TOWARDS SUSTAINABLE AGRI-FOOD SYSTEMS:
BALANCING BETWEEN MARKETS AND SOCIETY

Land property rights, agricultural intensification, and deforestation in Indonesia

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Contribution presented at the XV EAAE Congress, “Towards Sustainable Agri-food Systems: Balancing Between Markets and Society”

August 29th – September 1st, 2017

Parma, Italy

Abstract

The expansion of agricultural land remains one of the main drivers of deforestation in tropical regions, with severe negative environmental consequences. Stronger land property rights could possibly enable farmers to increase input intensity and productivity on the already cultivated land, thus reducing incentives to expand their farms by deforesting additional land. This hypothesis is tested with data from a panel survey of farm households in Sumatra, Indonesia, one of the hotspots of recent rainforest loss due to agricultural area expansion. The survey data are combined with satellite imageries to account for spatial patterns, such as historical forest locations. Results show that plots for which farmers hold formal land titles are cultivated more intensively than untitled plots, even after controlling for other relevant factors. Land titles also contribute to higher crop yields, hence confirming expectations. However, due to land policy restrictions, farmers located at the historic forest margins often do not hold formal titles for the land they cultivate. Without land titles, these farmers are less able to intensify and more likely to expand into the surrounding forest land to increase agricultural output. Indeed, forest closeness and past deforestation activities by households are found to be positively associated with current farm size. The findings suggest that the observed land policy restrictions are not conducive for forest conservation. In addition to improving farmer's access to land titles for non-forest land, better recognition of customary land rights and more effective protection of forest land without recognized claims could be useful policy responses.

1 Introduction

Deforestation remains a widespread problem, especially in tropical regions. Between 2010 and 2015, about 6 million hectares of tropical forest were lost annually (FAO, 2016), entailing severe negative consequences for biodiversity, ecological systems, and climate stability (Fearnside, 2005; Butler et al., 2009; Wilcove et al., 2013; Barnes et al., 2014). Agricultural area expansion is one of the main drivers of deforestation (Gibbs et al., 2010), and demand for agricultural output will further increase due to population and income growth. In addition to food, global demand for feed, fuel, and other biomass-derived renewable resources will grow substantially over the coming decades (Alexandratos et al., 2012; Valin et al., 2014). These developments threaten the conservation of the remaining tropical forest (Laurance et al., 2014). Increasing agricultural yields on the land already cultivated, through higher input intensity and use of better technology, could be one important way to meet the rising demand and reduce further deforestation (Green et al., 2005; Ewers et al., 2009; Phalan et al., 2011a; Stevenson et al., 2013). To be sure, agricultural intensification is not a magic bullet to conserve tropical forest and related ecosystem functions (Steffan-Dewenter et al., 2007; Perfecto et al., 2010; Tscharntke et al., 2012). Effects will vary with the type of intensification and also with the institutional and policy context in a particular setting. Better knowledge is required about how land-sparing agricultural intensification can be implemented locally, and why past efforts have often failed. Empirical research in this direction is scant.

Here, we propose that land property rights are fundamental for agricultural production and deforestation outcomes. Land is the main source of farmers' livelihoods and also a major means for accumulating and inheriting wealth. The institutions shaping access, use, and transfer of land are hence central for farmers' decision-making (Deininger et al., 2001). Ownership regulations for forest land and for agricultural land often differ. The available literature on the links between land property rights and deforestation focuses primarily on the effects of secure tenure for forest land (Araujo et al., 2009; Damnyag et al., 2012; Liscow, 2013; Robinson et al., 2014). For agricultural land, studies have analyzed effects of tenure security on input intensity and crop productivity (Deininger et al., 2011; Fenske, 2011; Bellemare, 2013), yet without linking this to potential deforestation outcomes. To address this gap, we use comprehensive data from Sumatra, Indonesia, one of the hotspots of recent rainforest loss due to agricultural area expansion (Margono et al., 2014; Gatto et al., 2015; Clough et al., 2016). Data from a farm household survey, a village survey, and satellite imageries are combined to examine relationships between land ownership rights, agricultural production intensity, and farm size expansion into forest areas.

Private land titles can increase agricultural intensity and productivity through three effects (Besley, 1995; Feder et al., 1991; Deininger et al., 2011). First, the *assurance effect*, incentivizing higher investment because farmers are more secure to also reap the benefits from long-term measures to improve land quality and yield potential. Second, the *collateralization effect*, allowing better access to investment capital because land titles can be used as collateral in formal credit markets. Third, the *realizability effect*, resulting from more efficient land allocation given that titled land facilitates land market transactions. The empirical literature largely confirms these effects (Banerjee et al., 2002; Goldstein et al., 2008; Holden et al., 2009; Deininger et al., 2011; Fenske, 2011; Grimm et al., 2015; Lawry et al., 2016), although in some cases the influence of land titling was found to be insignificant (Quisumbing et al., 2001; Brasselle et al., 2002; Jacoby et al., 2007; Bellemare, 2013).

An increase in farm productivity induced through land titles could reduce deforestation (Angelsen et al., 2001). Higher output from the already cultivated land reduces the pressure to convert additional forest land. Also, a more productive agricultural sector could spur broader economic development, reducing population growth, enhancing non-agricultural income opportunities for rural households, and improving land-governance capacities and institutions. Empirical evidence for these types of effects is scarce, although a few studies show indeed that higher farm productivity can help spare natural habitat from agricultural conversion (Barbier et al., 1997; Ewers et al., 2009; Phalan et al., 2011b). On the other hand, agricultural productivity growth could also be associated with higher rates of deforestation, for instance, by increasing the cost of forest conservation programs or by stimulating in-migration and road infrastructure investments in rural areas (Maertens et al., 2006; Phelps et al., 2013). Better understanding the complexities in concrete situations can help design appropriate policies aimed at promoting more sustainable development.

In Indonesia, much of the land that farmers use is not formally titled (Krishna et al., 2017). Privately owned land can be titled, but the costs for farmers are relatively high. Additionally, farmers located close to the forest suffer from ambiguous ownership structures. Most of the forest land is formally owned by the state and not eligible for private titling (Agrawal et al., 2008). But the boundaries are not always clear-cut. Some of the land that farmers have cultivated for long officially counts as forest land. Moreover, local communities have customary claims and deforest land even when the newly obtained plots cannot be titled (Resosudarmo et al., 2014). The motivation to do so will likely increase when farmers have no land titles and therefore limited ability and incentives to intensify production on their existing agricultural land. Given these conditions, we formulate three research hypotheses that are empirically tested in this paper. First, possession of land titles increases agricultural intensity and productivity. Second, farms close to the forest are less likely to have land titles due to ambiguous ownership structures. Third, due to lower incentives to intensify, farmers close to the forest expand their agricultural land into the forest, resulting in bigger farm sizes.

