The Future of Forests: Emissions from Tropical Deforestation with and without a Carbon Price, 2016–2050

Jonah Busch and Jens Engelmann

Abstract

We project the future of tropical deforestation from 2016-2050 with and without carbon pricing policies, based on 18 million observations of historical forest loss spanning 101 tropical countries. Our spatial projections of future deforestation incorporate topography, accessibility, protected status, potential agricultural revenue, and a robust observed inverted-U-shaped trajectory of forest cover loss with respect to remaining forest cover. We project that in the absence of new forest conservation policies, 289 million hectares of tropical forest will be cleared from 2016-2050—an area about the size of India and one-seventh of Earth's tropical forest area in the year 2000. We project that this tropical deforestation will release 169 GtCO2 to the atmosphere from 2016-2050—one-sixth of the remaining carbon that can be emitted if the rise in Earth's temperature is to be likely held below 2 °C. We estimate that a universally applied carbon price of $20/tCO2 from 2016-2050 would avoid 41 GtCO2 of emissions from tropical deforestation while a carbon price of $50/tCO2 would avoid 77 GtCO2. These prices correspond to average costs to land users of $9/tCO2 and $21/tCO2 respectively. By comparison if all tropical countries implemented anti-deforestation policies as effective as those in the Brazilian Amazon post-2004 then 60 GtCO2 of emissions would be avoided. Our analysis corroborates the conclusions of previous studies that reducing tropical deforestation is a sizable and low-cost option for mitigating climate change. In contrast to previous studies, we project that the amount of emissions that can be avoided at low-cost by reducing tropical deforestation will increase rather than decrease in future decades. Encouragingly, 89% of potential low-cost emission reductions are located in the 47 tropical countries that have already signaled their intention to reduce emissions from deforestation in exchange for performance-based finance (REDD+).

JEL Codes: Q11, Q23, Q24, Q54

Keywords: Agriculture, Climate Change, Forests, Marginal Abatement Cost (MAC) Curves, REDD+

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Introduction

Avoiding dangerous climate change while expanding economic prosperity is perhaps the defining challenge of the 21st century. Achieving both goals requires reducing greenhouse gas emissions where doing so has the lowest unit cost. Ideally, a global market for emission reductions would allow those who can reduce emissions most cheaply to sell their abatement services to others, and in doing so self-identify. In the absence of such a carbon market, policymakers face the challenge of prioritizing opportunities for low-cost abatement within and across technological sectors. They are guided in this endeavor by marginal abatement cost (MAC) curves, which estimate how much abatement is available where, when, how, and at what price.

Previous MAC curves have identified reducing tropical deforestation as a promising potential source of low-cost abatement relative to other sectors, especially in the near term (Grieg-Gran 2006, Kindermann et al 2008, Naucler and Enkvist 2009 (i.e. "the McKinsey MAC curves"), Strassburg et al 2009, Coren et al 2011) and enhancing tropical reforestation (Naucler and Enkvist 2009). Reducing all tropical forest loss and associated peatland conversion to zero has the biophysical potential to cut annual emissions by 5.5-10.3 $GtCO_2$/year (van der Werf et al 2009, Pan et al 2011, Baccini et al 2012, Grace et al 2014), of which 3.0-6.5 $GtCO_2$/year is from land-use change (Harris et al. 2012, Baccini et al 2012, Achard et al 2014, Grace et al 2014, Tubiello et al. 2014, Tyukavina et al. 2015) (Figure 1). Additionally, enhancing tropical reforestation has the potential to increase carbon sequestration above the current pace of 4.4-6.3 $GtCO_2$/year from forest regrowth (Pan et al 2011, Baccini et al 2012, Grace et al 2014).

We are motivated to revisit MAC curves for tropical deforestation by the recent availability of a revolutionary new data set on forest cover loss and gain (Hansen et al 2013). Previous MAC curves relied on self-reported data at the national level using inconsistent methods in five-year increments on forest cover change (FAO 2005). The "Hansen data" (Hansen et al 2013) now provide researchers with spatially and temporally consistent annual data for the 2001-2012 period that covers the globe at a resolution of 30 meters and disaggregates forest loss from forest gain. Data of this sort were previously available only for isolated places and time periods. Because these data are more recent, they have the added benefit of capturing Brazil's policy-driven reduction in Amazon deforestation post-2004 (Nepstad et al. 2014).

Constructing a MAC curve involves estimating how many emission reductions will be produced in a sector in response to a given carbon price. In the case of tropical forests, a carbon price could come from demand from an international carbon market or a fund such as the Green Climate Fund, or from domestic carbon pricing policies. Prior MAC curves inferred price-responsiveness indirectly by relying on an "opportunity-cost" assumption that land would be entirely maintained as forests wherever potential carbon payments exceed net revenue from alternative land uses, and would be entirely deforested otherwise. In this study we instead use a "revealed preference" approach, estimating price-responsiveness directly from historical land-use decisions (Plantinga et al 1999; Stavins 1999; Lubowski et al 2006; Pfaff et al 2007; Busch et al 2012). By using evidence from actual land-use decisions we implicitly account for the rich set of factors that affect land use in practice. Because there is as yet little direct empirical evidence with which to calibrate the responsiveness of deforestation to carbon prices, we turn to indirect evidence on the responsiveness of deforestation to agricultural prices. We calibrated the marginal effect of a carbon price on deforestation using the empirical relationship between the observed pattern of historical deforestation and variation across space and time in the benefits and costs of converting land from forest to agriculture. We assumed that land-use decision-makers[1] would be as responsive to carbon prices as to agricultural prices.

By using the Hansen satellite data we were able to observe and incorporate non-linear dynamics of forest loss that had previously been hidden from view due to the spatial and temporal coarseness of available data on forest cover change. That is, the Hansen data showed strong evidence of the first stages of a forest transition curve (Mather 1992): forest loss starts slow in areas of high forest cover, rapidly accelerates, plateaus, and then falls. Our MAC curves are the first to incorporate this inverted-U-shaped trajectory of deforestation into business-as-usual projections and to control for it in policy scenarios. The spatially explicit nature of the Hansen data also allows us to map the location of potential emission reductions at a given carbon price.

We produced abatement estimates under a broader set of policies than any previous MAC curve. That is, we explored both full participation across all sites in mandatory national carbon pricing policies (e.g. a cap-and-trade program or a symmetric tax-and-subsidy program) and selective participation in voluntary carbon pricing policies (e.g. carbon payments only), as in Busch et al (2009) and Busch et al (2012) but no other previous MAC curves. We incorporated the effects of leakage in the voluntary policy scenarios. We added a screen for national readiness to participate, as in Coren et al (2011) but no other previous MAC curves. And in a supplementary analysis we constructed MAC curves not only for reduced deforestation but for enhanced reforestation as well, as in Naucler and Enkvist (2009) but no other previous MAC curves.

This pan-tropical spatially explicit model of reduced emissions from deforestation in response to policies represents the third generation of the OSIRIS model. It builds upon a first-generation model that was pan-tropical but not spatially explicit (Busch et al 2009), and

1 We use the term "land-use decision makers" rather than "land owners" because most people who make decisions about land use and land cover in the tropics are not formal owners. Furthermore land-use and land-cover decisions are made both directly by land users and indirectly by administrators at various scales of government.

a second-generation model that was spatially explicit but for selected countries only, e.g. Indonesia (Busch et al 2012) and Bolivia (Andersen et al 2014).[2]

Methods

Data

We obtained data on annual pan-tropical forest cover loss from 2001-2012 by classifying 30 m Landsat-derived tree-cover loss data (Hansen et al 2013) into forest or non-forest using a tree-cover threshold of 25%. These data represent a radical step-change in improvement of quality along multiple dimensions, relative to the Forest Resources Assessment (FRA) data set (FAO 2005) that was used to construct previous MAC curves (Table 1). Whereas the FRA presents a single self-reported statistic on each nation's forest cover, the Hansen data present a wall-to-wall map of the world's forests at a resolution the size of a baseball diamond. Whereas the FRA presents statistics in five- to ten-year increments, the Hansen data are annual. And whereas the FRA data cobbles together widely disparate methods and definitions used across countries (and even within the same countries over time), the Hansen data apply the same methods and definitions uniformly worldwide every year. We chose not to use a later update to the Hansen et al (2013) data, because these updated data (GFW 2015) did not use consistent methods to calculate forest-cover loss between 2001-2010 and between 2011-2013.

In spite of its many advantages, the Hansen et al data set has some limitations that are important to be aware of. It does not distinguish natural forests from plantations or other tree cover (Tropek et al 2014; Hansen et al 2014). And its globally consistent algorithm means that it may (e.g. Burivalova et al 2015) or may not (e.g. Bellot et al 2014) be as locally accurate in some regions as locally calibrated data.

The Hansen data set also includes forest gain. As cautioned by Tyukaniva et al (2014), forest gain is not reciprocal to forest loss. It includes only those lands that experienced a transition from non-forest to forest between 2001-2012; it omits regrowing forests that had not yet reached 5 m in height by 2012, as well as growth within forests that were already established by 2000. We use data on forest gain only in one supplementary analysis.

We constructed an original data layer on annual potential gross agricultural revenue by adapting the methods of Naidoo and Iwamura (2007). Following Naidoo and Iwamura (2007), we determined the most lucrative crop (n=21) that could be grown in every location in every year (2001-2012) by multiplying potential crop yields based on global agro-ecological

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2 Like its predecessors, this model is open source, in R. It is available here: http://dx.doi.org/10.7910/DVN/CWCWIX

zones (IIASA/FAO 2012) by a production-weighted average of national farmgate prices (FAO 2014) for the top five producer countries. Potential crop yields were based on assumptions of medium inputs and current levels of irrigation. Notably, both global prices and potential agricultural yields are exogenous to local land-use decisions. Diverging from Naidoo and Iwamura (2007) but following Busch et al (2015), we used updated agro-ecological zone data from 2012, and used annual rather than decadal average prices. Furthermore, we included only those 21 crops that were plausibly associated with agricultural extensification to serve global commodity markets, and excluded 14 crops more likely associated with gardens or local markets.[3] All prices were converted to 2014 USD.

We excluded revenue from cattle, for which no data on potential production were available. Previous analyses (e.g. Naidoo and Iwamura (2007)) included revenue from cattle based on data on actual production; we chose not to use these data because actual production is not an exogenous determinant of deforestation. Furthermore, actual production may not even be correlated with potential production. For example, actual production of cattle is very high throughout India and zero in the interior of the Amazon, even though potential production in the two regions may not differ greatly. We included revenue from cattle based on actual production in a sensitivity analysis.

We did not account for logging revenues, for which no spatial data were available. The effect of this exclusion is ambiguous; some models have treated logging revenue as additional to agricultural revenue in encouraging conversion to agriculture, while other models have treated logging revenue as favoring forest cover in opposition to agriculture. We explored the addition of a uniform value per hectare of logging in a sensitivity analysis.

We compiled data on other geographic factors affecting the likelihood of deforestation. [4] These included average slope and elevation (Jarvis 2008), minimum Euclidean distance from the nearest national capital or city of more than 750,000 inhabitants in the same country ("large city") in the year 2010 (UNDESA 2012), protected areas of IUCN Category I-II

3 Included crops: bananas, barley, cocoa beans, coconuts, coffee, cotton, dryland rice, groundnuts, maize, oil palm, oranges, rapeseed, rye, sorghum, soybeans, sugar beet, sugar cane, wetland rice, wheat, tobacco, tea. Excluded crops: cabbage, carrots, cassava, chick peas, cow peas, flax, oats, olives, onions, peas, potatoes, sweet potatoes, tomatoes, yams.

4 In the absence of a universally agreed definition of deforestation (Romijn et al 2013), we use the term "deforestation" to describe forest cover loss, regardless of subsequent land use. This land-cover-based definition differs from a land-use-based definition, in which deforestation is only termed as such when forest cover loss is followed by subsequent conversion to agriculture, pasture, or other use. Lund (1999) found that 13 of 39 active definitions of deforestation are based on land-cover change while 22 are based on land-use change, and recommended that the UNFCCC define deforestation as a change in land cover as this definition is both more appropriate for measuring changes in carbon stocks and more intuitive to the general public. We agree.

(strictly protected areas) and Category III-VI (multiple-use protected areas) (WDPA 2014), and initial forest cover (Hansen et al 2013).

