Reductions in emissions from deforestation from Indonesia's moratorium on new oil palm, timber, and logging concessions

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To reduce greenhouse gas emissions from deforestation, Indonesia instituted a nationwide moratorium on new license areas ("concessions") for oil palm plantations, timber plantations, and logging activity on primary forests and peat lands after May 2011. Here we indirectly evaluate the effectiveness of this policy using annual nationwide data on deforestation, concession licenses, and potential agricultural revenue from the decade preceding the moratorium. We estimate that on average granting a concession for oil palm, timber, or logging in Indonesia increased site-level deforestation rates by 17–127%, 44–129%, or 3.1–11.1%, respectively, above what would have occurred otherwise. We further estimate that if Indonesia's moratorium had been in place from 2000 to 2010, then nationwide emissions from deforestation over that decade would have been 241–615 $MtCO_2e$ (2.8–7.2%) lower without leakage, or 213–545 $MtCO_2e$ (2.5–6.4%) lower with leakage. As a benchmark, an equivalent reduction in emissions could have been achieved using a carbon price-based instrument at a carbon price of \$3.30–7.50/tCO_2e (mandatory) or \$12.95–19.45/tCO_2e (voluntary). For Indonesia to have achieved its target of reducing emissions by 26%, the geographic scope of the moratorium would have had to expand beyond new concessions (15.0% of emissions from deforestation and peat degradation) to also include existing concessions (21.1% of emissions) and address deforestation outside of concessions and protected areas (58.7% of emissions). Place-based policies, such as moratoria, may be best thought of as bridge strategies that can be implemented rapidly while the institutions necessary to enable carbon price-based instruments are developed.

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Reducing deforestation in Indonesia can contribute to climate-change mitigation at a globally significant scale. Estimates of annual greenhouse gas emissions from deforestation in Indonesia and the associated degradation of peat soils ranged from 0.32 to 1.91 $GtCO_2e$ during 2000–2010 (1–6) (*SI Appendix*, Fig. S1) relative to a global total of 40–49 $GtCO_2e$ from 2000 to 2010 (7). Deforestation in Indonesia is largely driven by the expansion of profitable and legally sanctioned oil palm and timber plantations and logging operations (5, 8–13). National and provincial governments zone areas of forest land to be logged or converted to plantation agriculture, and then district governments issue licenses to individual companies for these purposes ("concessions") (14, 15). Substantial deforestation occurs outside of legally sanctioned concession areas as well.

In May 2010, the national government of Indonesia announced a moratorium prohibiting district governments from granting new concession licenses (16, 17). The moratorium covered licenses for three types of activities: (*i*) conversion of primary forests and peat lands to oil palm plantations (oil palm concessions); (*ii*) conversion of primary forests and peat lands to fast-growing tree plantations for pulp and paper (timber concessions); and (*iii*) logging of commercially valuable tree species within forests (logging concessions). The moratorium was enacted in the context of a national strategy for reducing emissions from deforestation (REDD+) (18), a national target of reducing greenhouse gas emissions projected to 2020 by 26–41% while increasing gross domestic product by 7% per year (19), and a \$1 billion bilateral cooperative agreement with Norway on reducing emissions from deforestation (20). The moratorium came into force in May 2011 (21) and was extended in May 2013 for an additional 2 y (22).

The moratorium was conceived as both a stepping-stone to reforming Indonesia's complex forest tenure system and a mechanism for reducing deforestation in its own right (23). The moratorium has been criticized for not covering secondary (i.e., logged) forests, for providing potential loopholes for food and energy security, for periodic downward revisions to the total moratorium area, for leaving a grace period between the announcement and the implementation of the moratorium during which licenses could still be obtained, and for not curtailing deforestation within existing concessions (24–27). Furthermore it has been noted that Indonesia's deforestation rate has continued an upward trend from 2000 through 2012, even after the implementation of the

Significance

Our paper is significant in a number of respects. First, we expand the literature on quasi-experimental evaluation of the causal impact of conservation measures to include agricultural concessions. Second, our report is rare in that we use panel data and techniques in a literature on spatially explicit land-use change econometrics that has necessarily relied upon cross-sectional analyses because of data-availability constraints. Third, our report is rare among land-use change scenario analyses in that we calibrate the effect of land-use designations empirically, rather than assuming idealized perfect effectiveness of conservation measures or complete conversion without such measures. Finally, we compare the effectiveness of place-based policies with alternative price-based instruments for climate-change mitigation within a globally significant landscape.

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moratorium in 2011 (28, 29). However, the effectiveness of the moratorium in reducing emissions from deforestation has yet to be quantified. Deforestation in recent years might have been even higher in the absence of a moratorium.

Here we have evaluated the effectiveness of the moratorium policy by analyzing annual nationwide data on deforestation, the boundaries and license dates of concessions, and potential agricultural revenue from 2000 to 2010, the decade preceding the moratorium. The decade preceding the moratorium is ideal for scenario analysis because we can't know where concessions would have been designated post-2011 without a moratorium, but we do know where pre-2010 concessions would not have been with a moratorium. Thus, we are able to construct a counterfactual scenario in which the moratorium policy in its current form was applied over the previous decade, and compare emissions under this simulated scenario to the emissions that actually occurred.

