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Structuring national and sub-national economic incentives to reduce emissions from deforestation in Indonesia

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Abstract

We estimate the impacts that alternative national and sub-national economic incentive structures for reducing emissions from deforestation (REDD+) in Indonesia would have had on greenhouse gas emissions and national and local revenue if they had been in place from 2000-2005. The impact of carbon payments on deforestation is calibrated econometrically from the pattern of observed deforestation and spatial variation in the benefits and costs of converting land to agriculture over that time period. We estimate that at an international carbon price of \$10/tCO_2e, a "basic voluntary incentive structure" modeled after a traditional payment-for-ecosystem-services (PES) program would have reduced emissions nationally by 62 MtCO_2e/yr, or 8% below the without-REDD+ reference scenario (95% CI: 45-76 MtCO2e/yr; 6-9%), while generating a programmatic budget shortfall. By making four policy improvements—paying for net emission reductions at the scale of an entire district rather than site-by-site, paying for reductions relative to estimated business-as-usual levels rather than historical levels, sharing a portion of district-level revenues with the national government, and sharing a portion of the national government's responsibility for costs with districts—an "improved voluntary incentive structure" would have reduced emissions by 175 MtCO_2e/yr, or 22% below the reference scenario (95% CI: 136-207 MtCO_2e/yr; 17-26%), while generating a programmatic budget surplus. A "regulatory incentive structure" such as a cap-and-trade or symmetric tax-and-subsidy program would have reduced emissions by 211/yr, or 26% below the reference scenario (95% CI: 163-247 MtCO_2e/yr; 20-31%), and would not have required accurate predictions of business-as-usual emissions to guarantee a programmatic budget surplus.

Keywords: Climate change; land-use change; REDD+; reference levels; economic incentives
JEL: Q20, Q23, Q50, Q54

Introduction

An emerging international mechanism known as REDD+[1] would offer payments to developing countries for voluntarily reducing emissions from deforestation below internationally agreed reference levels (UNFCCC 2010). Individual forested countries would decide upon the specific set of policies and measures to implement to achieve nationwide emission reductions. Accounting for these net emission reductions would ultimately take place at the national level, making national governments responsible for any internal geographical shifts of emissions ("leakage"), and providing incentivizes for systemic policy actions. But while governments would receive payments under REDD+, it is actors at the regional, provincial, local or household ("sub-national") scales who are directly responsible for many land-use change decisions. Thus the effectiveness of REDD+ in reducing emissions and generating revenue will depend on how national governments structure economic incentives so that sub-national actors will be encouraged to reduce emissions, and discouraged from increasing emissions.

Developed countries have typically approached emission reduction policy through regulation such as cap-and-trade or tax-and-subsidy programs. Such regulatory approaches are considered economically ideal because they produce marginal incentives to reduce emissions for all regulated actors across all emission levels. However, regulatory approaches may not be feasible where national governments are unable to universally monitor and enforce land-use regulations.

Developing countries may instead prefer to structures incentives for REDD+ so that sub-national actors might voluntarily choose to maintain forests rather than convert land to agriculture or other uses. A voluntary incentive structure for REDD+ would be characterized by four policy decisions. An "accounting scale" would determine the administrative level at which net emission reductions are calculated and payments made. Sub-national "reference levels" would be the level of emissions below which actors could be rewarded for reductions. A "revenue sharing" arrangement would determine the portion of international income from carbon payments that would accrue to actors that reduce emissions, and the portion that would remain with the national government. A "responsibility sharing" arrangement would determine the extent to which actors that increase emissions would be penalized, and the extent to which the national government would bear the cost of these increases through reduced international payments.

A voluntary incentive structure for REDD+ would face design challenges that a regulatory incentive structure would not. In a voluntary system, reference levels affect not only equity in the distribution of payments, as in a regulatory system, but effectiveness in reducing emissions as well (Cattaneo, 2010). Discrepancy between the reference level and counterfactual business-as-usual emission rates (Cattaneo, 2011) can aggravate an adverse selection problem due to information asymmetry in a voluntary system (Montero, 2000; van Benthem and Kerr, 2011). Actors with reference levels above their business-as-usual emission rates could claim windfall payments beyond their actual emission reductions. Meanwhile actors with reference levels below their business-as-usual rates could have insufficient incentive to

[1] REDD+ refers in its entirety to "policy approaches and positive incentives on issues relating to reducing emissions from deforestation and forest degradation in developing countries; and the role of conservation, sustainable management of forests and enhancement of forest carbon stocks in developing countries" (UNFCCC 2010). In this paper we examine only reducing emissions from deforestation.

participate in REDD+, and could even increase emissions above what they would have been in the absence of REDD+.

As a result, a country's choice of economic incentive structure for REDD+ will critically impact the level of greenhouse gas emission reductions it can achieve, the cost-effectiveness of these reductions, and the distribution of costs and benefits within the country. In this paper we develop a spatially explicit land-use change model for Indonesia[2] that allows us to compare the expected impact of alternative economic incentive structures on reductions in emissions from deforestation, and on the distribution of revenues and costs between a national government and local actors.

We make several important methodological advances on previous models that have estimated the abatement potential of REDD+. First, most previous studies have relied upon a deterministic "opportunity cost" assumption that deforestation would be avoided entirely wherever potential revenue from carbon payments exceeds net revenue from alternative land uses (Grieg-Gran 2006; Kindermann et al 2008; Naucler and Enkvist 2009; Busch et al 2009; Butler et al 2009; Venter et al 2009; Soares-Filho 2010; World Bank Institute 2011). In contrast, we calibrate the marginal impact of potential carbon payments on deforestation using the empirical relationship between the pattern of observed historical deforestation from 2000-2005 and spatial variation in the benefits and costs of converting land from forest to agriculture. Such a "revealed preference" approach to estimating the impact of payments based on evidence from actual land-use decisions implicitly accounts for the richer set of factors that affect land-use decisions in practice (e.g. Plantinga 1999; Stavins 1999; Lubowski 2006; Pfaff 2007a). Second, most previous studies have modeled land-use responses to a single parameter—the carbon price. By modeling land-use response to both the carbon price and the reference level, we are able to examine and compare a wider range of potential policies for REDD+. Third, as in global partial equilibrium models (Kindermann et al. 2008; Busch et al. 2009) but unlike other opportunity cost (Grieg-Gran 2006) or regional (Soares-Filho 2010) analyses, we model the "leakage" of deforestation, whereby reduced deforestation in one region produces market feedbacks that increase deforestation pressure elsewhere.

We select Indonesia as a case study due to its large forested area (94 million hectares in 2010; FAO 2010), high greenhouse gas emissions from deforestation and peat degradation (1.46 $GtCO_2e$/yr, or 3.3% of global greenhouse gas emissions; CAIT 2011), and globally significant commitment to emission reductions. In 2009 President Susilo Yudhoyono declared a national goal to reduce emissions by 26-41% below levels projected to 2020 (DNPI 2010). In May 2010 Indonesia and Norway signed a landmark $1 billion agreement on bilateral cooperation to reduce emissions from deforestation and forest degradation (Letter of Intent 2010). Drivers of deforestation in Indonesia include large-scale conversion for industrial agriculture, small-scale conversion for community use, establishment of timber plantations, and planned and unplanned timber extraction (Ministry of Forestry, 2008). The national and provincial governments are responsible for allocating the forest estate between land uses, while the right to approve permits for use was decentralized to district governments in 2002 (Government of Indonesia, 2002).

[2] The free, open-source Open Source Impacts of REDD+ Incentive Spreadsheet for Indonesia (OSIRIS-Indonesia v1.4) model and dataset (Busch et al 2011) are made publicly available in MS Excel 2007 at http://www.conservation.org/osiris

We compare four scenarios for how a nationwide REDD+ incentive structure could have been implemented in Indonesia from 2000-2005. First, we predict deforestation emissions in the absence of any carbon payment policies ("reference scenario"). These business-as-usual deforestation emissions are predicted according to observable site characteristics and econometrically estimated parameters. Second, we consider a basic REDD+ policy framework ("basic voluntary incentive structure") consistent with traditional Payment for Ecosystem Services (PES) programs, which offer voluntary incentives at the scale of the individual project or landowner (e.g. OECD 2010). Specifically, we model payments based on 3km x 3km site-scale reductions in emissions below reference levels based on observed historical deforestation rates, with no revenue sharing or responsibility sharing. Third, we sequentially add four potential policy improvements to the basic voluntary incentive structure ("improved voluntary incentive structure"). In this scenario payments are based on emission reductions at the district scale, below reference levels projected to perfectly match assumed business-as-usual rates of deforestation, with 20% of revenues shared with the national government, and 20% of the responsibility for costs shared with districts. Responsibility is devolved to each of the 401 districts to effectively implement jurisdiction-wide policies or payments to reduce net emissions within their borders. Finally, we consider a scenario that is consistent with a cap-and-trade or symmetric tax-and-subsidy program for deforestation emissions ("regulatory incentive structure"). In this scenario, districts which reduce emissions below their reference level are paid the full international carbon price, while districts which increase emissions above their reference level are penalized by the full international carbon price.

Results

In the absence of any carbon payments ("reference scenario"), deforestation predicted on the basis of observable land characteristics (691,000 ha/yr) was within 1% of observed historical deforestation (687,000 ha/yr), and predicted emissions (809 GtCO2e/yr) were within 6% of emissions estimated from observed deforestation (860 MtCO2e/yr). Correlation between observed deforestation and predicted deforestation decreased at the finer geographic scales of the province (R=0.81; n=31; Table SI6), the district (R=0.68; n=401; SI Figure SI3; Table SI6) and the 3km x 3km "site" (R=0.34; n=166,296; Figure 1a-b).

We estimate that every $1000/ha increase in net present potential agricultural revenue increased deforestation by 1.4% (95% CI: 1.0-1.9%) at low-forest cover sites, and 7.3% (95% CI: 5.6-9.0%) at high-forest cover sites, controlling for other factors (see Table SI3). The regions where the greatest emission reductions were expected to occur in response to site-level $10/tCO2e payments for reductions below business-as-usual rates with no leakage were the lowlands of Papua, Kalimantan, and Sumatra (Figure 2).

At an international carbon price of \$10/tCO_2e, a basic voluntary incentive structure for REDD+ would have reduced net national deforestation emissions by an estimated 62 MtCO2e/yr, or 8% below the reference scenario (95% CI: 45-76 MtCO2e/yr; 6-9%). In this scenario the national government would have paid $6.8 billion/yr to local sites for gross reductions below historical reference levels, but would have received just $610 million/yr by international buyers for net reductions below a national reference level, resulting in a programmatic budget shortfall over that period (Figure 3:1).