We calculated emission factors for deforestation and peat degradation based on data on forest biomass, peat soil, and non-peat soil. Emissions from deforestation were calculated based on the release of 100% of aboveground forest biomass carbon (Baccini et al 2012). We tested the sensitivity of our results to two alternative datasets of forest carbon stocks (Ruesch and Gibbs 2008; Saatchi et al 2011). We assumed the release of belowground forest biomass carbon using a below-to-aboveground biomass ratio of 0.26 (Mokany et al 2006) following Harris et al (2012). Because our aboveground forest biomass carbon data was centered on the year 2008, we inferred the biomass cover of forests cleared before 2008 by interpolating the average carbon density of remaining forest within each cell. That is, we assumed that average forest carbon density remained constant from 2001-2012, and that clearing within cells was not systematically biased toward higher- or lower-carbon forest. We obtained the distribution of peat soils from the distribution of histosols and gleysols (FAO 2008), following Yu et al (2010). We assumed peat emissions of 59.4 tCO_2/ha/yr (Murdiyarso et al 2011) for 30 years, resulting in 1,782 tCO_2/ha of committed emissions for peat soils. As a sensitivity analysis we considered a lower emission factor of 35.3 tCO_2/ha/yr (Hergoualc'h and Verchot 2014) for 30 years, resulting in 1,059 tCO_2/ha of committed emissions. On non-peat soils, we assumed soil emissions from deforestation to be 8.5% of soil carbon content in the top 30 cm (FAO/IIASA/ISRIC/ISSCAS/JRC 2008)—the pan-tropical average of the percent of soil carbon released by conversion of forest to shifting cultivation, pasture, and permanent crops (Powers 2011). In the sole supplementary analysis involving reforestation we assumed a global average rate of carbon sequestration by regrowing plantation trees of 10 tCO_2/ha/yr (ITTO 2006) for 30 years, resulting in 300 tCO_2/ha of committed sequestration from reforestation.

We did not consider emissions from forest degradation (e.g. logging) in this model. Including degradation would have increased our estimates of available emission reductions at a given carbon price. In coming years data on losses of carbon stocks within forests will become available (Goetz et al 2014), enabling new frontiers of analysis of determinants of carbon stock loss in addition to land-use change.

We restricted the geographic scope of our analysis to the pan-tropics as defined by Baccini et al (2012). Within this geographic scope we gridded and aggregated data to 1.5 million 0.05 degree x 0.05 degree grid cells (approximately 5.5 km x 5.5 km at the equator). By aggregating spatial data to relatively coarse grid-cell sizes we were able to capture the full wall-to-wall spatial variation in forest cover change within a manageable number of cells, with the tradeoff of losing fine-scale spatial specificity. Using coarser-resolution cells had the added benefits of diluting the effects of possible spatial misalignments between datasets, enabling easier interpolation of missing data within cells (e.g. for forest carbon density), and subsuming localized spatial autocorrelation. With twelve time-steps for each grid cell our full data set included 18 million observations of fractional cell-year level forest-cover loss, as well as 1.5 million observations of fractional cell-period level forest cover-gain.

Explanatory model of deforestation

We constructed a multivariate regression model to explain observed annual grid cell-level deforestation based on spatial and temporal variation in cells' geographic characteristics. Our model followed the theory that land-use decision makers will choose a rate of conversion from forest to agriculture that maximizes the present discounted value of a future stream of net benefits and costs of conversion. Given this theoretical framework we regressed annual deforestation from 2001-2012 on exogenous variables related to the costs and benefits of agricultural conversion. We proxied for the gross economic benefits of conversion using the estimated annual value of potential gross agricultural revenue. We proxied for fixed and variable costs of converting forest to agriculture using a constant term and a linear combination of sites' slope, elevation, natural logarithm of the distance to the nearest large city, and the percent of cell contained within a strict protected area or multiple-use protected area—variables consistently found to be determinants of deforestation (Ferretti-Gallon and Busch 2014). We accounted for access costs using a fourth-order polynomial on remaining forest cover, consistent with forests surrounded by more cleared land being easier to access and thus cheaper to clear. We alternatively applied third-order and fifth-order polynomials in a sensitivity analysis.

Explanatory variables related to potential agricultural revenue, protected areas, and forest cover were time variant, while those related to slope, elevation, and distance to cities were time-invariant. We included year dummies to control for other time-specific macroeconomic conditions not captured by variation in agricultural prices alone. To account for regional variation in drivers of deforestation (Rudel et al 2009; Fisher 2010) we constructed three separate models for each of the tropical regions (Sub-Saharan Africa; Latin America, Tropical Asia). We conducted a single full-tropics model as a sensitivity analysis.

Within the Latin America region we modeled the aggregate effect of Brazil's Program for Prevention and Control of Deforestation in the Amazon (PPCDAm) and associated public policies and private measures (protected areas, indigenous lands, satellite monitoring and law enforcement, jurisdictional credit restrictions, soy and cattle moratoria; Nepstad et al 2014) that collectively resulted in a 60-80% reduction in deforestation in the Amazon from its peak in 2004 (INPE 2014; Hansen et al 2013). The PPCDAm effect consisted of two components: a dummy variable for post-2004 (i.e. 2005-2012) Brazil, and an interaction term between post-2004 Brazil and agricultural prices, capturing policies to counteract agricultural pressure. We assumed that the entire post-2004 reduction in Amazon deforestation was attributable to Brazil's policies, controlling for other included variables.

We chose not to include in the explanatory model several other variables that are frequently used in spatially explicit econometric studies of deforestation (Ferretti-Gallon and Busch 2014). We did not include roads because the availability of data on road density (SEDAC 2013) varied too widely across countries to be useful for a comparative pan-tropical analysis, and in the long term roads are likely to be endogenously related to forest clearing. We did not include population as in the long term it too is likely to be endogenously related to forest clearing.

We estimated the influence of explanatory variables on deforestation in R using a Poisson quasi-maximum likelihood estimator (QMLE) (Wooldridge 2002, Burgess 2012, Busch 2012, Busch 2015), which is theoretically consistent with forest cover loss within a 5.5 km x 5.5 km grid cell being the count of many independent, discrete binary observations of forest cover loss or maintenance at the level of 30 m x 30 m satellite data. A Poisson QMLE model tolerates zero values, and generates a distribution of predicted values that fits the distribution of observed data, which is concentrated nearest to zero deforestation and diminishes toward greater levels of deforestation. We explored in a sensitivity analysis the use of other functional forms; these either did not improve model fit as measured by grid-cell level root-mean-square error (RMSE) (e.g. Tweedie), or did not fit the data well (e.g. Inverse Hyperbolic Sine Transformation).

Our econometric model was:

$$d_{it} = \exp(\beta_0 + \beta_1 A_{it} + P_{it}'\beta_2 + X_i'\beta_3 + \beta_4 F_{it} + \beta_5 F_{it}\hat{}2 + \beta_6 F_{it}\hat{}3 + \beta_7 F_{it}\hat{}4 + \beta_8 B_{it} + \beta_9 B_{it} A_{it} + \gamma_t + \epsilon_{it}) \quad (1)$$

Here d_{it} is fractional deforestation at grid cell *i* in year *t* (area of deforestation at grid cell *i* in year *t* divided by area of grid cell *i*). A_{it} is the time-variant value of potential gross revenue from agriculture per hectare at grid cell *i* in year *t*. P_{it} is a matrix of the time-variant fraction of a cell within a strict protected area or multiple-use protected area. X_i is a matrix of time-invariant observable grid cell characteristics: slope, elevation, and the natural logarithm of the distance to the nearest large city. The fourth-order polynomial on forest cover, F_{it}, captures the non-linear trajectory of deforestation. γ_t captures year-specific fixed effects not captured by variations in prices. The term β_0 captures unobserved constant determinants of deforestation. We did not include a time trend term, nor did we consider the potential dynamic effects of lagged variables (as in e.g. Wheeler et al 2013). The econometric model for Latin America contained three additional terms: a dummy variable for the Brazilian Legal Amazon, an interaction term for the Brazilian Legal Amazon and post-2004, and an interaction term for the Brazilian Legal Amazon, post-2004, and potential gross revenue from agriculture.

Localized spatial autocorrelation was alleviated to some extent by the large cell sizes. Residual spatial autocorrelation at larger scales may result in downward-biased standard errors; this is less of a concern for numerical modeling than for hypothesis testing.

Projection of business-as-usual deforestation

We projected future deforestation from 2013 to 2050 under a business-as-usual (no-policy) scenario using a dynamic recursive model. That is, in each year we predicted deforestation as a function of grid-cell level conditions in that year:

$$\hat{d}_{it} = \exp(\hat{\beta}_0 + \hat{\beta}_1 A_{it} + P_{it}{}'\hat{\beta}_2 + X_i{}'\hat{\beta}_3 + \hat{\beta}_4 F_{it} + \hat{\beta}_5 F_{it}\hat{}2 + \hat{\beta}_6 F_{it}\hat{}3 + \hat{\beta}_7 F_{it}\hat{}4 + \hat{\beta}_8 B_{it} + \hat{\beta}_9 B_{it} A_{it} + \gamma_t + \epsilon_{it}) \quad (2)$$

Here and in all cases below, the total aggregate level of deforestation or emissions was equal to the sum of deforestation or emissions across individual grid cells. With so many variables and assumptions affecting projections, we consider uncertainties by presenting sensitivity analyses rather than confidence intervals.

We assumed that future real agricultural prices (2013-2050) would remain constant at average 2001-2012 levels, as suggested by OECD/FAO (2013) for the period 2013-2022. We tested the sensitivity of our results to alternative assumptions that real agricultural prices would remain constant at 2001 levels (lower) or 2012 levels (higher). We assumed no further expansion of protected areas in the business-as-usual scenario. As a sensitivity analysis we included in the equation a squared term on price. We averaged year-specific fixed effects across the twelve years of historical analysis.

We calculated forest cover at the start of the year 2013 by subtracting observed forest loss between 2001-2012 from observed forest cover in the year 2000. Forest cover at the start of each subsequent year was calculated by subtracting predicted deforestation in the previous year from forest cover at the start of the previous year, subject to the constraint that forest cover could not drop below zero:

$$F_{it+1} = \max\{F_{it} - \hat{d}_{it}, 0\} \quad (3)$$

Effect of full participation in national carbon pricing policies

We next modeled the effect of a carbon pricing policy such as a national cap-and-trade program or symmetric carbon tax-and-subsidy for deforestation emissions, assuming full participation across all grid cells in all tropical countries. A carbon price reduced the potential to gain agricultural revenue from converting forests for crops relative to the potential to gain carbon revenue from conserving forests, reducing expected deforestation as a result. That is:

$$\hat{d}_{it} = \exp(\hat{\beta}_0 + \hat{\beta}_1(A_{it} - C_{it}) + P_{it}'\hat{\beta}_2 + X_i'\hat{\beta}_3 + \hat{\beta}_4 F_{it} + \hat{\beta}_5 F_{it}\hat{}2 + \hat{\beta}_6 F_{it}\hat{}3 + \hat{\beta}_7 F_{it}\hat{}4 + \hat{\beta}_8 B_{it} + \hat{\beta}_9 B_{it} A_{it} + \gamma_t + \epsilon_{it}) \quad (4)$$

Here the per-hectare carbon price is:

$$C_{it} = p_C * (3.67 * (AGB_i + BGB_i + (1-\alpha) * 0.085 * M_i) + \alpha P_i) \quad (5)$$

Where p_C is the price paid per ton of CO_2 emission reduction, AGB_i is aboveground biomass carbon in cell *i*, BGB_i is belowground biomass carbon in cell *i*, α is the fraction of cell *i* that is peat soil, M_i is the carbon content of the uppermost 30 cm of non-peat soil, and P_i is the emission factor for peat soil. 3.67 is the atomic ratio between carbon dioxide and carbon, and 0.085 is the assumed fraction of non-peat soil carbon emitted to the atmosphere from deforestation (Powers et al 2011). We introduced the carbon price starting in 2015.

We assumed that land-use decision-makers would respond equivalently to agricultural prices and carbon prices. However, land-use decision-makers might prefer agricultural revenue to an equal amount of carbon revenue since agricultural markets have been established for a much longer time and are deeply societally ingrained. Or conversely, land-use decision-makers might prefer carbon revenue to agricultural revenue if carbon revenue has lower input costs and therefore higher profit margins. Our model would not be affected by differences in fixed input costs but would be affected by differences in input costs that vary proportionally with revenue. We tested the sensitivity of our results to the assumption of equal price salience (Chetty et al 2009; Finkelstein 2009) of agricultural prices and carbon prices by applying a higher and lower coefficient on the influence of a carbon price.

In a sensitivity analysis we compared the MAC generated using our "revealed preference" approach to a MAC generated using the "opportunity cost" approach as applied by Grieg-Gran (2006), Strassburg et al. (2009), Busch et al (2009). As in those analyses, 100% of grid-cell-level deforestation is avoided in cases where potential carbon revenue exceeds the net present value of potential agricultural profit, where potential agricultural profit is calculated using a 30-year revenue stream of potential agricultural revenue discounted at 10% annually and profit is assumed to be 15% of revenue.

