Community forest management in Indonesia: avoided deforestation in the context of anthropogenic and climate complexities

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Abstract

Community forest management has been identified as a win-win option for reducing deforestation while improving the welfare of rural communities in developing countries. Despite considerable investment in community forestry globally, systematic evaluations of the impact of these policies at appropriate scales are lacking. We assessed the extent to which deforestation has been avoided as a result of the Indonesian government's community forestry scheme, Hutan Desa (Village Forest). We used annual data on deforestation rates between 2012 and 2016 from two rapidly developing islands: Sumatra and Kalimantan. The total area of Hutan Desa increased from 750 km^2 in 2012 to 2,500 km^2 in 2016. We applied a spatial matching approach to account for biophysical variables affecting deforestation and Hutan Desa selection criteria. Performance was assessed relative to a counterfactual likelihood of deforestation in the absence of Hutan Desa tenure. We found that Hutan Desa management has successfully achieved avoided deforestation overall, but performance has been increasingly variable through time. Hutan Desa performance was influenced by anthropogenic and climatic factors, as well as land use history. Hutan Desa allocated on watershed protection forest or limited production forest typically led to a less avoided deforestation regardless of location. Conversely, Hutan Desa granted on permanent or convertible production forest had variable performance across different years and locations. The amount of rainfall during the dry season in any given year was an important climatic factor influencing performance. Extremely dry conditions during drought years pose additional challenges to Hutan Desa management, particularly on peatland, due to increased vulnerability to fire outbreaks. This study demonstrates how the performance of Hutan Desa in avoiding deforestation is fundamentally affected by biophysical and anthropogenic circumstances over time and space. Our study improves understanding on where and when the policy is most effective with respect to deforestation, and helps identify opportunities to improve policy implementation. This provides an important first step towards evaluating the overall effectiveness of this policy in achieving both social and environmental goals.

Keywords: community forest management; Hutan Desa; impact evaluation; Indonesia; peatland; spatial matching

1 Introduction

Much of the world's biodiversity and terrestrial carbon is found in the remaining forests of developing countries, some of which are subject to high rates of deforestation and forest degradation (Hosonuma *et al.* 2012; Sloan & Sayer 2015). Deforestation contributes substantially to global greenhouse-gas emissions and consequently to climate change (Harris *et al.* 2012). At the same time, many people living in or close to these forests are highly dependent on forest resources and their livelihoods are threatened by deforestation and non-sustainable forest use (Sunderlin *et al.* 2005). Governments and international funding organizations are therefore seeking solutions to conserve forest resources and improve the welfare of local communities, while recognising indigenous forest rights (Persha *et al.* 2011). Community forest management programs have emerged as a popular strategy, with many developing nations at various stages of developing and implementing policies and trial projects (Resosudarmo *et al.* 2014; Rasolofoson *et al.* 2015, 2016). An estimated 4 million km^2 of land is being considered as community forest land in countries such as Indonesia, Madagascar, Bolivia, Colombia and Peru (Sunderlin *et al.* 2008).

Despite considerable investment in community forest programs globally, systematic evaluation of the impact of these policies at a landscape scale are lacking (Bowler *et al.* 2012), especially compared to studies investigating the effectiveness of protected areas in reducing deforestation. Impact evaluation studies of protected areas have used statistical matching to control for confounding factors, such as accessibility and agriculture productivity, to ensure that areas compared with and without the intervention of interest have similar baseline characteristics (Joppa & Pfaff 2010; Andam *et al.* 2013; Ferraro *et al.* 2013). In contrast, there are few examples of statistical matching applied to evaluations of community forestry (e.g. Somanathan *et al.* 2009; Rasolofoson *et al.* 2015, 2016; Wright *et al.* 2016). Additionally, previous studies on the effects of community forestry or other forest protection schemes in reducing deforestation have usually employed accumulated deforestation data over several years (Brun *et al.* 2015; Rasolofoson *et al.* 2015), which can overlook variability in performance at fine temporal resolutions, such as the impact of extreme climate events.

Indonesia is one of the most biodiverse countries in the world and has several types of government-approved community forestry schemes that are implemented in both primary and secondary natural forest. Indonesia also has high rates of forest loss (Abood *et al.* 2015) primarily due to agricultural expansion. The area of large-scale industrial plantation concessions has doubled since the early 2000's (Santika *et al.* 2015; Gaveau *et al.* 2016b). Complicated forest tenure systems, unclear legal status of customary land tenure, and vested interests from government and the private sector have undermined efforts to curb high deforestation rates (Brockhaus *et al.* 2011). This situation has led to the land rights of smallholders and local communities to be largely ignored by large-scale investors, with land-use conflicts being increasingly prevalent (Obidzinski *et al.* 2012; Abram *et al.* 2016); a pattern that is common in other tropical countries (e.g. De Oliveira 2008; Araujo *et al.* 2009).

Recognising the apparent success of community forest schemes in other countries, the government of Indonesia has recently announced an ambitious plan to allocate some 12.7 million hectares of land to marginalized communities between 2015 and 2019 under the Social Forestry

Initiative (RI 2014; MEF 2016a). The areas that have been allocated and proposed for social forestry are described in the Social Forestry Indicative Maps (PIAPS). Currently about 31% of the total PIAPS area is located on the island of Sumatra and about 29% in Kalimantan (equating to an area of 35,000 and 33,000 km^2, respectively). One scheme that has been put forward is *Hutan Desa* (HD) or Village Forest. The first HD was granted in Sumatra in 2009 and in Kalimantan in 2011, and the 2,500 km^2 that has been allocated to date has typically been granted in watershed protection forest (*Hutan Lindung*) and production forest (*Hutan Produksi*) (MEF 2016a).

HD aims to improve the social welfare and forest use rights of marginalized communities, by allowing forest to be managed communally through the authority of a village head following license approval by the central government (Myers & Ardiansyah 2014). The scheme has been advocated as a first step towards securing land tenure and resolving conflicts between local communities and forest concession companies (e.g. logging, timber or oil palm plantation), thus providing a pre-condition to REDD+ projects (Akiefnawati *et al.* 2010; Atmadja *et al.* 2014; Resosudarmo *et al.* 2014). There have been several small scale studies of the performance of HD and other community forestry management schemes in Indonesia. These studies, however, have been focussed on sites with long-term partnerships with non-governmental organizations (NGOs) (Akiefnawati *et al.* 2010; Feintrenie & Martini 2011; Intarini *et al.* 2014; De Royer *et al.* 2015). As such these studies represent a partial, and possibly biased, picture of the effectiveness of community forestry. The key lessons emerging have been that effectiveness is determined by multifaceted socioeconomic and political factors, the motivation of the local communities, and support from external organizations (Feintrenie & Martini 2011; Rianawati 2015; Sahide *et al.* 2016). Biophysical factors are likely to also influence the effectiveness of HD, and these are likely to vary spatially and temporally.

In addition to pressure from agriculture and problems with a weak land tenure system, forest management in Indonesia is further challenged by a changing climate, which has had major impact on the frequency and intensity of fires, and consequently there is a growing risk of wildfire-related deforestation (Langner & Siegert 2009). Under global warming, Indonesia is projected to experience significant changes in rainfall patterns, with substantial decreases in rainfall in coming years (Lestari *et al.* 2014) and increased frequency of extreme El Niño events (Cai *et al.* 2014). Therefore, identifying the likely performance of HD under prolonged dry conditions will further inform appropriate regional climate change adaptation measures.

This study aims to assess the relative performance of HD in avoiding deforestation in Indonesia. Our study covered the islands of Sumatra and Kalimantan (1 million km^2 total extent), with 2,500 km^2 of total HD area granted between 2009 and 2015. We extended a standard matching method (Dehejia & Wahba 2002) controlling for variables that could confound the analysis of effectiveness (such as land use history, accessibility, agricultural productivity and seasonal rainfall) and characteristics that influence whether sites are granted HD licences. We assessed the performance of HD based on a counterfactual analysis of the likelihood of deforestation in the absence of HD tenure.

2 Materials and methods

2.1. Study area and unit of analysis

Our study area covered the islands of Sumatra (470,000 km²) and Kalimantan (530,000 km²), the Indonesian portion of the island of Borneo (Fig. 1). Land use in these islands is jurisdictionally categorized into two broad classes: Forest Estate or *Kawasan Hutan* and Non-forest Estate or *Area Penggunaan Lain* (APL) (Fig. 1 and Table 1). Forest Estate is designated by the government to be permanently used for forestry and conservation purposes and under the authority of the Ministry of Environment and Forestry (MEF). This can contain both forested and deforested areas, including protected areas (PA, e.g. national parks, wildlife reserves, nature reserves), watershed protection forest or *Hutan Lindung* (HL), and three types of production forest: limited production forest or *Hutan Produksi Terbatas* (HPT), permanent production forest or *Hutan Produksi Tetap* (HP), and convertible production forest or *Hutan Produksi Konversi* (HPK). HP can be converted to plantations, but ought to remain for forestry uses (e.g. industrial timber plantation), whereas HPK can be cleared for agricultural purposes. Because land clearing is permitted in both HP and HPK, we categorized these as one group, namely HPTK. Non-forest Estate (APL) is land outside the Forest Estate and includes both forested lands (e.g. private forest, forest garden) and non-forested lands (e.g. settled areas, road network, and agricultural lands) (Budiharta *et al.* 2014). HD is typically granted on Forest Estate (HL, HPT, and HPTK) and rarely granted on APL.

We focussed on measuring the impact of HD tenure in avoiding deforestation in intact natural forest, i.e. 80-100% forest cover (Budiharta *et al.* 2014). About 65% of the HD area in Sumatra and Kalimantan had been granted in intact forest, and the remaining portion had been granted in degraded forest (including lightly and moderately degraded forest; 40-80% forest cover) or highly degraded land (0-40% forest cover) (Fig. A1 in Appendix). Thus, our study measured primarily the impact of HD on the conversion of intact forest to degraded forest.

As the spatial unit of the analysis, we used a grid cell with a spatial resolution of 1×1 km², compared to an average area of the HDs analysed of 25 km² (range 1.2-146.9 km²). We assessed the performance of HDs in avoiding deforestation in each island annually between 2012 and 2016. The first HD in Sumatra was granted in 2009 (in Lubuk Beringin village in Jambi province), and by 2010 only two additional HDs had been granted on the island. Due to small number of HDs , we excluded the analysis for 2010 and 2011. There were subsequently 26, 26, 36, 53 and 60 HDs assessed annually between 2012 and 2016, respectively (equating to a total HD area of 634, 634, 863, 1,134 and 1,317; a minimum area of 1.2 km², and with a total intact forest area of 468, 454, 613, 762 and 839 km², respectively). The first HD in Kalimantan were granted in 2011 and the number of HD assessed each year between 2012 and 2016 were 5, 11, 14, 30 and 33 (equating to a total HD area of 144, 302, 544, 1,069 and 1,195; a minimum area of 3.5 km², and with total intact forest area of 92, 114, 276, 599 and 576 km², respectively). We employed 2010 as the baseline year for the deforestation analysis.