We first answered the question: How much did the designation of a concession increase local (grid cell-level) deforestation above what would have occurred there without a concession? We used panel econometric techniques to control for potentially confounding geographic and time-variant factors and to construct upper and lower bounds around the magnitude of the treatment effect. Next, we answered the question: How much lower would Indonesia's emissions from deforestation have been from 2000 to 2010 if no new concessions had been granted on primary forests and peat lands during that period? We aggregated estimates of local (grid cell-level) land-use change to the national level, accounted for geographic displacement of deforestation caused by market feedbacks ("leakage"), and applied grid cell-specific carbon emission factors for deforestation and peat degradation. Finally, we answered the question: At what carbon price would a price-based instrument have achieved an equivalent reduction in emissions over the same time period? We compared the estimated emission reductions from the place-based moratorium policy with the estimated emission reductions from a hypothetical carbon price-based instrument, adapting the Open Source Impacts of REDD+ Incentives Spreadsheet (OSIRIS) Indonesia model (4). We examined both a mandatory carbon price-based instrument (e.g., a cap-and-trade or symmetric tax-and-subsidy program) and a voluntary carbon price-based instrument (e.g., a project-level REDD+ program with business-as-usual reference levels).

With this paper we contribute to several literatures. First, we expand the literature on quasi-experimental evaluation of the causal impact of conservation measures (30), such as protected areas (31–33), payment-for-ecosystem-services programs (33, 34), logging concessions (35), and clearing bans (36), to include agricultural concessions. Even though agricultural concessions are used to legally sanction deforestation on at least 150 million hectares of forest in at least 12 countries (37), and curtailing the expansion of such concessions represents a potentially promising policy for reducing emissions from deforestation, the effects of agricultural concessions on deforestation have only been estimated obliquely in econometric studies exploring other topics (4, 38, 39). Additionally, to our knowledge our paper is the first to transform area-based treatment effects to emissions-based treatment effects. Second, our paper is rare in that it uses panel data and techniques. Nearly all previous spatially explicit econometric studies of land-use change have necessarily relied upon cross-sectional analyses because of data availability constraints. In a meta-analysis of 117 such studies (40), only three have previously used panel methods (39, 41, 42). This paper is at the forefront of what is likely to be a proliferation of panel econometric analyses enabled by the recent availability of reliable, annual, globally consistent data on patterns of forest loss (28). Third, our paper is rare in that it calibrates the effect of land-use designations empirically. Nearly all previous land-use change scenario analyses have assumed idealized perfect effectiveness of conservation measures or complete conversion without such measures. A recent review of this literature found that only 1 of 71 peer-reviewed studies explicitly incorporated the difference in probable threat between reserved and nonreserved scenarios (43). Finally, our paper is to our knowledge the first to compare the effectiveness of place-based policies with alternative carbon price-based instruments for climate change mitigation within a landscape.

Results

We estimate that 11.45 Mha of deforestation occurred in Indonesia from 2000 to 2010, resulting in 8.59 $GtCO_2e$ of emissions from deforestation and peat land degradation (Fig. 1). Of this total, 2.27 Mha (19.9%) of deforestation occurred within oil palm concessions, resulting in 1.77 $GtCO_2e$ (20.6%) of emissions; 1.44 Mha (12.6%) of deforestation occurred within timber concessions, resulting in 1.30 $GtCO_2e$ (15.1%) of emissions; 0.60 Mha (5.2%) occurred within logging concessions, resulting in 0.35 $GtCO_2e$ (4.1%) of emissions; 0.162 Mha (1.4%) occurred within national parks, resulting in 0.129 $GtCO_2e$ (1.5%) of emissions; and 0.030 Mha (0.26%) occurred within protected areas other than national parks, resulting in 0.022 $GtCO_2e$ (0.25%) of emissions (Fig. 1). At least 0.96 Mha (8.3%) of the area deforested between 2000 and 2010 had been converted to oil palm plantation by 2010, resulting in 0.56 $GtCO_2e$ (6.5%) of emissions.

The designation of an oil palm concession increased the annual deforestation rate within a 3-km × 3-km grid cell by 17–127% relative to a counterfactual scenario without a concession, whereas timber concessions increased deforestation by 44–129%, and logging concessions increased deforestation by 3.1–11.1% (*SI Appendix*, Table S1). Put differently, deforestation would have been 15–65% lower if land that was designated as an oil palm concession had not been so designated, 31–56% lower if land that was designated as a timber concession had not been so designated, or 3.0–10.0% lower if land that was designated as a logging concession had not been so designated. The finding that oil palm, timber, and logging concessions increased deforestation was robust compared to alternative model specifications to control for confounding geographic and temporal factors, although the estimated magnitudes of these treatment effects were sensitive to model specifications (*SI Appendix*, Fig. S2). For oil palm and logging concessions, the lower bound of the estimated treatment effect, while positive, was not significantly different from zero. This was also the case in alternative geographically matched fixed-effects models (*SI Appendix*, Table S2). The finding that logging concessions increased deforestation contrasts with the findings of previous studies (4, 35, 39). The effect of oil palm, timber, and logging concessions was heterogenous across starting-forest cover quartile (*SI Appendix*, Table S3) and region (*SI Appendix*, Table S4). The significance of treatment effects was robust to the inclusion of a spatial lag variable to address potential spatial correlation (*SI Appendix*, Table S5).

