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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 2500 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.

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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 and 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 and 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 2000s (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). The areas that have been allocated and proposed for social forestry are described in the Social Forestry Indicative Maps (PIAPS) (MEF, 2016a). 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 2500 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 and 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 and 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 and 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 and 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 2500 km^2 of total HD area granted between 2009 and 2015. We extended a standard matching method (Dehejia and 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 km^2) and Kalimantan (530,000 km^2), 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

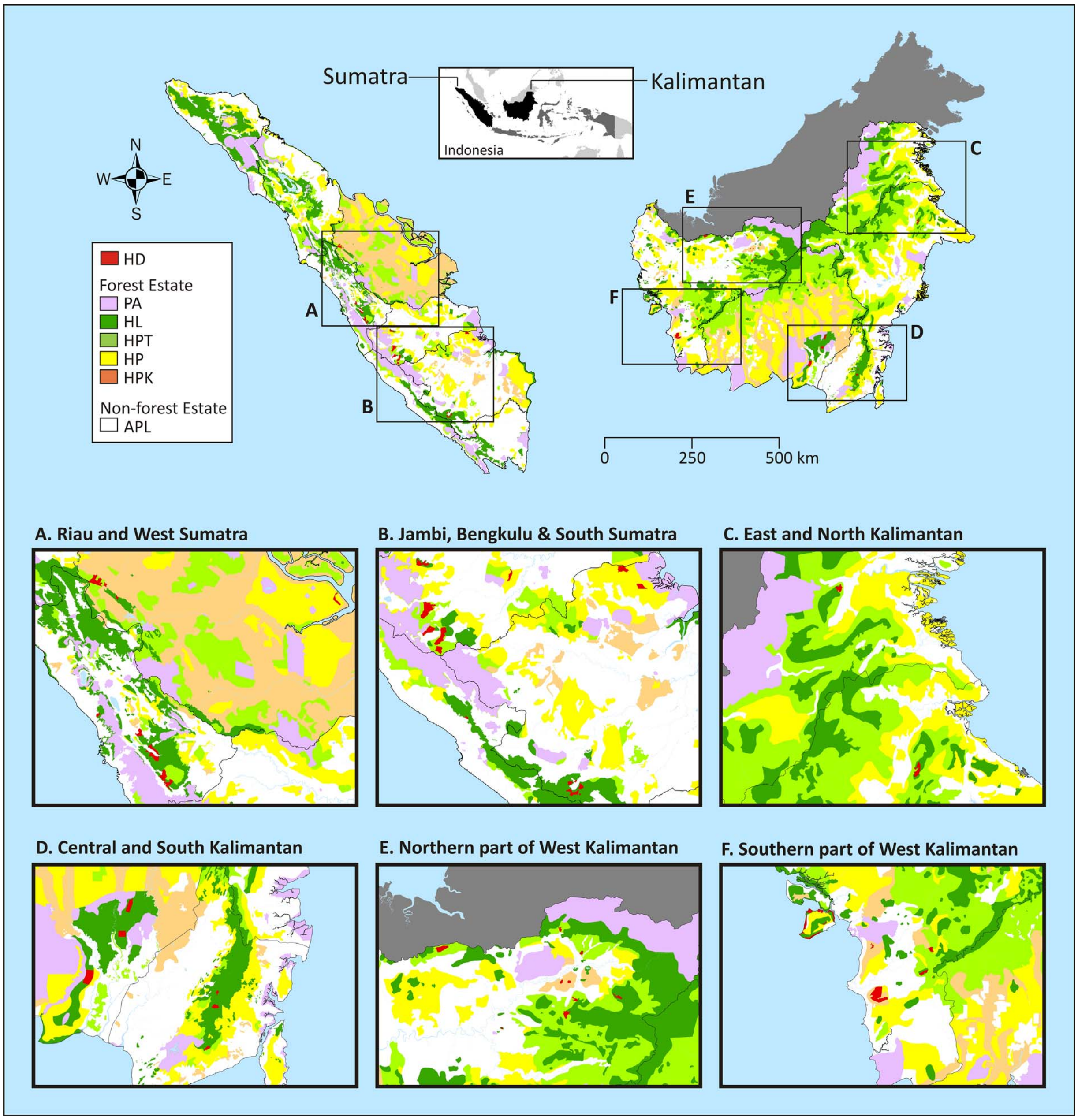

Fig. 1. Area currently allocated to *Hutan Desa* (HD), Forest Estate: strict protected areas (PA), watershed protection forest (HL), limited production forest (HPT), permanent production forest (HP), convertible production forest (HPK), and Non-forest Estate (APL), in Sumatra and Kalimantan. The main 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.