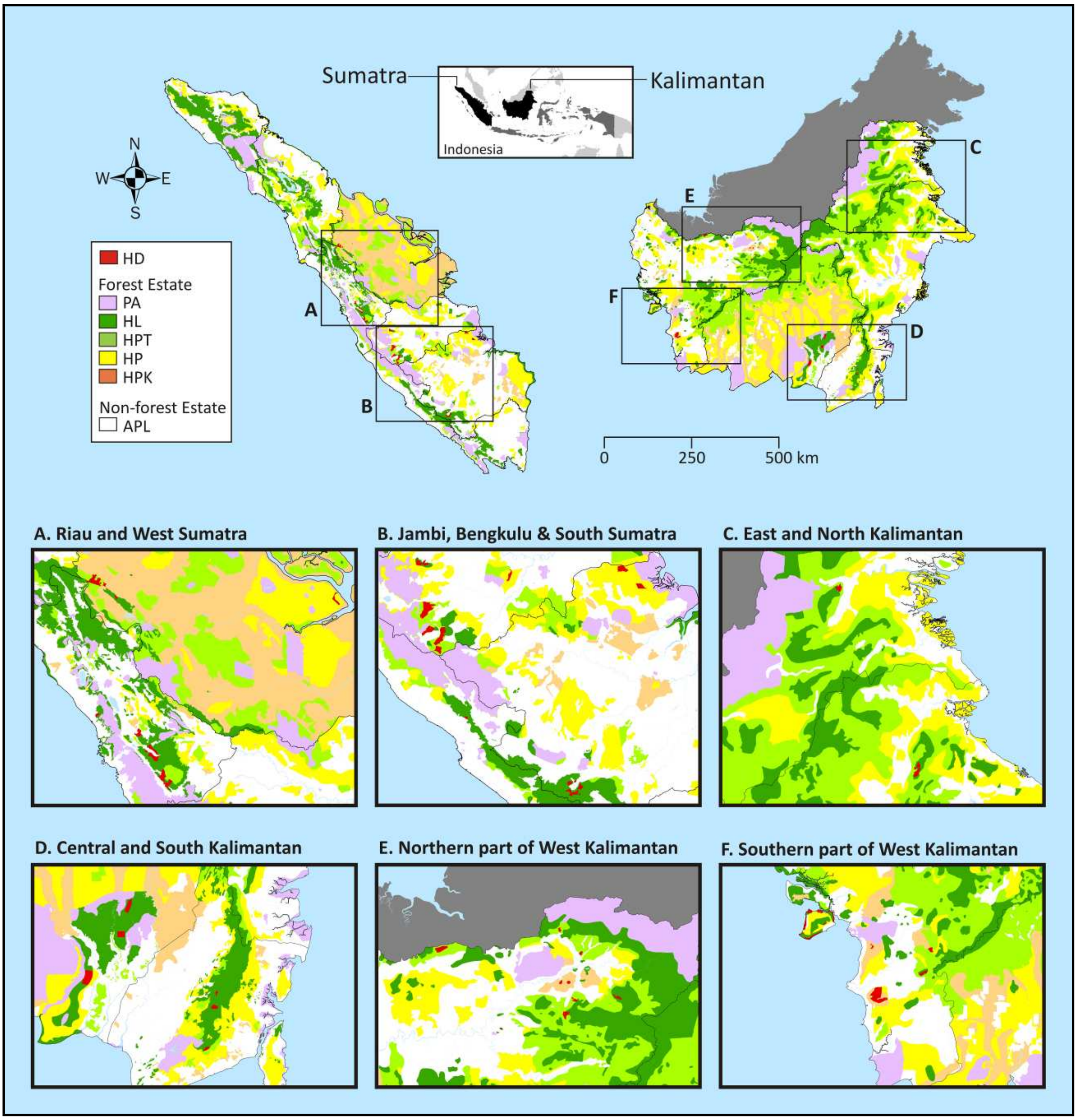

Fig. 1. Area currently allocated to *Hutan Desa* (HD), Forest Estate: strict protected areas (PA), watershed protection forest (HL), limited production forest (HPT), permanent production forest (HP), convertible production forest (HPK), and Non-forest Estate (APL), in Sumatra and Kalimantan. The main HD areas in Sumatra include: (A) Riau and West Sumatra provinces, and (B) Jambi, Bengkulu and South Sumatra provinces. The main HD areas in Kalimantan include: (C) East and North Kalimantan provinces, (D) Central and South Kalimantan provinces, (E) Northern part of West Kalimantan province, and (F) Southern part of West Kalimantan province. Black lines indicate provincial boundaries.

Table 1. (a) Description of land use types assessed in this study: village forest (HD), Forest Estate, including watershed protection forest (HL), limited production forest (HPT), permanent (HP) or convertible production forest (HPK) (namely HPTK), and Non-forest Estate (APL), with (b) the total area for each land use through time, and (c) forest area within each land use (based on combining the Global Forest Change data (Hansen *et al.* 2013, 2016) and spatial boundaries of natural forest data (Margono *et al.* 2014)). The value inside the parenthesis in (c) denotes the proportion of remaining forest area of the associated land use in the island. Description of protected areas (PA) is provided for comparison (shaded).

Land use	Abbreviation	(a) Descripton	**(b) Area** in km^2				**(c) Natural forest area** in km^2 (% of total land use area)			
			Sumatra		**Kalimantan**		**Sumatra**		**Kalimantan**	
			In 2012	In 2016	In 2012	In 2016	In 2012	In 2016	In 2011	In 2016
Village forest *(Hutan Desa)*	HD	Consists of 60 HDs in Sumatra granted from 2009-2015 and 33 HDs in Kalimantan granted from 2011-2015.	634	1,317	144	1,195	540 (85.2%)	1,015 (77.1%)	114 (79.2%)	755 (63.2%)
Forest Estate										
Watershed protection forest *(Hutan Lindung)*	HL	Forests that are protected primarily to maintain hydrological systems and prevent floods and landslides.	54,667	54,230	69,473	68,753	37,022 (67.7%)	36,019 (66.4%)	58,710 (84.5%)	57,947 (84.3%)
Limited production forest *(Hutan Produksi Terbatas)*	HPT	Production forest with limited rights (i.e. land clearing is prohibited).	38,166	38,015	112,782	112,611	15,305 (40.1%)	12,669 (33.3%)	90,727 (80.4%)	89,554 (79.5%)
Permanent production forest (HP) or convertible production forest (HPK) *(Hutan Produksi Tetap dan Hutan Produksi Konversi)*	HPTK	Production forest where land clearing is permitted. HP can be converted to plantations, but ought to remain as forest, whereas HPK can be cleared for agricultural purposes.	116,497	116,410	160,887	160,730	24,758 (21.3%)	20,062 (17.2%)	68,079 (42.3%)	63,355 (39.4%)
Protected areas	PA	Includes terrestrial Taman National (*National Park*), Cagar Alam (*Nature Reserve*), Suaka Margasatwa (*Wildlife Reserve*), Taman Hutan Raya (*Grand Forest Park*), and Taman Wisata Alam (*Nature Recreational Park*).	46,969	46,969	49,814	49,814	38,134 (81.2%)	37,762 (80.4%)	37,401 (75.1%)	37,123 (74.5%)
Non-forest Estate										
Areal Penggunaan Lain	APL	Area outside Forest Estate and includes both forested lands (e.g. private forest, forest garden) and non-forested lands (e.g. settlements, road network, and agricultural lands)	177,815	177,807	139,130	139,128	9,606 (5.4%)	8,175 (4.6%)	24,190 (17.4%)	19,503 (14.0%)

2.2 Data

Deforestation rates were derived from the Global Forest Change (GFC) dataset (Hansen *et al.* 2013, 2016), which describes the area of forest loss annually at the resolution of a 30×30 m^2 Landsat pixel between 2010 and 2016. The dataset does not distinguish between the loss of natural forest and the loss of tree plantations. Therefore, to restrict our analysis to the loss on natural forest, we used the extent of natural forest in 2010. This information was derived from Margono *et al.* (2014) (which was also derived from Landsat images) where natural forest comprised mature natural forest cover that had not been completely cleared in the last 30 years. The global forest dataset was then restricted to the extent of natural forest in 2010, and we analysed forest cover change annually within this area between 2010 and 2016 at a spatial resolution of 1×1 km^2. We also compared the extent of natural forest obtained for 2015 with the data provided by the Indonesian government (MEF 2016b; also based on Landsat imagery) for the same year and found high levels of agreement between the two datasets for Sumatra and Kalimantan. The overall agreement was 95.9% (with true positive rate 95.5% and true negative rate 95.8%) and Kappa index 86%.

We controlled for potentially confounding variables in the assessment of the performance of HD in terms of both selection of parcels for treatment and the outcome being measured (Table 2). For this we included both static and dynamic variables. Static variables are considered to be fixed or slowly changing through time, and dynamic variables are rapidly changing or fluctuate on an annual basis.

The static variables included those representing: (a) HD assignment, (b) socio-political factors, (c) accessibility, (d) agriculture productivity/value, and (e) land use history. HDs are granted a licence according to selection criteria and this introduces a non-random assignment of cells for treatment. To control for this we determined the dominant legalized land use zone (*LZONE*) of each parcel and the presence of a non-governmental organisation partnership (*NGO*). HD are typically granted in Forest Estate, either in the protection zone (HL) or the production zone (HPT or HPTK) (MEF 2016a). NGO partnerships is a critical criteria for selecting areas to be granted HD (Sahide 2011). We used provincial boundaries (*PROV*) as proxy for socio-political factors since decentralization of government functions to provincial levels has been identified as a key driver of deforestation, land degradation and conversion of forest to agriculture in Indonesia (Resosudarmo 2004; Moeliono & Limberg 2012). We used elevation (*ELEV*), slope (*SLOPE*), and proximity to large cities or arterial roads (*CITY)* as proxies for accessibility. Forest closer to roads and located at lower elevation and flat terrain tend to be cleared first because it is more accessible (Kinnaird *et al.* 2003; Linkie *et al.* 2004) and because high quality timber is also mostly found at low elevations (Laumonier 1997). We used long-term seasonal rainfall patterns (*DRY* and *WET*) and location on peat soil (*PEAT*) as proxies for agriculture productivity/value. The amount of rainfall during the dry and wet seasons is the most important factor affecting agricultural productivity in Indonesia (Oldeman & Frere 1982), therefore can potentially drive conversion of forest to agricultural land. Soil condition, such as soil type (peat or mineral soil) is also an important factor driving forest conversion to agriculture (Carlson *et al.* 2013). Additionally, forests located on peat soil are more susceptible to wildfire-induced deforestation than those located on mineral soil (Van der Werf *et al.* 2008). We used deforestation rates one year prior to HD tenure

(*DEFIN*), distance to agricultural settlements or transmigration areas mostly developed before 2000 (*SETT*) and distance to old established oil palm plantations, i.e. established between 1990 and 2005 (*OPOLD*) as proxies for land use history. Deforestation rates one year prior to HD tenure provide a baseline to control for initial conditions that may bias impact estimates. The decline in forest area in Kalimantan had been partly attributed to an increase in agricultural area, much of which is linked to old-established transmigration sites (Dennis & Colfer 2006). Studies from Sumatra and Kalimantan also indicate that fire-induced deforestation has occurred within close proximity to transmigration areas or oil palm plantations (Stolle *et al.* 2003; Carlson *et al.* 2013).

The dynamic variables included (a) climate, and (b) recent agricultural expansion. Extreme climate, such as prolonged dry months, can cause fire-induced deforestation (Field *et al.* 2009). We used the monthly mean rainfall during the dry season in a given year (May to September) (*TDRY*) and the monthly mean rainfall during the wet season in a given year (November to March of the following year) (*TWET*) as proxies for climate conditions. We used distance to newly established oil palm plantations, i.e. established after 2005 (*OPNEW*) as a proxy for recent agricultural development. To account for changes in patterns of establishment of old established oil palm plantations (pre 2005) and recent plantations (post 2005), we distinguished between these land-cover strata in the analyses. Old established oil palm plantations, especially those located in Kalimantan, have mostly been established on already cleared, degraded lands subjected to recurrent forest fires, whereas the recently developed plantations have been increasingly established at the expense of natural forest (Gaveau *et al.* 2016b).

2.3 Analysis methodology

2.3.1 Spatial matching

A matching method using a propensity score (Dehejia & Wahba 2002) was employed to select a set of control grid cells outside HD boundaries that exhibited the same baseline characteristics as grid cells with HD tenure. These characteristics were defined based on all variables described in Table 2.

We used a non-parametric generalized boosted regression model (Friedman 2001) for binary outcomes implemented in the R-package gbm (Ridgeway *et al.* 2016) to generate the propensity scores. The model allows flexibility in fitting non-linear surfaces for predicting treatment assignment and can incorporate a large number of covariates. In various applications, this modelling approach has been shown to outperform other methods that require model selection due to its flexibility (Ogutu *et al.* 2011; Yang *et al.* 2016). Lack of flexibility would potentially bias estimates of the effectiveness of HD due to misspecification of the functional form of the relationship between the covariates and HD treatment (Santika & Hutchinson 2009) and omission of important variables (McCaffrey *et al.* 2004). The gbm package calculated the relative influence of individual variables for predicting the HD assignment according to how often the variable is selected and its ability to improve the model (Friedman & Meulman 2003). The relative influence for all variables included in the model is summed to 100, where higher value represents greater influence in predicting the model response.