Implementing a series of four improvements to the basic voluntary incentive structure would have increased emission reductions while producing a programmatic budget surplus. First, aggregating accounting from site-level to district level would have increased emission reductions to an estimated 105 $MtCO_2e$/yr, or 13% below the reference scenario (95% CI: 72-123 $MtCO_2e$/yr; 9-15%), while reducing the budget shortfall from $6.0 billion/yr to $3.4 billion/yr (Figure 3:2). Second, projecting reference levels to perfectly match business-as-usual emissions would have increased emission reductions to an estimated 202 $MtCO_2e$/yr, or 25% below the reference scenario (95% CI: 160-229 $MtCO_2e$/yr; 20-28%), while reducing the budget shortfall to $77 million/yr (Figure 3:3). Third, sharing 20% of district revenues with the national government would have decreased emission reductions to an estimated 170 $MtCO_2e$/yr, or 21% below the reference scenario (95% CI: 134-197 $MtCO_2e$/yr; 17-24%), while producing a budget surplus of $283 million/yr (Figure 3:4). Finally, sharing 20% of the costs of forgone income from international carbon payments with districts that increased emissions would have increased emission reductions to an estimated 175 $MtCO_2e$/yr, or 22% below the reference scenario (95% CI: 136-207 $MtCO_2e$/yr; 17-26%), while producing a budget surplus of $331 million/yr (Figure 3:5).

At an international carbon price of $10/$tCO_2e$, a regulatory incentive structure for REDD+ would have reduced net national deforestation emissions by 211 MtCO2e/yr, or 26% below the reference scenario (95% CI: 163-247 $MtCO_2e$/yr; 20-31%), while producing a budget surplus of $1.0 billion/yr (Figure 3:7). In this scenario the allocation of reference levels to districts would affect the distribution of revenue between the national government and the districts, but unlike under a voluntary incentive structure, would not affect the amount of emission reductions achieved (Figure 3:5-8).

These estimates of abatement in response to a $10/tCO2e carbon price fall within the range of estimates of abatement potential from REDD+ in Southeast Asia produced by global forestry and land-use models: 50 MtCO2e/yr in the Generalized Comprehensive Mitigation Assessment Process Model (GCOMAP); 70 MtCO2e/yr in the Dynamic Integrated Model of Forestry and Alternative Land Use (DIMA); 875 MtCO2e/yr in the Global Timber Model (GTM)) (Kindermann et al, 2008); and 233 MtCO2e/yr in a bottom-up model of REDD+ in smallholder landscapes and fire prevention in Indonesia (DNPI, 2010).

Discussion

Structuring REDD+ using basic voluntary incentives, as in a traditional PES program, could reduce emissions, but at a programmatic budget deficit to the national government. Sites where historical reference levels greatly exceed the projected business-as-usual emissions would receive windfall payments beyond actual reductions. Meanwhile, some sites where historical reference levels are lower than business-as-usual emissions would opt out of participation in REDD, increasing emissions and undermining net national emission reductions. As a result, the national government would pay much more for gross site-level emission reductions than it would receive from international buyers for net national-level emission reductions. In principle a national program for REDD+ could be justified even with a programmatic budget shortfall, as income from REDD+ to the country as a whole would be positive under such a program. However, a national budget surplus would likely make national participation in REDD+ more politically palatable. Surplus revenue could be used as a performance buffer against leakage or reversals (Cortez et al 2010), and could fund systemic national policies and measures for reducing deforestation related to agriculture, infrastructure, land tenure or governance (Chomitz et al 2007; Pfaff et al 2010).

By implementing a combination of four policies that comprise an improved voluntary incentive structure for REDD+, governments could reduce emissions far more than using basic voluntary incentives, while producing a programmatic budget surplus. Projecting reference levels with perfect foresight of business-as-usual deforestation rates would lead to greater emission reductions and lower budget shortfall. Fewer windfall payments would be made to areas where historical emissions greatly exceed business-as-usual, while greater participation would be incentivized among areas where historical emissions are far below business-as-usual. In practice the ability to perfectly forecast business-as-usual emissions is unlikely, although future research should investigate what combination of historical rates and observable geographic characteristics provides the most accurate prediction of future emissions. In the absence of perfect prediction, aggregating the scale of accounting for net emission reductions from the site level to the district level would improve effectiveness and reduce shortfall, as over- and under-estimates of business-as-usual emissions at the site level would be averaged out at the higher spatial scale. Even so, leakage of emissions would ensure at least some budget shortfall, in the absence of mechanisms for raising revenue for the national government. Sharing a portion of the revenue accruing from local emission reductions with the national government could bring about a budget surplus from REDD+. But unless these resources are effectively redeployed to reduce deforestation, too much revenue retained at the national level would reduce incentives for local actions, and correspondingly decrease national-scale emission reductions and revenue (Table SI7). A national budget shortfall could also be reduced if local actors share for a portion of responsibility for the costs of lost international revenue arising from local increases in emissions. Bearing a portion of the cost of emissions makes participating in REDD+ more attractive to local actors than alternative land-uses.

Structuring REDD+ using regulatory incentives, such as a cap-and-trade or tax-and-subsidy program for deforestation emissions, would reduce emissions beyond what is possible through even an improved voluntary incentive structure. Under a regulatory system, the level of emission reductions achieved would not be impacted by the allocation of reference levels. This is because local actors would have the same marginal incentive to reduce emissions whether their emissions are above or below their allocation.

External factors can critically influence the effectiveness of REDD+ incentives (Table SI8). A higher carbon price from an international market or fund would fundamentally motivate greater emission reductions. This carbon price will be driven by global demand for emission reductions, and the extent to which those emission reductions can be purchased through REDD+. A national reference level, determined through international negotiations, would indirectly affect local actors' marginal incentives to reduce emissions. A higher national reference level would result in greater national revenue for any given level of net national emission reductions, which in turn would allow a national government to offer a higher carbon price or higher sub-national reference levels to local actors, either of which would incentivize these local actors to undertake greater reduction in emissions. Emission reductions and revenue would also be sensitive to an exogenous increase in agriculture prices, due for example to international leakage from REDD+ taking place in countries outside of Indonesia. This suggests the importance of coupling REDD+ with complementary agricultural policies (Angelsen 2009) such as shifting agricultural expansion into low-carbon landscapes (Koh and Ghazoul 2010).

The model developed here can potentially be extended to examine a number of interesting topics beyond the scope of the current analysis. These topics include a richer suite of land-use changes (e.g. logging and forest degradation; reforestation), policy decisions (e.g. land tenure; infrastructure; rural credit; agricultural subsidies and taxes; conservation of biodiversity and ecosystem services), or geographic regions.

Conclusion

Previous studies have established the potential of REDD+ as a cost-effective climate change mitigation option. But how countries choose to structure economic incentives for REDD+ will critically impact the level of greenhouse gas emission reductions achieved, the cost-effectiveness of these reductions, and the distribution of costs and benefits within countries. We have developed a spatial land-use change model for Indonesia that is able to estimate and map the impacts of alternative incentive structures on emission reductions and national and local revenue. Our study's findings extend beyond REDD+ in Indonesia to any geographic region or program in which emission reductions would be credited at an aggregate scale.

Our model can guide the design of effective and equitable national and sub-national economics incentive structures for REDD+. Countries can achieve the full economic potential for emission reductions by implementing a regulatory incentive structure, which also has the advantage that effectiveness in reducing emissions and maintaining a programmatic budget surplus would not require accurately predicting future deforestation patterns. On the other hand, an approach to REDD+ in which participation is voluntary on the part of sub-national actors may be more politically appealing. In this case, an improved economic incentive structure can be nearly as effective as a regulatory structure, if it is able to approximate business-as-usual emission rates for setting sub-national reference levels, aggregate accounting for net emission reductions to higher jurisdictional scales, and share revenues and responsibility for costs between the national government and local actors.

Materials and Methods

Data

Forest cover in the year 2000 was estimated by applying a 50% threshold to the Percent Tree Cover Layer of the 500 m Moderate Resolution Imaging Spectroradiometer (MODIS)-based Vegetation Continuous Fields (VCF) product for the year 2000 (Hansen et al, 2003). The 50% threshold was selected to distinguish mature forest from agricultural fallows using high-resolution, Landsat-based forest cover maps for parts of Indonesia. Use of this threshold has been further supported with similar analyses in other tropical regions (Leimgruber et al 2005; Harper et al 2007; Killeen et al 2007).

Our dependent variable, percent deforestation for the period 2000-2005, was derived by rescaling rates of deforestation from the most accurate data available on the distribution of deforestation (tree cover loss estimates from the 463 m MODIS VCF product; Hansen et al. 2008) upward by a factor of 2.147 to match the most accurate data available on the total rate of deforestation (derived from analysis of a stratified, random sample of 77 18.5km x 18.5km blocks of 28.5m-resolution Landsat images; Hansen et al 2008; Hansen et al 2009).

Our primary explanatory variable, net present potential gross agricultural revenue, was obtained from Naidoo and Iwamura (2007). In this data set the annual potential gross agricultural revenue in 2000 US$ was calculated by multiplying the annual yield of the highest-return agricultural commodity in every global agro-ecological zone (Fischer *et al*, 2002) by the average market price for that agricultural commodity from 1995-2005 (http://faostat.fao.org). Net present value was obtained by summing annual revenue over 30 years and applying a discount rate of 10%, following the use of the same data set in the Stern Review (Grieg-Gran, 2006).

Control variables included average slope and elevation (Jarvis et al, 2008), Euclidean distance from nearest national or regional roads and from provincial capitals (NGA, 2000), boundaries for 33 provinces and 440 districts from the year 2003, national parks and other protected areas from the year 2006, and logging concessions (HPH), timber concessions (HTI) and estate crop concessions (*kebun*) from the year 2005 (Minnemeyer et al, 2009).

Emissions from deforestation were calculated based on the release of 100% of above- and below-ground forest biomass carbon (Gibbs and Brown, 2007) plus 10% of soil carbon content in the top 30cm of non-peat soil (FAO 2008). On peat soils, soil emissions were estimated based on the average 30-year non-discounted emissions for the agricultural land type (large croplands; small-scale agriculture; shrublands) to which such forest are converted, weighted by the area of each of these land types in historical conversion across Indonesia (Hoojier, 2010). The resulting estimate of national average soil carbon emissions following deforestation on peatlands was 1474 tCO_2e/ha, which compares to a tropical average of 1,486±183 tCO_2e/ha calculated by Murdiyarso et al (2010). Alternative peat emission factors were explored in a sensitivity analysis (Table SI8). Peat extent was obtained for Sumatra (Wahyunto, 2003), Kalimantan (Wahyunto, 2004) and Papua (Wahyunto, 2006), which are considered to contain the vast majority of Indonesia's peat soils.