2 Data

2.1 Socio-economic data

This research builds on data collected in Jambi Province on the island of Sumatra, Indonesia. Jambi has been one of the regions with rapid loss of tropical rainforest over the last few decades. Forest cover in Jambi declined from 48% in 1990 to 30% in 2013 (Drescher et al., 2016). Nevertheless, 43% of Jambi's total area was categorized as state forest in 2000 (Komarudin et al., 2008). Agricultural production in Jambi is dominated by plantation crops, especially rubber (*Hevea brasiliensis*) and oil palm (*Elaeis guineensis*). Rubber is primarily grown by local farmers with only some involvement of large-scale companies. Companies are more involved in oil palm, but even in oil palm more than 40% of the area is cultivated by smallholder farmers (Euler et al., 2017).

A survey of farm households was conducted in Jambi in two rounds, 2012 and 2015, as part of a larger interdisciplinary research project (Drescher et al., 2016). A multi-stage sampling framework was used to obtain a representative sample of local farm households. At the first stage, five regencies of Jambi located in tropical lowland rainforest areas were selected. At the second stage, a total of 40 villages were randomly selected in these five regencies. In addition, five villages, where more intensive measurements by other teams of the same research project were ongoing (Drescher et al., 2016), were purposively selected, resulting in a total of 45 villages. In these villages, around 700 households were randomly selected proportional to village size. There are two types of villages in Jambi, autochthonous and transmigrant villages. Transmigrant villages were established as part of the government's transmigration program (Gatto et al., 2017). Most households in transmigrant villages were allocated titled land by the state and started producing plantation crops under contract with one of the large public or private companies. Hence, the institutional and agricultural production conditions are quite different. In this research, we only consider the 34 autochthonous villages in the sample, with 473 farm household observations in 2015 (and 471 household observations in 2012). Out of these, around 25% are migrants (Table S1), but these migrants in autochthonous villages did not come as part of the government's transmigration program (Gatto et al., 2015). Most of the households in the two survey rounds are identical. The attrition rate between 2012 and 2015 was 6%. Households that could not be surveyed again in 2015 (mostly due to out-migration) were replaced with other randomly selected households in the same villages.

In both survey rounds, household heads were interviewed with a structured questionnaire, capturing a wide range of variables related to the households' socioeconomic situation and the institutional context (Euler et al., 2017). Details about the different plots owned and cultivated by the farm households were also collected. In 2015, the 473 households cultivated a total of 902 plots with plantation crops; out of these 690 were cultivated with rubber, the rest with oil palm. For all these plots, data on general plot characteristics, such as size, location, and status of land titling, were elicited. In addition, detailed input-output data were captured for all plots in 2012 and for a random sub-sample of plots in 2015. For the analysis of agricultural productivity and intensity, we concentrate on productive rubber plots (those where the trees are old enough such that rubber is already being harvested). Input-output relationships in rubber and oil palm are quite different, so combining both crops in the same models would not make sense. Besides the interviews with household heads, village representatives were interviewed in all sample villages to capture data on village size, ethnic composition, and other village-level characteristics.

2.2 Soil and remote sensing data

In the farm household survey, respondents were asked to classify the soil fertility on each of their plots as low, medium, or high. In addition to these data on perceived soil quality, soil samples were taken in 2012 for a randomly selected subsample of 92 rubber plots. These soil samples were taken and analyzed by a different team of researchers (Guillaume et al., 2016). We use topsoil properties, such as bulk density, carbon content, and carbon/nitrogen ratio as additional explanatory variables in the rubber production models.

Land cover maps of Jambi Province from the years 1990 and 2013 were obtained using multi-temporal Landsat TM and OLI satellite imageries with a spatial resolution of 30x30 m. Land cover classification is based on automatic classification and additional qualitative, visual interpretation to reduce miss-classifications (Melati et al., 2014). In this research, we are particularly interested in the share of forest in the vicinity of the sample households, which we determined by evaluating land cover classifications in circles with specific radius around the households' residence. We use different alternatives with 2 km, 5 km, and 10 km radius. Households with a high share of forest in their vicinity are considered as being located at the forest margins.

3 Methods

The analysis is done in three steps: First, we present models that analyze the effect of land titles on agricultural productivity which address our first hypothesis. Second, we deliver additional evidence for this hypothesis showing models analyzing agricultural intensity. In the last step, we examine spatial patterns, showing models analyzing the prevalence of land titles at historic forest margins (hypothesis 2) and models examining farm sizes at historic forest margins (hypothesis 3).

3.1 Models to analyze agricultural productivity

To analyze the effect of land titles on productivity in rubber, we estimate household-level panel regression models of the following type:

Eq. (1): $\ln(PR_{it}) = \beta_0 + \beta_1\, SLT_{it} + \beta_2\, X_{it} + \mu_i + \varepsilon_{it}$ (household level)

where PR_{it} is total annual rubber yield per hectare of household i at time t. SLT_{it} is the share of household i's land cultivated with plantation crops that had a systematic land title at time t. The share can vary between 0 and 1. X_{it} is a vector of other farm and household characteristics that may also influence rubber yields, such as farm size, age, gender, and education of the household head, and a wealth index. The wealth index was constructed based on ownership of the following assets: television, different types of vehicles, refrigerator, and washing machine. A principal component analysis was used to determine the weight of each asset in the wealth index (Filmer et al., 2001). We also include the share of land with sporadic land titles in the vector X_{it} (further differences about systematic and sporadic land titles are explained below). While sporadic titles provide much weaker tenure security than systematic titles, they may still play some role for household decision-making. μ_i is the unobserved time-invariant heterogeneity of the model, while ε_{it} is the iid error term.

We also estimate similar models at the plot level:

Eq. (2): $\ln(PR_{pit}) = \beta_0 + \beta_1\, LT_{pit} + \beta_2\, X_{it} + \beta_3\, S_{pit} + \mu_i + \varepsilon_{pit}$ (plot level)

where PR_{pit} is the annual rubber yield per hectare on plot p of household i at time t. LT_{pit} is a dummy variable taking the value 1 if the plot was systematically titled at time t. S_{pit} includes additional plot characteristics such as age of the rubber trees and variables related to plot location.