Table 2. Confounding variables used to assess HD performance and whether the variables are static (i.e. vary spatially but are fixed through time) and dynamic (i.e. vary both spatially and temporally).

Static/ Dynamic	Variable	Description	Type (Scale)	Data source
Static	**HD ASSIGNMENT**			
	LZONE	Legalized land use zone	Categorical (HL, HPT, HPTK)	MEF (2016b)
	NGO	NGO involvement	Binary	PIAPS (MEF 2016a)
	SOCIO-POLITICAL			
	PROV	Provincial boundaries	Categorical	BAKOSURTANAL (National Coordinating Agency for Surveys and Mapping)
	ACCESIBILITY			
	ELEV	Elevation	Continuous (log(m))	SRTM 90m Digital Elevation Database v4.1 (Jarvis *et al.* 2008)
	SLOPE	Slope	Continuous (log(degree))	SRTM 90m Digital Elevation Database v4.1 (Jarvis *et al.* 2008)
	CITY	Distance to large cities or arterial roads	Continuous (log(km))	Provincial map, BAKOSURTANAL
	AGRICULTURE PRODUCTIVITY/ VALUE			
	DRY	Long-term monthly rainfall during dry season	Continuous (mm)	Worldclim (Hijmans *et al.* 2004)
	WET	Long-term monthly rainfall during wet season	Continuous (mm)	Worldclim (Hijmans *et al.* 2004)
	PEAT	Majority of soil type (peat versus mineral soil)	Binary	MEF (2016b)
	LAND USE HISTORY			
	DEFIN	Deforestation rates a year prior to HD tenure	Categorical (<5 ha, 5-10 ha, 10-25 ha, >25 ha)	Global Forest Change data (Hansen *et al.* 2013, 2016) and data from Margono *et al.* (2014)
	SETT	Distance to agricultural settlements and transmigration areas developed before 2000	Continuous (log(km))	MEF (2016b)
	OPOLD	Distance to old established oil palm plantations (i.e. developed between 1990 and 2005)	Continuous (log(km))	MEF (2016b); Gaveau *et al.* (2016a)

Table 2 cont.

Static/ Dynamic	Variable	Description	Type (Scale)	Data source
Dynamic (annually 2010-2015)	**CLIMATE**			
	TDRY	Monthly rainfall during the dry season	Continuous (mm)	TRMM Multi-Satellite Precipitation Analysis (TMPA) v. 7 (Huffman *et al.* 2007)
	TWET	Monthly rainfall during the wet season	Continuous (mm)	TRMM Multi-Satellite Precipitation Analysis (TMPA) v. 7 (Huffman *et al.* 2007)
	RECENT AGRICULTURE DEVELOPMENT			
	OPNEW	Distance to newly established (i.e. after 2005) oil palm plantations	Continuous (log(km))	MEF (2016b); Gaveau *et al.* (2016a)

After generating the propensity scores, we then matched the locations of HD tenure with those outside HD based on these scores using the nearest neighbour approach implemented in the R-package Matching (Sekhon 2015). Various calliper widths (i.e. between 0.1 and 0.3 with increment 0.05), of the propensity scores' standard deviations using the nearest neighbour approach were tested, and little influence on results, and so we report our analysis based on calliper width 0.2, a width previously shown to be optimal (Austin 2011; Wang *et al.* 2013). We also ensured that the categorical baseline characteristics (i.e. variables *LZONE*, *NGO*, *PROV*, *PEAT* and *DEFIN*) of the control locations were similar to the characteristics of locations with HD tenure. The matching method was applied separately for each year between 2012 and 2016. We ensured that all variables were balanced across HD and control groups in the matched dataset (Figs. A2 and A3 and Table A1). To investigate the potential leakage or displacement of deforestation outside the HD area as a result of activities within it, we selected matched controls from: 1) grid cells within a 10 km buffer from the HD boundaries, and 2) grid cells within the wider landscape outside HD area. The number of grid cells included after matching and the main characteristics of grid cells being excluded in the matched dataset is provided in Table A2 and Fig. A9, respectively.

2.3.2 The overall performance of HD

After the matched dataset was obtained, we estimated the contribution of HD in avoiding deforestation by comparing the deforestation rates in grid cells with HD tenure with the rates in control grid cells without HD tenure. A grid cell *i* within HD management *j* is considered to be effective at avoiding deforestation if the difference between the deforestation rate in the control grid cell ($C_{i,j,t}$) and the rate in the treated grid cell ($H_{i,j,t}$), i.e. $A_{i,j,t}$, where $A_{i,j,t} = C_{i,j,t} - H_{i,j,t}$, is positive. The estimate of overall effectiveness at year *t*, i.e. $\bar{A}_t$, is then obtained by fitting an ordinary least square regression with $A_{i,j,t}$ as a response and a binary variable representing the treated and the control grid cell and all variables described in Table 2 as predictors (Gelman & Hill 2007). Because our units of analyses (1×1 km² grid cells) were contained within the boundary of HD management units, they are not statistically independent. This can lead to bias in standard errors and associated confidence intervals, thus biasing inference about treatment effectiveness. To overcome this issue, we adjusted the standard errors by correcting the covariance matrix to account for different HD management clusters (White 1980). We performed separate analyses for controls located within a 10 km buffer zone and controls located within the wider non HD area. Leakage can potentially exist if the avoided deforestation rates of HD estimated from the matched controls within the buffer zone is considerably different than those estimated from the wider landscape.

To assess whether or not our estimate based on matching was robust to the possible presence of an unobserved confounder we applied a sensitivity analysis based on the principle of randomization inference (Rosenbaum 2005) and implemented in R-package rbounds (Keele 2014). Rosenbaum's approach relies on the sensitivity parameter Γ that measures the degree of departure from random assignment (in this case) of HD. In this approach, the threshold value of Γ, namely Γ_C, was calculated at the point at which hidden bias would eliminate the HD effect. A study is defined as sensitive to hidden bias or likely that the HD effect can be explained by an unobserved covariate if the value of Γ_C is close to 1, and a study is defined as robust if the value of Γ_C is large.

2.3.3 HD performance across different land use zone histories and soil types

While the value of $\bar{A}_t$ is an informative measure of the overall HD performance each year, it is also of interest how performance varies spatially. We assessed how performance varies with land use history prior to HD tenure (protection HL, limited production HPT, or convertible production HPTK) and soil type (mineral soil and peat soil). The assignment of land to different land use zones is made by the government of Indonesia accounting for landscape characteristics such as topography, slope, remoteness, timber values, and degradation status. Thus, the land use zone not only informs land use regulation, but also reflects a composite measure of biophysical characteristics. We therefore assessed different combinations of land use zone history and soil type, with the exception of HPT on peat soils as this soil type rarely supports high quality timber and therefore is rarely assigned to HPT. Peat soils located within close proximity to large cities and arterial roads are usually heavily degraded and therefore typically assigned to HPTK. Peat soils with intact forest are usually assigned to HL.

The performance of HD across different land use zone histories each year was first estimated by fitting an ordinary least squares regression model with the avoided deforestation rate ($A_{i,j,t}$) as a response and variable *LZONE* as a predictor. To further investigate the performance across different land use zone histories and soil types, we repeated a similar procedure but with variable *LZONE* and *PEAT* as predictors. We then obtained the mean avoided deforestation rates within each land use zone history and soil type, and the 95% CI for the mean. To assess how the performance of HD varied across detailed biophysical locations for each land use history (i.e. HL, HPT, and HPKT) or soil type (i.e. mineral soil and peat soil), we fitted a generalized boosted regression model with the avoided deforestation rates ($A_{i,j,t}$) as a response variable and all variables in Table 2 (excluding *LZONE* or *PEAT*) as predictors.

3 Results

3.1 The overall performance of HD

The mean avoided deforestation rates (ha/km²) within the boundary of HD in Sumatra and Kalimantan was mostly positive between 2012 and 2016 (Fig. 2). In Sumatra poor performance was observed in 2014, and in Kalimantan markedly poor performance was observed in 2015. In general HD areas appeared to perform relatively better at avoiding deforestation in Sumatra than in Kalimantan during this time period. The mean avoided deforestation rates contributed by the HDs decreased through time (Fig. 2). As a result, the total avoided deforestation (in ha) contributed by this land use (ignoring negative rates in 2014 for Sumatra and in 2015 for Kalimantan) was relatively constant (Table A3b), despite the increasing extent of HD area (Table A3a). The range of confidence intervals of the mean avoided deforestation rates tended to increase through time in both islands (Fig. 2), indicating that the performance of HD has become increasingly more variable.

Sensitivity analysis indicated that our estimate on HD performance each year based on matching was robust to the possible presence of an unobserved confounder. This was indicated by reasonably large values for the sensitivity parameter threshold Γ_C (Table A3c). The mean annual avoided deforestation for HD in Sumatra between 2012 and 2016 was similar in matched controls located within a 10 km buffer from the HD boundaries and matched controls from a wider landscape. The same trend was observed for Kalimantan (ignoring the severe El Niño in 2015) (Table A4). This suggests that leakage or displacement of deforestation to areas adjacent to the HD boundaries was minimal overall.

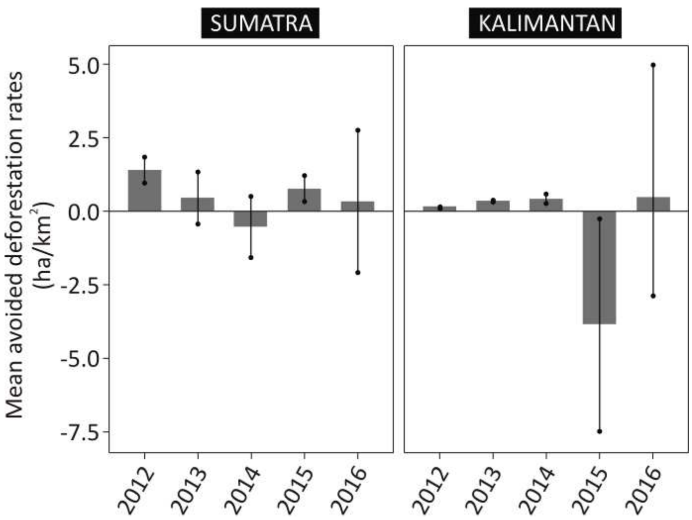

Fig. 2. The estimated mean avoided deforestation rates (ha/km²) contributed by HD in Sumatra and Kalimantan every year between 2012 and 2016, obtained through spatial matching. The vertical line denotes the 95% confidence interval (CI) for the mean.

3.2 HD performance by land use history and soil type

3.2.1 HD locations

In Sumatra, two-thirds of the intact forest area within the boundary of HD was granted on previous HPT (Fig. 3), whereas in Kalimantan more than half of the intact forest area within HD was granted on previous HL. Intact forest within the boundary of HD granted on HPTK was more common in Kalimantan than in Sumatra.

Peat forests were typically found in HD granted on HPTK in Sumatra and Kalimantan, and it was the major forest type found in this category (Fig. 3). In Kalimantan, peat forests were also found in HD on HL, constituted about half of the total area of HD on HL.

HD granted on HL or HPT located on mineral soil were mostly located at high altitudes, on steep slopes, and relatively far from oil palm plantations (Figs. A5 and A6). HD granted on HPTK on peat soil were mainly located at low altitudes and on flat terrain, and in close proximity to oil palm plantations (either old or new plantations). In Kalimantan HD granted on HPTK on peat soil were also generally located within close proximity to large cities or arterial roads, and agricultural settlements or transmigration area. HD granted on HL on peat soil in Kalimantan were also generally located at low altitude and on flat terrain, but at moderate distances to oil palm plantations, large cities or arterial roads, and agricultural settlements. This land use was also generally located in areas receiving low monthly rainfalls during both wet and dry seasons compared to HD granted on HPTK on peat soil. The amount of monthly rainfall during the dry season (May to September) in most HD on HL on peat soil appeared to be relatively low in 2014, and followed by extreme drought in 2015 due to an El Niño (Fig. A7a). The amount of monthly rainfall during the wet season in November 2014 to March 2015 in most HD on HL on peat soil was also substantially lower than in other years (Fig. A7b), suggesting that this land use had experienced prolonged drought in 2015.

