326,086,038,235	3,310,707,410,287

Source: IEEM+ESM results.

Table SI 3. Carbon results aggregated to biome level in elemental C stored.

Biome	BASE 2020	BASE 2050	COMBI 2050	POLICY 2050
Amazon Cerrado	30,245,831,929	25,880,280,972	25,908,954,906	28,652,033,571
Cerrado	18,063,792,211	17,465,256,532	17,505,920,788	17,881,539,782
Non-Amazon	25,713,405,436	24,225,428,387	24,244,754,777	25,257,637,888
Amazon	119,665,471,086	112,201,340,646	112,606,109,663	117,523,922,664

Source: IEEM+ESM results.

Table SI 4. Phosphorus flows that reach the stream aggregated to the biome level in kg per year.

Biome	BASE 2020	BASE 2050	COMBI 2050	POLICY 2050
Amazon Cerrado	32,135,187	66,845,070	68,433,039	43,484,204
Cerrado	58,719,478	66,235,271	67,613,222	61,546,378
Non-Amazon	67,581,676	86,057,862	87,441,073	73,990,528
Amazon	9,809,424	21,386,832	20,678,361	12,770,843

Source: IEEM+ESM results.

Table SI 5. Nitrogen flows that reach the stream aggregated to the biome level in kg per year.

Biome	BASE 2020	BASE 2050	COMBI 2050	POLICY 2050
Amazon Cerrado	335,692,919	454,949,408	463,048,791	371,543,199
Cerrado	427,128,767	452,776,001	462,531,719	439,914,669
Non-Amazon	460,124,738	542,883,982	549,632,095	502,127,907
Amazon	385,913,291	452,337,343	445,040,709	399,226,951

Source: IEEM+ESM results.

Table 4 Soil loss results aggregated to a biome level in tons per hectare.

Biome	BASE 2020	BASE 2050	COMBI 2050	POLICY 2050
Amazon Cerrado	96,662,276	94,403,589	94,503,940	95,418,418
Cerrado	104,266,375	103,050,005	102,975,269	103,566,841
Non-Amazon	1,560,351,983	1,578,322,508	1,578,976,773	1,559,835,730
Amazon	1,701,901,677	1,728,489,981	1,725,906,721	1,708,785,469

Source: IEEM+ESM results.

Table SI 6 presents regional changes in ecosystem services and Biodiversity Intactness Index results between BASE in 2050 and Amazon tipping point in 2050.

Table SI 6. Regional changes in ecosystem service and Biodiversity Intactness Index results between BASE in 2050 and Amazon tipping point in 2050 in percent.

Region ID	Region	Country	AWY	Phosphorus	Nitrogen	Sediment	BII	Carbon
1	Maranhão	Brazil	0.0%	10.1%	7.7%	-1.2%	-0.6%	-0.4%
2	Tocantins	Brazil	-0.1%	0.8%	3.3%	-15.4%	0.7%	-1.7%
3	Bahia	Brazil	0.0%	10.1%	-10.7%	-17.1%	-1.1%	-9.0%
4	Goiás	Brazil	0.1%	32.0%	-23846.0%	-0.3%	-6.5%	-10.9%
5	Minas Gerais	Brazil	0.3%	105.4%	683.6%	24.7%	-5.2%	-11.8%
6	Distrito Federal	Brazil	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
7	Mato Grosso do Sul	Brazil	0.1%	2.6%	10.8%	-1.3%	-1.1%	-1.4%
8	Sao Paulo	Brazil	0.3%	52.7%	40.5%	-19.4%	-47.5%	-396.9%
9	Piaui	Brazil	0.0%	2.2%	2.1%	-2.0%	-1.0%	16.4%
10	Non-Amazon	Brazil	-0.1%	5.0%	3.6%	-7.8%	0.0%	32.3%
11	Non-Amazon	Peru	0.2%	14.7%	10.0%	5.7%	5.7%	-4.4%
12	Non-Amazon	Colombia	0.0%	3.0%	3.2%	3.5%	0.5%	-0.4%
13	Non-Amazon	Ecuador	0.0%	0.9%	0.8%	0.4%	1.4%	-1.4%
14	Non-Amazon	Bolivia	-0.1%	90.3%	285.1%	91.2%	3.3%	-2.1%
15	Parana	Brazil	3.7%	36.4%	30.6%	68.2%	-320.6%	79.3%
16	Mato Grosso	Brazil	0.0%	4.5%	6.9%	-2.4%	-0.7%	-0.7%
17	Acre	Brazil	0.0%	0.2%	0.2%	0.2%	-0.4%	0.3%
18	Rondônia	Brazil	0.0%	5.5%	4.5%	2.0%	0.0%	0.0%
19	Para	Brazil	0.0%	14.1%	12.0%	2.6%	-0.1%	0.1%
20	Roraima	Brazil	0.0%	4.3%	6.3%	1.9%	-1.1%	1.0%
21	Amapá	Brazil	0.0%	-92.1%	9.4%	-38.2%	42.8%	-39.4%
22	Amazonas	Brazil	0.0%	-22.4%	-3.0%	-3.3%	-3.0%	3.2%
23	Amazon	Colombia	0.0%	4.8%	-0.1%	14.4%	-0.6%	0.5%
24	Amazon	Ecuador	-0.1%	2.8%	2.5%	2.4%	-1.2%	1.1%
25	Amazon	Peru	1.1%	-44.1%	-41.8%	-44.8%	45.2%	-45.5%
26	Amazon	Bolivia	0.1%	-75.3%	-70.5%	2528.9%	-1.5%	0.1%

Source: IEEM+ESM results.

Table SI 7 presents regional changes in ecosystem services and Biodiversity Intactness Index results between BASE in 2050 and the policy scenario in 2050.