Data were standardized into a single equal-area projection of uniform extent and gridded into 226,348 3km x 3km grid cells across Indonesia using ArcGIS 9.3.1. This grid cell resolution was selected to comply with size limitations of MS Excel. We removed grid cells for which values were missing from the agricultural revenue dataset (n=25,431) or other data sets (n=5,451) leaving 195,466 grid cells representing 91.8% of the land area and 95.8% of the forest area of the original data.

Comparison of data with other published sources

Observed deforestation in Indonesia from 2000-2005 was 687,000 ha/yr (Figure 1a), producing estimated emissions from deforestation of 860 $MtCO_2e$/yr, of which an estimated 592 $MtCO_2e$/yr was from forests on peat soil. Deforestation compares to estimates that range from 310,000 ha/yr (FAO 2010) to 703,000 ha/yr (Ministry of Forestry, 2008) to 1.87 million ha/yr (FAO 2005) over the 2000-2005 time period, or 1.1 million ha/yr in 2005 (DNPI, 2010). Emissions compare to estimates of 502 $MtCO_2e$/yr from deforestation, of which 186 $MtCO_2e$/yr was associated with peat (Ministry of Forestry, 2008); 1.459 $GtCO_2e$/yr over the time period from land use, land use change and forestry (CAIT, 2010); and 1.610 $GtCO_2e$/yr emissions in 2005 from land use change, of which 770 $MtCO_2e$/yr was from peat (DNPI, 2010).

Predicted deforestation without REDD+

We predicted site-level deforestation without carbon payments based on an empirical comparison of the pattern of observed historical deforestation and spatial variation in observable site characteristics. Our empirical model builds on 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 percent deforestation from 2000-2005 on cost and benefit variables for all 166,343 3km x 3km grid cells for which forest cover was present in the year 2000 (Eq. 1). 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 road, natural logarithm of the distance to the nearest provincial capital, and the percent of cell contained within a national park, other protected area, logging concession, timber concession, or estate crop concession, following empirical literature on determinants of deforestation (e.g. Nelson and Hellerstein, 1995; Laurence et al 2002; Chomitz and Thomas 2003; Pfaff et al 2007b). We proxied for the gross economic benefit of conversion using estimated net present value of potential gross agricultural revenue. The combination of explanatory variables included in the regression was selected to maximize the district-level correlation between observed and predicted deforestation (Table SI6) without directly stratifying by geographic boundaries. The selected variables also provided the best combination of parsimony and fit, as determined by the Akaike Information Criterion (AIC) (Table SI6).

Recognizing that the statistical relationship between deforestation and site characteristics may vary across a country as large and geographically diverse as Indonesia, we stratified sites into four classes based on forest cover, with approximately 42,000 sites in each class (Table SI1). Stratifying based on a larger number of forest cover classes did not improve the AIC. Explanatory variables (Table SI2) were interacted with classes in the regression.

We estimated the influence of explanatory variables on deforestation (Eq. 1) in Stata 9.2 using a Poisson quasi-maximum likelihood estimator (QMLE) (Wooldridge, 2002), which is theoretically consistent with 3km x 3km forest cover loss being a count of independent, discrete binary 463m x 463m forest cover loss/maintenance observations from the remote sensing data (see also Burgess et al). A Poisson model tolerates zero values, and generates a distribution of predicted values which fits the distribution of observed data, which is concentrated nearest to zero deforestation and diminishes toward greater levels of deforestation. Because the data for percent deforestation is slightly overdispersed (mean=0.067; variance=0.078; n=166,343), we considered a negative binomial regression, resulting in outputs that are highly correlated with those of the Poisson regression (Table SI5, Table SI6). Standard errors were specified to be robust to heteroskedacticity. We did not treat for autocorrelation, consistent with an assumption that any autocorrelative effects between neighboring properties were subsumed within the 3km x 3km grid cell size. Alternative functional forms, explanatory variables, and stratification classes were explored to confirm robustness (Tables SI3-SI5).

Explanatory variables used to construct the reference scenario were significantly correlated with observed deforestation, producing coefficients with expected signs and plausible magnitudes (Table SI3). Consistent with results widely observed elsewhere, deforestation was found to be higher at lower and flatter sites, and closer to roads and cities, controlling for other factors. Deforestation was lower in national parks and other protected areas, and higher in timber and estate crop concessions, controlling for other factors. This likely reflects variation in underlying unobservable site characteristics associated with the non-random allocation of these land-use designations, in addition to the impact of the designations themselves (Pfaff et al, 2009). Deforestation was lower in logging concessions, controlling for other factors, possibly reflecting a logging moratorium issued in May 2002, or that degradation due to selective logging may not have been identified in our deforestation data set. Potential gross agricultural revenue was significantly and positively correlated with observed deforestation. The 95% confidence interval around the coefficient on potential gross agricultural revenue was used to generate 95% confidence intervals around expected abatement under alternative REDD+ incentive structures.

We used the econometric model (Eq. 1) to predict deforestation at every site in the absence of REDD+ (Eq. 2) (the "reference scenario"). This generates an effective land rental value for every site (Eq. 3), based not only on potential gross agricultural revenues but also on costs, which can be adjusted based on carbon payments to predict deforestation at every site under REDD+ (Figure SI1).

Expected deforestation with REDD+

The expected equilibrium with REDD+ of deforestation at every 3km x3km site is modeled based on the REDD+ participation decisions and land-use decisions made by districts in response to the economic incentive structure set by the national government. The district was selected as the logical default sub-national actor in Indonesia because of the control of the district chief (*bupati*) over the distribution of permits for use of forested land; alternative accounting scales (3km x 3km site-level; province-level) were explored in a sensitivity analysis (Table SI7). Districts receive payments based entirely on their own performance in reducing emissions, consistent with either a REDD+ system in which the national government acts as an intermediary, buying emission reductions from sub-national producers and selling to international buyers (Angelsen and Wertz-Kanounnikoff, 2008), or a REDD+ system in which sub-national producers sell emission reductions directly to international buyers, with the national government responsible for the cost of "truing up" to the balance of net national emission reductions (a "nested" approach; Pedroni et al 2009; Cortez et al 2010). For any structure of national economic incentives, a system of four equations—districts' land use, districts' participation, aggregate deforestation, and leakage—was resolved in equilibrium using OSIRIS v1.4 (Busch et al, 2011). The distribution of expected deforestation in equilibrium is used to calculate the associated emissions and revenue.

Districts' land use

In response to the national economic incentive structure, every district decides how much forest will be converted to agriculture at every site within its boundaries under two possible cases (Figure SI2). In the first case, the district "opts in" to the voluntary REDD+ program by reducing its deforestation emissions below its reference level. In this case, expected deforestation at every site within the district is shifted in the econometric model based on the marginal incentives provided by the carbon price and revenue sharing (Eq. 4-5). In the second case, the district "opts out" by increasing its emissions above its reference level. In this case, expected deforestation at every site within the district is shifted in the econometric model based on the marginal incentives provided by the carbon price and responsibility sharing (Eq. 6-7). We do not explicitly consider the specific internal measures employed by the districts to obtain these shifts in site-level deforestation.

Districts' participation decision

Every district makes a binary decision whether or not to participate in REDD+ based on whether opting in or opting out results in greater combined potential revenue from agriculture and carbon. That is, a district opts in if and only if the carbon revenue from opting in exceeds the forgone agricultural revenue from opting out, less any penalty from opting out (Eq. 8). In the "basic voluntary incentives structure" scenario this participation decision is made at the site scale rather than the district scale. A parameter reflecting districts' preference for agricultural revenue relative to carbon revenue is initially set to 1.0, indicating that a dollar of income from carbon payments is equivalent to a dollar of income from agriculture. This parameter is allowed to vary in a sensitivity analysis (Table SI8).

Aggregate impacts

Expected deforestation at all sites is used to calculate district-level deforestation (Eq. 9-10), district-level emissions (Eq. 11-12), carbon revenue accruing districts that opt in to REDD+ (Eq. 13), penalties to districts that opt out of REDD+ (Eq. 14), and deforestation nationwide (Eq. 15-16).

Leakage of deforestation

A decrease in deforestation in any district due to REDD+ raises potential agricultural revenue nationwide, which endogenously increases the pressure to deforest in other districts (Murray 2008). The magnitude of leakage in our model is influenced through an "effective elasticity" parameter (Eq. 17) which is functionally equivalent to the price elasticity of an exponential demand curve for frontier agriculture (Busch et al 2009), but is assumed to also incorporate feedback in the domestic labor and agricultural capital markets. This effective elasticity parameter was calibrated so that leakage of deforested area matched estimates generated by a 35-sector, 5-region general equilibrium model of the Indonesian economy (IRSA-Indonesia-5; Resosudarmo et al, 2009), in which a 10% exogenous decrease in estate crop production in each one of five regions in turn (Java/Bali; Sumatra; Kalimantan; Sulawesi; Eastern Indonesia) produced an average increase in production elsewhere within the country of 18% of the initial decrease in production. A sensitivity analysis explored variations in intranational and international leakage.

Parameter choices and sensitivities

We tested the sensitivity of estimated impacts to a variety of policy variables (Table SI7) and model parameters (Table SI8). We selected a default price of 2008 US$10/tCO2e for ease of comparison with other studies (e.g. Kindermann et al 2008; DNPI 2010); higher carbon prices resulted in greater abatement. We selected 20% revenue sharing and 20% responsibility sharing as illustrative values in the sophisticated voluntary incentive structure. Greater levels of revenue sharing resulted in less overall abatement but enabled a programmatic budget surplus, while greater levels of responsibility sharing resulted in greater participation and greater overall abatement. Optimal levels of revenue and responsibility sharing would depend on a country's relative preference for program effectiveness and equity of distribution of revenues across scales. Scaling sub-national reference levels downward from business-as-usual rates resulted in less participation and less overall abatement but enabled a programmatic budget surplus.

Lower effective elasticity, associated with greater intranational leakage, and higher agricultural prices, associated with greater international leakage, resulted in fewer net emission reductions and less national government revenue. District-level implementation and monitoring costs diminished net reductions and revenue very little, as some small districts opted out but larger districts continued to participate in REDD+. Governance and institutional barriers, proxied by increases to the preference for agricultural revenue relative to carbon revenue, resulted in diminished emission reductions. Enforcement costs, management costs and forgone logging revenue, proxied through increases to site-level transaction costs, also resulted in diminished emission reductions (Table SI8).