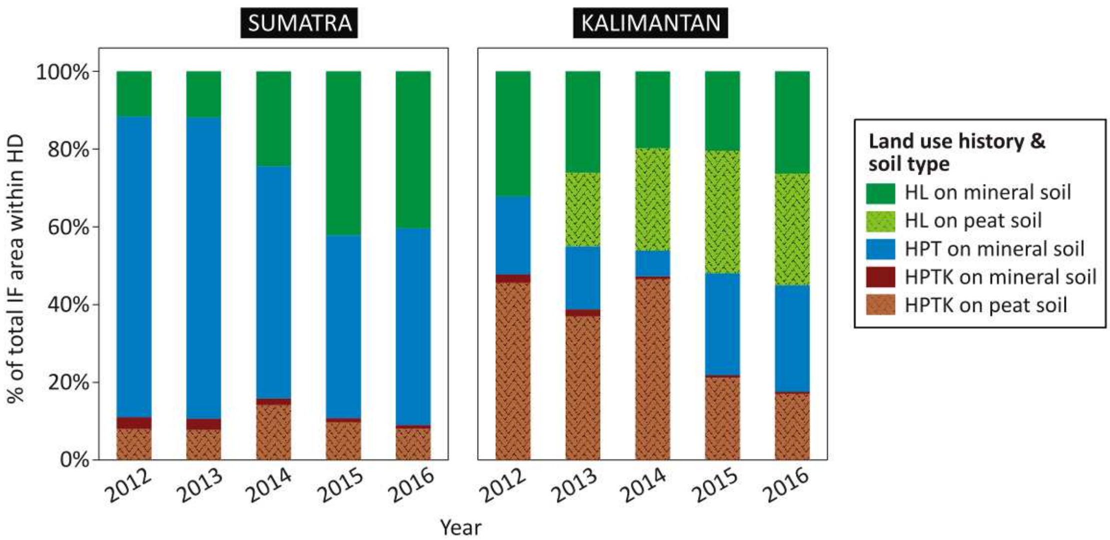

Fig. 3. The proportions of different land use histories (protection HL, limited production HPT, and permanent and convertible production HPTK) and soil types (mineral soil and peat soil) in intact forest within the boundaries of HD in Sumatra and Kalimantan.

3.2.2 HD performance across different land use histories

The performance of HD varied across different locations characterized by land use histories. In Sumatra, HDs granted on HL appeared to have moderate mean avoided deforestation rates between 2012 and 2016 (0.9 ha/km², on average), whereas for HDs on HPT the rates were milder (0.6 ha/km²) (Fig. 4). The confidence intervals for the means each year for these two land uses were also quite small, indicating that the performance were roughly similar across different HD locations within these respective zones. However, for HDs on HPTK the rates were higher than the rates for HDs on HL or HPT (1.5 ha/km²), but they fluctuated markedly across different years. In each year, the confidence intervals for the means were also substantial, indicating that performance across different HD locations on HPTK was highly heterogeneous.

Excluding observations during the extreme El Niño in 2015, we found a similar comparative performance for HDs granted on HL, HPT and HPTK in Kalimantan (Fig. 4). HDs granted on HL or HPT had moderate mean avoided deforestation rates (0.6 ha/km²), whereas HD on HPTK had slightly higher rates (0.8 ha/km²). The confidence intervals of the means for HD on HPTK were higher than HD on HL or HPT. Thus, it appeared that the performance of HD on HL or HPT was generally moderate but consistent across time and space, whereas the performance of HD on HPTK was generally higher, but also highly heterogeneous.

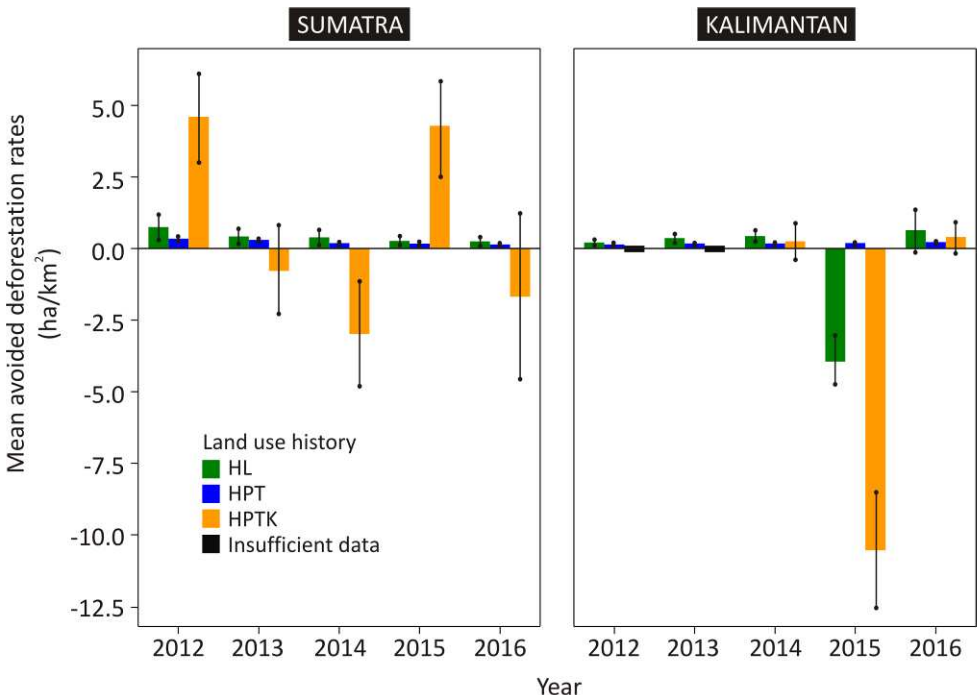

Fig. 4. The estimated mean avoided deforestation rates (ha/km²) contributed by HDs in Sumatra and Kalimantan every year between 2012 and 2016 across different land use histories (protection HL, limited production HPT, and permanent and convertible production HPTK). Vertical line indicates the 95% confidence interval (CI) for the mean. We excluded cases with insufficient samples in the matched dataset (<20).

3.2.3 Area of poor performing HDs

Generalized boosted regression models indicated how the individual variables affected the performance of HD. Based on this analysis, we inferred that HDs that had performed poorly on HPTK in Sumatra are mainly those located in area of high agriculture values, i.e. in lowland (*ELEV*<30 m), had generally high rainfalls during the wet season (*WET*>240 mm/month) and recently received relatively high rainfalls during the dry season (*TDRY*>130 mm/month). These HDs were located near to new industrial agriculture (*OPNEW*<2 km) or far from existing agriculture areas, i.e. *SETT*>15 km, *OPOLD*>20 km, and *OPNE*W>20 km (Fig. 5).

During the severe El Niño in 2015, the performance of HDs granted on HL and HPTK in Kalimantan fell drastically (Fig. 4). Poor performance appeared to occur mostly in HDs located on peat soil (Fig. 6), particularly in areas that were highly accessible (i.e. in lowland (*ELEV*<40 m), were close to large cities or major roads (*CITY*<15 km)), had high agriculture values (i.e. within proximity to agriculture settlements or transmigration areas (*SETT*<20 km) and oil palm plantations (*OPOLD*<20 km, but not too close to the new plantations (*OPNEW*>2 km)), and were vulnerable to severe drought (i.e. have low amount of long-term mean monthly rainfall during the wet season (*WET*<250 mm/month) and received extremely low amount of rain during the dry season (*TDRY*<120 mm)) (Fig. 7).

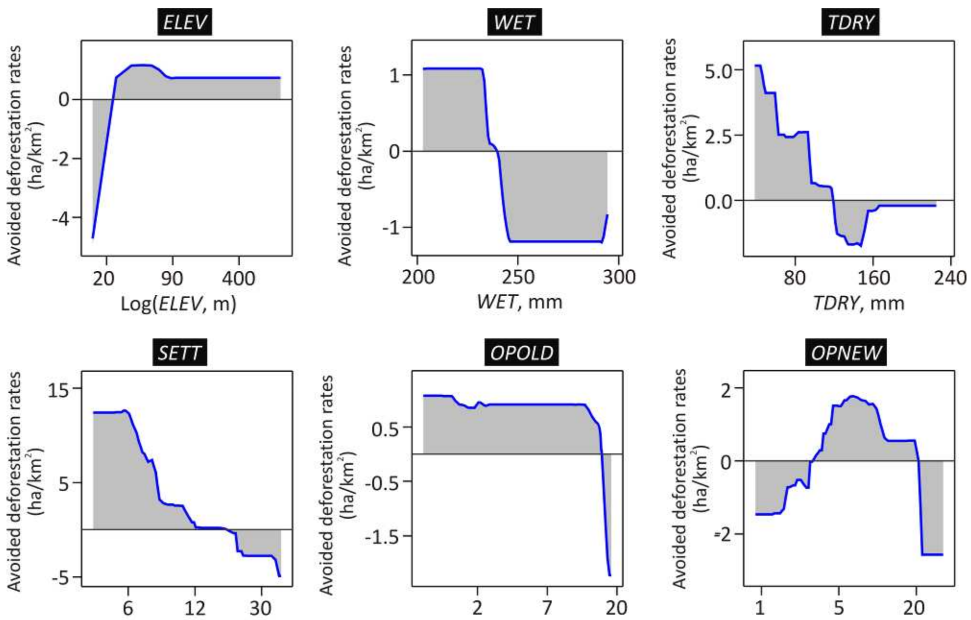

Fig. 5. The influence of individual variables on the avoided deforestation rates of HD on HPTK in Sumatra, obtained from the generalized boosted regression models analysis. Influential variables include: elevation (*ELEV*), long-term mean monthly rainfall during the wet season (*WET*), the monthly mean rainfall during the dry season (*TDRY*) in any given year, distance to agricultural settlements or transmigration areas (*SETT*), and distance to oil palm plantations: old (*OPOLD*) and new ones (*OPNEW*).

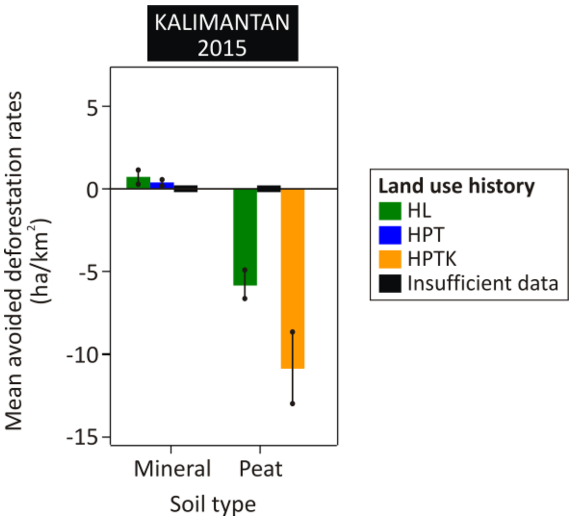

Fig. 6. The estimated mean avoided deforestation rates (ha/km²) contributed by HDs in Kalimantan in 2015 across different land use histories (protection HL, limited production HPT, and permanent and convertible production HPTK) and soil types (mineral soil and peat soil). Vertical line indicates the 95% confidence interval (CI) for the mean. We excluded cases with insufficient samples in the matched dataset (<20).