Effect of leakage

We modeled the effect of displacement of deforestation due to market feedbacks ("leakage"), whereby reduced deforestation in one location raised agricultural prices and therefore potential revenue from agriculture pan-tropically, resulting in increased deforestation elsewhere. That is, A_{it} was scaled up by a parameter τ to become τA_{it}in equations (2), and (4). The parameter by which the agricultural price was scaled up, τ, was inversely proportional to the total reduction in pan-tropical deforestation in that year:

$$\tau = \left(\frac{\sum_i \widehat{d_{it}}\ BAU}{\sum_i \widehat{d_{it}}\ with\ policy}\right)^e \quad (6)$$

The "effective elasticity" parameter *e* is functionally equivalent to the price elasticity of demand for frontier agriculture (Busch et al. 2009). We calibrated *e* to match cross-regional leakage estimated by the separate Global Change Assessment Model (GCAM) (Wise et al. 2014), a general equilibrium model of the world economy, which also incorporated pan-tropical economy-wide feedbacks in the labor and productive capital markets. In that model a 10% decrease in deforestation in one region led to an area of increased deforestation in other regions equal to 16.5% of the area of decreased deforestation in the initial region. We did not explore potential interregional variation in leakage.

In each year, we solved the system of equations (2), (4), and (6) simultaneously for τ through an iterative routine.

Effect of selective participation in carbon-pricing policies

We modeled the effect of a pan-tropical carbon pricing policy in which participation was selective. That is, the decision whether or not to apply a carbon price was made at the level of each grid cell, based on whether expected revenue from carbon payments would exceed expected annual revenue from forgone agricultural production for that grid-cell. This is equivalent, for example, to a voluntary carbon market for site-level REDD+ projects or a government-run REDD+ program that selects early-action areas. Lump-sum carbon payments were annualized for comparison with annual agricultural revenue based on a revenue stream of 30 years at a 10% discount rate, consistent with other studies in this field since Grieg-Gran (2006). A lower discount rate of 5% was used in a sensitivity analysis. Grid cells where a carbon price was not applied experienced a trajectory of deforestation from 2013-2050 following formulas (2) and (3). Grid cells where a carbon price was applied experienced a trajectory of deforestation following formulas (3) and (4) from 2015 onward.

Screening results by intention to participate

We examined how results varied by tropical forest countries' expressed level of interest in participating in an international financial mechanism for REDD+. The first of three classes of countries were those that had already entered a pay-for-performance agreement as of January, 2015 (n=7: Brazil, Colombia, Ecuador, Indonesia, Guyana, Liberia, Peru). The second class of countries were those that had signaled their intention to enter a pay-for-performance agreement contingent upon finance through their participation in either the Forest Carbon Partnership Facility (FCPF), Forest Investment Program (FIP), or United

Nations REDD programme (UN-REDD) as of January, 2015 (n=40).[5] The third class of countries were those that had not yet signaled intention to participate in REDD+ (n=54).

We tested the sensitivity of our results to a variety of model assumptions, including future agricultural prices, carbon stock data sets, carbon pools included, peat emission factor, functional form, the sensitivity of land-use change to changes in prices, and whether or not Brazil would continue to maintain its PPCDAm and associated measures.

We also tested the sensitivity of results to the inclusion of per-hectare transaction costs, management costs, or co-benefits of forest conservation. Because we had no data on how such costs and benefits vary across space, we applied a uniform value per hectare of forests across the tropics. The effective price of carbon might be lower than the nominal price in the presence of transaction costs related to carbon measurement, legal establishment of property rights, or other bureaucratic administration of carbon transfers. Similarly, forest conservation might include management costs related to enforcing forest protection laws. On the other hand, the effective price of carbon might be higher than the nominal price to the extent land-use decision makers derive utility from the non-carbon benefits of forests, e.g. sustainable forest products and environmental services (Brandon 2014; Mullan 2014).

Forest gain

We modeled one supplementary scenario that included forest gain, as caveated above. We applied the same independent variables to a cross-sectional model of reforestation during the 2001-2012 period:

$$r_i = \exp\left(a_0 + a_1 A_i + P_{it}' a_2 + X_i' a_3 + a_4 F_i + a_5 F_i^2 + a_6 F_i^3 + a_7 F_i^4 + \gamma_t + \epsilon_i\right)/12 \tag{7}$$

Where r_i is the forest cover gain during the 2000-2012 period. We divided total 2000-2012 reforestation by 12 to approximate the rate of annual reforestation. We found a_1 to be positive, though this result was not robust to alternative specifications. A positive correlation between agricultural revenue and forest gain is consistent with forest gain being primarily the establishment of tree-crop plantations rather than restoration of forest on cleared land. As a

5 Argentina, Bangladesh, Belize, Bolivia, Burkina Faso, Cote d'Ivoire, Cambodia, Cameroon, Central African Republic, Chile, Costa Rica, Democratic Republic of the Congo, Dominican Republic, El Salvador, Ethiopia, Ghana, Guatemala, Honduras, Kenya, Laos, Madagascar, Mexico, Mozambique, Nicaragua, Nigeria, Panama, Papua New Guinea, Paraguay, Philippines, Republic of Congo, Solomon Islands, Sri Lanka, Sudan, Suriname, Tanzania, Thailand, Togo, Uganda, Vietnam, Zambia

result, we treated reforested land as a subset of non-forested land rather than a reversion to the equivalent of uncleared forest.

As with deforestation, we projected future reforestation from 2013 to 2050 under a business-as-usual scenario using a dynamic recursive model. That is, in each year annual predicted reforestation was a function of grid-cell level conditions in that year:

$$\hat{r}_{it} = \exp\left(\hat{a}_0 + \hat{a}_1 A_{it} + P_{it}{}'\hat{a}_2 + X_i'^{\hat{a}_3} + \hat{a}_4 F_{it} + \hat{a}_5 F_{it}^2 + \hat{a}_6 F_{it}^3 + \hat{a}_7 F_{it}^4 + \gamma_t + \epsilon_{it}\right)/12 \tag{8}$$

Total reforested land was the sum of land reforested in a given year plus land reforested prior to that year, subject to the constraint that the area of reforested land cannot exceed the total area of non-forested land:

$$R_{it+1} = \min\{R_{it} + \hat{r}_{it}, C_i - L_{it}\} \tag{9}$$

Where L_i is the land area of cell *i*.

Analogous to reduced deforestation, a carbon price increased the potential to gain carbon revenue from replanting forests relative to other agricultural uses of non-forested land, increasing expected reforestation as a result. That is:

$$\begin{aligned}\hat{r}_{it} = {} & \exp(\hat{a}_0 + \hat{a}_1(A_{it} + C_{it}) + P_{it}{}'\hat{a}_2 + X_i{}'\hat{a}_3 + \hat{a}_4 F_{it} + \hat{a}_5 F_{it}\hat{}2 + \hat{a}_6 F_{it}\hat{}3 + \\ & \hat{a}_7 F_{it}\hat{}4 + \gamma_t + \epsilon_{it})/12\end{aligned} \tag{10}$$

The expected revenue from reforestation was increased by the magnitude of the carbon payment. Here potential carbon revenue from reforestation is:

$$C_{it} = p_C * S_i \tag{11}$$

Where S_i is the carbon per hectare sequestered through reforestation. The cost of reforestation was not considered.

Results

Tropical forest cover loss totaled 96.6 million hectares from 2001-2012 across the 101 tropical countries included in our study—an area the size of Texas and Colorado combined. Of this total, 18.5 million hectares (19%) occurred in Africa, 28.9 million hectares (30%) occurred in Asia, and 49.2 million hectares (51%) occurred in Latin America. 52.7 million hectares (55%) occurred in the seven countries that had entered a payment-for-performance agreement by January 2015, an additional 32.4 million hectares (34%) occurred in the 40 countries that had not entered a payment-for-performance agreement but were participating in the FCPF, FIP, or UN-REDD, and 11.5 million hectares (12%) occurred in the remaining 54 countries.

Emissions from forest cover loss and peat degradation totaled 47.1 $GtCO_2$ from 2001-2012 across the 101 tropical countries included in our study—a level of emissions similar to the 55 $GtCO_2$ emitted by the European Union during that period (CAIT 2014), with an annual rate of emissions above that of the European Union since 2009. Of this total, 7.1 $GtCO_2e$ (15%) occurred in Africa, 20.8 $GtCO_2$ (44%) occurred in Asia, and 19.2 $GtCO_2$ (41%) occurred in Latin America (Figure 2). 26.9 $GtCO_2$ (57%) occurred in the seven countries that had entered a payment-for-performance agreement by January 2015, an additional 13.7 $GtCO_2$ (29%) occurred in the 40 countries that had not entered a payment-for-performance agreement but were participating in the FCPF, FIP, or UN-REDD, and 6.5 $GtCO_2$ (14%) occurred in the 54 other countries. 24.6 $GtCO_2e$ (52%) of total emissions were from aboveground biomass; 6.4 $GtCO_2$ (14%) of emissions were from belowground biomass; 1.5 $GtCO_2$ (3.2%) of emissions were from non-peat soils; 14.6 $GtCO_2$ (31%) of emissions were from peat soils. Our estimate of annual emissions from forest loss and peat emissions from 2001-2012, 3.9 $GtCO_2e$/yr, is comparable to the estimates of most other studies of emissions during this period (Figure 1).

We found strong empirical evidence that deforestation follows an inverted-U shape with respect to remaining forest cover (Figure 3a). Grid cells that were covered by very high levels of forest cover experienced low levels of deforestation, on average. Cells' average level of deforestation rose as less forest cover remained. The average level of deforestation reached its peak when forests covered between 75-90% of a cell, before declining again in cells with forest cover nearer to zero. This inverted-U-shaped relationship is robust to region (Figure 4a) and year (Figure 4b). The implied trajectory of forest cover through time is an inverted-S shape (Figure 5), consistent with the first stages of a theorized forest transition curve (Mather 1992). While this relationship is perhaps not surprising, our study is the first to our knowledge to confirm it empirically at the site level, and the first to incorporate it into projections of future deforestation. We don't find that the final stage of the forest transition curve is an empirical regularity; i.e., at no level of forest cover does forest gain systematically overtake forest loss across the tropics, though it does do so in some locations.

Determinants of deforestation generally conformed to expectations, though the magnitude of their influence varied across continents. Generally, deforestation was higher at lower slope, lower elevation, outside of protected areas, and closer to cities (Table 2). Exceptions included the time-invariant factors of elevation and distance to cities in Latin America and slope in Africa. Strict protected areas reduced deforestation more than multiple-use protected areas across all continents, controlling for other factors. Across all continents, greater potential agricultural revenue increased deforestation. We estimated that every additional \$100/ha/yr in potential agricultural revenue increased the rate of deforestation by an average of 1.60% in Africa, 2.42% in Asia, and 0.98% in Latin America, all else equal. At an average potential agricultural revenue of \$2,304/ha/yr, \$3,278/ha/yr, and \$2,978/ha/yr in each continent respectively, this implies a price elasticity of demand for deforestation of 0.37, 0.79, and 0.29 in each continent respectively.

Our econometric model of deforestation performed well on two validation tests, providing confidence in the descriptive and predictive abilities of the model. First, we compared our in-sample predictions of aggregate country-year-level deforestation to observed aggregate country-year-level deforestation (Figure 6), obtaining a correlation coefficient of 0.92 (between 0.91-0.95 in each region). Second, we trained a variant of our model only on the 2001-2006 sub-sample of data and used this model to predict deforestation at the grid-cell level for the 2007-2012 sub-sample, which we then compared to actual deforestation at the grid-cell level for 2007-2012 (correlation coefficient=0.43), obtaining a smaller (more accurate) Root Mean Squared Error (RMSE) than obtained by a naïve persistence model (1.07 vs. 1.14). Furthermore, the trend in year dummies was not significant in any of the three regions, justifying our decision to exclude a time trend term.

In the business-as-usual scenario, pan-tropical forest loss was projected to slowly climb for decades and even accelerate in the 2040s as areas of high forest cover in Latin America that are currently experiencing little deforestation come under greater threat (Figure 7). Note that because we based our projections on fundamental characteristics of site-years rather than on extrapolations of past trends, trends observed in 2001-2012 historical data might or might not persist in our projections of future deforestation. Our projection of rising future deforestation occurred as a result of the inverted-U-shaped trajectory of deforestation rather than due to any temporal trend in historical data; in the absence of consideration of the inverted-U-shaped trajectory of deforestation, projected annual deforestation would instead decline gradually in future decades.