Due to the sampling framework used, households and plots are clustered at the village level. We account for possible heteroscedasticity by using cluster-corrected standard errors (Pepper, 2002; Cameron et al., 2011). For interpretation of the estimation coefficients, functional form has to be considered. SLT_{it} in Eq. (1) is a continuous variable, so that β_1 is interpreted as the percentage effect on rubber yield. LT_{pit} in Eq. (2) is a dummy variable, so that the percentage effects is calculated as $\{\exp[\beta_1 - 0.5 \times \mathrm{Var}(\beta_1)] - 1\}$ (van Garderen et al., 2002).

The models in Eqs. (1) and (2) are estimated with random effects (RE) panel estimators. Studies with micro-level data to assess the effects of land titling often struggle with endogeneity issues (Brasselle et al., 2002). Endogeneity bias occurs when unobserved characteristics are jointly correlated with land titling and crop productivity. Valid instruments for land titles, which are exogenous and fulfill the exclusion restrictions, are usually hard to find (Fenske, 2011; Bellemare, 2013; Grimm et al., 2015). We use different strategies to test for endogeneity and reduce related bias to the extent possible. First, we include a wide range of plot- and household-level control variables to reduce the likelihood of unobserved heterogeneity. In robustness checks, we also include various measures of soil quality, which has rarely been done in previous research (Bellemare, 2013). Second, in addition to using random effects, we also estimate the productivity models with fixed effects (FE) estimators and balanced plot- and household-level panel data. The variation in land titling within plots and households between 2012 and 2015 is small, but sufficient to obtain FE estimates. We use the Hausman test (Wooldridge, 2002) to compare between the RE and FE models (Table S2). Test results fail to reject the hypothesis that the RE models produce consistent estimates. Third, in addition to model estimates with all observations, we split the sample into migrants and non-migrants and estimate separate models for these two groups. We expect heterogeneous impacts of land titling, because customary land claims that apply to autochthonous people do not apply to migrants from outside the region.

3.2 Models to analyze agricultural intensity

To analyze the effect of land titles on intensity of rubber production, we estimate plot-level panel regression models of the following type:

Eq. (3): $INV_{pit} = \beta_0 + \beta_1\, LT_{pit} + \beta_2\, X_{it} + \beta_3\, S_{pit} + \mu_i + \varepsilon_{pit}$ (plot level)

Eq. (4): $\ln(LS)_{pit} = \beta_0 + \beta_1\, LT_{pit} + \beta_2\, X_{it} + \beta_3\, S_{pit} + \mu_i + \varepsilon_{pit}$ (plot level)

where INV_{pit} is total annual expenditures on material inputs applied per hectare on plot *p* by household *i* at time *t*. Material inputs include chemical fertilizers and pesticides (incl. herbicides). LS_{pit} is annual labor input (incl. family and hired labor) measured in hours per hectare. The other variables are defined as above. Since more than 50% of the sample farmers did not use any material inputs during the survey years, we do not take logs of INV_{pit} and use a linear functional form instead. Given censoring of the dependent variable at 0, we use a Tobit specification for the model in Eq. (3). To test the effect of INV_{pit} and LS_{pit} on crop productivity, we also estimate additional specifications of Eq. (2) with these inputs included as explanatory variables.

3.3 Spatial regression models

To estimate the effect of historical forest closeness on the probability of holding a land title, we estimate the following plot-level probit model:

Eq. (5): $P(LT_{piv}) = \beta_0 + \beta_1 F_{iv} + \beta_2 Z_{piv} + \beta_3 Z_{iv} + \beta_4 Z_v + \varepsilon_{piv}$ (plot level)

where LT_{piv} is a dummy indicating whether or not plot p of household i in village v was systematically titled in 2015, and F_{iv} is the share of forest land in 1990 in a circle with specific radius around the household residence. F_{iv} can take values between 0 (no forest in 1990) to 1 (completely forested in 1990). The reference year 1990 was chosen because most of the formal land classifications in Indonesia took place in the 1980s (Indrarto et al., 2012). We estimate separate models, using radii of 2 km, 5 km, and 10 km to construct F_{iv}. In each of these models, plots that are located outside the specific radius are excluded from estimation. A further robustness check is performed, replacing F_{iv} with a binary variable indicating if the plot was acquired by the household through deforestation. Z_{piv}, Z_{iv} and Z_v are further plot-, household-, and village-level controls. Eq. (5) includes both rubber and oil palm plots.

It is likely that land titling is also affected by spatial factors such as local policies or environmental conditions. This can possibly lead to spatial patterns in the models in Eq. (5). All models were tested for spatial autocorrelation using Moran's I, Anselin's, and Florax's Lagrange Multiplier tests (Baltagi, 2003). These tests failed to reject the hypothesis of zero spatial autocorrelation. For completeness, spatial lag and spatial error models are reported in Table S5.

We hypothesize that households close to the forest are less likely to hold land titles and therefore have stronger incentives to expand their farms into the forest. After controlling for other factors, this should lead to larger farm sizes at the forest margins. To test this hypothesis, we regress farm size in 2015 on forest closeness in 1990 and a set of control variables. Again, we used Moran's I, Anselin's, and Florax's Lagrange Multiplier tests (Baltagi, 2003) to test for spatial patterns. These tests reject the hypothesis of zero spatial autocorrelation, so we estimate spatial lag models of the following type:

Eq.(6): $\ln(FS_{iv}) = \rho W \ln(FS_{iv}) + \beta_0 + \beta_1 F_{iv} + \beta_2 V_{iv} + \beta_3 V_v + \varepsilon_{iv}$ (household level)