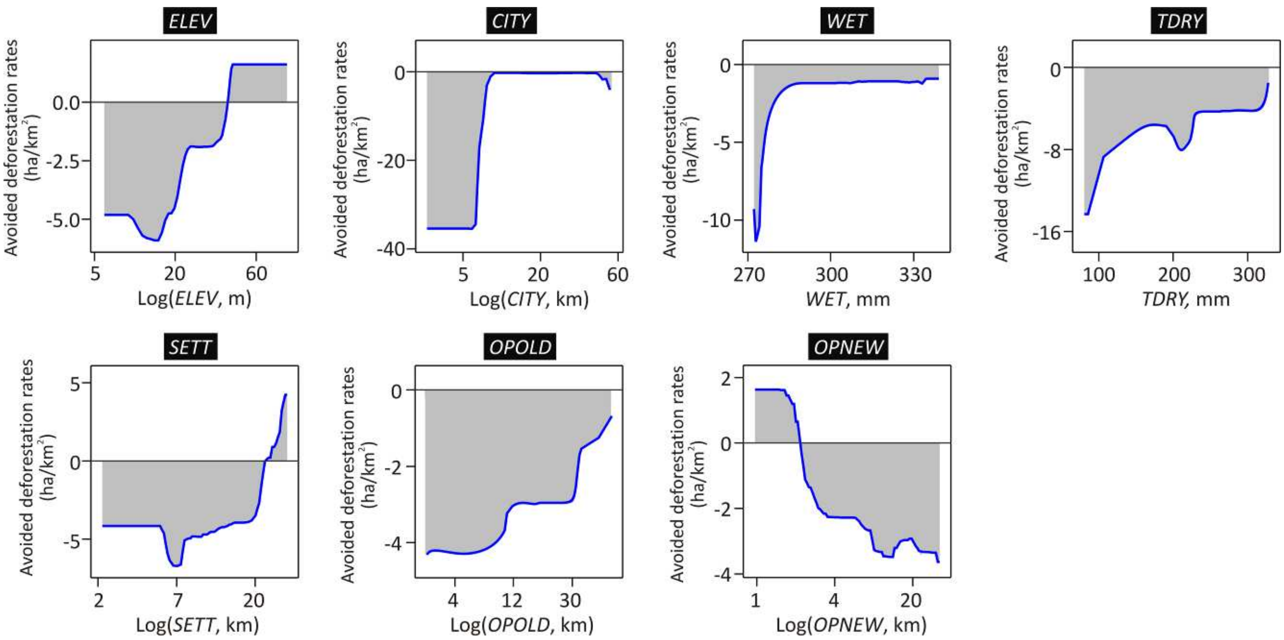

Fig. 7. The influence of individual variables on the avoided deforestation rates of HD on peat soil (HL or HPTK) in Kalimantan, obtained from the generalized boosted regression models analysis. Influential variables include: elevation (*ELEV*), distance to large cities or arterial roads (*CITY*), long-term mean monthly rainfall during the wet season (*WET*), the monthly mean rainfall during the dry season in any given year (*TDRY*), distance to agricultural settlements or transmigration areas (*SETT*), and distance to oil palm plantations: old (*OPOLD*) and new ones (*OPNEW*).

4 Discussion

Here we present the first landscape-scale analysis of the performance of community forestry tenure in abating deforestation in Indonesia, using data from the islands of Sumatra and Kalimantan. We found that community forest management under the *Hutan Desa* (HD) concept has successfully achieved avoided deforestation overall. However, the rates of avoided deforestation contributed by HDs varied across spatial and temporal scales. Avoided deforestation was moderate and consistent across different years and locations for HDs granted on HL and HPT land use classes, but for HDs granted on HPTK the rates fluctuated over time and varied markedly across different locations. This comparative performance corresponds to varying anthropogenic pressure and therefore likely also the complexity of issues associated with land use locations and histories.

HD granted on HL and HPT are generally located in areas with relatively low anthropogenic pressure (e.g. steep slopes, high altitude, and relatively far from old established agricultural plantations) (Figs. A5 and A6). HL is under the supervision of local government (previously at the regency level, but now transferred to the provincial government), and there is generally a lack of on-ground operational management and monitoring (Burkard 2009). Some areas in HPT have logging concession permits and are undergoing logging activities, whereas some areas are unoccupied and unmanaged with or without logging permits. Such idle land presents an opportunity for illegal exploitation of trees for timber (Li 2005) and anthropogenic pressure generally arises from illegal logging activities and shifting cultivation by local farmers (Peluso 1995; Resosudarmo 2004; Purwanto 2016). Lack of clarity over the boundaries of HL has posed additional issues, such as the allocation of logging permits that legalize timber extraction in HL under regional autonomy laws in the late 1990s (McCarthy 2002). The establishment of HD on HL and HPT appears to provide institutional support in terms of tenure clarity and appears to reduce illegal logging and shifting cultivation (Limberg *et al.* 2005). Because anthropogenic pressure is generally low in HL and HPT, a reduction in deforestation rate could be expected to be moderate and consistent across different locations with the introduction of HD tenure.

In contrast, HPTK are generally located in areas with intense anthropogenic pressure (e.g. on lowlands, more attractive to logging either legally or illegally, near to old established agriculture, large cities, and major roads) (Figs. A5 and A6), where competition for land is fierce (Sahide & Giessen 2015) and typically involves a complex network of actors and stakeholders (Santoso 2016). HPTK has also been typically assigned to degraded peat soil, which often experience recurrent fires, particularly in extreme dry seasons. Our study suggests that HDs on HPTK can generally perform higher, on average, than HDs on HL or HPT, provided these areas experience common anthropogenic pressures that the scheme is designed to mitigate, such as in our case study in Sumatra. However, because pressure from human activities is intense in HPTK, and the issues associated with this land use can be highly intricate, the introduction of HD can yield a wide variety of outcomes across different years and locations. Extreme events can be particularly challenging, as demonstrated in our study for Kalimantan during a severe El Niño in 2015. In this year, HD on HPTK was largely unable to mitigate the overwhelming pressure, which led to a devastating outcome. Poor performances of HDs on HPTK have been particularly prevalent on peat soil, and in areas that were highly accessible and within proximity to market, or in areas where agricultural activities have existed for a long time, such as those where old established plantations (developed before 2005) were in close proximity (Fig. 7).

Our findings add to the emerging consensus showing forest conservation policies that integrate local communities perform better, in general, in zones with higher anthropogenic pressure than in zones with lower pressure (Ferraro *et al.* 2013; Nolte *et al.* 2013; Pfaff *et al.* 2014). A similar pattern was found in the Brazilian Amazon, where protection scheme that permits some local deforestation on sites with high clearing pressure had more avoided deforestation than from the scheme that bans clearing on sites further from deforestation pressure (Pfaff *et al.* 2014). However, our findings also suggest that in zones with high anthropogenic pressure, the effect of such policies can be highly heterogeneous across time and space (Blackman 2015). In zones with lower anthropogenic pressure, conversely, the positive effect of policy may be moderate on average, but the outcome is more homogenous. Understanding the returns, risk and uncertainties in the avoided deforestation across different zones is imperative, especially when designing portfolio of areas for community forestry investments. We should avoid the trap of assuming that community forestry in areas of high anthropogenic pressure is always effective, as our study demonstrates the risk of failing is inevitably high, and such extreme events such as the 2015 El Niño drought are likely to occur more frequently in the future. An optimal investment should consider a portfolio that aims to maximize outcome while minimizing the risk of failing (Rubinstein 2002). This implies distributing community forestry allocations across different zones displaying varying levels of anthropogenic pressure, rather than issuing licenses within a single zone type, but with additional support for the cases where benefits can be high to help protect them in years of extreme pressure.

We found no evidence of leakage in Indonesia HD: avoided deforestation was similar whether rates were estimated from controls near to HD boundaries or using controls from the wider landscapes. However, Baylis *et al.* (2013) indicate that the impact of forest protection (strict protected areas) across major Indonesian islands can either be positive or negative, i.e. deforestation rates can either decrease or increase, up to 40 km from park boundaries. There is therefore some room for leakage in the HD system even if it is not yet detectable. Baylis *et al.* found that leakage tends to be strongly negative in Sumatra, but mildly positive in Kalimantan, which, if mirrored in HD areas, would explain why the avoided deforestation effect of HDs found in our study for Sumatra were generally higher than those for Kalimantan. How the performance of HD is affected by leakage across various distances from the HD boundaries will require further investigations.

Climatic variables, particularly the amount of rainfall during the dry period in drought years significantly reduced HD performance in abating deforestation, particularly those located on peatland and where the surrounding area has been highly degraded and recurrent fires had occurred. This was evident during the severe El Niño conditions in 2015, when the rates of deforestation escalated in HD granted on HL in intact forest on peat soil (Fig. 4) located in extremely dry areas (<100 mm per month) in Kalimantan (Fig. 7). These areas, within the boundary of HD that performed relatively well during non-drought years, experienced deforestation most likely induced by fires during 2015. The combined effects of El Niño-induced droughts and land-use change have dramatically increased the frequency of forest fire in humid tropical regions, particularly in Southeast Asia and South America, over the last decades (Barlow & Peres 2004; Wooster *et al.* 2012). Indonesia is expected to experience more intense droughts in the future due to global warming (Trenberth *et al.* 2014; Nur'utami & Hidayat 2016). Hence, climate change both at the global level and as a direct result of regional deforestation will pose additional challenges to the management of HD located on degraded peatland. This not only impacts deforestation rates, but also attempts to mitigate land use CO_2 emissions. This suggests that increased effort, technical capacity, and financial assistance will be required to maintain and improve the performance of these HDs. Managing and restoring peatland is a highly complex task (Holden 2005; Erwin 2009; Wijedasa *et al.* 2016). As a country with the largest share of tropical peat carbon globally (65%; Page *et al.* 2011), Indonesia recognizes these challenges and the government has recently established a peat restoration agency to tackle peat management issues. The success of HD management on peatland will require close cooperation with this agency in terms of capacity building and funding.

In this study we performed a detailed analysis of avoided deforestation rates on an annual basis. Previous studies looking at the effect of community forestry or other forest protection schemes in reducing deforestation have applied longer time intervals, i.e. aggregated deforestation data over several years (Brun *et al.* 2015; Rasolofoson *et al.* 2015). Longer time intervals may provide a reliable inference about community forestry performance under the condition that threats to deforestation are predominantly anthropogenic and largely consistent over the entire interval range. In the occurrence of extreme events, such as severe climate fluctuations or change, the effectiveness of community forestry can be overwhelmed, and this can potentially bias the performance downward overall. Our annual analyses also provide a clear depiction of the trend in community forestry performance across zones of different anthropogenic pressure through time. As demonstrated in this study, the performance of HD on HPTK fluctuated markedly each year between 2012 and 2016 (Fig. 4), and this may reflect the varying annual anthropogenic intensity over the entire landscape (both inside and outside HD tenure), either driven by political, social, and economical factors occurring in that particular year. This kind of insight could have possibly been overlooked if we had used an aggregated time interval.

Our analysis applied a spatial matching approach to assess the performance of HD tenure in avoiding deforestation. Other methods exist to evaluate the impact of land use policies, and this includes the Difference-in-Differences (DID) approach (Abadie 2005), which aims to asses performance by comparing the outcome of interest before and after policy implementation (Blackman 2013; Miteva *et al.* 2015; Shah & Baylis 2015). Despite the attractiveness, a DID approach is impractical to be applied to our HD data. The DID approach essentially requires matching locations inside and outside HD tenure, before and after the issuance of HD licences, based on a set of baseline variables. That is, this method requires matching locations with similar characteristics over time and space (Stuart *et al.* 2014). Using the existing spatial matching approach, about a third of the HD data had to be excluded from the analysis due to the absence of matched locations outside HD tenure (Table A2). With DID approach, we expected that the number of matched locations can even be smaller than using the spatial matching, and this can potentially have an impact on the reliability of our analysis and inference.

Although the term of Hutan Desa literally stands for village forest, its scope includes not only conservation of forest ecosystems, but also how well the forest is able to function and provide welfare and livelihoods to communities in surrounding areas (Bae *et al.* 2014). In line with the recent agenda of the Sustainable Development Goals initiated by the United Nations, and in spirit with other community forestry schemes emerging in developing countries (Sachs 2012), HD also aims to improve village social welfare, improve sustainable livelihood options for local communities, deliver restoration activities, and facilitate improved management of existing degraded land (Pohnan *et al.* 2015). As this land use scheme also aims to improve welfare and livelihoods of the local communities and facilitate recognition of their village rights, this analysis represents only a partial story on HD effectiveness. Our analyses show that a third of the total HD area in Sumatra and Kalimantan has been granted on degraded land (<80% forest cover), and the area granted on this type of land has been increasing through time (Fig. A1). Analysing degradation trajectory in fragmented forest landscapes is challenging mainly because of two reasons. First, it requires accurate and fine spatial data on the existing level of degradation as a baseline. Fragmented forests are more difficult to identify than large blocks of intact forest from the satellite images, and precise degradation stage in fragmented forests are difficult to capture (Dong *et al.* 2014). Second, it requires fine temporal resolution of data to capture temporary clearance and regrowth over time (Miettinen *et al.* 2014), and in the humid tropical region frequent cloud cover makes it difficult to obtain these cloud-free satellite images during a certain period (Hansen *et al.* 2016). Analysing the impact of HD tenure at halting further forest degradation or improving degraded areas presents a future research challenge.