As a result annual emissions from deforestation are projected to climb steadily through the 2020s and 2030s, before accelerating slightly around 2040 (Figure 8). Because deforestation is projected to shift into higher-carbon forests, annual emissions from deforestation are projected to rise by 42% between 2016 and 2050 as annual deforestation rises by 16%. This projection of rising emissions from deforestation over time is consistent with the findings of the Global Change Assessment Model (Thompson et al. 2010), but is at odds with the findings of the partial equilibrium models presented in Kindermann et al (2008). The projection of rising emissions also contrasts with the projected emissions in partial equilibrium models and integrated assessment models reviewed in Lubowski and Rose (2014), though those were projections of mitigation scenarios rather than business-as-usual scenarios.

From 2016-2050, 289 million hectares of tropical forest are projected to be cleared—an area about the size of the land area of India (World Bank 2014), and one-seventh the total area of tropical forest in 2000 (Hansen et al 2013). This loss of tropical forest is projected to release 169 $GtCO_2$ to the atmosphere–one-sixth of the remaining planetary carbon budget of 1,000 $GtCO_2$ that provides a two-thirds probability of global temperatures rising less than 2°C (IPCC 2014). Our projected tropical forest loss is larger than that of a recent report which projected that 232 million hectares of forest will be cleared worldwide by 2050 (WWF/IIASA 2011).

The introduction of a carbon pricing policy would decrease emissions from deforestation below business-as-usual rates (Figure 9). A carbon price of \$20/tCO_2 would reduce emissions from deforestation by 4.4 GtCO_2 (21.1%) from 2016-2020[6] and by 40.9 GtCO_2 (24.2%) from 2016-2050. Of these emission reductions, 5.7 GtCO2e (14%) would occur in Africa, 19.3 GtCO_2 (47%) would occur in Asia, and 15.8 GtCO_2 (39%) would occur in Latin America (Figure 1). 25.9 GtCO_2 (63%) would occur in the seven countries that had entered a payment-for-performance agreement by January 2015, 11.1 GtCO_2 (27%) would occur in the 40 countries that had not entered a payment-for-performance agreement but were participating in the FCPF, FIP, or UN-REDD, and 3.9 GtCO_2 (9.5%) would occur in the 54 other countries. "Hotspot" regions of the tropics where the most emissions from deforestation can be reduced below \$20/tCO_2 include Island Southeast Asia, many regions of Mainland Southeast Asia, Central and West Africa, many regions of the Amazon, and eastern Central America (Figure 10). A carbon price of \$50/tCO_2 would reduce emissions from deforestation by 8.5 GtCO_2 (40.9%) from 2016-2020 and by 77.1 GtCO_2 (45.7%) from 2016-2050.

Our projected abatement was toward the lower end of the range of previously published MAC curves for the period 2016-2020 (Figure 11). This is because our empirically-derived estimates of land-use decision makers' behavioral response ("revealed preference") yielded a smaller behavioral response to prices than implied by the opportunity cost approach used in previous analyses, and also because our newer data accounted for reductions in deforestation made by Brazil after 2004.

Future projections hinge on the extent to which Brazil continues its policy commitments in the Amazon. If Brazil fails to sustain the achievements of its Program for Prevention and Control of Deforestation in the Amazon (PPCDAm) and associated measures and instead reverts to the pre-2004 policy environment, then projected tropical forest loss from 2016-2050 would be one-quarter higher (365 million hectares), with associated emissions that are one-third higher (224 GtCO_2). On the other hand, if PPCDAm-like policies are implemented across all tropical countries with equivalent effectiveness, then tropical forest loss and associated emissions would be one-third lower (192 million hectares and 111 GtCO_2 respectively), avoiding 7.2 GtCO_2 from 2016-2020 and 57.8 GtCO_2 from 2016-2050. If all tropical countries adopted PPCDAm-like policies in combination with a carbon price, emissions from 2016-2050 would be one half lower (85 GtCO_2) at a price of \$20/tCO_2 and nearly-two thirds lower (63 GtCO_2) at a price of \$50/tCO_2.

We projected that low-cost abatement opportunities would increase further into the future (Figure 12), in contrast to previous studies that projected that low-cost abatement would decline (Kindermann et al 2008). This is because business-as-usual deforestation increases through time in our model but declines through time in previous models. Whereas

6 The five-year period from January 1, 2016 to December 31, 2020

Kindermann et al (2008) found the largest sources of marginal abatement to be Africa and Latin America, we found the largest sources of marginal abatement to be Asia and Latin America.

Introducing leakage to the model reduced the available abatement at any given price by raising agricultural prices faced by land-use decision makers, bringing MAC curves inward (Figure 13). Introducing selective participation within countries also reduced available abatement, especially at low carbon prices, underscoring the importance of national-level programs and broad participation across countries.

Reforestation, i.e., the limited portion of reforestation that is covered by the Hansen forest gain class, was projected to remove 12.9 $GtCO_2$ from the atmosphere from 2016-2050. A carbon price of \$20/tCO_2 would enhance removals from reforestation by 0.21 $GtCO_2$ (13.2%) from 2016-2020 and by 1.44 $GtCO_2$ (11.2%) from 2016-2050. A carbon price of \$50/tCO_2 would enhance removals from reforestation by 0.61 $GtCO_2$ (37.6%) from 2016-2020 and by 4.07 $GtCO_2$ (31.6%) from 2016-2050.

These results were sensitive to a variety of model assumptions, including assumed future agricultural prices, carbon pools considered in emission factors, peat emission factor, the use of an inverse hyperbolic functional form, and the regression coefficient on price variables (Table 3). The model was less sensitive to the use of alternative carbon stock data sets, the use of a Tweedie functional form, the inclusion of cattle revenue, other-order polynomials on prices, and a single pan-tropical model. One drawback of the Poisson QMLE model is that its exponential functional form makes successive reductions successively more costly by construction, and it is impossible to ever reduce cell-level deforestation to zero. Allowing more flexible treatment of prices through a quadratic term increased emission reductions substantially. The inclusion of transaction costs and management costs reduced emission reductions, while the inclusion of co-benefits increased emission reductions.

Discussion

There has been a recent revolution in the availability of data on forest cover change. The publication of Hansen et al (2013) has provided information on global forest loss and gain with accuracy, consistency, and spatial and temporal resolution previously available only for isolated places and times.

An analysis of these newly available forest cover change data reveals that the trajectory of forest loss follows a predictable inverted-U shape with respect to remaining forest cover that is robust across region and time. While long theorized and observed in the historical record of some countries, our study is the first to empirically document this relationship at the site level. We conjecture that the nearly universal prevalence of this inverted-U-shaped trajectory in deforestation can be explained by the geometry of radial expansion of non-forested land within a bounded two-dimensional surface. Thus geometry may offer an alternative explanation to macroeconomic development factors ("the Environmental Kuznets Curve" (Choumert et al 2013)) for observed rising-then-falling rates of deforestation at the regional or national level. We leave further exposition of this conjecture for future study.

The inverted-U-shaped trajectory in deforestation with respect to forest cover has important implications for predictions of future deforestation. Regions with high forest cover and currently low rates of deforestation (da Fonseca et al 2007) should be expected to experience accelerating rates of deforestation in the future; areas with intermediate forest cover that are currently experiencing high rates of deforestation should be expected to experience falling levels of deforestation. This robust relationship can better inform projected reference levels for REDD+; we leave full exploration of these implications for future study.

In light of new data and a new understanding of the dynamic trajectory of forest loss, we have undertaken new projections of future pan-tropical forest loss in scenarios with and without carbon pricing policies. Our model projected that future business-as-usual tropical deforestation will rise rather than fall as projected by previous models, resulting in an area of forest loss the size of India over the next 35 years.

From our projections we have constructed marginal abatement cost curves for reducing emissions from deforestation. These MAC curves provide information to decision-makers on how much, where, when, and at what price climate change abatement can be achieved. Corroborating the findings of previous MAC curves, our analysis found reducing emissions from deforestation to be a relatively low cost mitigation option, with 4.4 $GtCO_2$ avoided in response to a price of $\$20/tCO_2$ from 2016-2020 and 40.9 $GtCO_2$ avoided in response to a price of $\$20/tCO_2$ from 2016-2050. In contrast to previous marginal abatement cost curves, our analysis projected that the amount of abatement that is available from tropical forests below a given carbon price will increase rather than decrease in future decades.

Tropical forests offer a plentiful source of low-cost emission reductions relative to other regions and sectors. The 923 $MtCO_2$ of emissions that can be avoided in tropical forests in 2020 in response to a price of $\$20/tCO_2$ is 4.5 times the 206 $MtCO_2$ available at the same price in the European Union (Kim et al. 2006; JGCRI 2015), and 55 times the 17 $MtCO_2$ available at the same price in California (Air Resources Board 2010)—two regions with carbon pricing policies already in place. That marginal abatement costs are so much lower in tropical forests than in developed countries suggests the potential benefit of international carbon trading, or at the very least international results-based carbon payments.

It is worth noting that the average cost of emission reductions implied by our curves is considerably less than the marginal carbon price in a pure market setting—a $\$20/tCO_2$ carbon price implies a $\$9/tCO_2$ average cost to land users, while a $\$50/tCO_2$ carbon price implies a $\$21/tCO_2$ average cost, with the difference between the carbon price and the average cost in a pure market setting accruing to land users as producer surplus. In practice how the costs and revenues of reducing emissions from deforestation would be distributed across land users, forest country governments, and potential rich-country funders of carbon payments could come in many possible permutations, depending on the types of carbon pricing policies implemented by forest country governments (i.e. carbon payments vs. carbon taxes) as well as the volume of international carbon payments from rich-country governments to forest-countries. These costs and prices compare favorably to the social cost of carbon, estimated by the United States Government to be \$40/tCO_2 in 2014 USD and rising over time (EPA 2015))

In many cases forest-country governments might be able to achieve a given level of reductions at lower cost than indicated by our curves by implementing other policies besides carbon pricing, although restrictive policies would push opportunity costs onto would-be land users. For example, we estimate that if all countries across the tropics adopted PPCDAm-like policies with equivalent effectiveness, then 58 GtCO_2 would be avoided from 2016-2050. A combination of PPCDAm-like policies and carbon prices would avoid 84 GtCO_2, reducing emissions by half. The values generated by our regionally calibrated curves are just a starting point for analyses of national policies, for which many other local factors are important as well.

Encouragingly, most of the countries where low-cost abatement is available have already signaled their willingness to reduce deforestation in exchange for results-based payments. The seven tropical forest countries that already entered payment-for-performance agreements contain 63% of the low-cost (<\$20/tCO_2) emission reductions between 2016-2050. Another 40 tropical forest countries have enrolled in the FCPF Readiness Fund, UN-REDD, or the Forest Investment Program; these countries together contain 89% of the low-cost emission reductions between 2016-2050.

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Table 1. Improvements across multiple dimensions forest data between FAO FRA (2005, 2010) used to construct previous MAC curves and Hansen et al (2013) used in this analysis.

	FAO FRA (2005, 2010)	Hansen et al (2013)
Data layers	Forest cover (1990, 2000, 2005, 2010), and by extension, forest cover change (1990–2000; 2000–2005; 2005–2010)	Forest cover (2000) Annual forest cover loss (2000–2012) 12-year forest cover gain (2000–2012)
Spatial resolution	Single national-level statistic	30 m spatial resolution
Temporal resolution	Every 5-10 years	Every 1 year
Definition of forest	Either biophysical land cover or legal/economic land use	Biophysical land cover only
Distinction between natural forests and plantations	Variable across countries	None
Data completeness	Some countries' data points were extrapolations of previous measurements	All data points measured in all years
Comparability across countries	Different definitions and methods used by different countries	Standard definitions and methods applied globally
Consistency through time	Different definitions and methods used at different times within some countries	Standard definitions and methods applied through time
Political economy	Some ministries may have faced incentives to over-report or underreport forest cover or forest cover change	Unbiased remotely-sensed data
Transparency of methods	Highly variable across countries	Peer-reviewed academic publication and open-access website
Validation/ground-truthing	Highly variable across countries	MODIS NDVI; Lidar
Official status	Formally endorsed by ~200 national governments and the United Nations	Independent

Table 2. Determinants of forest loss by continent. Dependent variable is percent of cell deforested.