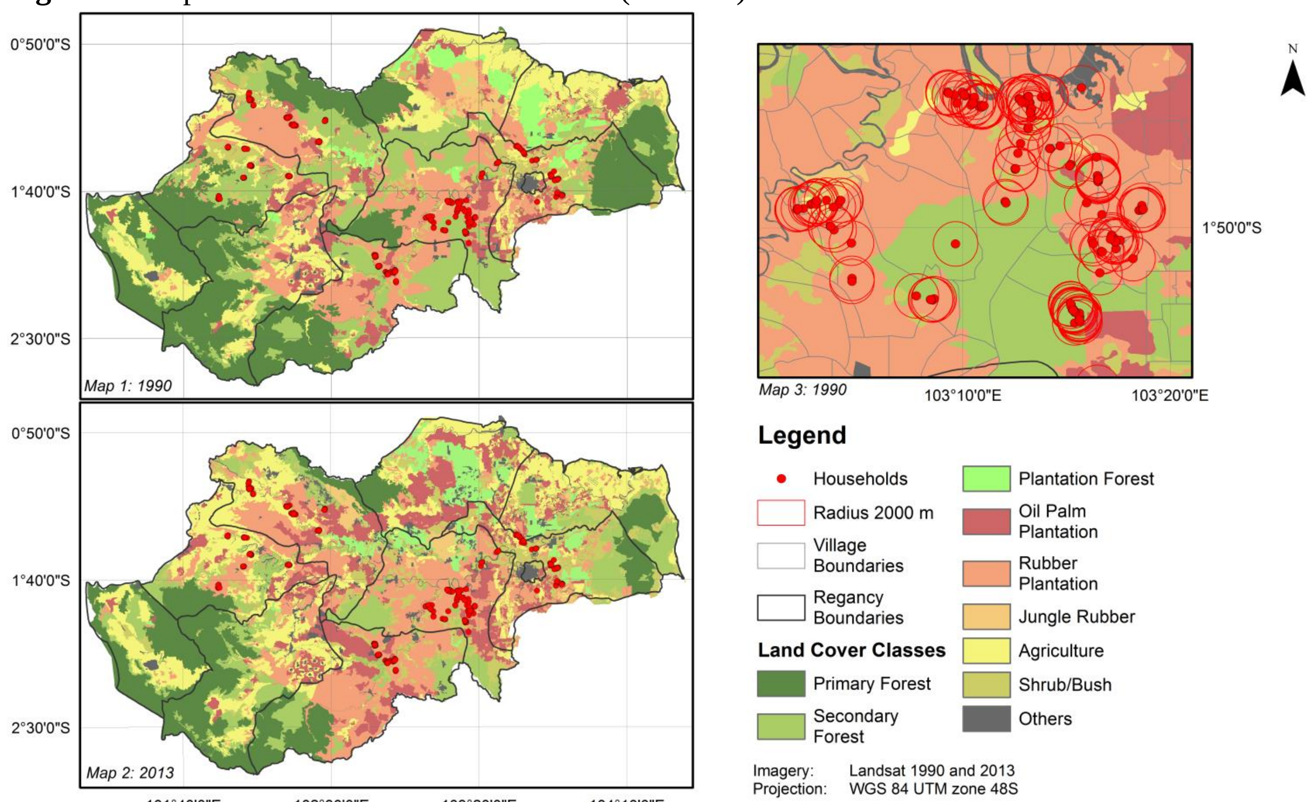
where FS_{iv} is total farm size of household i in village v measured in hectares, F_{iv} is the share of forest land in 1990 (as defined above). V_{iv} and V_v are household- and village-level controls. W is an N×N spatial weights matrix (N=Number of households) based on the inverse Euclidian distance between the households' residence. The parameter ρ measures the degree of spatial correlation. W is row standardized, such that for each i, $\sum_j w_{ij} = 1$ (Baltagi, 2003). The spatial lag $\rho W \ln(FS_{iv})$ can be interpreted as a weighted average of the farm sizes of neighboring households. For comparison, spatial error and ordinary least squares models are reported in Table S6.

4 Results

4.1 Descriptive statistics

Locations of the households are depicted in Figure 1 (Maps 1 and 2). Responses during the survey interviews suggest that households are actively engaged in deforestation. This is also confirmed by land cover maps. In 1990, about 17% of the area within a 5 km radius around farmers' residence was covered with forest; by 2013, this forest share was reduced to 3%. Much of the previous forest land is now grown with rubber and oil palm. Even though the area cultivated with oil palm grew faster during the last two decades (Gatto et al., 2015), rubber remains the dominant crop in the study region. About 30% of the sample farms grow oil palm, whereas 86% grow rubber (Table S1). This is also the reason why we focus on rubber for the analysis of crop productivity and production intensity. The average farm size is around 4 hectares (ha).

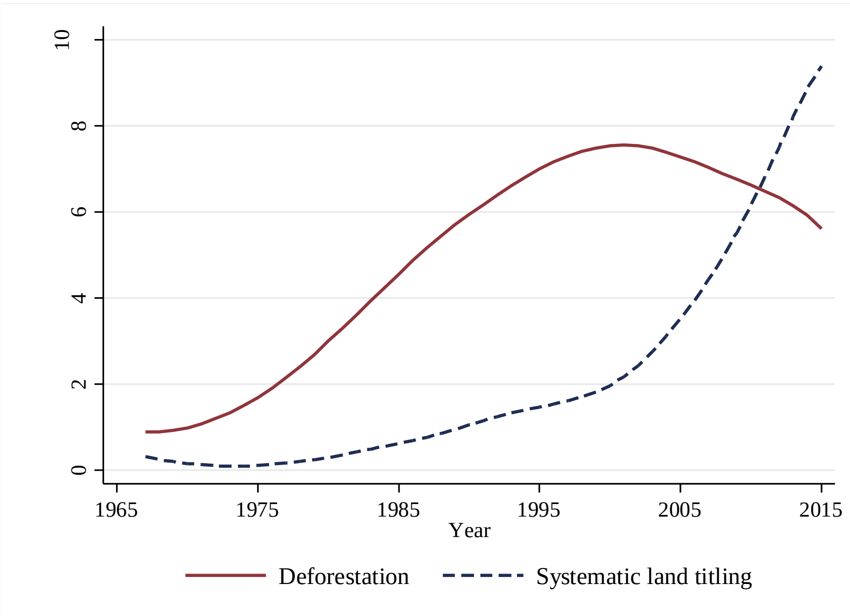
Figure 1: Maps of land uses in Jambi Province (Sumatra) in 1990 and 2013



Notes: Maps 1 and 2 depict Jambi Province in 1990 and 2013 respectively. Map 3 is one example from a sub-region (Harapan Rainforest) with eight sample villages in 1990. The red circles indicate a 2 km radius around the sample households' residence. Circles with different radius (2, 5, 10 km) were used to calculate the share of forest land around households.