HD licences are granted by the Ministry of Environment and Forestry through a rigorous selection process, where the approval of the licence is based on the provision of a management plan with goals towards sustainable development and conservation of ecosystems, strong participation from local community members, and collaborative relationships with external partners and NGOs (Sahide 2011). A likely assumption of the authorities is that management capacity and effort under the HD scheme are relatively consistent in different contexts. Our results demonstrate that varying levels of management ought to be implemented in areas with different levels of human pressure. This could be represented in the quality of technical assistance in HD development, amounts of financing, and support for local leadership.

In summary, here we show that based on the objective of avoiding deforestation, HD are performing well. Strong and complex anthropogenic pressures and climate extremes are the main challenges to HD management in the future. Our analysis is a first step towards understanding the overall performance of this community forestry scheme under a multi-objective setting. With rapid development in Indonesia and an emerging civil society, the performance of HD and other community forestry schemes, such as Hutan Kemasyarakatan (Community Forest) and Hutan Adat (Indigenous Forest), will be contested. Understanding how each of these schemes can benefit communities, their wellbeing and livelihoods, and the natural environment, is imperative to informing a sustainable development strategy that achieves these multiple objectives.

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APPENDIX
Supplementary Figures and Tables

Community forest management in Indonesia: avoided deforestation in the context of anthropogenic and climate complexities

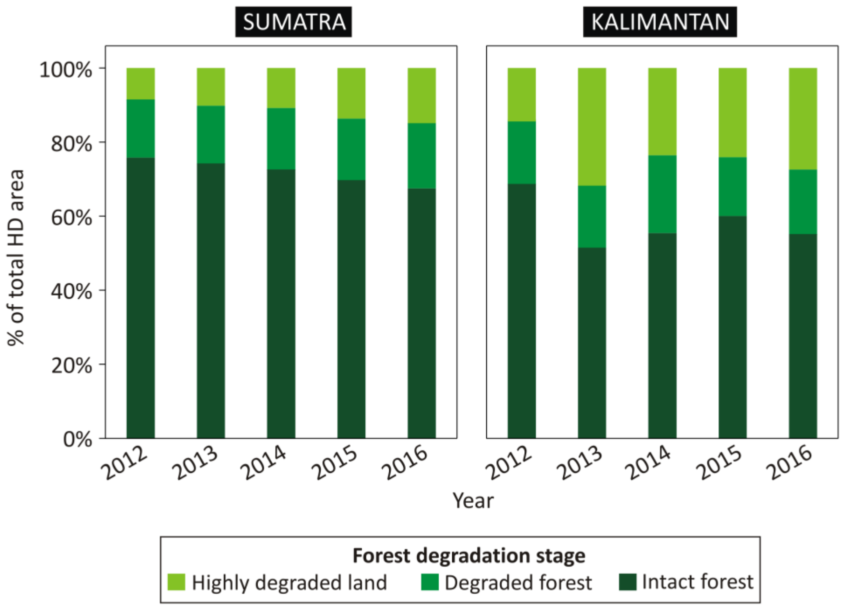

Fig. A1. The proportion of intact forest (80-100% forest cover), degraded forest (40-80% forest cover), and highly degraded land (0-40% forest cover), within the boundaries of HDs in Sumatra and Kalimantan annually between 2012 and 2016.

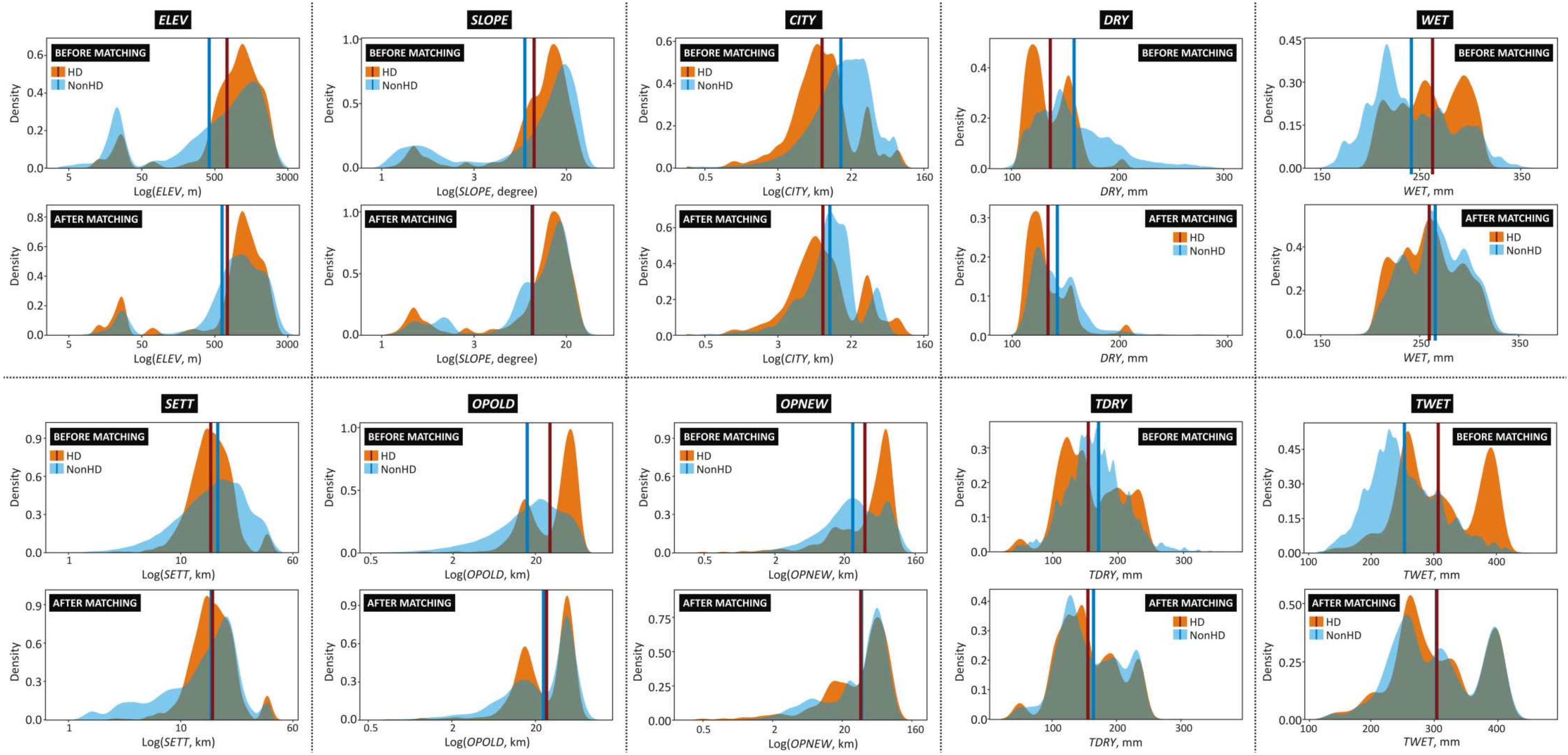

Fig. A2. The distributions of continuous variables characterizing the locations of HD versus non HD with intact forest (forest cover ≥80%) in Sumatra, before and after matching, collectively from 2012 to 2016 data (see Table A1 for the annual distributions of variables). Variables include: elevation (*ELEV*), *SLOPE*, distance to large cities or arterial roads (*CITY*), long-term mean monthly rainfall during the dry and wet season (*DRY* and *WET*), distance to agricultural settlements or transmigration areas (*SETT*), distance to oil palm plantations: old (*OPOLD*) and new ones (*OPNEW*), and the monthly mean rainfall during the dry and wet season in any given year (*TDRY* and *TWET*). The degree of overlap between the distributions of variables for the two land uses increased after matching. Vertical lines indicate the mean value for each land use, and the gap between the two lines decreased after matching.

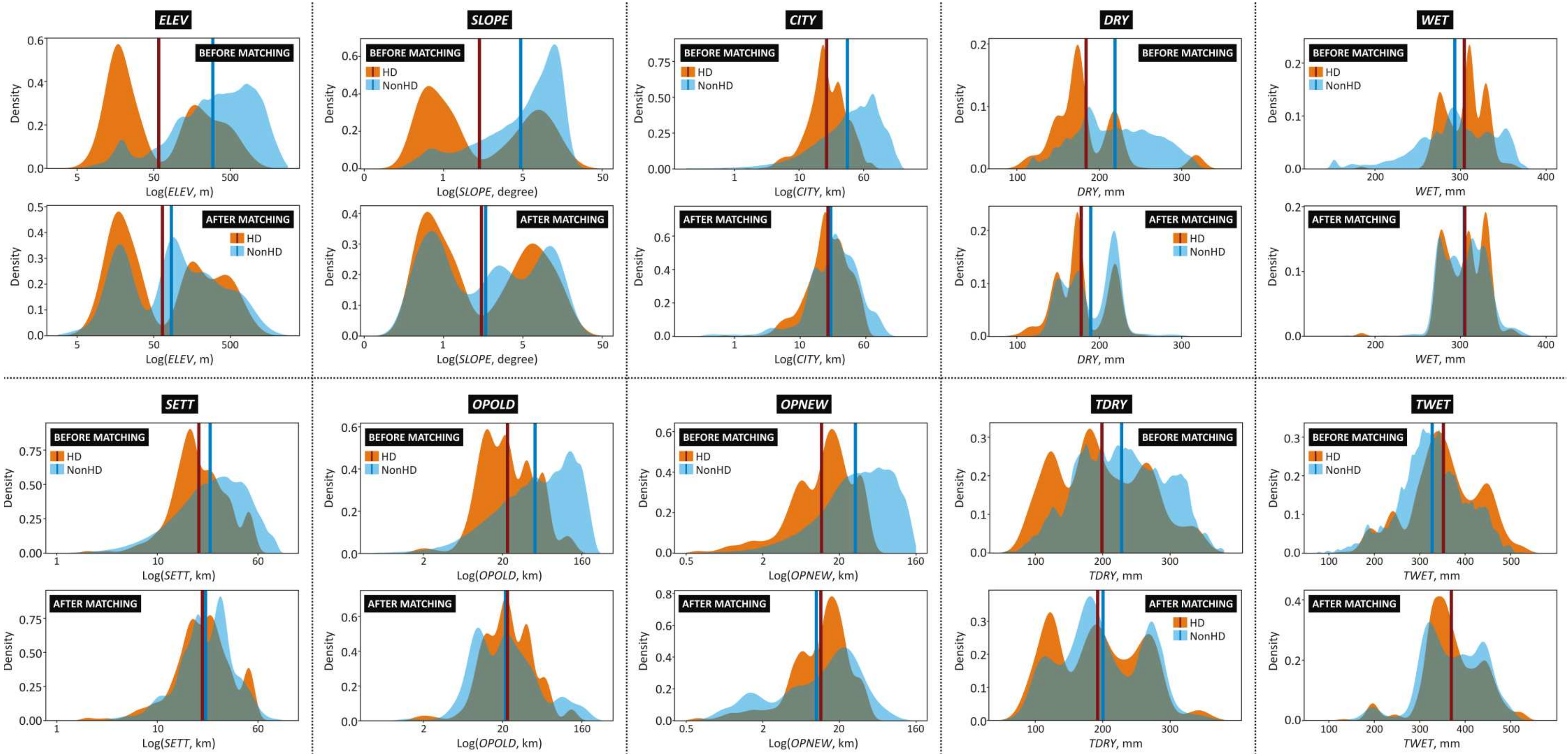

Fig. A3. The distributions of continuous variables characterizing the locations of HD versus non HD with intact forest (forest cover ≥80%) in Kalimantan, before and after matching, collectively from 2012 to 2016 data (see Table A1 for the annual distributions of variables). Variables include: elevation (*ELEV*), *SLOPE*, distance to large cities or arterial roads (*CITY*), long-term mean monthly rainfall during the dry and wet season (*DRY* and *WET*), distance to agricultural settlements or transmigration areas (*SETT*), distance to oil palm plantations: old (*OPOLD*) and new ones (*OPNEW*), and the monthly mean rainfall during the dry and wet season in any given year (*TDRY* and *TWET*). The degree of overlap between the distributions of variables for the two land uses increased after matching. Vertical lines indicate the mean value for each land use, and the gap between the two lines decreased after matching.