	Africa	Asia	Latin America
Potential agricultural revenue ($/ha/yr)	0.00016***	0.00024***	0.00010***
	(0.00002)	(0.00001)	(0.00001)
Elevation (m)	-0.00032***	-0.00065***	0.00013***
	(0.00003)	(0.00005)	(0.00002)
Slope (°)	0.01179***	-0.06304***	-0.07302***
	(0.00413)	(0.00273)	(0.00235)
Strict protected area (% of cell)	-1.38095***	-0.89739***	-1.19250***
	(0.15393)	(0.09397)	(0.07248)
Multiple-use protected area (% of cell)	-1.18687***	-0.58712***	-0.65710***
	(0.12092)	(0.07289)	(0.04002)
Log of distance to city (km)	-0.15140***	-0.03491***	0.07302***
	(0.01540)	(0.01043)	(0.00999)
Forest cover (% of cell)	41.42456***	37.94963***	39.32265***
	(1.08212)	(1.50334)	(0.91682)
Forest cover^2	-139.88080***	-107.36830***	-124.00650***
	(4.10453)	(4.81548)	(2.99081)
Forest cover^3	191.23350***	138.30410***	172.91070***
	(5.75821)	(6.15011)	(3.88568)
Forest cover^4	-89.07934***	-64.48375***	-85.02912***
	(2.66478)	(2.70344)	(1.73147)
Brazilian Amazon			0.84992***
			(0.02574)
Brazilian Amazon * post-2004			-0.15915**
			(0.05659)
Brazilian Amazon * post-2004 * potential agricultural revenue			-0.00013***
			(0.00001)
Constant	-10.75845***	-11.08210***	-11.11308***
	(0.15653)	(0.19444)	(0.12783)
Year FE	Yes	Yes	Yes
Observations	9,124,032	2,820,216	6,052,416
Note:			*p<0.10 **p<0.05 ***p<0.01

Table 3. Sensitivity of results to alternative model assumptions.

	Deforestation 2016-2050 (ha)	Emissions from deforestation 2016-2050 (tCO_2)	Reduced emissions from deforestation at \$20/tCO_2 (tCO_2)	Reduced emissions from deforestation at \$50/tCO_2 (tCO_2)
Base scenario	289	169	41	77
Alternative future prices				
2001 prices	235	135	31	59
2012 prices	421	254	58	117
Alternative carbon stock data				
Saatchi et al. (2011)	289	160	39	74
Ruesch and Gibbs (2008)	288	193	49	93
Alternative emission factors				
Peat EF = 1,059 tCO_2/ha	289	148	29	59
AGB+BGB only	289	112	17	36
AGB only	289	89	11	24
Alternative functional form				
Tweedie	304	176	45	83
Inverse Hyperbolic	31	16	3	5
Quadratic prices	323	193	76	104
Alternative consideration of forest cover				
No forest cover terms	213	119	40	70
3rd order polynomial	270	156	40	75
5th order polynomial	293	173	44	83
Opportunity cost approach	289	169	154	168
Single pan-tropical model	316	177	38	73
Inclusion of cattle revenue	289	169	36	71
Alternative consideration of PPCDAm (Brazil post-2004)				
No consideration of PPCDAm	301	180	35	68
Brazil abandons PPCDAm under BAU	365	225	46	95
Rest of tropics adopts PPCDAm-like policies	192	111	n.a.	n.a.
Rest of tropics adopts PPCDAm-like policies plus carbon price	289	169	84	106
Net transaction costs, management costs, and co-benefits				
+\$2000/ha	289	169	8	47
+\$1000/ha	289	169	20	62
-\$1000/ha	289	169	45	85
-\$2000/ha	289	169	58	97
Alternative carbon price salience	289	169	23	49
x0.5	289	169	23	49
x2	289	169	67	109
Alternative discount rate	289	169	27	57
5%	289	169	27	57
	Reforestation 2016-2050 (ha)	Removals from reforestation 2016-2050 (tCO_2)	Enhanced removals from reforestation at \$20/tCO_2 (tCO_2)	Enhanced removals from reforestation at \$50/tCO_2 (tCO_2)
Consideration of reforestation	43	13	1.4	4.1

Figure 1. Annual pan-tropical emissions during the 2000s, by study.

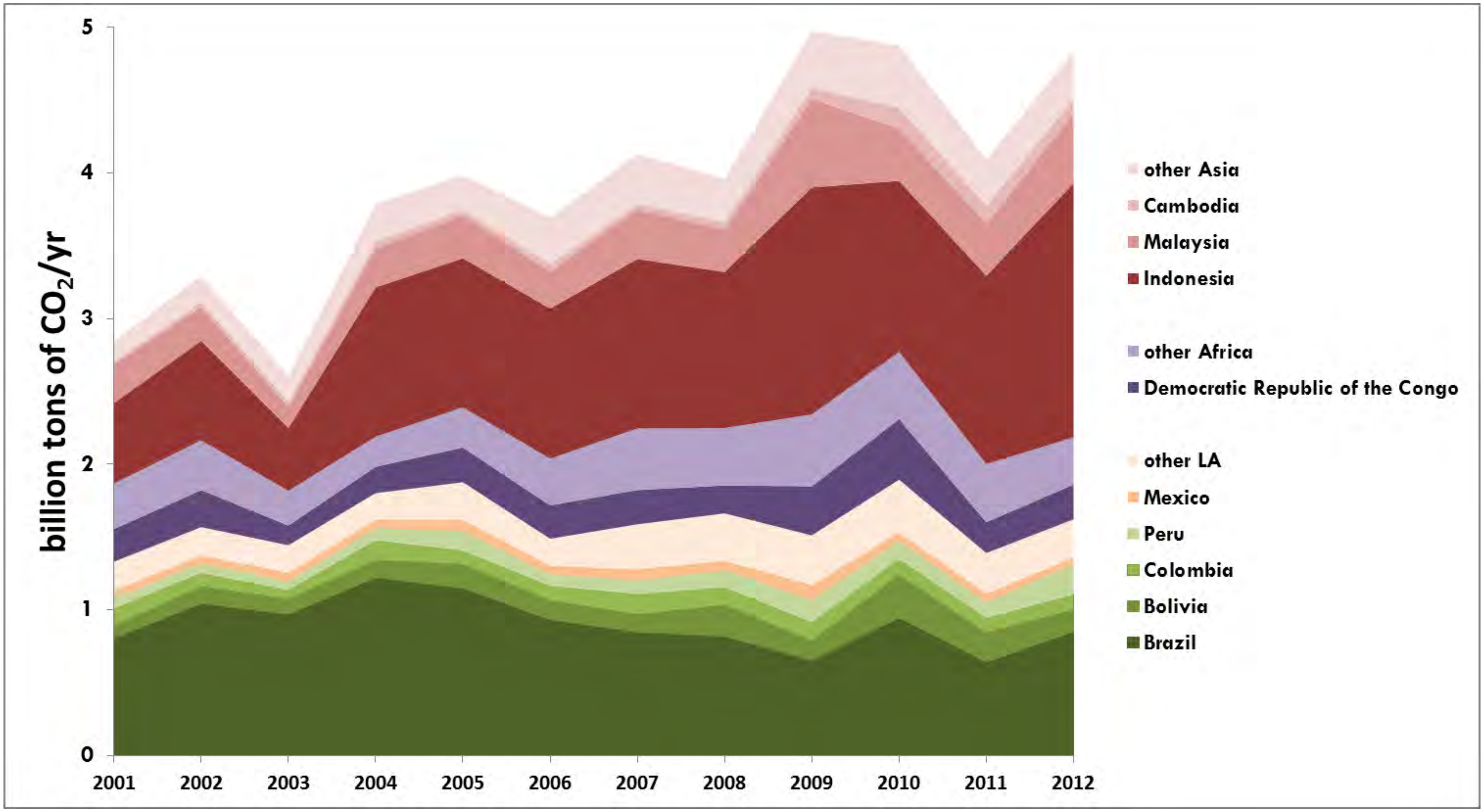

Figure 2. Gross emissions from tropical forest cover loss and peat conversion from 2001-2012, by country.

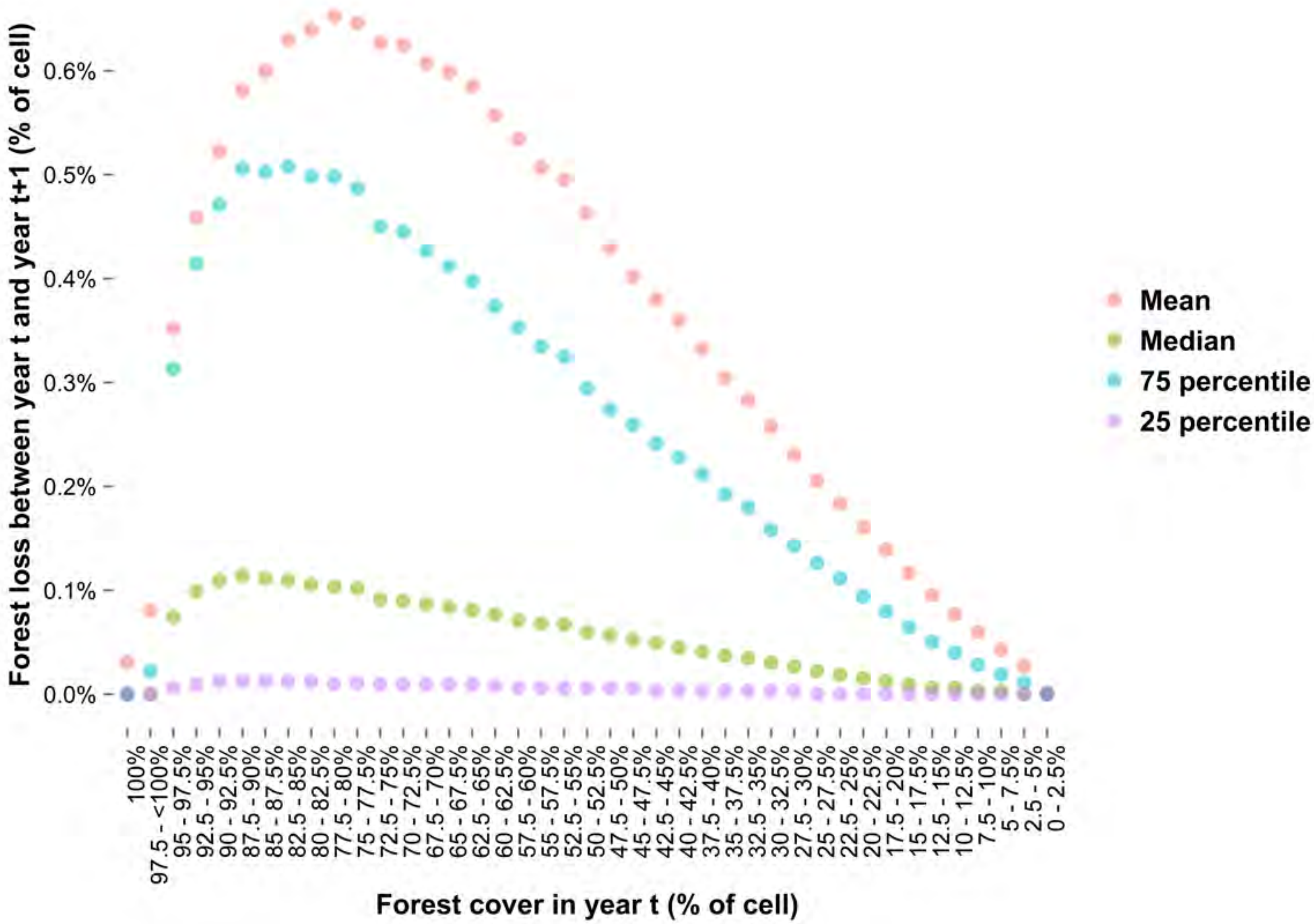

Figure 3. Cell-year-level forest loss vs. forest cover, 2001-2012. n~18,000,000.