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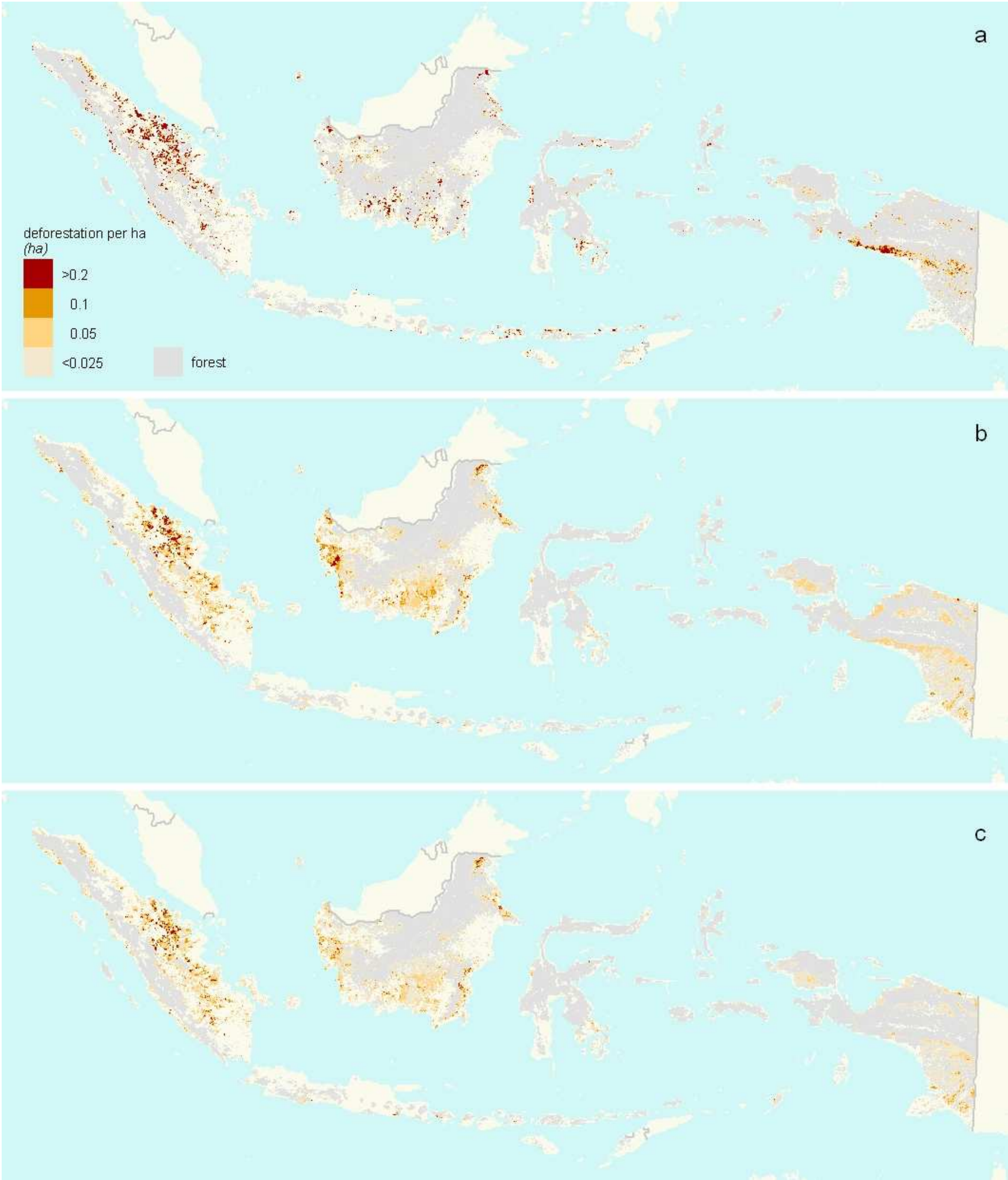

Figure 1 –Deforestation in Indonesia, 2000-2005. a) observed deforestation (687 kha/yr; 860 mtCO_2e/yr); b) modeled probability of deforestation without REDD+ (691 kha/yr; 809 mtCO_2e/yr); c) modeled probability of deforestation with "improved voluntary incentive structure" for REDD+ (597 kha/yr; 633 mtCO_2e/yr). Results are outputs of OSIRIS-Indonesia v1.4 using the following parameter assumptions: carbon price=$10/t$CO_2$e; "effective" price elasticity of demand for frontier agriculture=3.8; exogenous agricultural price increase=0%; peat emission factor=1474 tCO_2e/ha; social preference for agricultural revenue=1.0; start-up and transaction costs=$0.

Figure 2 – Probable spatial distribution of abatement under REDD+, Indonesia 2000-2005. Expected abatement provided in response to a price of \$10 tCO_2e paid for voluntary site-level emission reductions below business-as-usual levels. Darker blue represents greater voluntary abatement of emissions from deforestation in response to incentive payments. Expected abatement is greatest where deforestation emissions would be high in the absence of REDD+ but low in the presence of REDD+. Results are outputs of OSIRIS-Indonesia v1.4 using the following parameter assumptions: carbon price=\$10/tCO_2e; "effective" price elasticity of demand for frontier agriculture=0.0; exogenous agricultural price increase=0%; peat emission factor=1474 tCO_2e/ha; social preference for agricultural revenue=1.0; start-up and transaction costs=\$0; site-level accounting; national government share of revenue=0%; national government share of responsibility=100%.

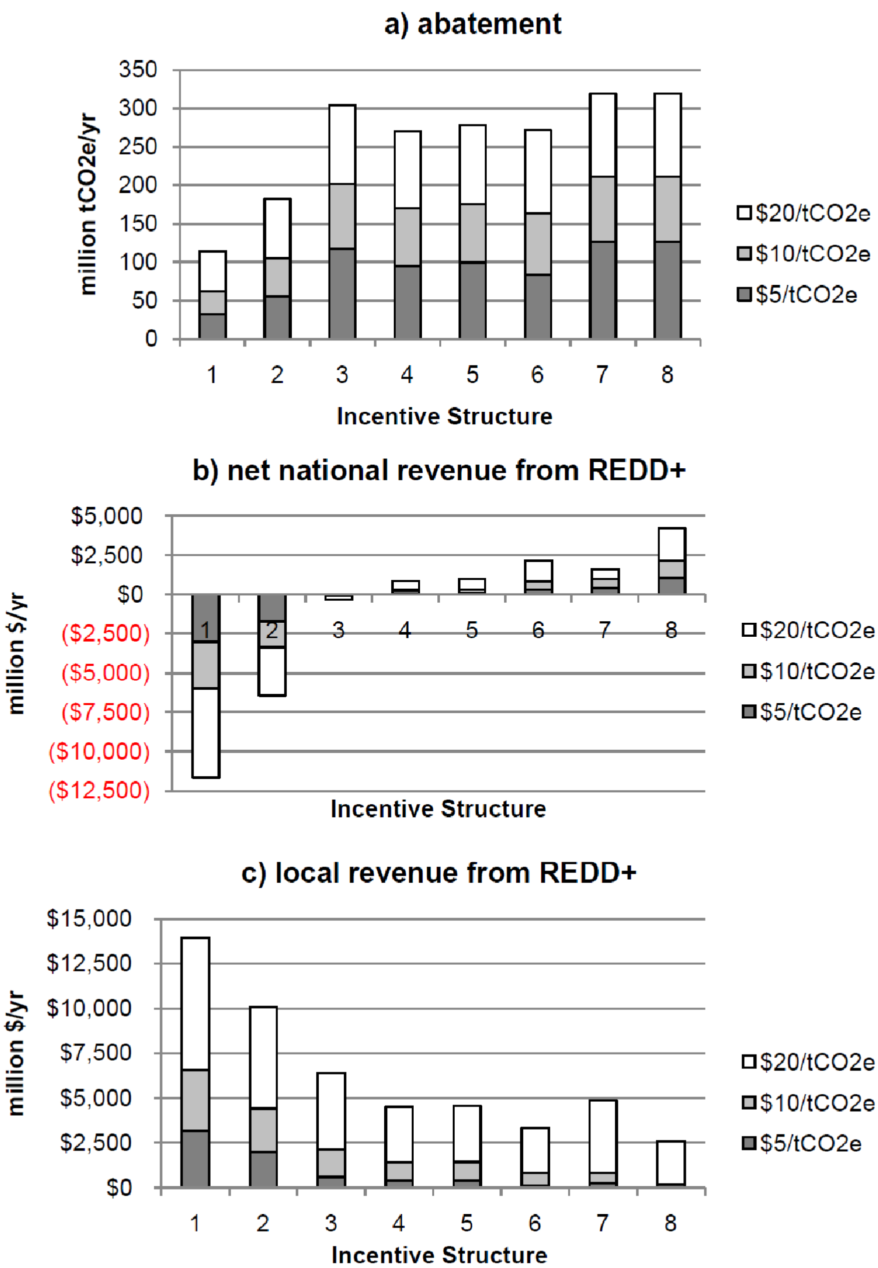

Figure 3 – Abatement, national revenue and local revenue under alternative national economic incentive structures for REDD+. Incentive structures: (1) site-scale accounting; historical reference levels; no benefit sharing; no responsibility sharing ("basic voluntary incentive structure"); (2) Basic VIS + district-scale accounting; (3) Basic VIS + district-scale accounting + business-as-usual reference levels; (4) Basic VIS + district-scale accounting + business-as-usual reference levels + 20% revenue sharing; (5) district-scale accounting + business-as-usual reference levels + 20% revenue sharing + 20% responsibility sharing ("improved voluntary incentive structure"); (6) Improved VIS + 10% reduction to district reference levels; (7) district-scale accounting + business-as-usual reference levels + 0% revenue sharing + 100% responsibility sharing + 10% reduction to district reference levels ("regulatory incentive structure"); (8) Regulatory IS + 26% reduction to district reference levels. Results are outputs of OSIRIS-Indonesia v1.4 using the following parameter assumptions: carbon price=$10/tCO$_2$e; "effective" price elasticity of demand for frontier agriculture=0.0; exogenous agricultural price increase=0%; peat emission factor=1474 tCO$_2$e/ha; social preference for agricultural revenue=1.0; start-up and transaction costs=$0.