Most of the plots that sample farmers cultivate are not formally titled, but held under customary tenure. In 2015, only 10% of the rubber plots had a systematic land title, which is a document that all formal authorities recognize. Figure 2 shows that systematic land titling is a rather recent phenomenon in the study area, which has gained in importance since the late-1990s, when the frequency of deforestation activities started to decline. In addition to systematic land titles, so-called sporadic titles exist, which are cheaper for farmers to obtain but only recognized by local authorities and thus also of limited value as collateral in formal credit markets (Krishna et al., 2017; Kunz et al., 2016). About 22% of the rubber plots have a sporadic land title (Table S1).

Figure 2: Land titling and deforestation activities by farmers (1965-2015)



Notes: Based on farmer recall data from 902 plots. The graph shows the number of plots that were obtained through deforestation and the number of plots for which farmers obtained a systematic land title in a particular year. The curves were constructed using locally-weighted time series smoothing.

4.2 Land titles and agricultural productivity

To analyze whether land property rights have an effect on agricultural productivity, we estimated regression models with rubber yield as dependent variable and land titles as explanatory variables, as explained in Eqs. (1) and (2). Results are shown in Table 1. In all model specifications, systematic land titles have positive and significant coefficients, while sporadic land titles have insignificant effects. In the household-level models, the different rubber plots of a household are combined. Compared to a situation with no land titles, systematic titling of all plots (share of land with systematic title equal to 1) leads to an increase in crop productivity of 35% (column 1). In column (2), we only include households that migrated to the villages from outside the region. For these households, the productivity effect of systematic land titles is even larger. It is not unexpected that migrants benefit more from land titles. First, migrants often belong to a different ethnicity than autochthonous households. Given smaller family networks in the local context, migrants depend more on formal credit markets to access financial capital (collateralization effect). Second, for migrants, customary land claims do not hold, so that formal property rights play a more important role for tenure security (assurance effect).

In the plot-level models in Table 1, each of the rubber plots is considered separately. Plots with a systematic land title have 16% higher yields than plots without title (column 3). The effect is smaller than in the household-level models. This is plausible, because the same household can have titled and untitled plots, so that spillovers may occur. For instance, a title for one plot will usually suffice as collateral to obtain a credit to pay for farm inputs that can be used to increase productivity on all of the household' plots. Also in the plot-level specifications, the effect for migrants (column 4) is larger than the effect for the total sample of farmers.

It is possible that there are unobserved factors that influence land titling and productivity simultaneously, which could lead to bias in the coefficient estimates. For instance, land with better soil quality will result in higher yields and may also have a higher likelihood to be titled. The measures of perceived soil quality are included in the model in column (5) of Table 1. In addition, column (6) shows precise soil quality measurements as explanatory variables for the random sub-sample for which these measurements are available. In both these models, the coefficient for systematic land titles remains positive and significant. As soil quality may also be correlated with other relevant unobserved factors, we conclude that the finding of a positive effect of land titles on crop productivity is robust to unobserved heterogeneity.

4.3 Land titles and agricultural intensity

Estimation results with indicators of input intensity as dependent variables, as explained in Eqs. (3) and (4), are shown in Table 2. Possession of systematic land titles significantly increases the use of material inputs (chemical fertilizers and pesticides). The marginal effect of 114 thousand IDR/ha in column (1) is equivalent to a 35% increase over sample mean expenditures for such inputs. Among migrant farmers, the effect is even larger (column 2). For labor input (column 3), we also find a positive effect of systematic land titles, which is somewhat smaller (13%) than that for material inputs. For migrant farmers, the effect of systematic land titles on labor is insignificant (column 4). On the other hand, sporadic land titles seem to increase labor input among migrants. As mentioned, sporadic titles are of limited value in formal credit markets, but – unlike material inputs – farmers rarely take a credit to pay for hired labor.

We expect that the effect of land titles on agricultural productivity is partly channeled through higher input intensity. Indeed, when including input use in the productivity model (columns 5 and 6 in Table 2), material and labor inputs both have significantly positive effects, whereas the effect of systematic land titles on productivity declines (compare with column 3 in Table 1). However, the land title effect remains positive and significant, suggesting that other transmission channels also play an important role.

4.4 Spatial patterns of land titling

Now we take a spatial perspective and report the results of plots being titled depending on forest closeness (see Eq. 5). As mentioned, plots located in areas designated as state forest are not eligible for titling, even though the boundaries are not clear-cut. Table 3 shows plot-level probit regression estimates with a dummy for systematic land titles in 2015 as dependent and the share of forest in 1990 as explanatory variables (column 1-3). Controlling for other factors, location at forest margins (areas that were more forested in the past) decreases the likelihood of systematic land titling by 13-18 percentage points. Column (4) in Table 3 shows a model with a somewhat different specification, confirming that plots that were deforested by households themselves are less likely to be titled.

Without land titles, farmers at the forest margins are less able and willing to increase productivity, so they may have stronger incentives to increase their farm size by further expanding into forest land. To test this hypothesis, we regress farm size in 2015 on the share of forest in 1990 (see Eq. 6). The estimation results are shown in columns (5) to (7) of Table 3. As expected, farms at the forest margins are significantly larger than farms further away from the forest. The model in column (8) of Table 3 also confirms that household deforestation activities have directly contributed to larger farm sizes.

Table 1: Land titles and agricultural productivity

	Household-level models		Plot-level models		Plot-level models with soil quality controls	
	(1)	(2)	(3)	(4)	(5)	(6)
	Full sample	Migrants	Full sample	Migrants	Full sample	Sub-sample with soil quality measures
Share of land with systematic title	0.351***	0.586***	0.152**	0.370***	0.183**	0.697***
	(0.085)	(0.107)	(0.063)	(0.098)	(0.071)	(0.265)
Share of land with sporadic title	0.019	0.111	-0.017	0.039	-0.036	-0.131
	(0.071)	(0.090)	(0.071)	(0.073)	(0.079)	(0.254)
Size of rubber area (ha)	-0.030*	-0.006	-0.086***	-0.132***	-0.088***	-0.097*
	(0.016)	(0.028)	(0.017)	(0.029)	(0.021)	(0.049)
Wealth index (quintiles)	0.011	-0.023	0.031**	0.021	0.035*	0.134***
	(0.017)	(0.031)	(0.015)	(0.021)	(0.019)	(0.049)
Perceived soil quality included	No	No	No	No	Yes	No
Soil quality measurements included	No	No	No	No	No	Yes
Chi2 / F- statistic	297.453***	232.371***	312.312***	2332.550***	485.131***	3.63***
Number of observations	665	174	851	231	741	92

Notes: All models have the logarithm of rubber yield (kg/ha) as dependent variable. All models were estimated with random effects panel estimators using data from 2012 and 2015, except for the model in column (6), which only includes 2012 data and was estimated with ordinary least squares. Coefficient estimates are shown with robust standard errors clustered at village level in parentheses. The share of land titled in the plot-level models is 1 if the plot was titled and 0 otherwise. Additional covariates that were included in estimation are shown in Table S2. * $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$.