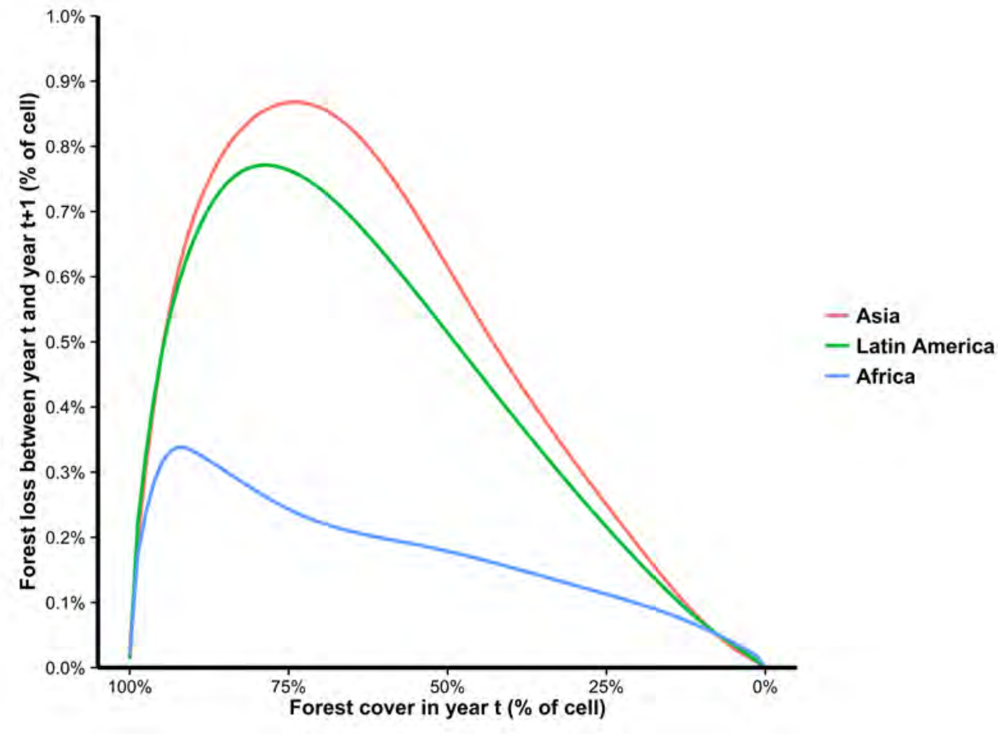

Figure 4a. Forest loss vs. starting forest cover, by continent

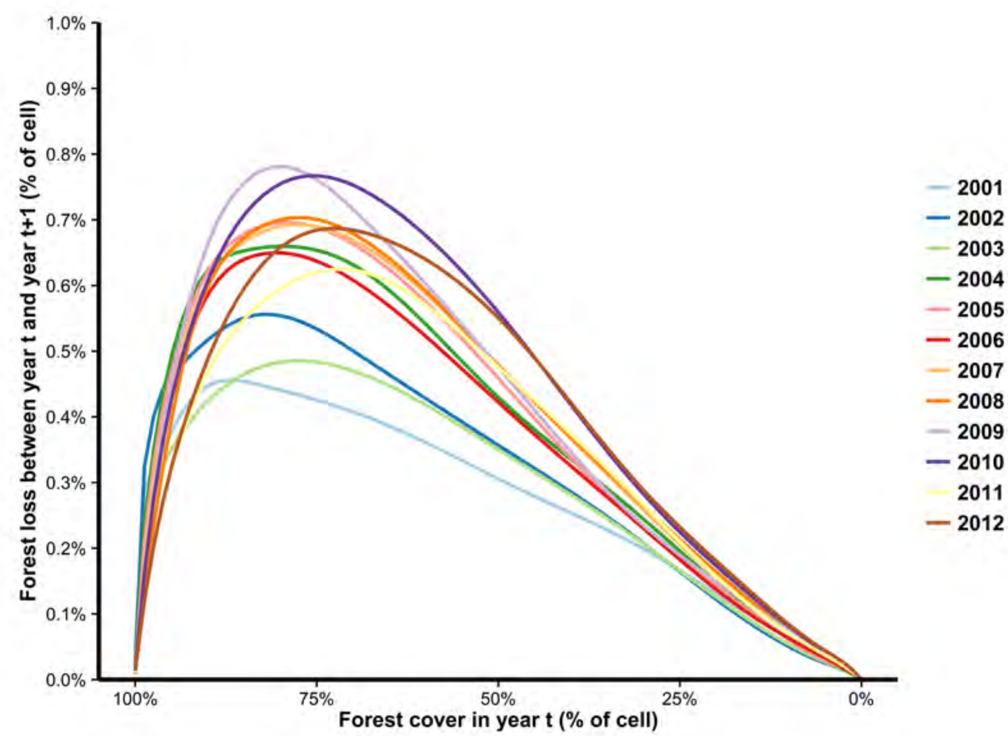

Figure 4b. Forest loss vs. starting forest cover, by year

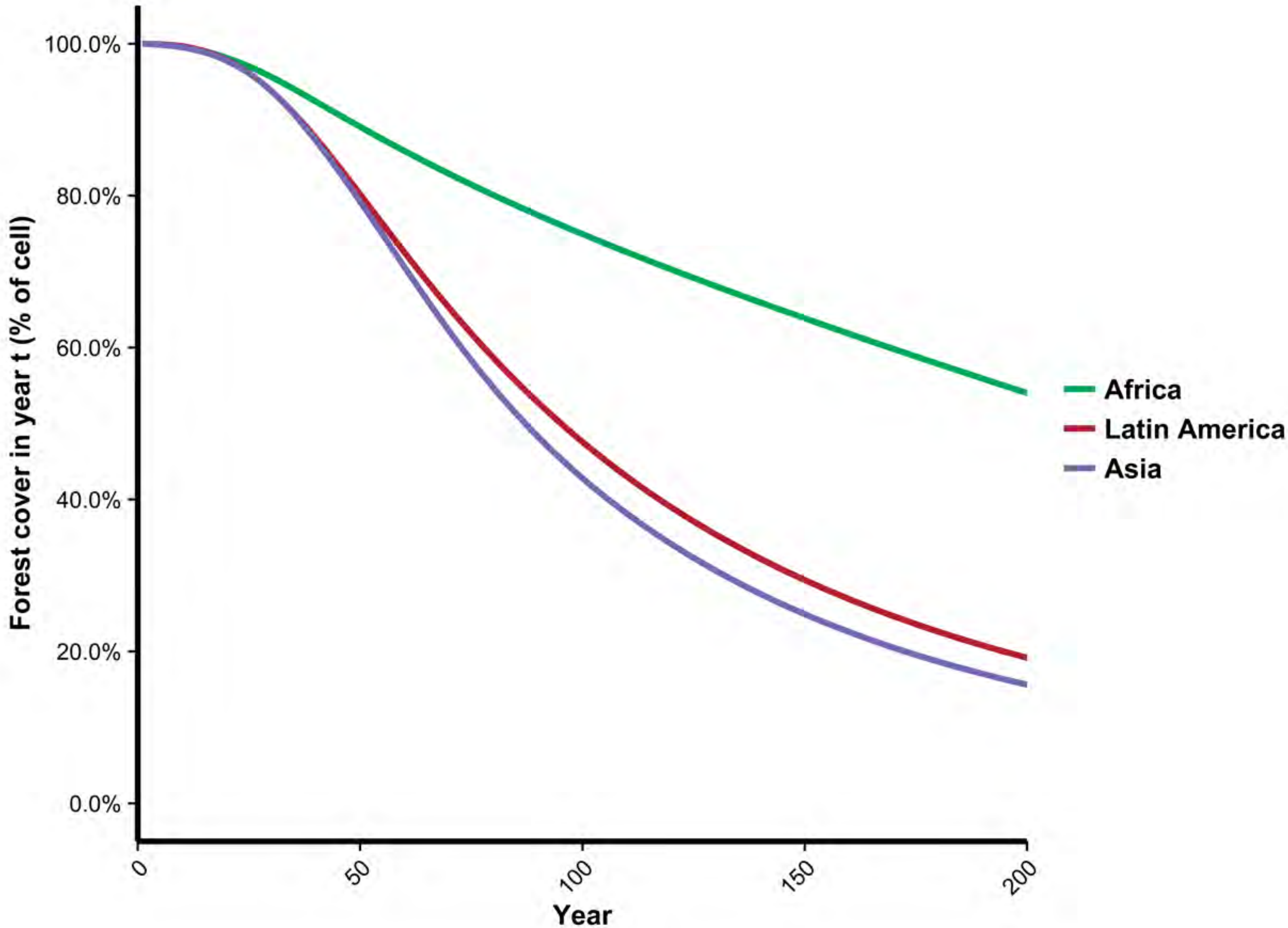

Figure 5. Implied trajectory of forest cover through time

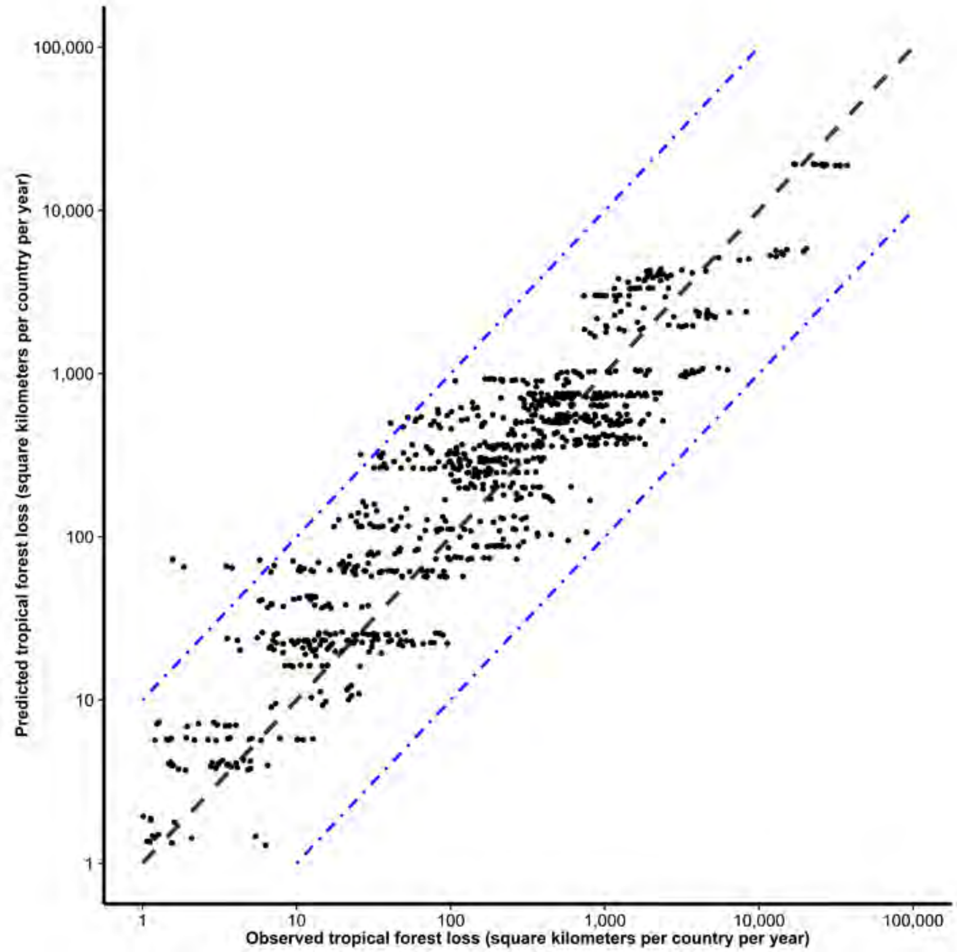

Figure 6. Observed forest loss vs. predicted (in-sample) country-year-level forest loss. Note that axes are in log-scale. Dashed black line indicates that predicted loss is exactly equal to observed loss; dashed blue lines indicate that predicted loss differs from observed loss by a factor of ten.