Supplemental Information

Table SI1 – Forest cover classes

Forest cover class	Minimum forest cover within class	Maximum forest cover within class	Number of cells within class
No forest	0.0%	0.0%	29,123
Low	2.8%	27.8%	40,141
Low-medium	30.6%	69.4%	43,055
Medium-high	72.2%	94.4%	43,141
High	97.2%	100.0%	40,006

Table SI2 – Summary statistics

Variable	Forest cover class	Mean	Std. Dev.	Min	Max
Deforestation rate (%/5yr)	None	-	-	-	-
	Low	10.1%	36.9%	0%	1251%[3]
	Low-medium	5.5%	21.0%	0%	297%
	Medium-high	3.4%	16.7%	0%	288%
	High	2.4%	13.9%	0%	248%
NPV of potential agricultural revenue ($/ha)	None	$4,335	$5,104	$-	$187,644
	Low	$2,811	$3,675	$-	$187,644
	Low-medium	$2,173	$3,880	$-	$187,644
	Medium-high	$1,644	$2,354	$-	$164,483
	High	$1,304	$1,386	$-	$91,738
Slope (°)	None	3°	4°	0°	36°
	Low	4°	5°	0°	40°
	Low-medium	7°	7°	0°	40°
	Medium-high	10°	8°	0°	37°
	High	12°	7°	0°	35°
Elevation (m)	None	153	457	0	4496
	Low	177	420	0	4375
	Low-medium	348	585	0	4046
	Medium-high	487	581	0	3794
	High	565	540	0	3345
Distance from road (km)	None	37	76	0	606
	Low	39	71	0	603
	Low-medium	67	88	0	602
	Medium-high	80	91	0	600
	High	85	96	0	514
Distance from capital (km)	None	164	157	1	816
	Low	183	159	1	790
	Low-medium	238	167	3	778
	Medium-high	260	162	1	755
	High	283	177	3	752
National park (%)	None	3%	16%	0%	100%
	Low	3%	16%	0%	100%
	Low-medium	5%	20%	0%	100%
	Medium-high	8%	26%	0%	100%
	High	13%	33%	0%	100%
Other protected area (%)	None	2%	14%	0%	100%
	Low	3%	16%	0%	100%
	Low-medium	4%	19%	0%	100%
	Medium-high	5%	20%	0%	100%
	High	6%	22%	0%	100%
Logging concession (%)	None	4%	18%	0%	100%
	Low	1%	11%	0%	100%
	Low-medium	4%	18%	0%	100%
	Medium-high	5%	22%	0%	100%
	High	5%	21%	0%	100%
Timber concession (%)	None	3%	17%	0%	100%
	Low	1%	11%	0%	100%
	Low-medium	1%	11%	0%	100%
	Medium-high	1%	8%	0%	100%

[3] Deforestation rate exceeds 100% in some cases because total deforestation rates from MODIS data were scaled based on LANDSAT data. See Data.

	High	0%	6%	0%	100%
Estate crop concession (%)	None	3%	16%	0%	100%
	Low	1%	9%	0%	100%
	Low-medium	1%	7%	0%	100%
	Medium-high	0%	4%	0%	100%
	High	0%	3%	0%	100%
Forest zoned for conservation (%)	None	5%	21%	0%	100%
	Low	1%	11%	0%	100%
	Low-medium	3%	16%	0%	100%
	Medium-high	5%	21%	0%	100%
	High	6%	24%	0%	100%
Forest zoned for protection (%)	None	4%	20%	0%	100%
	Low	1%	9%	0%	100%
	Low-medium	1%	12%	0%	100%
	Medium-high	2%	13%	0%	100%
	High	2%	15%	0%	100%
Forest zoned for production (%)	None	15%	36%	0%	100%
	Low	5%	21%	0%	100%
	Low-medium	7%	25%	0%	100%
	Medium-high	7%	26%	0%	100%
	High	7%	25%	0%	100%
Forest zoned for conversion (%)	None	10%	30%	0%	100%
	Low	3%	16%	0%	100%
	Low-medium	3%	18%	0%	100%
	Medium-high	2%	16%	0%	100%
	High	2%	12%	0%	100%

Table SI3 – Determinants of forest cover loss: Model specifications 1-3. Robust standard errors; n=166,297. *A coefficient of 0.1 indicates that each unit increase in the driver variable is correlated with a 10% increase in the probability of deforestation.*

Regression Model		(1)		(2)		(3)	
Description		Poisson; stratified by forest cover; includes concession boundaries		Poisson; stratified by forest cover; no concession boundaries		Poisson; stratified by forest cover; includes forest allocation	
Driver	Forest cover class	Coefficient	z value	Coefficient	z value	Coefficient	z value
NPV of potential agricultural revenue (1000$/ha)	Low	0.0142	6.15	0.0153	6.82	0.0144	6.08
	Low-medium	0.0116	5.15	0.0144	7.39	0.0134	6.31
	Medium-high	0.0161	3.63	0.0213	5.36	0.0205	5.26
	High	0.0732	8.38	0.0742	8.65	0.0713	8.23
Slope (°)	Low	-0.024	-3.26	-0.031	-4.28	-0.026	-3.56
	Low-medium	-0.079	-11.52	-0.091	-12.91	-0.086	-12.25
	Medium-high	-0.119	-20.66	-0.133	-21.94	-0.126	-20.72
	High	-0.143	-20.44	-0.151	-21.15	-0.146	-20.03
Elevation (m)	Low	-0.00185	-12.09	-0.00197	-12.64	-0.00186	-11.97
	Low-medium	-0.00152	-11.54	-0.00167	-11.97	-0.00169	-11.74
	Medium-high	-0.00165	-17.04	-0.00192	-17.62	-0.00194	-17.56
	High	-0.00259	-18.19	-0.00291	-18.58	-0.00285	-18.05
Log distance from road (km)	Low	0.007	0.63	0.019	1.70	-0.048	-4.2
	Low-medium	-0.069	-6.59	-0.088	-9.19	-0.167	-15.84
	Medium-high	-0.125	-8.32	-0.202	-16.30	-0.279	-18.76
	High	-0.190	-8.26	-0.272	-14.31	-0.348	-16.57
Log distance from capital (km)	Low	-0.098	-4.8	-0.105	-5.44	-0.142	-7.21
	Low-medium	-0.325	-17.55	-0.338	-19.10	-0.338	-18.75
	Medium-high	-0.293	-11.14	-0.313	-12.07	-0.245	-9.77
	High	0.042	1.15	0.013	0.37	0.079	2.27
National park (%)	Low	-0.688	-5.75	-0.815	-6.82		
	Low-medium	-0.378	-3.63	-0.521	-5.01		
	Medium-high	-0.684	-6.19	-0.833	-7.45		
	High	-0.160	-1.6	-0.270	-2.71		
Other protected area (%)	Low	-0.570	-5.19	-0.701	-6.43		
	Low-medium	-0.615	-5.26	-0.722	-6.21		
	Medium-high	-0.865	-9.72	-0.936	-10.44		
	High	-0.945	-9.38	-1.044	-10.57		
Logging concession (%)	Low	-0.2907	-2.95				
	Low-medium	-0.4221	-6.94				
	Medium-high	-0.2799	-4.7				
	High	-0.03339	-0.55				
Timber concession (%)	Low	0.4302	6.01				
	Low-medium	0.8694	15.21				
	Medium-high	1.17	16.92				
	High	1.008	9.4				
Estate crop concession (%)	Low	0.999	14.24				

	Low-medium	1.143	16.04				
	Medium-high	1.152	10.27				
	High	1.233	7.3				
Forest zoned for conservation (%)	Low					0.318	2.73
	Low-medium					0.527	6.05
	Medium-high					0.361	3.39
	High					0.651	4.77
Forest zoned for protection (%)	Low					-0.210	-1.88
	Low-medium					-0.094	-1.03
	Medium-high					-0.125	-1.17
	High					0.362	2.77
Forest zoned for production (%)	Low					0.699	14.66
	Low-medium					0.661	14.12
	Medium-high					0.480	6.7
	High					0.531	4.52
Forest zoned for conversion (%)	Low					0.628	11.61
	Low-medium					0.660	11.82
	Medium-high					0.585	7.02
	High					0.959	7.76
Forest cover class (0/1)	Low	0.004	0.02	-0.525	-2.39	0.136	0.57
	Low-medium	1.182	5.25	0.814	3.70	1.265	5.35
	Medium-high	1.305	5.34	1.215	5.01	1.371	5.37
	High	(dropped)		(dropped)		(dropped)	
Intercept		-1.729	-8.35	-1.062	-5.26	-1.743	-7.93

Table SI4 – Determinants of forest cover loss: Model specifications 4-6. Robust standard errors; n=166,297. *A coefficient of 0.1 indicates that each unit increase in the driver variable is correlated with a 10% increase in the probability of deforestation.*

Regression Model		(4)		(5)		(6)	
Description		Poisson; unstratified		Poisson; unstratified; weighted by forest cover		Poisson; stratified by region	
Driver	Region	Coefficient	z value	Coefficient	z value	Coefficient	z value
NPV of potential agriculatural revenue (1000$/ha)	All regions	0.0162	10.93	0.0175	232		
	Java					-0.0001	-0.05
	Sumatra					0.024	2.97
	Kalimantan					0.026	2.08
	Sulawesi					0.029	2.27
	E. Indonesia					0.025	7.14
Slope (°)	All regions	-0.090	-24.5	-0.111	-788		
	Java					0.005	0.27
	Sumatra					-0.119	-17.93
	Kalimantan					-0.141	-14.66
	Sulawesi					-0.057	-4.75
	E. Indonesia					-0.021	-4.16
Elevation (m)	All regions	-0.00188	-24.79	-0.00185	-687		
	Java					-0.0019	-6.88
	Sumatra					-0.0023	-15.13
	Kalimantan					-0.0033	-10.34
	Sulawesi					-0.0029	-10.36
	E. Indonesia					-0.0012	-13.55
Log distance from road (km)	All regions	-0.064	-9.80	-0.098	-337		
	Java					0.041	0.33
	Sumatra					-0.025	-2.29
	Kalimantan					0.121	8.06
	Sulawesi					0.021	0.83
	E. Indonesia					-0.076	-2.45
Log distance from capital (km)	All regions	-0.204	-17.11	-0.231	-433		
	Java					0.059	0.38
	Sumatra					0.033	1.1
	Kalimantan					0.104	3.6
	Sulawesi					0.054	1.07
	E. Indonesia					-0.078	-1.71
National park (%)	All regions	-0.537	-9.89	-0.438	-196		
	Java					-1.629	-4.64
	Sumatra					-1.170	-7.27
	Kalimantan					-1.071	-7.64
	Sulawesi					0.674	2.99
	E. Indonesia					0.318	5.81
Other protected area (%)	All regions	-0.664	-11.04	-0.770	-329		
	Java					-3.150	-3.77
	Sumatra					-0.945	-7.56
	Kalimantan					-0.51	-3.98
	Sulawesi					-0.536	-3.34
	E. Indonesia					-0.666	-7.82