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 km^2, compared to an average area of the HDs analysed of 25 km^2 (range 1.2–146.9 km^2). 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, 1134 and 1317; a minimum area of 1.2 km^2, and with a total intact forest area of 468, 454, 613, 762 and 839 km^2, 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, 1069 and 1195; a minimum area of

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 a combination of 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 km²				(c) Natural forest area in km² (% 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%)

3.5 km^2, and with total intact forest area of 92, 114, 276, 599 and 576 km^2, respectively).

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) 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; derived 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 and 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 and 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 and 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

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 90 m Digital Elevation Database v4.1 (Jarvis et al., 2008)
	SLOPE	Slope	Continuous (log(degree))	SRTM 90 m 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) and Gaveau et al. (2016a)
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) and Gaveau et al. (2016a)

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 and 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., 2015) 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 and 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 and 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.

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. A4, respectively.

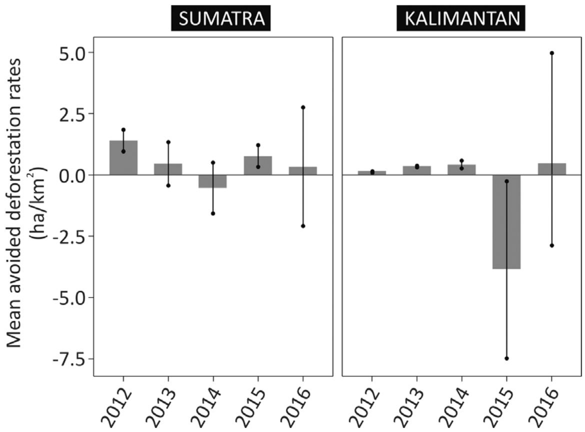

Fig. 2. The estimated mean avoided deforestation rates (ha/km^2) contributed by HD in Sumatra and Kalimantan every year between 2012 and 2016, obtained through spatial matching. The vertical line denotes the 95% confidence interval (CI) for the mean.

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 and Hill, 2007). Because our units of analyses (1×1 km^2 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/km^2) 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, despite the increasing extent of HD area (Table A3). 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 A3). 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.

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

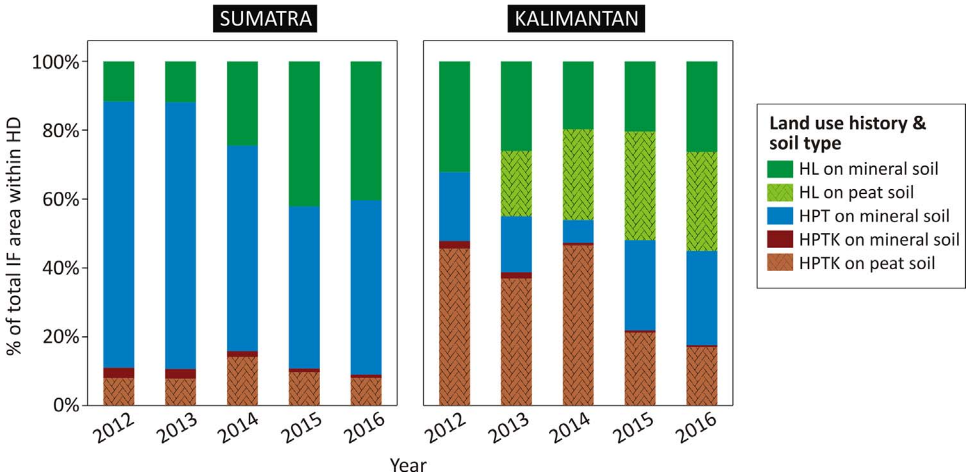

Fig. 3. The proportions of different land use histories (protection HL, limited production HPT, and permanent and convertible production HPTK) and soil types (mineral soil and peat soil) in intact forest within the boundaries of HD in Sumatra and Kalimantan.