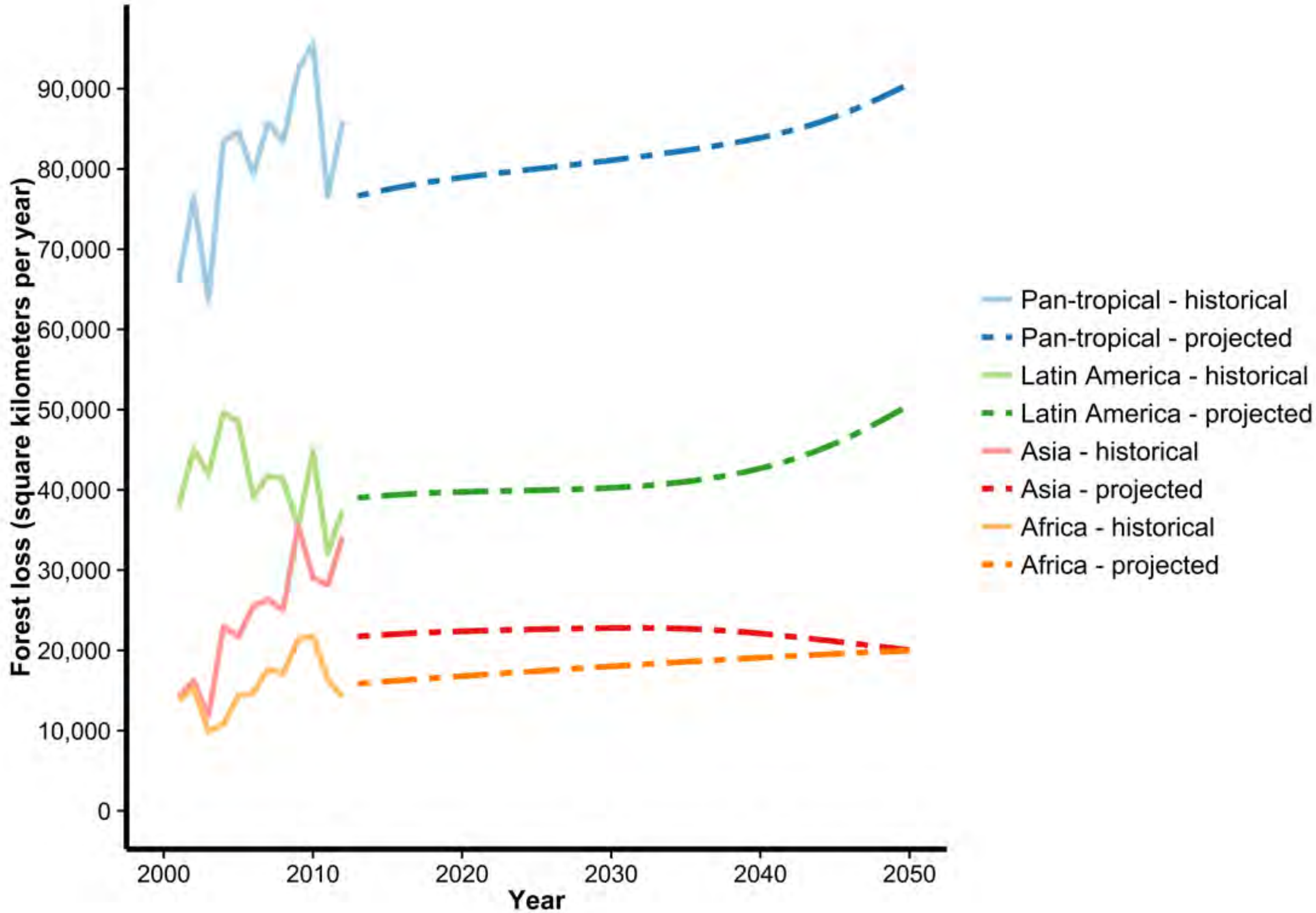

Figure 7. Projected business-as-usual pan-tropical forest loss.

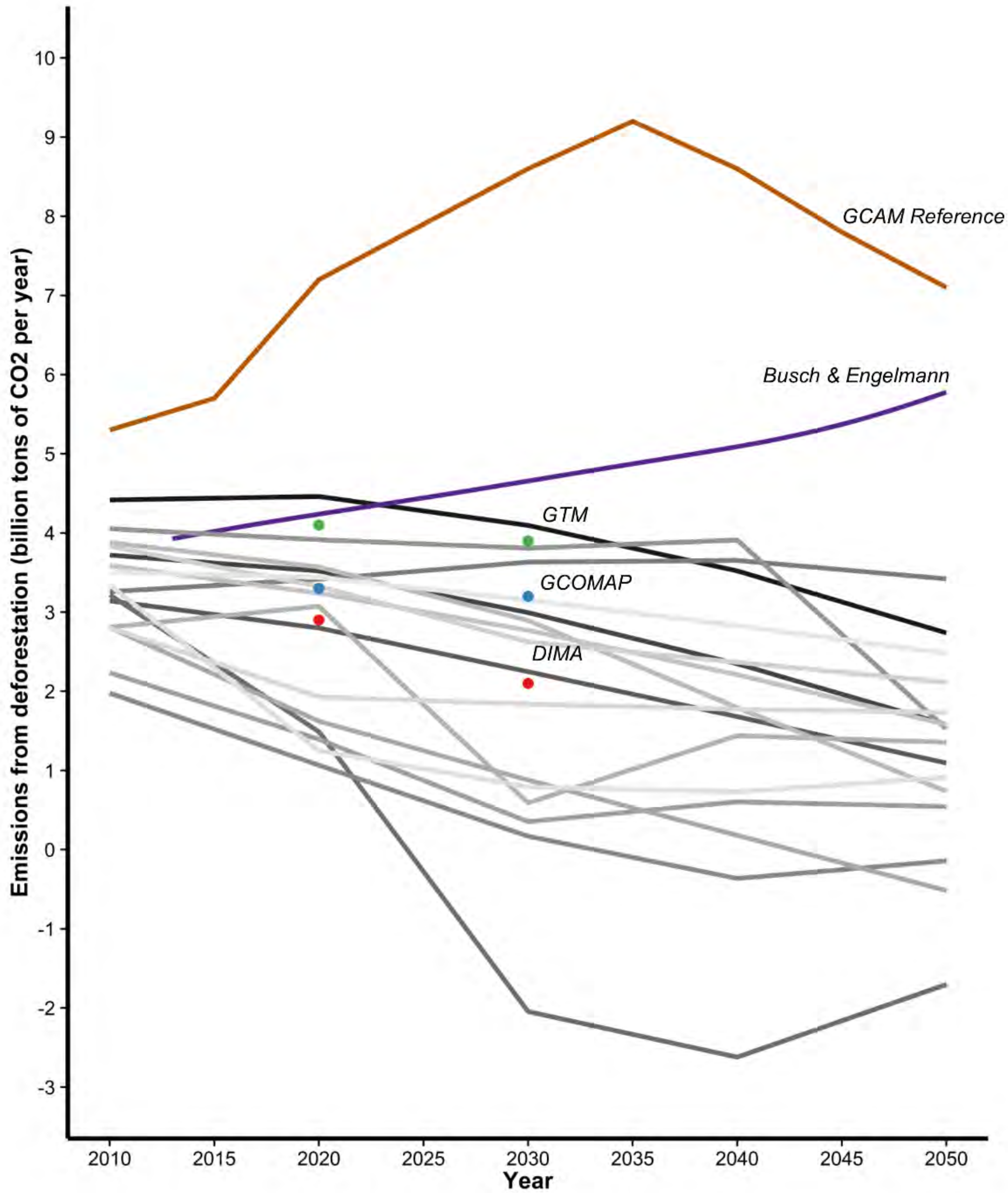

Figure 8. Projected emissions from tropical deforestation, 2016-2050, by study. Colored lines represent business-as-usual scenarios (Kindermann et al 2008, Wise et al 2014) while grey lines represent mitigation scenarios produced by partial equilibrium models and integrated assessment models. (Lubowski and Rose, 2014).

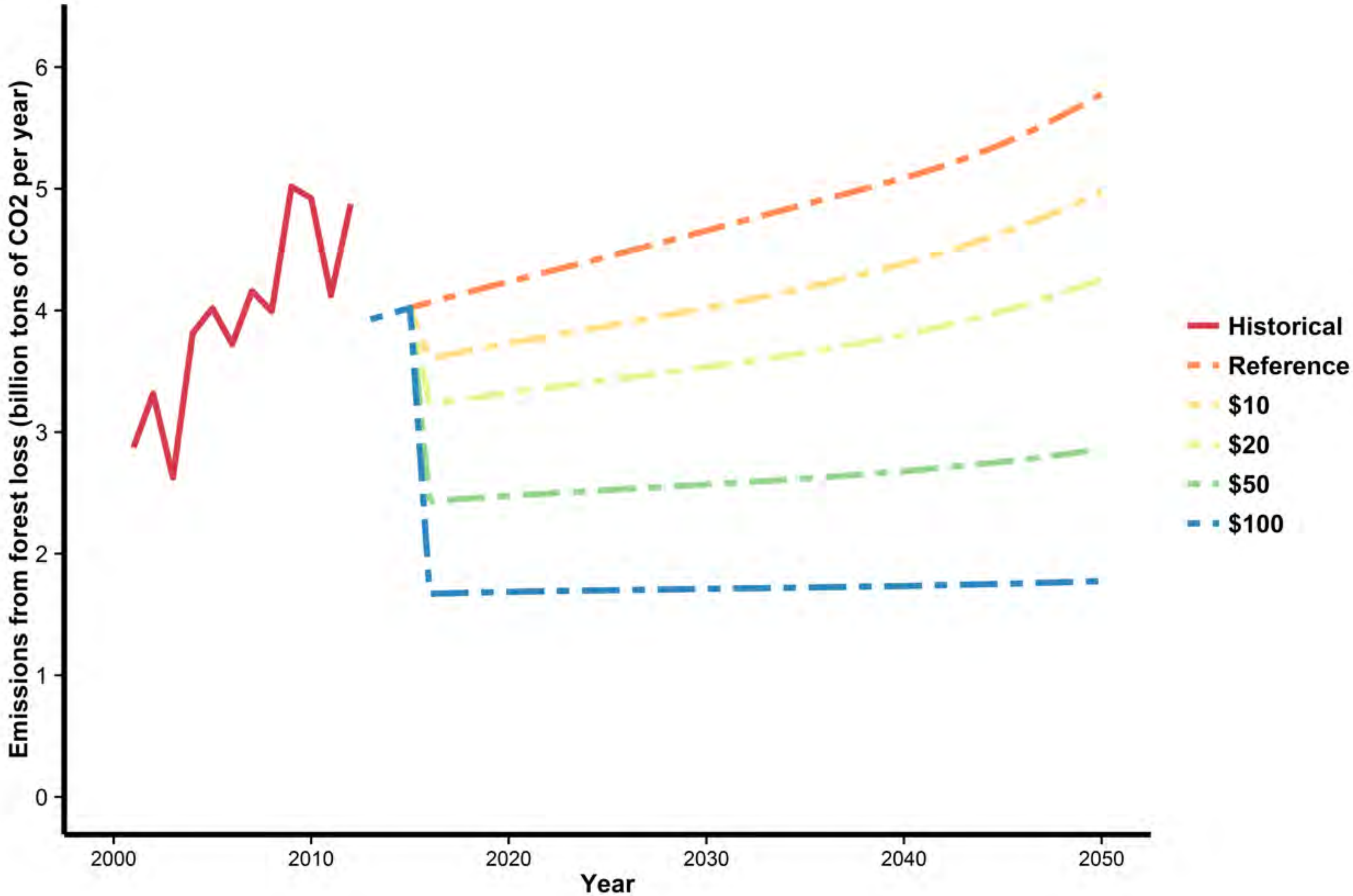

Figure 9. Future emissions from pan-tropical deforestation and associated peat degradation under alternative carbon prices

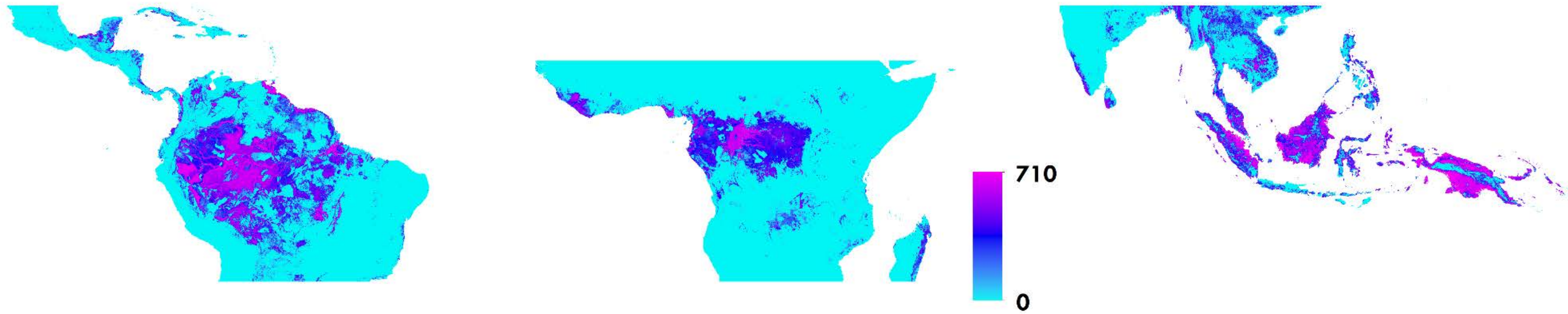

Figure 10. Avoided emissions from deforestation and peat degradation in response to a carbon price of $\$20/tCO_2$, 2016-2050.