We estimated that if the current moratorium policy had been in place from 2000 to 2010, nationwide deforestation would have been reduced by 153–399 kha (1.3–3.5%) without leakage, or by 116–305 kha (1.0–2.7%) with leakage. Nationwide emissions from deforestation and peat land degradation over the decade would have been reduced by 241–615 $MtCO_2e$ (2.8–7.2%) without leakage, or by 213–545 $MtCO_2e$ (2.5–6.4%) with leakage (Table 1). Reductions in the rate of emissions exceeded reductions in the rate of deforestation because the moratorium targeted forests and peat lands that were disproportionately rich in carbon. The potential for the moratorium policy to achieve emission reductions was constrained by the geographic and temporal scope of the moratorium, which covered only 1,287 $MtCO_2e$ (15.0%) of the 8,689 $MtCO_2e$ total emissions from deforestation and peat produced over the 2000–2010 period (Fig. 1). Under an alternative definition of primary forest (29), the moratorium would have covered 908 $MtCO_2e$ (10.6%) of total emissions, and would

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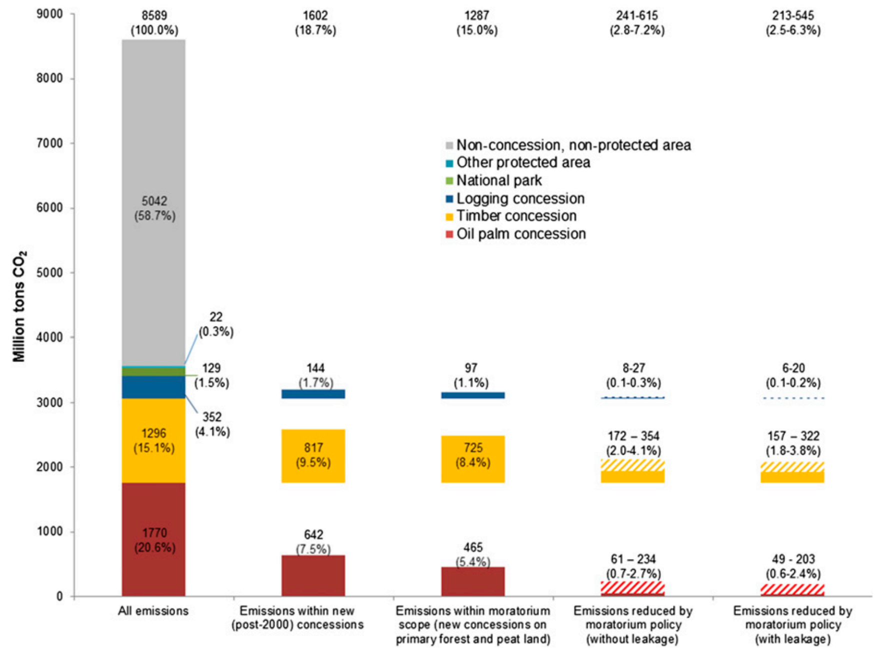

Fig. 1. Emissions and reductions in emissions from deforestation and peat degradation by land-use designation, Indonesia, 2000–2010. $MtCO_2e$ (percent of total decadal emissions).

have reduced nationwide emissions from deforestation by 156–357 $MtCO_2e$ (1.8–4.2%) without leakage, or 125–303 $MtCO_2e$ (1.5–3.5%) with leakage.

Expanding the scope of the moratorium policy to cover secondary forests in addition to primary forests would have increased the coverage of the moratorium to 1,602 $MtCO_2e$ (18.7% of total emissions), and would have increased the reduction in emissions to 287–756 $MtCO_2e$ (3.3–8.8%) without leakage, or 237–620 $MtCO_2e$ (2.8–7.2%) with leakage. Further expanding the scope of the moratorium policy to cover clearing within existing concessions in addition to new concessions would have increased the coverage of the moratorium to 3,418 $MtCO_2e$ (39.8% of total emissions), and would have increased the reduction in emissions to 538–1,571 $MtCO_2e$ (6.3–18.3%) without leakage, or 433–1,268 $MtCO_2e$ (5.1–14.8%) with leakage.

We estimated that every additional \$100 per hectare per year in potential agricultural revenue increased the rate of deforestation by an average of 1.02–1.18%, all else equal. At an average potential agricultural revenue of \$2,506 per hectare per year (*SI Appendix*, Table S6), this implies a price elasticity of demand for deforestation of 0.26–0.30. As a benchmark, we estimated the carbon price at which an equivalent level of emission reductions to that obtained by the moratorium policy could have been achieved using an idealized nationwide carbon-pricing instrument. Equivalent reductions could have been achieved using a mandatory carbon-pricing instrument, such as a cap-and-trade or symmetric tax-and-subsidy program at a carbon price of \$3.30–\$7.50, or using a voluntary carbon-pricing instrument, such as a project-level REDD+ program with business-as-usual reference levels at a carbon price of \$12.95–\$19.45. If the carbon-pricing instrument were

Table 1. Total decadal deforestation and emissions under alternative policy scenarios, Indonesia 2000–2010