Logging concession (%)	All regions	-0.3177	-9.05	-0.197	-154		
	Java					-	-
	Sumatra					0.170	2.37
	Kalimantan					-0.627	-8.96
	Sulawesi					-0.662	-5.26
	E. Indonesia					-0.003	-0.1
Timber concession (%)	All regions	0.813	22.86	0.999	654		
	Java					-	-
	Sumatra					0.918	20.57
	Kalimantan					0.402	5.39
	Sulawesi					0.232	0.52
	E. Indonesia					-0.798	-8.1
Estate crop concession (%)	All regions	1.107	23.99	1.152	513		
	Java					-	-
	Sumatra					0.681	12.11
	Kalimantan					1.287	14.08
	Sulawesi					1.188	4.69
	E. Indonesia					-0.017	-0.09
Region (0/1)	Java					(dropped)	
	Sumatra					0.790	2.21
	Kalimantan					0.062	0.26
	Sulawesi					0.233	1.25
	E. Indonesia					0.215	1.44
Intercept		-1.036	-19.35	-0.809	-313	-3.372	-4.81

Table SI5 – Determinants of forest cover loss: Model specifications 7-9. Robust standard errors; n=166,297. *A coefficient of 0.1 indicates that each unit increase in the driver variable is correlated with a 10% increase in the probability of deforestation.*

Regression Model		(7)		(8)		(9)	
Description		Poisson; stratified by forest cover		Logit; stratified by forest cover		Negative binomial; stratified by forest cover	
Driver	Forest cover class	Coefficient	z value	Coefficient	z value	Coefficient	z value
NPV of potential agricultural revenue (1000$/ha)	Low	0.0121	5.03	0.0039	1.41	0.0142	6.14
	Low-medium	0.0104	4.32	-0.0028	-1.16	0.0116	5.15
	Medium-high	0.0139	3.00	0.0118	2.16	0.0161	3.63
	High	0.0512	4.21	0.0795	9.18	0.0733	8.28
Slope (°)	Low	-0.017	-2.15	0.0021	0.59	-0.024	-3.26
	Low-medium	-0.072	-10.16	-0.0352	-16.15	-0.079	-11.51
	Medium-high	-0.108	-18.89	-0.0457	-23.3	-0.119	-20.66
	High	-0.118	-16.97	-0.0635	-30.61	-0.143	-20.44
Elevation (m)	Low	-0.002	-10.77	-0.00094	-13.95	-0.0019	-12.09
	Low-medium	-0.001	-9.72	-0.00040	-13.99	-0.0015	-11.54
	Medium-high	-0.001	-15.3	-0.00041	-15.85	-0.0017	-17.05
	High	-0.002	-16.47	-0.00040	-14.07	-0.0026	-18.19
Log distance from road (km)	Low			0.033	5.08	0.007	0.63
	Low-medium			0.084	12.46	-0.069	-6.6
	Medium-high			0.184	23.5	-0.125	-8.32
	High			0.256	26.37	-0.190	-8.26
Log distance from capital (km)	Low			0.068	5.07	-0.098	-4.8
	Low-medium			0.123	8.51	-0.325	-17.54
	Medium-high			0.309	18.66	-0.293	-11.12
	High			0.331	17.87	0.043	1.18
Remoteness	Low	-0.0000944	-3.07				
	Low-medium	-0.0003043	-18.71				
	Medium-high	-0.0002532	-15.52				
	High	-0.000045	-2.42				
National park (%)	Low	-0.565	-4.75	-0.219	-3.16	-0.689	-5.75
	Low-medium	-0.232	-2.24	-0.232	-4.24	-0.378	-3.63
	Medium-high	-0.418	-3.84	-0.275	-6.63	-0.683	-6.19
	High	0.048	0.47	-0.095	-2.62	-0.159	-1.6
Other protected area	Low	-0.545	-4.78	-0.096	-1.38	-0.570	-5.19
	Low-medium	-0.764	-7.66	-0.194	-3.32	-0.615	-5.27
	Medium-high	-0.856	-10.36	-0.098	-1.82	-0.865	-9.73
	High	-0.763	-7.87	-0.027	-0.53	-0.945	-9.38
Logging concession	Low	-0.518	-4.75	-0.370	-8.49	-0.292	-2.95
	Low-medium	-0.450	-2.24	-0.353	-12.17	-0.422	-6.95
	Medium-high	-0.347	-3.84	-0.270	-10.24	-0.280	-4.71
	High	0.096	0.47	-0.141	-5.07	-0.034	-0.56
Timber concession	Low	0.303	-4.78	0.050	1.16	0.430	6.02
	Low-medium	0.762	-7.66	0.166	3.49	0.869	15.21
	Medium-high	0.900	-10.36	0.455	7.02	1.170	16.91
	High	1.134	-7.87	0.402	5.09	1.008	9.41
Estate crop	Low	1.062	-4.72	0.203	3.87	0.999	14.23
	Low-medium	1.107	-7.55	0.551	6.89	1.143	16.04
	Medium-high	1.197	-6.56	0.779	6.03	1.152	10.27
	High	1.368	1.72	0.619	3.72	1.233	7.31
Forest cover class	Low	0.303	3.49	1.275	11.03	0.008	0.04
	Low-medium	0.301	3.45	1.740	14.56	1.186	5.28
	Medium-high	0.352	3.68	0.581	4.55	1.308	5.35
	High	(dropped)		(dropped)		(dropped)	
Intercept		-2.571	-32.36	-1.868	-19.35	-1.734	-8.37

Table SI6 – Model specifications compared.

Regression Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Description	Poisson; stratified by forest cover; includes concession boundaries	Poisson; stratified by forest cover; no concession boundaries	Poisson; stratified by forest cover; includes forest allocation	Poisson; unstratified	Poisson; unstratified; weighted by forest cover	Poisson; stratified by region	Poisson; stratified by forest cover	Logit; stratified by forest cover	Negative binomial; stratified by forest cover
Correlation coefficient (R) between modeled and observed deforestation (between modeled and observed emissions)									
Site-level	0.34 (0.41)	0.29 (0.35)	0.30 (0.36)	0.33 (0.39)	0.33 (0.40)	0.39 (0.45)	0.19 (0.22)	0.09 (0.22)	0.34 (0.41)
District-level	0.68 (0.72)	0.59 (0.63)	0.63 (0.66)	0.63 (0.67)	0.66 (0.70)	0.78 (0.82)	0.52 (0.52)	0.40 (0.48)	0.68 (0.72)
Province-level	0.81 (0.84)	0.72 (0.73)	0.77 (0.78)	0.77 (0.79)	0.80 (0.83)	0.92 (0.95)	0.63 (0.63)	0.55 (0.59)	0.81 (0.84)
Region-level	0.82 (0.79)	0.74 (0.67)	0.79 (0.73)	0.78 (0.73)	0.82 (0.78)	0.98 (0.97)	0.66 (0.54)	0.62 (0.55)	0.82 (0.79)
National total deforestation (1000ha/yr; observed=687)	692	693	695	710	685	705	531	8862	692
National total emissions (million tCO2e/yr; observed=860)	809	802	819	820	801	831	586	8149	809
R^2	0.14	0.12	0.13	0.13	0.17	0.16	0.12	0.08	-
AIC	58,805	59,961	59,427	59,310	2,380,000	57,209	48,969	212,827	58,806
BIC	59,246	60,282	59,827	59,420	2,380,000	57,730	49,365	213,268	59,257
Correlation coefficient (R) between modeled deforestation (emissions) and model (1)									
Site-level	1.00 (1.00)	0.83 (0.86)	0.80 (0.83)	0.95 (0.97)	0.97 (0.98)	0.86 (0.90)	0.83 (0.80)	0.28 (0.57)	1.00 (1.00)
District-level	1.00 (1.00)	0.98 (0.98)	0.98 (0.98)	0.99 (0.99)	1.00 (1.00)	0.93 (0.94)	0.94 (0.91)	0.72 (0.83)	1.00 (1.00)
Province-level	1.00 (1.00)	0.99 (0.98)	0.99 (0.99)	1.00 (0.99)	1.00 (1.00)	0.95 (0.95)	0.96 (0.94)	0.85 (0.88)	1.00 (1.00)
Region-level	1.00 (1.00)	0.99 (0.99)	1.00 (0.99)	1.00 (0.99)	1.00 (1.00)	0.90 (0.91)	0.96 (0.93)	0.83 (0.87)	1.00 (1.00)

Table SI7 – Impact of economic incentive policies on climate and revenue

		$10/tCO$_2$e			$20/tCO$_2$e		
		A	**N**	**D**	**A**	**N**	**D**
Policy variables							
Accounting scale; reference level design	Site-level; historical	62	-$5,970	$6,590	114	-$11,656	$13,929
	Site-level; C-I	91	-$3,996	$4,906	186	-$7,273	$10,998
	Site-level; BAU	199	-$125	$2,117	303	-$476	$6.543
	District; historical	105	-$3,356	$4,408	182	-$6,446	$10,088
	District; C-I	128	-$2,139	$3,424	231	-$3,935	$8,552
	District; BAU*	202	-$77	$2,095	304	-$331	$6,409
	Province; historical	115	-$2,392	$3,456	192	-$4,686	$8,529
	Province; C-I	130	-$1,637	$2,941	255	-$2,559	$7,654
	Province; BAU	205	-$41	$2,096	310	-$198	$6,392
Revenue sharing	0%*	202	-$77	$2,095	304	-$331	$6,409
	20%	170	$283	$1,415	270	$876	$4,525
	40%	135	$504	$844	227	$1,702	$2,838
	60%	95	$550	$396	169	$1,982	$1,412
	80%	40	$310	$85	95	$1,496	$396
	100%	0	$0	$0	0	$0	$0
Cost sharing	0%	211	$0	$2,117	319	$0	$6,434
	20%	210	-$3	$2,116	318	-$14	$6,433
	40%	210	-$8	$2,117	317	-$41	$6,439
	60%	208	-$18	$2,114	315	-$87	$6,451
	80%	208	-$33	$2,118	313	-$160	$6,467
	100%*	202	-$77	$2,095	304	-$331	$6,409
District reference level as % of BAU emissions	0%	0	$0	$0	0	$0	$0
	20%	0	$0	$0	0	$0	$0
	40%	0	$0	$0	23	$362	$95
	60%	28	$221	$60	197	$2,653	$1,285
	80%	150	$743	$760	271	$1,925	$3,493
	100%*	202	-$77	$2,095	304	-$331	$6,409
	120%	209	-$1,626	$3,717	313	-$3,348	$9,612

(A) Abatement (MtCO_2e/yr)
(N) National Government Revenue (million $/yr)
(D) District Revenue (million $/yr)
*default parameter value

Table SI8 – Sensitivity of marginal abatement cost to variation in key parameters. Results are outputs of OSIRIS-Indonesia v1.4 using the following default parameter assumptions: carbon price=\$10/tCO_2e; “effective” price elasticity of demand for frontier agriculture=0.0; exogenous agricultural price increase=0%; peat emission factor=1474 tCO_2e/ha; social preference for agricultural revenue=1.0; start-up and transaction costs=\$0.