Table SI 7. Regional changes in ecosystem service and Biodiversity Intactness Index results between BASE in 2050 and the policy scenario in 2050 in percent.

Region ID	Region	Country	AWY	Phosphorus	Nitrogen	Sediment	BII	Carbon
1	Maranhão	Brazil	1.2%	-67.2%	-64.5%	-53.0%	62.6%	-63.2%
2	Tocantins	Brazil	0.5%	-68.3%	-71.3%	-77.4%	61.2%	-60.0%
3	Bahia	Brazil	0.1%	-68.6%	-93.7%	-86.0%	66.0%	-72.0%
4	Goiás	Brazil	0.2%	-110.5%	-19453.7%	-64.7%	60.8%	-70.4%
5	Minas Gerais	Brazil	0.4%	-91.6%	44.1%	-23.9%	64.8%	-77.1%
6	Distrito Federal	Brazil	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
7	Mato Grosso do Sul	Brazil	1.3%	-63.0%	-59.6%	-57.9%	61.0%	-63.6%
8	Sao Paulo	Brazil	0.2%	-1.6%	3.2%	-3.7%	42.9%	-413.6%
9	Piaui	Brazil	0.1%	-82.0%	-83.2%	-55.9%	68.8%	-68.2%
10	Non-Amazon	Brazil	-0.1%	3.9%	3.0%	-169.8%	0.0%	2.2%
11	Non-Amazon	Peru	0.8%	-35.1%	-25.0%	-76.6%	69.7%	-70.2%
12	Non-Amazon	Colombia	4.7%	-80.0%	-70.1%	-102.3%	70.6%	-71.8%
13	Non-Amazon	Ecuador	-0.9%	-34.1%	-25.3%	-92.0%	55.8%	-59.7%
14	Non-Amazon	Bolivia	0.2%	-74.4%	-122.6%	-5.6%	63.6%	-64.2%
15	Parana	Brazil	2.5%	18.3%	12.1%	-47.5%	-59.6%	40.8%
16	Mato Grosso	Brazil	1.6%	-67.3%	-70.1%	-34.8%	61.8%	-63.6%
17	Acre	Brazil	2.4%	-72.6%	-68.3%	-78.5%	66.9%	-70.3%
18	Rondônia	Brazil	4.2%	-64.3%	-65.9%	-73.9%	64.0%	-64.1%
19	Para	Brazil	2.5%	-76.4%	-79.6%	-85.0%	66.9%	-67.1%
20	Roraima	Brazil	0.3%	-70.5%	-130.5%	-79.9%	68.1%	-68.1%
21	Amapá	Brazil	0.0%	95.1%	-12.4%	-153.7%	69.5%	-76.7%
22	Amazonas	Brazil	0.3%	-45.0%	-66.0%	-128.3%	68.7%	-69.7%
23	Amazon	Colombia	8.6%	-62.2%	-72.5%	-59.3%	75.0%	-74.9%
24	Amazon	Ecuador	3.4%	-72.7%	-65.7%	-71.5%	69.4%	-69.1%
25	Amazon	Peru	2.1%	-87.4%	-83.5%	-91.2%	89.3%	-89.3%
26	Amazon	Bolivia	0.2%	-36.3%	-8.3%	1243.0%	65.8%	-65.0%

Source: IEEM+ESM results.

Supplementary Information 5
Additional Scenarios

This section presents additional scenarios developed to reflect a more optimistic view of the possibilities for mitigating the average climate change impact on agricultural productivity and yields. We introduce two new scenarios, YIELD75 and YIELD90, where YIELD75 mitigates 75% of the average climate change impact on agriculture and YIELD90 which mitigates 90% of the average climate change impact on agriculture. These scenarios are more optimistic than the YIELD50 scenario which assumes a climate change impact mitigation of 50%. Finally, we implement a revised policy scenario, POL3, which is the joint implementation of NDEFOR2, YIELD90 and NFIR.

Table SI 8. Cumulative impacts on GDP and Genuine Savings as difference from the tipping point scenario in millions of USD.

	YIELD75	YIELD90	POL3
GDP			
Brazil	-36,662	-16,082	-19,478
Peru	-5,635	-1,167	-1,709
Colombia	-9,904	-7,333	-16,130
Bolivia	-5,402	-3,359	-6,384
Ecuador	-4,369	-3,348	-6,999
Genuine Savings			
Brazil	-7,422	-240	80,111
Peru	-428	573	13,597
Colombia	-2,913	-1,165	82,614
Bolivia	-975	-327	11,034
Ecuador	-195	243	30,754

Source: IEEM+ESM results.

Focusing on Brazil, in YIELD75, the GDP impact of climate change would be less when compared with the original YIELD50 scenario, from a reduction of US$73,928 million to US$36,662 million. In the case of Genuine Savings, results would be less, from US$15,886 million in YIELD50 to US$16,082 million in YIELD90. Finally, with POL3, GDP impacts would result in losses equivalent to US$19,478 million compared to losses of US$81,245 million in the original POL scenario for Brazil. Genuine Savings and wealth would be greatly compromised in the revised POL3 scenario amounting to US$80,111 million compared with US$162,804 million in the original POL scenario.

Table SI 9. Net Present Value based on adjusted equivalent variation by country and scenario in millions of USD.

	YIELD75	YIELD90	POL3
Brazil	-15,838	-7,415	14,353
Peru	-2,045	-574	1,565
Colombia	-689	-474	6,423
Bolivia	-652	-395	-425
Ecuador	-391	-290	1,652

Source: IEEM+ESM results.

Considering NPV in Brazil, the revised POL3 would result in smaller returns on the investment. NPV in POL is US$17,770 million compared to US$14,353 million in POL3.