	Without leakage			With leakage		
Scenario	Total	Absolute reduction	Percent reduction	Total	Absolute reduction	Percent reduction
Without moratorium						
Deforestation (kha)	11,453			11,453		
Emissions ($MtCO_2e$)	8,589			8,589		
Current moratorium scope: new oil palm, timber, and logging concessions on primary forests and peat lands						
Deforestation (kha)	11,054–11,300	153–399	1.3–3.5	11,148–11,337	116–305	1.0–2.7
Emissions ($MtCO_2e$)	7,974–8,348	241–615	2.8–7.2	8,043–8,376	213–545	2.5–6.4
Equivalent mandatory carbon price ($\$/tCO_2e$)	3.30–6.60			3.35–7.50		
Equivalent voluntary carbon price ($\$/tCO_2e$)	13.15–18.70			12.95–19.45		
Current moratorium scope + secondary forests						
Deforestation (kha)	10,660–11,175	278–793	2.4–6.9	10,842–11,241	212–611	1.9–5.3
Emissions ($MtCO_2e$)	7,833–8,302	287–756	3.3–8.8	7,969–8,352	237–620	2.8–7.2
Equivalent mandatory carbon price ($\$/tCO_2e$)	4.00–9.25			3.70–8.55		
Equivalent voluntary carbon price ($\$/tCO_2e$)	14.35–21.55			13.60–20.40		
Current moratorium scope + secondary forests + existing concessions						
Deforestation (kha)	9,518–10,803	650–1,935	5.7–16.9	9,929–10,943	510–1,525	4.5–13.3
Emissions ($MtCO_2e$)	7,017–8,051	538–1,571	6.3–18.3	7,321–8,155	433–1,268	5.1–14.8
Equivalent mandatory carbon price ($\$/tCO_2e$)	7.50–20.10			6.85–18.20		
Equivalent voluntary carbon price ($\$/tCO_2e$)	19.80–32.50			18.40–30.60		

applied only to the lands affected by the moratorium (i.e., new oil palm, timber, and logging concessions on primary forests and peat lands) rather than to the entire country, equivalent reductions could have been achieved at a carbon price of \$12.65–\$31.20 (mandatory) or \$24.60–\$42.80 (voluntary). These prices do not include the costs of developing new institutions to enable carbon payments or penalties.

Discussion

Curtailing licenses to convert areas of forest land to agriculture represents a potentially promising policy for slowing deforestation and associated emissions. Indonesia's moratorium policy, if put in place from 2000 to 2010 as currently formulated, would have reduced emissions by 213–545 $MtCO_2e$ (2.5–6.4%) over 10 y after accounting for leakage. Despite the heavy policy attention on oil palm, the majority of these emission reductions (around 58–74%) would have come from timber concessions, as timber concessions were designated more rapidly than oil palm concessions between 1999–2010 (+121% for timber concessions vs. +64% for dated oil palm concessions) (*SI Appendix*, Fig. S3), and had higher average carbon density (140 tC/ha vs. 128 tC/ha) and greater average area of peat (65% vs. 36%) than oil palm concessions (*SI Appendix*, Table S6). Less than 5% of the emission reductions would have come from within logging concessions.

Although emission reductions from the moratorium would have been sizeable in absolute terms, the moratorium would have been insufficient to achieve Indonesia's target of reducing emissions by 26–41% because its geographic and temporal scope covered only 15.0% of emissions from deforestation over the 2000–2010 period. To have achieved a 26% reduction in emissions, the moratorium would have had to address the 21.1% of emissions from deforestation on existing palm oil and timber concessions and the 58.7% of emissions from deforestation outside of sanctioned concessions and protected areas.

The estimated impact of a 10-y moratorium (2.5–6.4% reduction in emissions) is low relative to the scope of the moratorium (15.0% of emissions) because the moratorium merely reduces deforestation toward rates observed without a concession; it does not reduce rates to zero. Deforestation from 2000 to 2010 was high even on lands where no concession officially sanctioned clearing. This finding suggests the potential to reduce emissions through enforcement or other policy actions on lands outside of moratorium areas.

Alternatively, equivalent emission reductions could have been achieved through price-based instruments at a price of \$3.30–\$7.50/tCO_2e (mandatory) or \$12.95–\$19.45/tCO_2e (voluntary). These prices appear reasonable in light of carbon prices above \$10/tCO_2e during the first commitment period of the European Union Emission Trading Scheme. However, this idealized benchmark does not include the costs of building institutions that would enable carbon payments or penalties. Such costs could be high, given the challenges of reforming Indonesia's traditionally natural resource-dependent political economy, which involve transparency, anticorruption efforts, and institutional capacity (44).

We can build on the historical analysis to make an indicative estimate regarding the effectiveness of the moratorium currently in place. Note that we produce this indicative estimate by applying several additional assumptions to the 2000–2010 data and analysis, rather than by empirically evaluating data from the post-2011 period. Assuming that in the absence of a moratorium, concessions in the post-2011 period would have continued to have been designated at the same rate as during the 2000–2010 period, and on lands with similar carbon density, we indicatively estimate that emissions from deforestation would have been roughly 1.0–2.7% higher without a 4-y moratorium (e.g., 2011–2015) than with a moratorium (see *SI Appendix* for calculations). Although any reduction is sizable in absolute terms given the magnitude of Indonesia's overall emissions, the lower bounds of the estimated impact of a 4-y moratorium are not far from zero. That the effect of a moratorium policy compounds the longer it is in place suggests the value of extending the moratorium policy further into the future.

The challenge of reconciling agricultural production and climate stability (45, 46) is not unique to Indonesia. Global expansion of agricultural land is projected to continue through 2050 (47). The expansion of commercial agriculture is the primary driver of tropical deforestation (48), which contributes 10–15% of global greenhouse gases emissions from tropical deforestation (3, 49–51). Reconciling agricultural production and climate stability requires shifting the expansion of agriculture away from forests and peat lands toward lower-carbon landscapes.