		Basic Voluntary Incentive Structure			**Improved Voluntary Incentive Structure**			**Regulatory Incentive Structure**		
		A	**N**	**D**	**A**	**N**	**D**	**A**	**N**	**D**
Model Parameters										
Carbon Price (tCO2e/yr)	$5	32	-$3,003	$3,162	99	$95	$403	126	$404	$276
	$10*	62	-$5,970	$6,590	175	$331	$1,431	211	$808	$1,349
	$15	89	-$8,857	$10,196	234	$659	$2,868	272	$1,213	$2,945
	$20	114	-11,656	$13,929	278	$1,030	$4,564	319	$1,617	$4,875
Effective elasticity	0	71	-$5,894	$6,606	206	$413	$1,652	242	$808	$1,618
	1.9	66	-$5,935	$6,598	192	$379	$1,541	227	$808	$1,486
	3.8*	62	-$5,970	$6,590	175	$331	$1,431	211	$808	$1,349
	5.7	58	-$6,002	$6,582	161	$281	$1,343	195	$808	$1,235
Exogenous agricultural price increase	0%*	62	-$5,970	$6,590	175	$331	$1,431	211	$808	$1,349
	20%	54	-$6,039	$6,575	170	$312	$1,395	206	$808	$1,313
	50%	41	-$6,143	$6,555	158	$270	$1,326	199	$808	$1,259
Peat emission factor (tCO_2e/ha)[1]	947.5	40	-$5,004	$5,401	120	$224	$984	147	$686	$836
	1474.2*	62	-$5,970	$6,590	175	$331	$1,431	211	$808	$1,349
	2099.8	95	-$7,098	$8,044	256	$490	$2,076	298	$954	$2,092
Social preference for agricultural revenue	1.0*	62	-$5,970	$6,590	175	$331	$1,431	211	$808	$1,349
	2.0	58	-$5,989	$6,571	167	$316	$1,358	211	$808	$1,349
	3.0	56	-$5,999	$6,554	162	$310	$1.318	211	$808	$1,349
National reference level as % of BAU emissions	80%	62	-$7,587	$6,590	175	-$1,286	$1,431	211	-$808	$1,349
	100%	62	-$5,970	$6,590	175	$331	$1,431	211	$808	$1,349
	120%	62	-$4,353	$6,590	175	$1,948	$1,431	211	$2,425	$1,349
District-level start-up and transaction costs ($/district/5yr)	$0*				175	$331	$1,431	211	$808	$1,349
	$1 million				174	$329	$1,420	211	$808	$1,349
	$5 million				171	$325	$1,396	211	$808	$1,349
	$10 million				170	$322	$1,382	211	$808	$1,349
Per-hectare start-up and transaction costs ($/ha/5yr)	$0*	62	-$5,970	$6,590	175	$331	$1,431	211	$808	$1,349
	$1,000	59	-$5,974	$6,563	169	$323	$1,370	202	$808	$1,268
	$5,000	46	-$5,985	$6,449	127	$247	$1,025	173	$808	$996
	$10,000	32	-$5,994	$6,318	82	$161	$658	143	$808	$709

(A) Abatement (MtCO_2e/yr)
(N) National Government Revenue (million \$/yr)
(D) District Revenue (million \$/yr)
*default parameter value
[1] Range of peat emission factors based on “low,” “likely” and “high” estimates from Hoojier et al (2010).

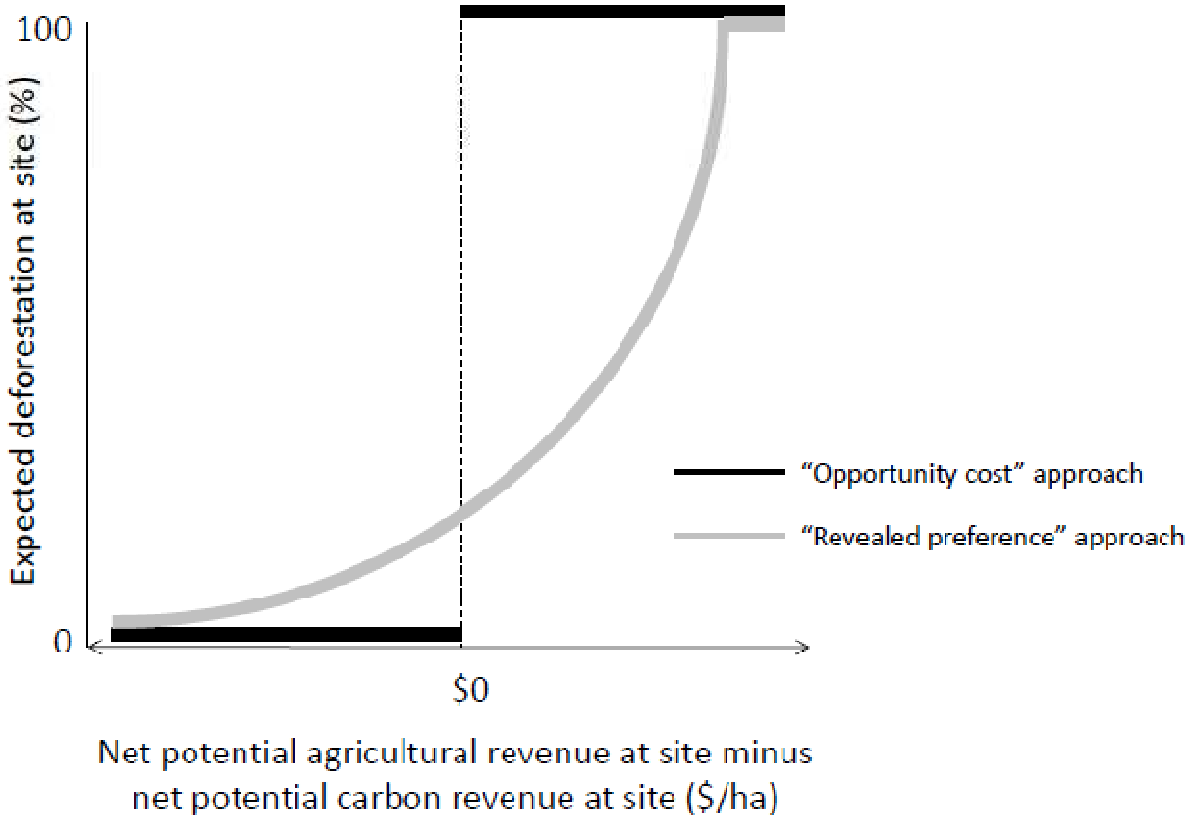

Figure SI1 – Predicted site-level deforestation as a function of potential agricultural and carbon revenue. Many previous studies have estimated the abatement potential of REDD+ policies based on the deterministic assumption that deforestation could be avoided entirely if and only if revenue from carbon payments exceeds income from alternative land uses ("opportunity cost approach"). We estimate the marginal impact of potential carbon payments on site-level deforestation by using a Poisson regression to determine the empirical relationship between the pattern of observed historical deforestation and spatial variation in the benefits and costs of converting forested land to agriculture ("revealed preference approach").

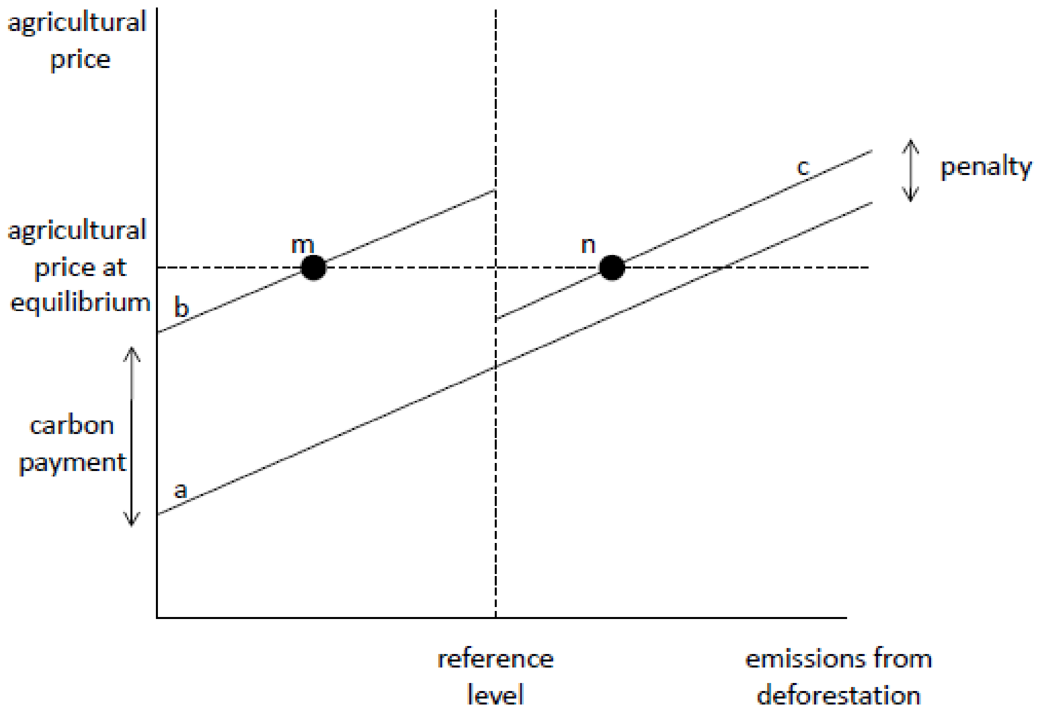

Figure SI2 – District-level allocation of land between forest and agriculture. Based on Figure 2 in Busch et al 2009. Line *a* represents the district-level supply curve for emissions-producing agricultural expansion into forest in the absence of a REDD+ mechanism. Greater potential agricultural revenue per hectare produces greater emissions from deforestation. Line *b* represents the district supply curve if the district opts into REDD+ by reducing its emissions below its reference level. This supply curve is shifted inward by the carbon payment, which is a function of the carbon price and the revenue sharing arrangement. Line *c* is the district supply curve is the district opts out of REDD+ by increasing its emissions above its reference level. This supply curve is shifted inward by the penalty, which is a function of the carbon price and the responsibility sharing arrangement. The district chooses the quantity of emissions from agricultural expansion *m* or *n* which provides greater total carbon revenue and agricultural revenue at the equilibrium agricultural price.