Table 2: Land titles and agricultural intensity

	Plot-level models					
	(1)	(2)	(3)	(4)	(5)	(6)
	Material input (000 IDR/ha) Full sample	Material input (000 IDR/ha) Migrants	Log of labor input (hours/ha) Full sample	Log of labor input (hours/ha) Migrants	Log of yield (kg/ha) Full sample	Log of yield (kg/ha) Full sample
Systematic land title (=1)	114.148**	204.127**	0.125*	0.122	0.141**	0.145**
	(48.649)	(97.340)	(0.070)	(0.104)	(0.062)	(0.062)
Sporadic land title (=1)	-9.365	26.157	0.055	0.198*	-0.015	-0.026
	(36.395)	(61.016)	(0.056)	(0.105)	(0.073)	(0.062)
Plot size (ha)	-7.491	-14.137	-0.104***	-0.063	-0.084***	-0.053***
	(9.024)	(21.056)	(0.021)	(0.038)	(0.017)	(0.014)
Wealth index (quintiles)	38.959***	9.467	-0.007	-0.011	0.029*	0.027*
	(11.018)	(22.878)	(0.023)	(0.042)	(0.015)	(0.014)
Material input (million IDR/ha)					0.076***	
					(0.027)	
Labor input (Log of hours/ha)						0.334***
						(0.034)
Chi2	139.889***	82.550***	4202.748***	482.462***	357.550***	1033.791***
Number of observations	1101	286	1015	269	850	846

Notes: All models were estimated with random effects panel estimators using data from 2012 and 2015. Coefficient estimates are shown with robust standard errors clustered at village level in parentheses. Due to left-censoring of the dependent variable, a Tobit specification was used in columns (1) and (2). IDR, Indonesian rupiah. Additional covariates that were included in estimation are shown in Table S3. * $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$.

Table 3: Historical forest coverage, land titles, and farm size

	Plot-level models (systematic land title =1)				Household-level models (log of farm size in ha)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	2 km radius	5 km radius	10 km radius	All plots	2 km radius	5 km radius	10 km radius	All plots
Share of forested area in 1990	-0.180***	-0.128**	-0.180***		0.268*	0.337**	0.453**	
	(0.057)	(0.050)	(0.065)		(0.146)	(0.155)	(0.198)	
Deforestation (=1)				-0.060**				0.258***
				(0.028)				(0.086)
Wealth index (initial, quintiles)	0.003	0.009	0.018*	0.029**	0.142***	0.144***	0.146***	0.140***
	(0.015)	(0.012)	(0.010)	(0.011)	(0.034)	(0.034)	(0.034)	(0.034)
Migrant (=1)	-0.042	-0.020	0.009	-0.014	0.137	0.135	0.132	0.148
	(0.035)	(0.030)	(0.025)	(0.029)	(0.101)	(0.101)	(0.101)	(0.101)
Wald chi2 / squared correlation	74.830***	95.021***	77.205***	75.126***	0.208	0.210	0.211	0.217
Number of observations	433	660	750	594	462	462	462	462

Notes: Models in columns (1) to (4) were estimated as probit models. Rubber and oil palm plots are included. Average marginal effects are shown with robust standard errors clustered at village level in parentheses. Models in columns (5) to (8) were estimated as spatial lag models. The spatial lag coefficient ρ ranges from 0.231 to 0.24 significant at $p \leq 0.01$; the goodness of fit measure is the squared correlation. Coefficient estimates are shown with standard errors in parentheses. Additional covariates that were included in estimation are shown in Table S4. * $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$.

5 Discussion

Using data from farm households in Jambi Province, Sumatra, we have shown that secure land property rights contribute to higher agricultural intensity and productivity. Higher productivity on the land already cultivated can lower the need to convert additional forest land and thus reduce deforestation. Yet, the effectiveness of this mechanism depends on the spatial patterns of land titling and intensification. While it is particularly important that farmers at the forest margins have secure land property rights, our data have revealed that farmers close to forested areas are unlikely to hold formal land titles. Like many other developing countries (Agrawal et al., 2008), Indonesia considers forest land as state property. However, forest governance is constrained by unclear boundaries, limited capacity to monitor, and overlaps of state and customary land claims (Indrarto et al., 2012). While land that was deforested in violation of state law is not eligible for titling, farmers are rarely prosecuted and punished for deforestation activities. Without land titles, farmers at the forest margins have little incentive to intensify and rather expand their farms by deforesting additional land. Indeed, farms at the forest margins were found to be larger in size.

These results confirm the three hypotheses that we developed at the beginning of this study. In other words, the potential of land titles to contribute to agricultural intensification and lower deforestation is not fully realized in this particular setting. Addressing the existing inconsistencies between state and customary land institutions at the forest margins would be important to encourage land-sparing agricultural intensification. This does not mean that farmers encroaching forest land should easily be granted land titles for the newly deforested plots. But a regime that does not effectively impede deforestation and at the same time excludes farmers at the forest margins from the legal property system is probably the worst recipe for forest protection and agricultural development. Besides improving farmer's access to land titles for non-forest land, better recognition of customary land rights and more effective protection of forest land without recognized claims could be useful policy responses.

We acknowledge that the relationships are complex and that we were not able to establish all relevant effects unambiguously. Further research is required to confirm some of the mechanisms. First, we did not show that being located at the forest margins affects agricultural productivity and intensity directly. The reason is that forest closeness is correlated with many unobserved factors that could also influence yield. Beyond soil characteristics, microclimate and the abundance of various types of organisms may play important roles (Guillaume et al., 2016). Second, higher agricultural productivity may lead to higher land rents, which could make further forest conversion more attractive for outside agents and thus induce in-migration. However, another recent study with data from Jambi showed that autochthonous farm households are much more involved in deforestation than migrants (Krishna et al., 2017). Third, higher use of material inputs and technologies may possibly lead to a substitution of capital for manual labor, with the freed labor becoming available to deforest and cultivate additional land. However, higher fertilizer use tends to increases labor demand. Another material input that is used more widely by farmers with land titles is herbicides, which could be labor-replacing in general. Yet, the labor input for manual weeding in this setting is small, so that increasing herbicide use leads to better weed control and higher yields rather than significant reduction in the use of manual labor.