Shifting agricultural expansion away from forests can be encouraged through place-based policies, such as protected areas or moratoria on agricultural concessions, which proscribe where agricultural conversion may occur on a landscape. Alternatively, shifting agricultural expansion away from forests can be encouraged through price-based instruments, such as carbon payments, payment-for-ecosystem-services programs, taxes on deforestation, or price premiums for zero-deforestation agricultural products, all of which attempt to raise the private value of maintaining land as forest relative to converting land to agriculture.

Price-based instruments have several advantages over place-based policies. From an economic standpoint, price-based instruments induce land-holders to internalize the marginal public costs of deforestation, while allowing these land-holders to decide their own level of deforestation based on their private information about the costs and benefits of converting forests to other land uses. A common carbon price ensures that emission reductions will occur where they cost least. From a geographical standpoint, price-based instruments can be applied across a broader range of territory than place-based policies. From the standpoint of political economy, price-based instruments have the potential to create winners as well as losers within the land-use sector.

However, place-based policies have certain advantages as well. Place-based policies can be spatially targeted for greatest impact, for example when local conservation or contiguity of forest patches has value (52). Importantly, place-based policies do not require the development of new institutions or property-rights arrangements that have slowed the implementation of price-based instruments (53, 54).

Perhaps the most effective mitigation strategy is to implement place-based policies rapidly while developing and field-testing eventual price-based instruments. This sequence of strategies is taking place in Indonesia, where the nationwide moratorium has been in place since May 2011, and a provincial carbon payment program originally scheduled for Central Kalimantan in 2011 remains in preparatory stages.

Methods

Data. We obtained data on annual forest loss in Indonesia from 2000 to 2010 by classifying tree cover and tree cover loss at 30-m resolution (28) into forest or nonforest by applying a tree-cover threshold of 30%, following the official definition of forest in Indonesia (1). These data do not distinguish between natural forests and tree plantations. We did not consider forest regrowth. Results were not sensitive to alternative definitions of forest based on higher tree-cover thresholds nor to limiting forests to primary forests as defined by ref. 29 (*SI Appendix*, Tables S7 and S8).

We obtained license dates and boundaries of concessions for palm oil, timber, and logging from the most recent publicly released data (55). We obtained designation dates and boundaries of national parks and other protected areas from ref. 56.

We constructed an original dataset on potential agricultural revenue by adapting the methods of Naidoo and Iwamura (57). Following ref. 57, we determined the most lucrative crop (n = 21) that could be grown in any location in each of 10 y (2000–2009), based on global agro-ecological zones (58) and a production-weighted average of national farmgate prices in 2005

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USD (59) for the top five producer countries. Diverging from Naidoo and Iwamura (57), we used updated agro-ecological zone data, annual rather than decadal average prices, and 21 rather than 38 crop types (we excluded garden vegetables, tubers, legumes, and livestock, which were responsible for unintuitively high estimates of per-hectare agricultural potential in some areas). Palm oil was estimated to be the most potentially lucrative crop in most cells in most years (69.0% of cell-years, 2000–2009), but this varied from a low of 35.8% in 2002 to a high of 79.6% in 2007. Other most-lucrative crops included sugar cane (11.6%), bananas (5.6%), cotton (5.3%), cocoa (4.0%), tea (1.9%), rice (1.0%), and coffee (1.06%) (*SI Appendix*, Table S9).

We compiled control variables on average slope and elevation (60) and average Euclidean distance from nearest national or regional roads and from provincial capitals (61).

We calculated emission factors for deforestation and peat degradation based on data on biomass, nonpeat soil, and peat soil. Emissions from deforestation were calculated based on the release of 100% of aboveground forest biomass carbon (50) and belowground forest biomass carbon, using a below-to-aboveground biomass ratio of 0.24 (62). Because our aboveground forest biomass carbon data were 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 that average forest carbon density remained constant from 2000 to 2010, and that clearing within cells was not systematically biased toward higher or lower carbon forest. On mineral (nonpeat) soil, we assumed soil emissions from deforestation to be 10% of soil carbon content in the top 30 cm (63). Following ref. 4, we estimated soil emissions from deforestation occurring on peat lands in Sumatra (64), Kalimantan (65), and Papua (66) to be the average 30-y nondiscounted 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 (67). We did not consider carbon sequestered by regrowing plantation trees.

We obtained data on the distribution of oil palm plantations in 2010 from ref. 10. Plantation cover was likely underestimated in this dataset as satellite data did not identify the most recent plantings. In the absence of an official national map of secondary (disturbed by logging) forest we assumed that all forest with a carbon density of <150 tC/ha was secondary forest and all forest with a carbon density of >150 tC/ha was primary forest. We explored the sensitivity of our results to an alternative definition of primary forest (29).

We drew upon the best available data for each layer, which in some cases was of high quality and in other cases was at best a first approximation. Datasets for which improvements would be particularly valuable at reducing uncertainty include peat extent and emission factors, potential agricultural revenue, and concession boundaries and dates.

We gridded and aggregated these data to 195,466 3 km × 3-km grid cells that collectively covered 96% of the forest area of Indonesia. Aggregating spatial data to relatively coarse cell sizes allowed us to capture the full wall-to-wall data across Indonesia within a manageable number of cells, with the trade-off of losing fine-scale spatial specificity. Using coarser-resolution cells has the additional 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 correlation. For summary statistics, see *SI Appendix*, Table S6.