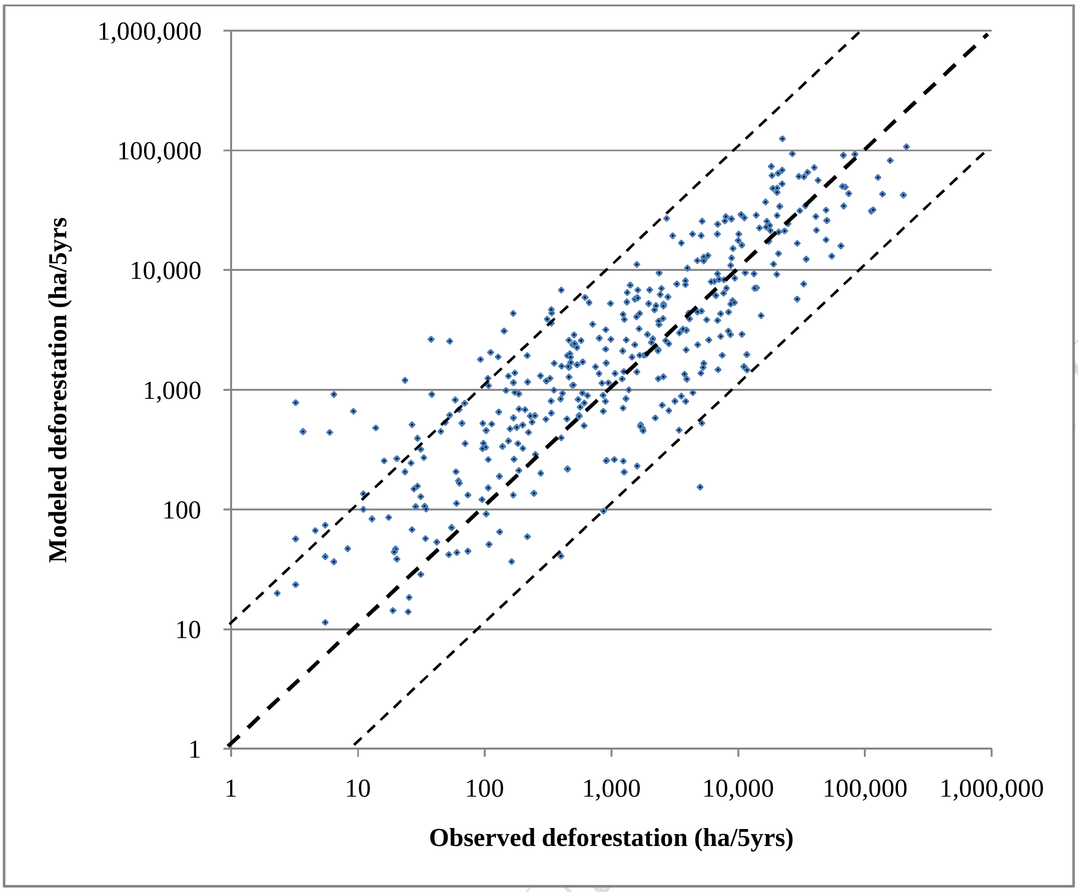

Figure S3 – Observed deforestation and modeled deforestation compared for forested districts of Indonesia, 2000-2005. (n=401; R=0.68) Modeled deforestation predicted using model specification 1 (Poisson; stratified by forest cover). Heavy dotted 45^{o} line indicates modeled deforestation equal to observed deforestation within a district. Light dotted lines indicate the boundaries within which modeled deforestation is within a factor of ten of observed deforestation.

Equations

Eq. 1 – Predicting the probability of deforestation in the absence of REDD+ based on observable site characteristics

$$y_i = \exp\,(\beta_{k0} + X_i{}'\beta_{k1} + \beta_{k2}A_i + \epsilon)$$

Here $y_i = (F_i^o - F_i^{'})/F_i^o$ is percent deforestation at site *i*, where F_i^o is forest cover at site *i* at the start of the 2000-2005 observation period, and $F_i^{'}$ is forest cover at site *i* at the end of the observation period. $k \in 1{:}\,4$ are classes of observations stratified by initial forest cover (Table SI1). X_i is a matrix of observable site characteristics, including slope, elevation, natural logarithm of the distance to the nearest road, natural logarithm of the distance to the nearest provincial capital, and the percent of site within a national park, other protected area, logging concession (HPH), timber concession (HTI), or estate crop concession (*kebun*). A_i is the net present value of gross agricultural revenue potential per hectare at site *i*. The term β_{k0} captures unobserved constant components of the expected net benefits of deforestation.

Eq. 2 – Predicted probability of deforestation at sites in the absence of REDD+

$$\hat{y}_{i-without\ REDD+} = \exp\,(\hat{\beta}_{k0} + X_i{}'\hat{\beta}_{k1} + \hat{\beta}_{k2}A_i)$$

Here $\hat{y}_{i-without\ REDD+}$ is the expected probability of deforestation at site *i* in the absence of REDD+. The distribution across the country of all $\hat{y}_{i-without\ REDD+}$ is the reference scenario.

Eq. 3 – Effective land rental value at a site

$$A_i + \frac{\hat{\beta}_{k0} + X_i{}'\hat{\beta}_{k1}}{\hat{\beta}_{k2}}$$

Effective land rental value at a site includes not only potential gross agricultural revenue but also costs.

Eq. 4 – Probability of deforestation at a site in a district that opts in to REDD+

$$\hat{y}_{i-with\ REDD+;\ opt\ in} = \exp\,(\hat{\beta}_{k0} + X_i{}'\hat{\beta}_{k1} + \hat{\beta}_{k2}((1 + \tau_1 + \tau_2)A_i - R_i))$$

Here τ_1 is the endogenous increase in price due to intranational leakage, and τ_2 is the exogenous increase in price due to international leakage. R_i is the marginal carbon revenue per hectare of forest accruing to a district that has opted in to REDD+.

Eq. 5 – Carbon revenue per hectare of forest accruing to a district which has opted in to REDD+

$$R_i = p_C * (1 - r) * E_i$$

Here p_c is the price paid by international buyers for carbon emission reductions, $r \in [0,1]$ is the portion of world carbon price withheld by the national government under a revenue sharing arrangement (e.g. r=0 world signify that carbon price accrues entirely to the district), and E_i is the emission reductions resulting from a decrease in deforestation at parcel i (tCO_2e/ha).

Eq. 6 – Probability of deforestation at a sites in a district that opts in to REDD+

$$\hat{y}_{i-with\ REDD+;\ opt\ out} = \exp\left(\hat{\beta}_{k0} + X_i'\hat{\beta}_{k1} + \hat{\beta}_{k2}((1 + \tau_1 + \tau_2)A_i - C_i)\right)$$

Here C_i is the marginal cost per hectare of deforestation incurred by a district which has opted out of REDD+.

Eq. 7 – Cost per hectare of deforestation incurred by a district which has opted out of REDD+

$$C_i = p_C * (1 - l) * E_i$$

Here $l \in [0,1]$ is the share of cost for emission increases borne by the national government under a responsibility-sharing arrangement (e.g. l=1 would signify that cost is borne entirely by the national government).

Eq. 8 – Districts' participation decision

$$p_C * (1 - r)[RL_j - \textstyle\sum_{i\epsilon j}(\hat{y}_{i-with\ REDD+;\ opt\ in} * F_i^o * E_i)] \ >$$

$$\gamma[\textstyle\sum_{i\epsilon j}(\hat{y}_{i-with\ REDD+;\ opt\ out} - \hat{y}_{i-with\ REDD+;\ opt\ in}) * F_i^o * (1 + \tau_1 + \tau_2) * A_i]$$

$$- p_C * (1 - l) * \sum_{i\epsilon j}(\hat{y}_{i-with\ REDD+;\ opt\ out} * F_i^o * E_i - RL_j)$$

Here RL_j is the reference level for district j, and F_i^o is the starting forest cover at site i. Parameter γ represents the district's preference for agricultural revenue relative to carbon revenue.

Eq. 9 – Expected aggregate deforestation within a district, without REDD+

$$D_{j,without\ REDD+} = \sum_{i\in j}(\hat{y}_{i-without\ REDD+} * F_i^o)$$

Eq. 10 – Expected aggregate deforestation within a district, with REDD+

$$D_{j,with\ REDD+} = \sum_{i \in j} (\hat{y}_{i-with\ REDD+} * F_i^o)$$

Eq. 11 – Expected aggregate emissions within a district, without REDD+

$$E_{j,without\ REDD+} = \sum_{i \in j} (\hat{y}_{i-without\ REDD+} * F_i^o * E_i)$$

Eq. 12 – Expected aggregate emissions within a district, with REDD+

$$E_{j,with\ REDD+} = \sum_{i \in j} (\hat{y}_{i-with\ REDD+} * F_i^o * E_i).$$

Eq. 13 – Expected carbon revenue accruing to district from opting in to REDD+

$$B_j = \max\{0, \left(RL_j - E_{j,with\ REDD+}\right) * p_c * (1 - r)\}.$$

Eq. 14 – Expected cost incurred by a district from opting out of REDD+

$$C_j = \max\left\{0, (E_{j,without\ REDD+} - RL_j) * p_c * (1 - l)\right\}$$

Eq. 15 – Expected aggregate deforestation nationwide, without REDD+

$$D_{without\ REDD+} = \sum_{j} D_{j,without\ REDD+}$$

Eq. 16 – Expected aggregate deforestation nationwide, with REDD+

$$D_{with\ REDD+} = \sum_{j} D_{j,with\ REDD+}$$

Eq. 17 – Endogenous increase in potential agricultural revenue due to decreased aggregate deforestation nationwide

$$\tau_1 = (\frac{D_{without\ REDD+}}{D_{with\ REDD+}})^e$$

The "effective elasticity" parameter e is functionally equivalent to the price elasticity of demand for frontier agriculture, but is assumed to also incorporate feedback in the domestic labor and productive capital markets.