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.

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/km^2, on average), whereas for HDs on HPT the rates were milder (0.6 ha/km^2) (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

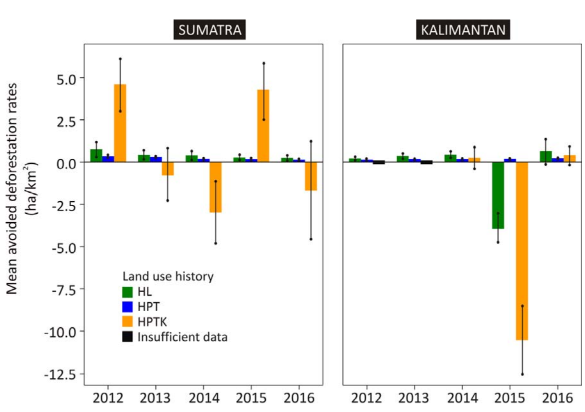

Fig. 4. The estimated mean avoided deforestation rates (ha/km^2) contributed by HDs in Sumatra and Kalimantan every year between 2012 and 2016 across different land use histories (protection HL, limited production HPT, and permanent and convertible production HPTK). Vertical line indicates the 95% confidence interval (CI) for the mean. We excluded cases with insufficient samples in the matched dataset (< 20).

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/km^2), 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/km^2), whereas HD on HPTK had slightly higher rates (0.8 ha/km^2). 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.

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* < 4 km) or far from existing agriculture areas, i.e. *SETT* > 20 km, *OPOLD* > 16 km, and *OPNEW* > 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) and/or 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* < 275 mm/month) and received relatively low amount of rain during the dry season (*TDRY* < 220 mm)) (Fig. 7).

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)

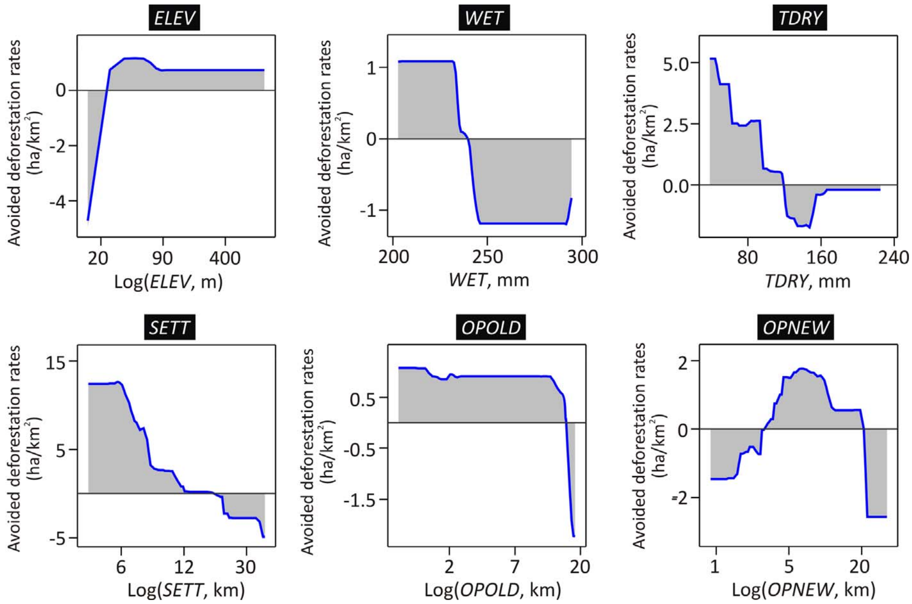

Fig. 5. The influence of individual variables on the avoided deforestation rates of HD on HPTK in Sumatra, obtained from the generalized boosted regression models analysis. Influential variables include: elevation (*ELEV*), long-term mean monthly rainfall during the wet season (*WET*), the monthly mean 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*).