Empirical Approach. We sought to estimate the causal impact of the designation of a concession on deforestation. That is, how much higher the rate of deforestation was with a concession than would have occurred without that concession in place. This question is complicated because the amount of deforestation that would have occurred without a concession is an unobserved counterfactual. It cannot be assumed that the rate of deforestation would have been 0% without a concession, because a great deal of deforestation occurred on land outside of concessions. Nor can it be assumed that areas within concessions would have experienced rates of deforestation equal to those experienced on lands outside of concessions, because lands where concessions were designated were more lucrative for agriculture and more accessible to markets (*SI Appendix*, Table S6), and thus likely to have experienced higher rates of deforestation anyway. Similarly, comparing deforestation rates before and after the designation of a concession, or before and after the moratorium, would not account for trends in deforestation rates that would have occurred even without the policy.

To produce bias-free estimates of the impact of concessions on deforestation, we controlled for geographical characteristics and temporal trends that affected the likelihood of deforestation in the absence of a concession. We did so by applying panel econometric techniques to a dataset with spatial and temporal heterogeneity in treatments (land-use designations) and outcomes (deforestation). We placed upper and lower bounds around the treatment effect of land-use designations using a fixed-effects model within a matched area, and a pooled regression model in which a lagged dependent variable was included as a regressor, following refs. 68 and 69. Results from both models are presented in Fig. 1. Our estimation strategy is described in detail in *SI Appendix*.

We explored the sensitivity of our results to several alternative econometric specifications. We included cross-sectional regressions, which have been used by nearly all spatially explicit econometric studies of deforestation to date (40). That is, we estimated the impacts of land-use designations in place by 2000 on deforestation from 2000 to 2010. We included a pooled regression that did not include the lagged-dependent variable as a regressor. We included fixed-effects regressions that had no geographic buffer, or a 6-km buffer around cells with concessions by 2010, or that were limited to within cells with concessions by 2010. We included models that added a spatially lagged dependent variable as one control for spatial correlation (Fig. 1).

Data were not available on the construction dates of roads nor on the locations and dates of oil palm and timber mills. These data represent potentially important omitted variables. Thus, our estimates are best thought of not as the effect of concessions in isolation from the effect of mills and roads, but rather as the effect of concessions in combination with contemporaneous and associated expansion of roads and mills.

Aggregation to Indonesia-Wide Policy. To simulate the aggregate effect of a nationwide moratorium on concessions from 2000 to 2010, we subtracted the local effects of an oil palm concession (+17–117%), timber concession (+45–123%), or logging concession (+4.0–4.5%) from the deforestation rate in every grid-cell years at which such concessions were in place on primary forest or peat land during the decade. That is, a grid cell that was fully covered by an oil palm concession, timber concession, or logging concession that experienced a deforestation rate of 1.00% per year was simulated to have instead experienced under a moratorium a deforestation rate of 0.46–0.86% per year, 0.45–0.69% per year, or 0.957–0.962% per year, respectively. Where grid cells were partially covered by concessions, we applied fractional rates.

For oil palm concessions with unknown license dates (92.3% of total by area), we randomly drew a license date from the area-weighted distribution of license dates of dated concessions. We applied the same technique to timber concessions (16.2% missing data), national parks (34.7% missing data), and other protected areas (27.5% missing data). Dates were available for 100% of logging concessions.

We simulated the effects of displacement of deforestation (leakage) using a 10-period dynamic resursive adaptation of OSIRIS-Indonesia, a previously static spatial partial equilibrium model for frontier agricultural land described fully in ref. 4. In this model the effect of carbon payments on cell-level land-use change was inferred from the relationship between higher potential agricultural revenue and higher deforestation in panel regression analysis. Every additional $100 per hectare per year of potential agricultural revenue was associated with a 1.02–1.18% increase in deforestation (*SI Appendix*, Table S1), from which we assumed that every additional $1 per hectare per year of potential carbon revenue or penalty would have been associated with a 1.02–1.18% decrease in deforestation. Thus, the cell-level behavioral response function was characterized simply by an assumed exponential structure and single empirically calibrated parameter: the price elasticity of demand for deforestation. Any reduction in deforestation increased the price of frontier agricultural commodities nationwide, which correspondingly increased deforestation elsewhere. The magnitude of the price response generating this displacement was calibrated to match estimates of leakage generated by a 35-sector, 5-region general equilibrium model of the Indonesian economy model (70).

We converted deforestation (hectare) into emissions (tCO_2e) by multiplying the area of deforestation in each grid cell by grid cell-specific emission factors for above- and belowground biomass and peat. We simulated the effects of alternative scope of the moratorium policy by sequentially expanding the scope to cover secondary forests and deforestation within existing concessions (Table 1).

Comparison with Carbon Price. We calculated the effects of alternative carbon pricing instruments using the same 10-y period recursive adaptation of OSIRIS-Indonesia. In a "mandatory" carbon pricing scenario, sites corresponding to grid cells received a carbon payment for any reductions in emissions below business-as-usual reference levels and were penalized by the same amount for any increase in emissions. In a "voluntary" carbon-pricing scenario, sites received a carbon payment for any reductions in emissions below business-as-usual reference levels but were not penalized for increases in emissions. All results were reported in 2013 USD. The mandatory and voluntary carbon prices that would have achieved equivalent emission reductions to moratorium scenarios are reported in Table 1.