Two seemingly contrasting agricultural options for environmental conservation are widely discussed: extensive farming with higher levels of ecological functions but also higher land demand, and intensive farming with lower levels of ecological functions and lower land demand (Green et al., 2005; Rudel et al., 2009; Tscharntke et al., 2012). Which of these options is preferable is highly context-specific. Different settings and different valuations of ecosystem functions can produce a wide range of optimal land allocations and degrees of intensity (Steffan-Dewenter et al., 2007). In tropical rainforest areas, as analyzed here, highly-productive farming with lower land demand and effective forest protection could possibly be the best option to promote sustainable development. The reason is that no agricultural system is able to sustain the same level of biodiversity and ecosystem functions as provided by tropical rainforest (Burney et al., 2010; Clough et al., 2016).

Sumatra had experienced significant deforestation even before land titling started. Hence, from today's perspective the question whether land titles could have reduced deforestation is mainly hypothetical. However, a better understanding of the potential effects of land titles and the links between the spatial patterns of property rights and land-sparing intensification can possibly help protect forest in current and future deforestation hotspots with similar conditions in Indonesia and elsewhere. This study has made an attempt to contribute in this direction.

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ADDITIONAL INFORMATION. Supplementary Information accompanies this paper.

STATEMENT. The authors declare no competing financial interests.

ACKNOWLEDGMENTS. This study was financed by the Deutsche Forschungsgemeinschaft (DFG) in the framework of the collaborative German - Indonesian research project CRC990.We thank Bernhard Brümmer, Anne Mareike Holtkamp, Dian Melati, Hermanto Siregar and I Nengah Surati Jaya for their constructive comments on previous versions of this manuscript and for sharing their data. We thank village leaders and local plot owners for granting us access to their properties.

AUTHORS CONTRIBUTION. C.K. conducted the regression analyses and coordinated the writing of the paper. K.U. conducted the spatial analysis. C.K., K.U., V.V.K., and M.Q. designed the study, and assembled the data sets. C.K., K.U., V.V.K., M.Q., and Z.A. participated in discussions about data analysis and interpretation and contributed to writing of the paper.

DATA AVAILABILITY. The data used in this study are archived with openly accessible, keyword-searchable metadata and data holder contact details for data requests (EFForTs-IS, 2017). Datasets used in this study have the following identification numbers: 12620, 13500, 13501, 13520, 13660, 13642, 13643, 13644, 13647, 13648, 13649, 13650, 13651 (household-level data); 13521, 13600, 13601, 13620 (plot-level data); 11422, 11423, 13680 (village-level data); 11987 (soil data); 12026, 12027, 12030 (land cover maps).

SUPPLEMENTARY MATERIALS

Table S1: Summary statistics

	2012			2015		
	Number of obs.	Mean	Std. deviation	Number of obs.	Mean	Std. deviation
Plot-level variables (rubber plots)						
Yield per year (kg/ha)	643	1144.683	1083.612	466	1489.196	1086.691
Material input per year (000 IDR/ha)	643	322.521	672.179	466	141.655	419.497
Labor input per year (hours/ha)	643	692.655	630.828	466	1057.674	1122.030
Systematic land title (=1)	645	0.074		690	0.100	
Sporadic land title (=1)	645	0.180		690	0.222	
Plot size (ha)	645	2.242	1.948	690	2.084	1.809
Age of rubber trees (years)	645	14.763	10.647	689	17.026	10.479
Employing sharecropping tenants (=1)	645	0.143		690	0.223	
Distance from household residence (km)	645	4.802	8.226	689	4.902	12.791
Distance from road (km)	645	1.170	1.757	689	0.885	1.410
Household-level variables						
Age of household head (years)	471	44.996	12.213	473	47.072	11.408
Female-headed household (=1)	471	0.059		473	0.080	
Education of household head (years in school)	471	7.476	3.620	473	7.150	3.742
Migrated to village (=1)	471	0.255		473	0.256	
Number of adults in household	471	2.975	1.243	473	2.987	1.190
Total farm size (ha)	471	4.200	4.642	473	4.134	4.615
Size of rubber area (ha)	406	2.684	3.037	406	2.968	3.167
Oil palm farmer (=1)	471	0.285		473	0.309	
Rubber farmer (=1)	471	0.866		473	0.860	
Rubber farmer using fertilizer/pesticide (=1)	408	0.519		406	0.345	
Oil palm farmer using fertilizer/pesticide (=1)	134	0.819		146	0.818	
Formal credit taken (=1)	471	0.166		473	0.288	
Informal credit taken (=1)	471	0.193		473	0.173	
Own business (=1)	471	0.200		473	0.277	
Share of land with systematic land title	471	0.060		473	0.089	
Share of land with sporadic land title	471	0.167		473	0.189	
Village-level variables						
Number of households per village	34	674.485	617.922	34	735.118	973.537
Share of households of Melayu ethnicity	34	0.651	0.312	34	0.696	0.308

Notes: In 2015, plot level input and output data were not collected for all, but only for a random sub-sample of plots.