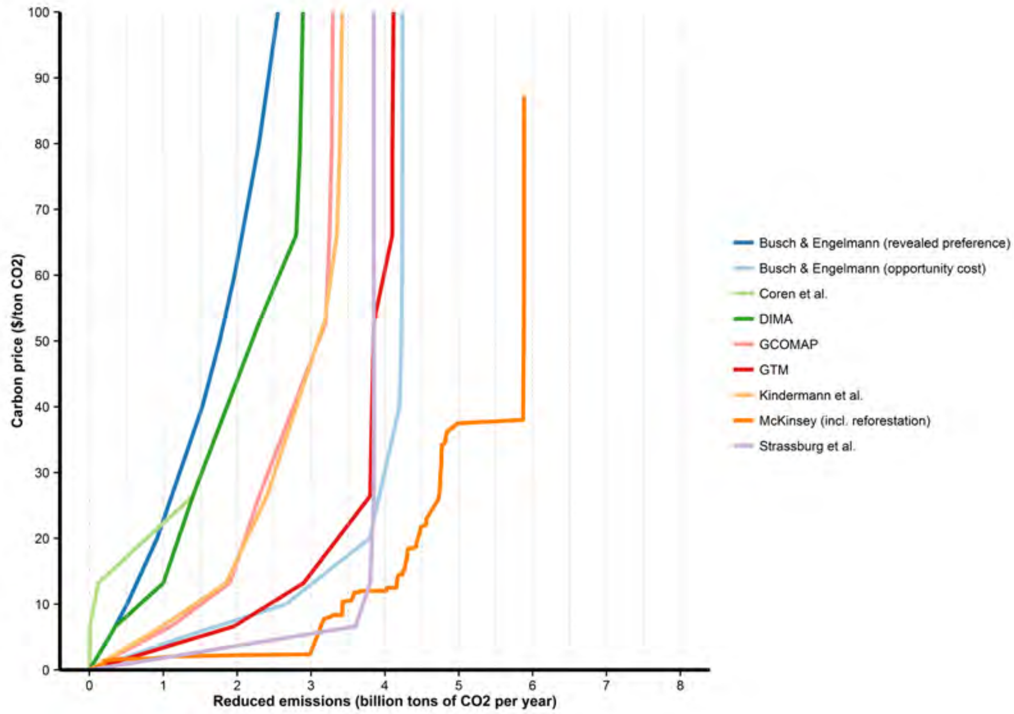

Figure 11a. Marginal abatement cost curve for pan-tropical forest loss, 2020, by study. Sources: Coren et al (2011), Kindermann et al. (2008), Naucler and Enkvist (2009), Strassburg et al. (2009).

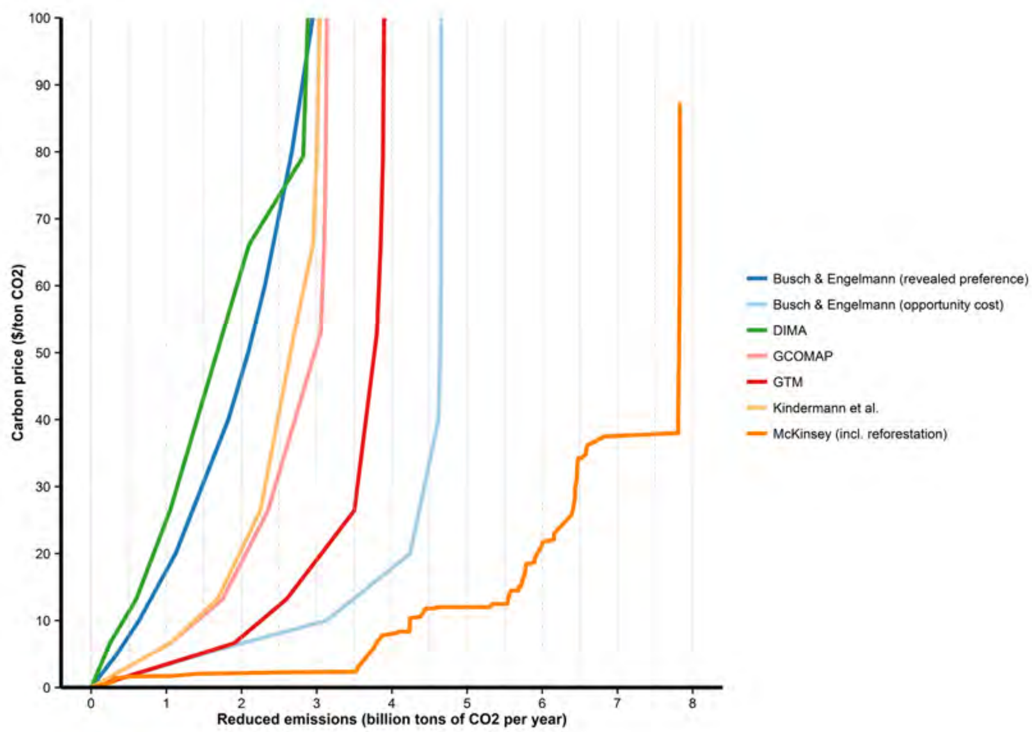

Figure 11b. Marginal abatement cost curve for pan-tropical forest loss, 2030, by study. Sources: Kindermann et al. (2008), Naucler and Enkvist (2009), Strassburg et al. (2009).

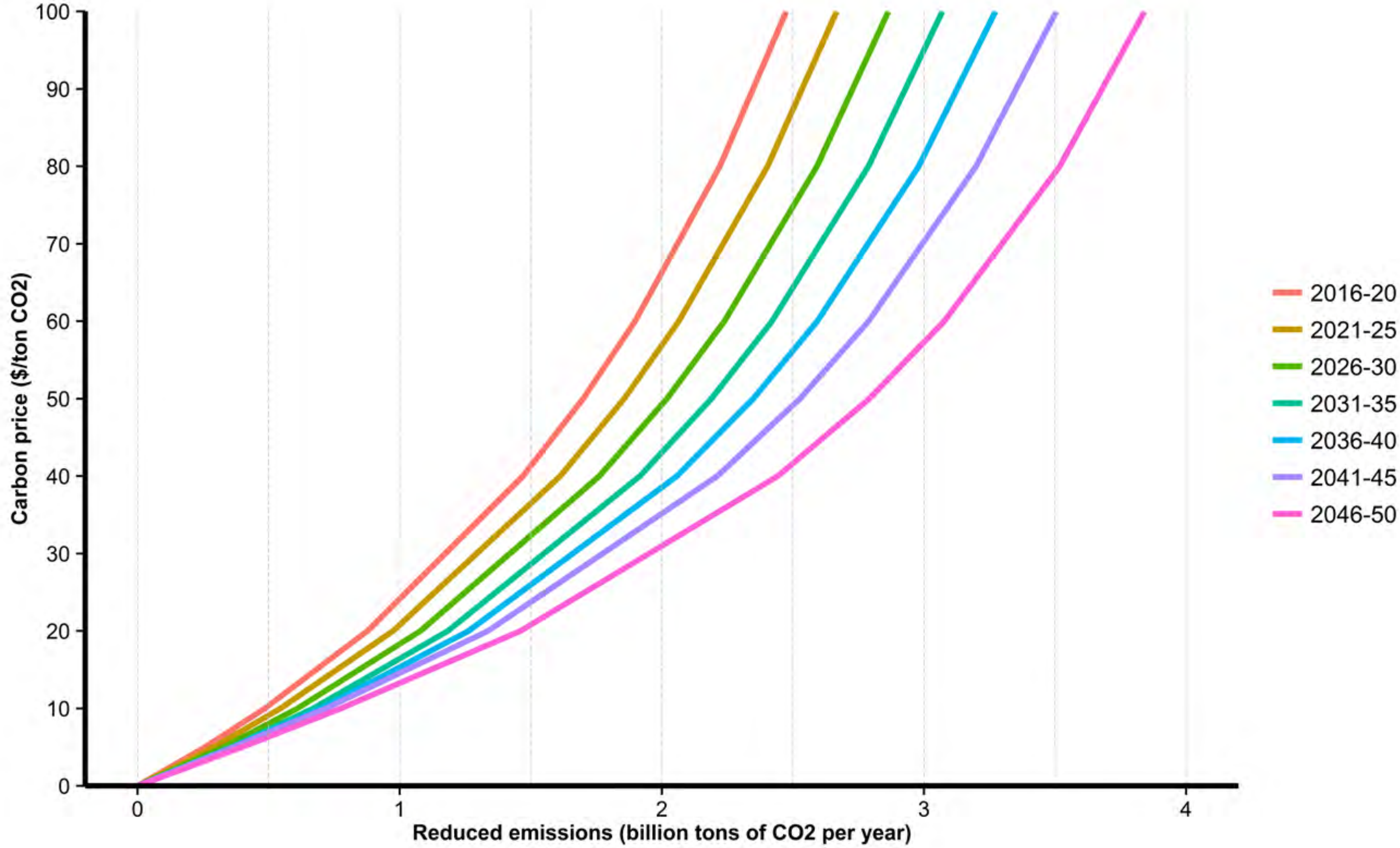

Figure 12. Marginal abatement cost curve for pan-tropical forest loss, by time period

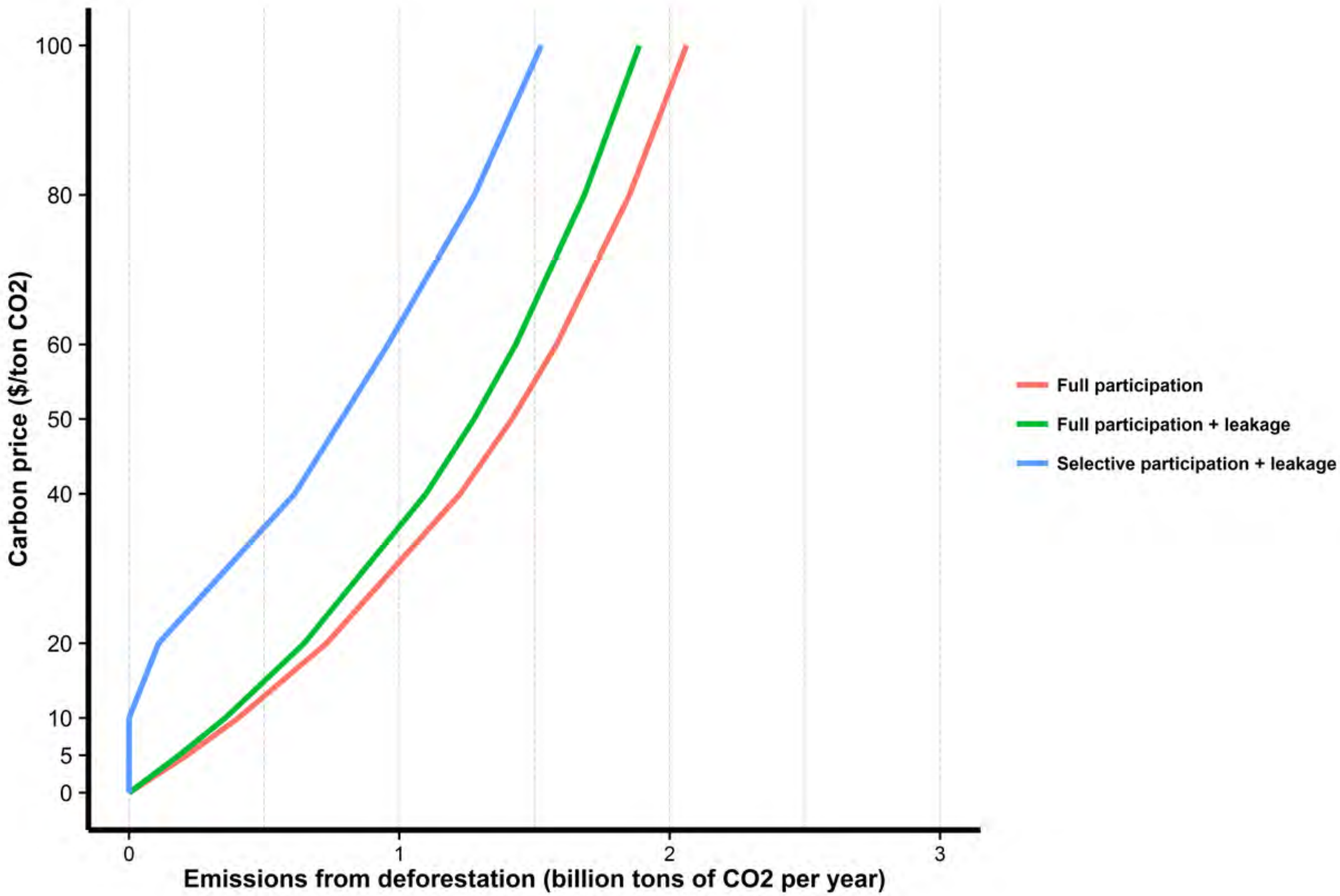

Figure 13. Marginal abatement cost curve for tropical deforestation and peat degradation by participation and leakage, 2016-2020.