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1. Ministry of Forestry (2008) *Reducing Emissions from Deforestation and Forest Degradation in Indonesia*. Indonesian Forest Climate Alliance Consolidation Report. (Ministry of Forestry, Jakarta, Indonesia).
2. DNPI (2010) *Indonesia's Greenhouse Gas Abatement Cost Curve* (Dewan Nasional Perubahan Iklim, Jakarta, Indonesia).
3. Harris NL, et al. (2012) Baseline map of carbon emissions from deforestation in tropical regions. *Science* 336(6088):1573–1576.
4. Busch J, et al. (2012) Structuring economic incentives to reduce emissions from deforestation within Indonesia. *Proc Natl Acad Sci USA* 109(4):1062–1067.
5. Abood SA, Huay Lee JS, Burivalova Z, Garcia-Ulloa J, Koh LP (2014) Relative contributions of the logging, fiber, oil palm, and mining industries to forest loss in Indonesia. *Cons Lett*, 10.1111/conl.12103.
6. WRI (2014) *Climate Analysis Indicators Tool v2.0*. (World Resources Institute, Washington, DC). Available at cait2.wri.org/wri. Accessed November 6, 2014.
7. IPCC (2014) *Fifth Assessment Report Summary for Policymakers* (Working Group III, Intergovernmental Panel on Climate Change, Geneva, Switzerland).
8. Butler R, et al. (2009) REDD in the red: Palm oil could undermine carbon payment schemes. *Cons Lett* 2(2):67–73.
9. Fisher B, et al. (2011) The high costs of conserving Southeast Asia's lowland rainforests. *Front Ecol Environ* 9(6):329–334.
10. Miettenen J, et al. (2012) 2010 land cover map of insular Southeast Asia in 250-m spatial resolution. *Remote Sensing Lett* 3(1):11–20.
11. Carlson KM, et al. (2012) Carbon emissions from forest conversion by Kalimantan oil palm plantations. *Nature Climate Change* 3:283–287.
12. Lee JSH, et al. (2013) Environmental impacts of large-scale oil palm enterprises exceed that of smallholdings in Indonesia. *Cons Lett* 7(1):25–33.
13. Gunarso P, et al. (2013) *Oil Palm and Land Use Change in Indonesia, Malaysia and Papua New Guinea*. (Roundtable on Sustainable Palm Oil, Kuala Lumpur, Malaysia).
14. Government of Indonesia (2002) Government Regulation 34/2002 (Ministry of Forestry, Jakarta, Indonesia).
15. Burgess R, et al. (2012) The political economy of deforestation in the tropics. *Q J Econ* 127(4):1707–1754.
16. Government of Indonesia (2011) Presidential Instruction 10/2011 (Office of the President, Jakarta, Indonesia).
17. Purnomo A (2012) *Protecting Indonesia's Forests, Pros-Cons Policy of Moratorium on Forests and Peatlands, Kepustakaan Populer Gramedia* (KPG, Jakarta, Indonesia), 130 pp.
18. Government of Indonesia (2012) *REDD+ National Strategy* (REDD+ Task Force, Jakarta, Indonesia).
19. Government of Indonesia (2010) *Reducing emissions by 26% While Targeting GDP Growth of 7* (Office of the President, Jakarta, Indonesia).
20. Government of Norway (2010) *Letter of Intent on Cooperation on Reducing Greenhouse Gas Emissions from Deforestation and Forest Degradation* (Ministry of the Environment, Oslo, Norway).
21. Government of Indonesia (2011) Presidential Regulation 61/2011 (Office of the President, Jakarta, Indonesia).
22. Government of Indonesia (2013) Presidential Instruction 6/2013 (Office of the President, Jakarta, Indonesia).
23. Austin K, et al. (2014) *Indonesia's Forest Moratorium: Impacts and Next Steps* (World Resources Institute, Washington, DC).
24. Murdiyarso D, et al. (2011) *Indonesia's Forest Moratorium: A Stepping Stone to Better Forest Governance?* Working Paper 76. (CIFOR, Bogor, Indonesia).
25. Edwards DP, Laurance WF (2011) Carbon emissions: Loophole in forest plan for Indonesia. *Nature* 477(7362):33.
26. Sloan S, et al. (2012) Does Indonesia's REDD+ moratorium on new concessions spare imminently threatened forests? *Cons Lett* 5(3):222–231.
27. Sloan S (2014) Indonesia's moratorium on new forest licenses: An update. *Land Use Policy* 38:37–40.
28. Hansen MC, et al. (2013) High-resolution global maps of 21st-century forest cover change. *Science* 342(6160):850–853.
29. Margono B, et al. (2014) Primary forest cover loss in Indonesia over 2000-2012. *Nature Climate Change* 4:730–735.
30. Blackman A (2013) Evaluating forest conservation policies in developing countries using remote sensing data: An introduction and practical guide. *For Policy Econ* 34: 1–16.
31. Gaveau DLA, et al. (2009) Evaluating whether protected areas reduce tropical deforestation in Sumatra. *J Biogeogr* 36(11):2165–2175.
32. Nelson A, Chomitz KM (2011) Effectiveness of strict vs. multiple use protected areas in reducing tropical forest fires: A global analysis using matching methods. *PLoS ONE* 6(8):e22722.
33. Miteva DA, et al. (2012) Evaluation of biodiversity policy instruments: What works and what doesn't? *Oxf Rev Econ Policy* 28(1):69–92.
34. Pattanayak SK, et al. (2010) Show me the money: Do payments supply environmental services in developing countries? *Rev Environ Econ Policy* 4(2):254–274.