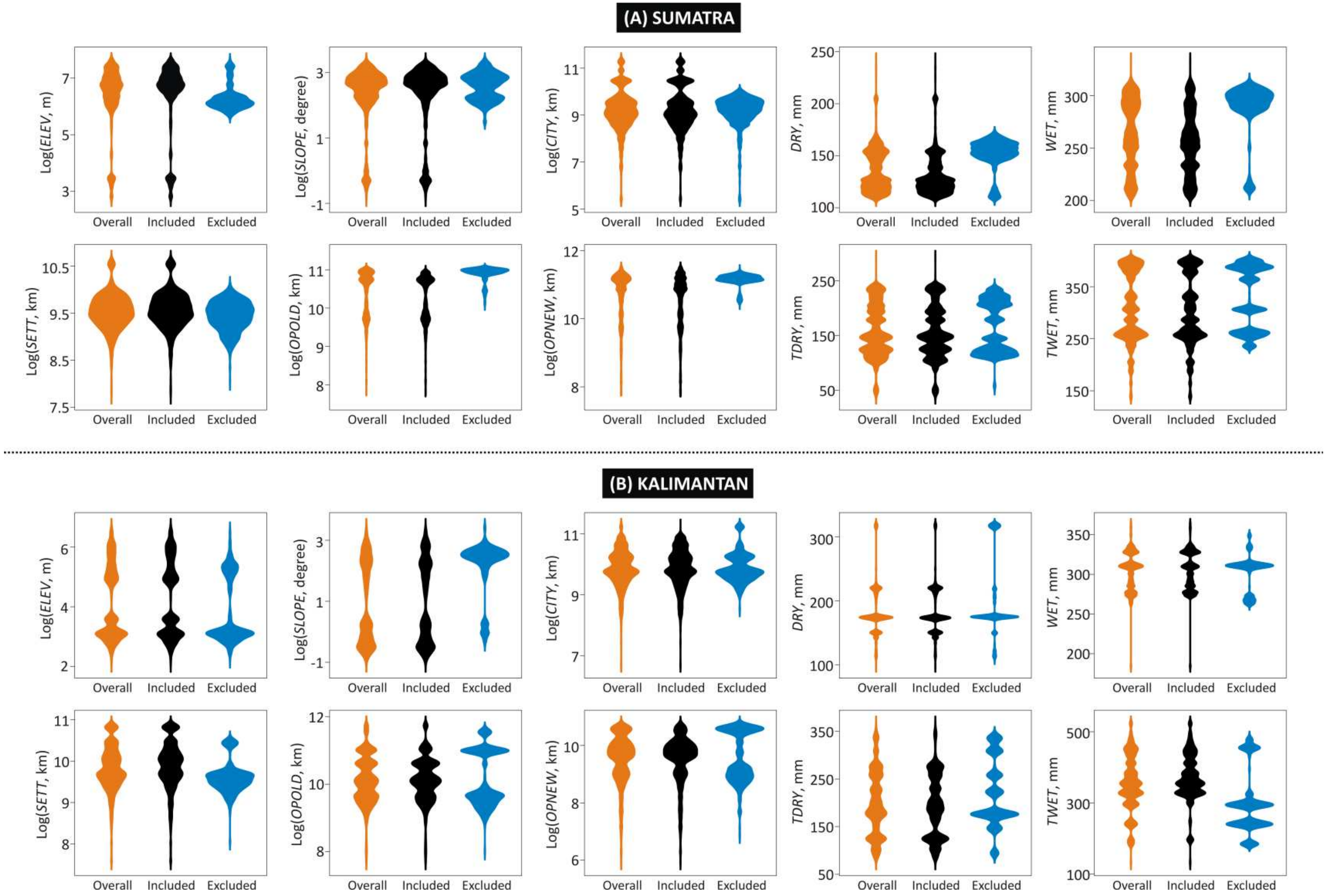

Fig. A4. Biophysical characteristics of HD grid cells overall (*orange*), selected (included) in matched dataset (*black*), and excluded from the matched data (*blue*) for (A) Sumatra and (B) Kalimantan, depicted through bean plot. Bean plot is similar to box plot, but it also shows the kernel probability density of the data at different values. Biophysical characteristics include elevation (*ELEV*), slope (*SLOPE*), distance to large cities or arterial roads (*CITY*), long-term mean monthly rainfall during the dry and wet season (*DRY* and *WET*), distance to agricultural settlements or transmigration areas (*SETT*), distance to oil palm plantations: old (*OPOLD*) and new ones (*OPNEW*), and the monthly mean rainfall during the dry and wet season in any given year (*TDRY* and *TWET*).

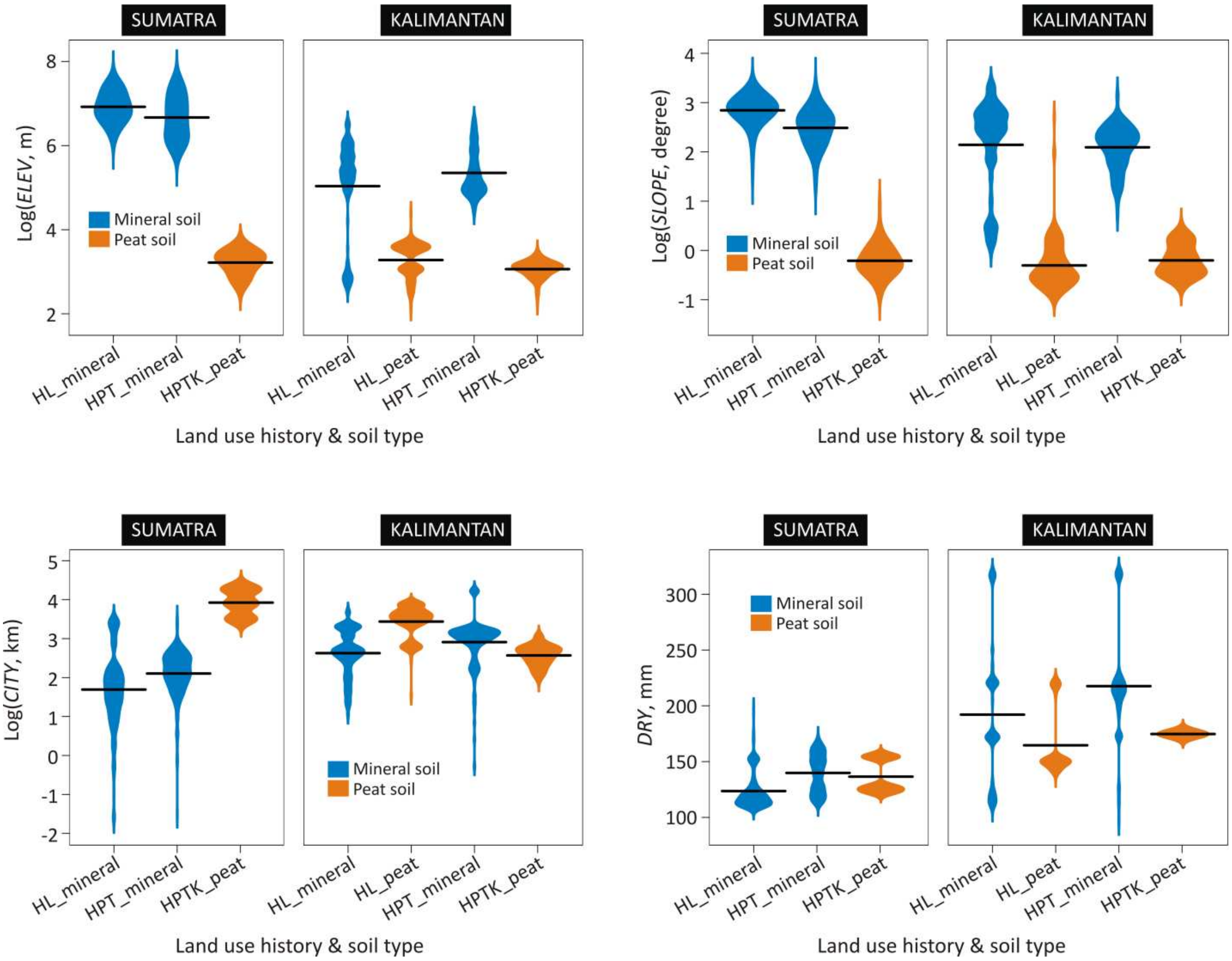

Fig. A5. Biophysical characteristics of HD across different land use histories (protection HL, limited production HPT, and permanent and convertible production HPTK) and soil types (mineral soil and peat soil) in Sumatra and Kalimantan, depicted through bean plot. Bean plot is similar to box plot, but it also shows the kernel probability density of the data at different values; black line in each plot represents the mean value. Biophysical characteristics include elevation (*ELEV*), slope (*SLOPE*), distance to large cities or arterial roads (*CITY*), and long-term mean monthly rainfall during the dry season (*DRY*).

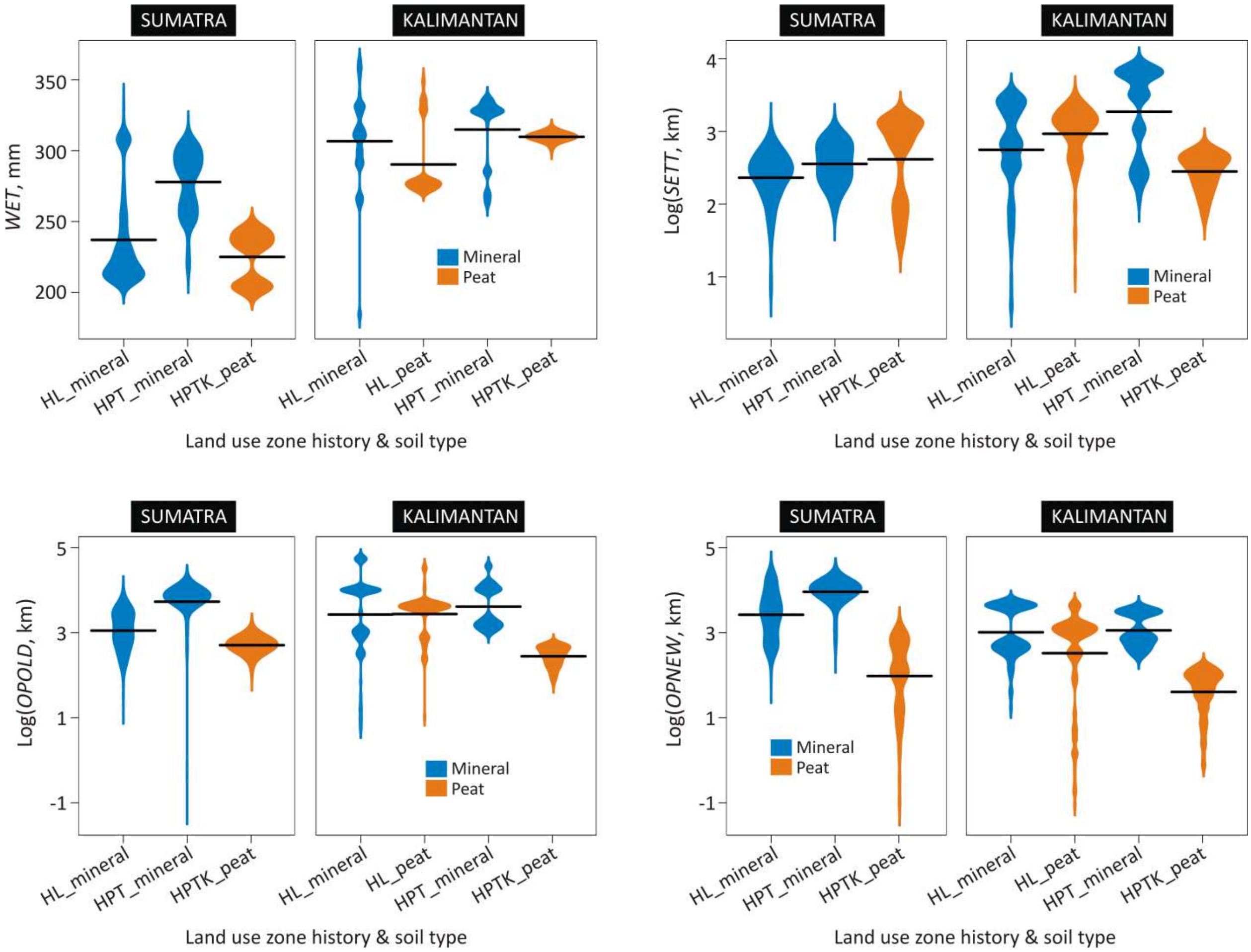

Fig. A6. Biophysical characteristics of HD across different land use histories (protection HL, limited production HPT, and permanent and convertible production HPTK) and soil types (mineral soil and peat soil) in Sumatra and Kalimantan, which include the long-term mean monthly rainfall during the wet season (*WET*), distance to agricultural settlements or transmigration areas (*SETT*), and distance to oil palm plantations: old (*OPOLD*) and new ones (*OPNEW*).