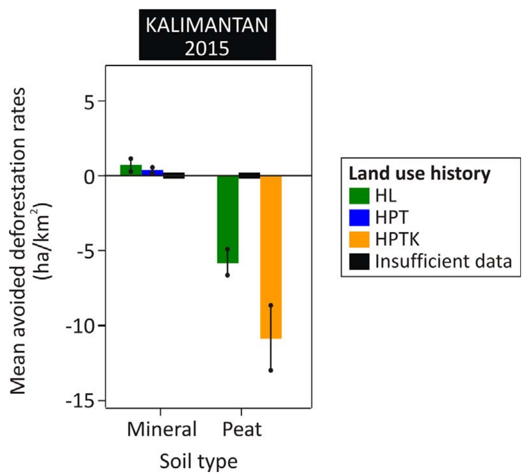

Fig. 6. The estimated mean avoided deforestation rates (ha/km^2) contributed by HDs in Kalimantan in 2015 across different land use histories (protection HL, limited production HPT, and permanent and convertible production HPTK) and soil types (mineral soil and peat soil). Vertical line indicates the 95% confidence interval (CI) for the mean. We excluded cases with insufficient samples in the matched dataset (< 20).

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 and 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

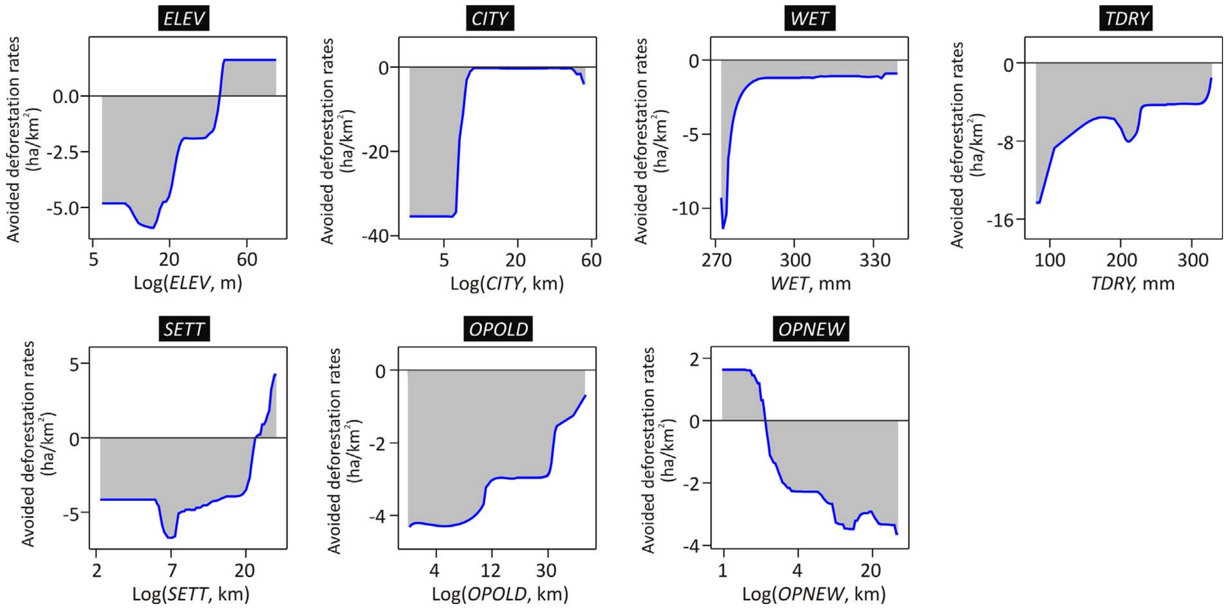

Fig. 7. The influence of individual variables on the avoided deforestation rates of HD on peat soil (HL or HPTK) in Kalimantan, obtained from the generalized boosted regression models analysis. Influential variables include: elevation (*ELEV*), distance to large cities or arterial roads (*CITY*), long-term 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*).

(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. 6) located in extremely dry areas (< 100 mm per month) in Kalimantan (Fig. A7a). 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 and 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 and 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 and 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

Supplementary figures and tables associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.gloenvcha.2017.08.002.

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