35. Gaveau DLA, et al. (2013) Reconciling forest conservation and logging in Indonesian Borneo. *PLoS ONE* 8(8):e69887.
36. Assuncao J, et al. (2013) *DETERring Deforestation in the Brazilian Amazon* (Climate Policy Initiative Report. PUC-Rio, Rio de Janeiro, Brazil).
37. de Leon R (2013) *Global Capital, Local Concessions* (Rights and Resources Initiative, Washington, DC).
38. Nelson GC, et al. (2001) Deforestation, land use, and property rights: Empirical evidence from Darien, Panama. *Land Econ* 77(2):187–205.
39. Wheeler D, et al. (2013) Economic dynamics and forest clearing: A spatial econometric analysis for Indonesia. *Ecol Econ* 85:85–96.
40. Ferretti-Gallon K, Busch J (2014) *What Drives Deforestation and What Stops It? A Review of Spatially Explicit Econometric Studies* (Center for Global Development, Washington, DC).
41. VanWey LK, et al. (2007) Household demographic change and land use/land cover change in the Brazilian Amazon. *Popul Environ* 28(3):163–185.
42. Weinhold D, Reis E (2008) Transportation costs and the spatial distribution of land use in the Brazilian Amazon. *Glob Environ Change* 18(1):54–68.
43. Maron M, et al. (2013) Calculating the benefit of conservation actions. *Cons Lett* 6(5): 359–367.
44. Luttrell C, et al. (2014) The political context of REDD+ in Indonesia: Constituencies for change. *Environ Sci Policy* 35:67–75.
45. Foley JA, et al. (2011) Solutions for a cultivated planet. *Nature* 478(7369):337–342.
46. Smith P, et al. (2013) How much land-based greenhouse gas mitigation can be achieved without compromising food security and environmental goals? *Glob Change Biol* 19(8):2285–2302.
47. Nelson GC, et al. (2014) Climate change effects on agriculture: Economic responses to biophysical shocks. *Proc Natl Acad Sci USA* 111(9):3274–3279.
48. Rudel TK, Defries R, Asner GP, Laurance WF (2009) Changing drivers of deforestation and new opportunities for conservation. *Conserv Biol* 23(6):1396–1405.
49. van der Werf GR, et al. (2009) CO_2 emissions from forest loss. *Nat Geosci* 2:737–738.
50. Baccini A, et al. (2012) Estimated carbon dioxide emissions from tropical deforestation improved by carbon-density maps. *Nature Climate Change* 2:182–185.
51. Edenhofer O, et al. (2014) *Summary for Policymakers. 5th Assessment Report* (Working Group III, Intergovernmental Panel on Climate Change, Geneva, Switzerland).
52. Busch J, Grantham H (2013) Parks vs. Payments: Reconciling divergent policy responses to biodiversity loss and climate change from tropical deforestation. *Environ Res Lett* 8:034028.
53. Wunder S (2013) When payments for environmental services will work for conservation. *Cons Lett* 6(4):230–237.
54. Libecap G (2013) Addressing global environmental externalities: Transaction costs considerations. *J Econ Lit* 52(2):424–479.
55. Ministry of Forestry (2010) *Timber Concessions, Logging Concessions, and Palm Oil Concessions* (Forestry Planning Directorate General, Jakarta, Indonesia).
56. Minnemeyer S, et al. (2009) *Interactive Atlas of Indonesia's Forests* (World Resources Institute, Washington, DC).
57. Naidoo R, Iwamura T (2007) Global-scale mapping of economic benefits from agricultural lands: Implications for conservation priorities. *Biol Conserv* 140(1-2):40–49.
58. IIASA/FAO (2012) *Global Agro-Ecological Zones (GAEZ v3.0)* (IIASA, Laxenburg, Austria and FAO, Rome, Italy).
59. FAO (2014) *FAOSTAT Database* (Food and Agriculture Organization of the United Nations, Rome, Italy).
60. Jarvis A, et al. (2008) *Hole-Filled Seamless SRTM Data V4 International Center for Tropical Agriculture* (CIAT, Palmira, Colombia).
61. NGA (2000) *Vector Smart Map (VMap) Level 0* (National Geospatial-Intelligence Agency, Bethesda, MD).
62. Cairns MA, et al. (1997) Root biomass allocation in the world's upland forests. *Oecologia* 111(1):1–11.
63. FAO/IIASA/ISRIC/ISSCAS/JRC (2008) *Harmonized World Soil Database (version 1.0)* (FAO, Rome/IIASA, Laxenburg, Austria).
64. Wahyunto, et al. (2003) *Peatland Distribution and Carbon Content in Sumatera, 1990–2002* (Wetlands International, Ede, The Netherlands).
65. Wahyunto, et al. (2004) *Peatland Distribution Area and Carbon Content in Kalimantan, 2000–2002* (Wetlands International, Ede, The Netherlands).
66. Wahyunto, et al. (2006) *Peatland Distribution, Area and Carbon Content in Papua, 2000–2001* (Wetlands International, Ede, The Netherlands).
67. Hoojier A, et al. (2010) Current and future CO_2 emissions from drained peatlands in Southeast Asia. *Biogeosci* 7:1505–1514.
68. Guryan J (2004) Desegregation and black dropout rates. *Am Econ Rev* 94(4):919–943.
69. Angrist JD, Pischke J-S (2009) *Mostly Harmless Econometrics* (Princeton Univ Press, Princeton, NJ).
70. Resosudarmo BP, et al. (2009) *Implementation of the IRSA-Indonesia5* (Australia National Univ, Canberra, Australia).

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