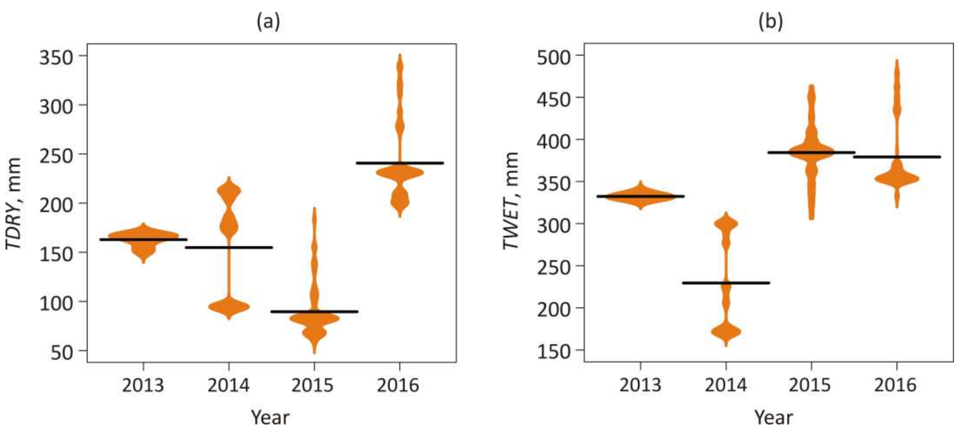

Fig. A7. Variability in (a) the monthly mean rainfall during the dry season (*TDRY*) and (b) wet season (*TWET*), each year between 2013 and 2016 for HDs granted on HL on peat soil in Kalimantan.

Table A1. Balancing check of variables before and after matching.

Variable	Year	SUMATRA						KALIMANTAN					
		Before matching			After matching			Before matching			After matching		
		Mean HD	Mean control	P value	Mean HD	Mean control	P value	Mean HD	Mean control	P value	Mean HD	Mean control	P value
ELEV	2012	6.34	5.74	<0.001	6.39	6.31	0.159	4.33	5.52	<0.001	5.43	5.60	0.122
	2013	6.36	5.82	<0.001	6.42	6.29	0.080	4.07	5.53	<0.001	4.67	4.97	0.162
	2014	6.17	5.85	<0.001	6.18	6.02	0.072	3.46	5.54	<0.001	4.02	4.33	0.092
	2015	6.42	5.90	<0.001	6.48	6.44	0.245	4.18	5.55	<0.001	4.08	4.11	0.171
	2016	6.35	5.92	<0.001	6.27	6.14	0.092	4.37	5.57	<0.001	4.24	4.27	0.103
SLOPE	2012	2.25	2.01	<0.001	2.22	2.21	0.870	1.25	1.93	<0.001	2.47	2.46	0.975
	2013	2.27	2.08	<0.001	2.24	2.15	0.303	0.93	1.94	<0.001	1.57	1.66	0.716
	2014	2.19	2.11	0.075	2.14	2.14	0.997	0.44	1.95	<0.001	1.33	1.45	0.501
	2015	2.37	2.15	<0.001	2.37	2.37	0.985	0.90	1.96	<0.001	0.75	0.84	0.295
	2016	2.37	2.16	<0.001	2.30	2.30	0.984	1.07	1.97	<0.001	0.85	0.99	0.088
CITY	2012	9.31	9.74	<0.001	9.33	9.39	0.107	9.58	10.48	<0.001	9.50	9.80	0.064
	2013	9.30	9.73	<0.001	9.39	9.38	0.852	9.62	10.49	<0.001	9.61	9.73	0.291
	2014	9.31	9.72	<0.001	9.31	9.42	0.094	9.67	10.50	<0.001	9.74	9.81	0.342
	2015	9.11	9.72	<0.001	9.07	9.12	0.093	9.93	10.51	<0.001	9.87	9.87	0.965
	2016	9.12	9.71	<0.001	9.20	9.22	0.743	9.95	10.51	<0.001	9.91	9.91	0.935
DRY	2012	138.0	159.4	<0.001	131.8	133.3	0.248	173.7	218.7	<0.001	172.2	172.2	0.998
	2013	137.8	159.2	<0.001	139.6	140.5	0.289	169.2	218.9	<0.001	165.5	165.7	0.899
	2014	135.0	159.0	<0.001	139.5	140.1	0.312	182.3	219.0	<0.001	196.4	196.5	0.974
	2015	132.7	158.8	<0.001	132.9	134.8	0.174	187.2	219.2	<0.001	176.6	179.5	0.481
	2016	139.7	158.7	<0.001	138.6	142.8	0.094	186.0	219.5	<0.001	177.9	179.0	0.577
WET	2012	273.4	242.3	<0.001	273.6	275.5	0.452	301.0	293.1	<0.001	291.9	292.4	0.713
	2013	273.2	241.7	<0.001	272.8	275.7	0.514	295.8	293.2	0.061	286.3	288.1	0.301
	2014	259.9	241.4	<0.001	259.8	263.0	0.102	308.1	293.2	<0.001	312.3	311.9	0.893
	2015	255.5	241.4	<0.001	255.2	257.8	0.632	304.7	293.3	<0.001	306.6	306.7	0.943
	2016	260.7	241.1	<0.001	260.6	260.8	0.851	304.6	293.4	<0.001	305.7	303.9	0.279
SETT	2012	9.69	9.64	0.224	9.69	9.68	0.862	9.79	10.07	<0.001	10.01	9.95	0.373
	2013	9.70	9.53	<0.001	9.62	9.60	0.398	9.71	10.07	<0.001	9.83	9.82	0.846
	2014	9.64	9.55	0.018	9.60	9.60	0.821	9.49	10.04	<0.001	9.49	9.69	0.025
	2015	9.49	9.37	<0.001	9.48	9.48	0.783	9.89	10.03	<0.001	9.92	9.98	0.140
	2016	9.46	9.34	<0.001	9.45	9.48	0.424	9.94	10.03	<0.001	9.95	9.98	0.236
OPOLD	2012	10.54	9.75	<0.001	10.38	10.39	0.886	9.81	10.80	<0.001	10.07	10.03	0.524
	2013	10.55	9.79	<0.001	10.34	10.34	0.979	9.82	10.81	<0.001	10.01	9.99	0.329
	2014	10.32	9.80	<0.001	10.16	10.16	0.965	9.64	10.82	<0.001	9.78	9.79	0.986
	2015	10.32	9.83	<0.001	10.19	10.12	0.081	10.27	10.83	<0.001	10.17	10.12	0.361
	2016	10.20	9.84	<0.001	10.02	9.99	0.094	10.32	10.84	<0.001	10.18	10.17	0.969
OPNEW	2012	10.91	10.35	<0.001	10.77	10.85	0.370	9.45	10.52	<0.001	9.93	10.01	0.181
	2013	10.84	10.33	<0.001	10.63	10.66	0.763	9.41	10.49	<0.001	9.82	10.01	0.078
	2014	10.41	10.22	<0.001	10.24	10.34	0.088	9.35	10.40	<0.001	9.75	9.75	0.999
	2015	10.52	10.13	<0.001	10.40	10.38	0.622	9.57	10.33	<0.001	9.46	9.45	0.902
	2016	10.41	10.14	<0.001	10.21	10.17	0.487	9.62	10.34	<0.001	9.43	9.39	0.193
TDRY	2012	114.0	145.9	<0.001	114.3	116.3	0.057	154.9	219.9	<0.001	161.8	161.9	0.987
	2013	184.5	162.9	<0.001	178.0	178.0	0.999	243.2	268.9	<0.001	234.7	245.6	0.162
	2014	149.0	175.6	<0.001	151.5	153.5	0.171	175.4	214.0	<0.001	189.6	192.1	0.142
	2015	114.3	143.2	<0.001	113.5	113.5	0.988	143.2	159.8	<0.001	135.0	139.6	0.251
	2016	214.1	198.1	<0.001	212.9	215.1	0.094	265.8	278.2	<0.001	254.6	256.1	0.537
TWET	2012	260.0	249.3	<0.001	259.1	259.1	0.984	316.4	324.6	<0.001	330.7	330.7	0.996
	2013	380.2	284.9	<0.001	375.4	374.2	0.664	311.2	337.4	<0.001	323.4	328.4	0.116
	2014	240.1	210.6	<0.001	238.4	236.1	0.329	250.8	288.6	<0.001	249.1	261.1	0.078
	2015	289.6	250.1	<0.001	286.1	284.7	0.595	364.9	358.2	<0.001	367.5	364.1	0.195
	2016	358.2	270.6	<0.001	350.0	350.8	0.826	399.8	328.9	<0.001	411.5	411.6	0.992

Table A2. Total locations (1 km^2 grid cells) with intact forest (≥80% forest cover) within HD boundaries and those selected via matching. The main characteristic of grid cells being excluded from the matched dataset is shown in Fig. A4.

Island	Year	Locations with intact forest within HD boundaries (grid cells)	
		Total	Matched data (% total)
Sumatra	2012	468	330 (71%)
	2013	454	306 (67%)
	2014	613	483 (79%)
	2015	762	624 (82%)
	2016	839	587 (70%)
Kalimantan	2012	92	47 (51%)
	2013	114	70 (61%)
	2014	276	150 (54%)
	2015	599	513 (86%)
	2016	576	457 (79%)

Table A3. (a) Total extent of intact forest (≥80% forest cover) within HD boundary. (b) The estimated total avoided deforestation (ha) across all HDs on each island per year. (c) The robustness of the spatial matching analysis against hidden bias due to an unobserved confounder, as indicated by the value of the sensitivity parameter Γ_C.

Island	Year	(a) Total extent of intact forest within HD boundaries (km^2)	(b) Total avoided deforestation (ha) †	(c) Spatial matching robustness (Γ_C) ‡
Sumatra	2012	468	462	2.57
	2013	454	175	1.89
	2014	613	-55	1.72
	2015	762	380	1.61
	2016	839	73	1.59
Kalimantan	2012	92	6	1.89
	2013	114	42	4.82
	2014	276	95	1.77
	2015	599	-1,020	2.65
	2016	576	297	1.99

† Negative values indicate that the deforestation rate is higher than with HD tenure.
‡ Larger Γ_C indicates a more robust analysis against hidden bias.

Table A4. The mean avoided deforestation rates of HD annually between 2012 and 2016 obtained based on matched controls located within a 10 km buffer from the HD boundaries and based on controls in wider landscape.

Island	Year	Mean avoided deforestation rates	
		Buffer zone controls	Wider landscape controls
Sumatra	2012	1.61	1.63
	2013	0.68	0.62
	2014	-0.74	-0.73
	2015	1.12	1.08
	2016	0.34	0.37
Overall		0.602	0.594
Kalimantan	2012	0.15	0.17
	2013	0.39	0.38
	2014	0.56	0.58
	2015	-3.64	-3.79
	2016	0.59	0.61
Overall (excluding 2015)		0.423	0.435