Table S2: Land titles and agricultural productivity

	Household-level models				Plot-level models				Plot-level models with soil quality controls	
	(1) Full sample (RE)	(1a) Balanced panel (FE)	(2) Migrants (RE)	(2a) Non-migrants (RE)	(3) Full sample (RE)	(3a) Balanced panel (FE)	(4) Migrants (RE)	(4a) Non-migrants (RE)	(5) Full sample (RE)	(6) Sub-sample with soil quality measures (OLS)
Share of land with systematic. title	0.351***	0.352	0.586***	0.328***	0.152**	0.025	0.370***	0.095	0.182***	0.697**
	(0.085)	(0.298)	(0.107)	(0.098)	(0.063)	(0.269)	(0.098)	(0.070)	(0.071)	(0.265)
Share of land with sporadic title	0.019	-0.098	0.111	-0.038	-0.017	0.070	0.039	-0.070	-0.036	-0.131
	(0.071)	(0.199)	(0.090)	(0.123)	(0.071)	(0.203)	(0.073)	(0.106)	(0.079)	(0.254)
Total farm size (ha)	-0.025	0.049	-0.007	-0.020	-0.020*	0.014	0.021	-0.023*	-0.018	-0.123**
	(0.022)	(0.033)	(0.038)	(0.026)	(0.012)	(0.029)	(0.021)	(0.013)	(0.016)	(0.054)
Size of rubber area (ha)	-0.030*	-0.064***	-0.006	-0.040**	-0.086***	-0.138***	-0.132***	-0.080***	-0.088***	-0.097*
	(0.016)	(0.023)	(0.028)	(0.018)	(0.017)	(0.049)	(0.029)	(0.018)	(0.022)	(0.049)
Wealth index (quintiles)	0.011	-0.006	-0.023	0.021	0.031**	0.015	0.021	0.042*	0.034*	0.134***
	(0.017)	(0.040)	(0.031)	(0.022)	(0.015)	(0.038)	(0.021)	(0.022)	(0.019)	(0.049)
Number of adults	-0.007	0.036	0.128	-0.062	0.019	-0.003	-0.014	0.021	0.005	0.011
	(0.065)	(0.044)	(0.095)	(0.081)	(0.021)	(0.046)	(0.029)	(0.024)	(0.022)	(0.059)
Own business (=1)	0.019	0.033	0.001	0.024	-0.045	0.026	0.126	-0.118*	-0.026	-0.351*
	(0.024)	(0.099)	(0.041)	(0.029)	(0.056)	(0.096)	(0.085)	(0.070)	(0.065)	(0.195)
2012 (=1)	-0.075	-0.107**	-0.126	-0.062	-0.114**	-0.138***	-0.080	-0.132***	-0.117**	
	(0.049)	(0.051)	(0.136)	(0.050)	(0.046)	(0.050)	(0.100)	(0.049)	(0.048)	
Age of household head (years)	-0.001		0.002	-0.002	-2.E-4		0.004	-0.003	-0.001	-0.024***
	(0.003)		(0.004)	(0.003)	(0.003)		(0.005)	(0.003)	(0.003)	(0.009)
Female-headed household (=1)	-0.227**		-0.480***	-0.141	-0.196*		-0.472***	-0.056	-0.192	0.055
	(0.113)		(0.140)	(0.130)	(0.105)		(0.178)	(0.098)	(0.126)	(0.362)
Education (years of schooling)	0.010		0.004	0.012	0.017*		0.008	0.021**	0.016*	0.015
	(0.010)		(0.012)	(0.011)	(0.009)		(0.011)	(0.010)	(0.010)	(0.020)
Farm size squared (ha)	0.001***		0.000	0.001**	0.001***		7.E-5	0.001***	0.001**	0.008***
	(0.001)		(0.001)	(0.001)	(4.E-4)		(0.001)	(5.E-4)	(0.001)	(0.003)
Non-random village (=1)	-0.165**		-0.215***	-0.126	-0.191***		-0.227**	-0.137**	-0.167**	
	(0.068)		(0.072)	(0.078)	(0.067)		(0.099)	(0.056)	(0.066)	
Migrant (=1)	0.056				0.040				0.019	-0.115
	(0.065)				(0.066)				(0.067)	(0.200)
Age of rubber trees (years)					0.017*		0.028	0.013	0.023**	-0.004
					(0.009)		(0.017)	(0.010)	(0.009)	(0.038)
Age of trees (years squared)					-4.E-4*		-0.001	-3.E-4*	-0.001***	1.E-06
					(-2.E-4)		(0.000)	(-2.E-4)	(2.E-4)	(0.001)
Employing sharecroppers (=1)					0.118*		0.171	0.098	0.077	0.360**
					(0.064)		(0.110)	(0.069)	(0.062)	(0.178)
Distance from residence (km)					-0.002		-0.025***	0.003	-0.003	-0.012
					(0.003)		(0.008)	(0.004)	(0.006)	(0.013)
Distance from road (km)					0.005		0.055**	-0.007	0.009	0.013
					(0.016)		(0.026)	(0.019)	(0.017)	(0.066)
Altitude of residence (m)									-2.E-4	
									(0.001)	
Medium soil fertility (=1)									0.012	
(Ref.=low fertility)									(0.122)	
High soil fertility (=1)									-0.042	
(Ref.=low fertility)									(0.112)	

	Household-level models				Plot-level models				Plot-level models with soil quality controls	
	(1) Full sample (RE)	(1a) Balanced panel (FE)	(2) Migrants (RE)	(2a) Non-migrants (RE)	(3) Full sample (RE)	(3a) Balanced panel (FE)	(4) Migrants (RE)	(4a) Non-migrants (RE)	(5) Full sample (RE)	(6) Sub-sample with soil quality measures (OLS)
Soil bulk density										-0.600
										(0.456)
Soil carbon content										-0.088
										(0.099)
Carbon content (squared)										0.003
										(0.003)
Carbon/nitrogen ratio										0.032
										(0.037)
Constant	7.233***	7.105***	7.188***	7.279***	7.126***	7.494***	6.967***	7.220***	7.163***	8.760***
	(0.150)	(0.211)	(0.244)	(0.171)	(0.199)	(0.234)	(0.347)	(0.237)	(0.256)	(0.852)
Chi2 / F-statistic	297.453***	1.986***	232.371***	123.891***	312.312***	1.89**	2332.550***	550.142***	482.379***	3.634***
Hausman test (chi2)		2.24				4.67				
Number of observations	665	564	174	491	851	516	231	620	741	92

Notes: All models have the logarithm of rubber yield (kg/ha) as dependent variable. Coefficient estimates are shown with robust standard errors clustered at village level in parentheses. The share of land titled in the plot-level models is 1 if the plot was titled and 0 otherwise. RE, random effects; FE, fixed effects; OLS, ordinary least squares. * $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$.

Table S3: Land titles and agricultural intensity

	Plot-level models					
	(1) Material input (000 IDR/ha) Full sample	(2) Material input (000 IDR/ha) Migrants	(3) Log of labor input (hours/ha) Full sample	(4) Log of labor input (hours/ha) Migrants	(5) Log of yield (kg/ha) Full sample	(6) Log of yield (kg/ha) Full sample
Systematic land title (=1)	114.148**	204.127**	0.125*	0.122	0.141**	0.145**
	(48.649)	(97.340)	(0.070)	(0.104)	(0.062)	(0.062)
Sporadic land title (=1)	-9.365	26.157	0.055	0.198*	-0.015	-0.026
	(36.395)	(61.016)	(0.056)	(0.105)	(0.073)	(0.062)
Total farm size (ha)	14.887**	23.495	-0.035*	0.006	-0.022**	-0.002
	(7.195)	(17.456)	(0.018)	(0.035)	(0.011)	(0.010)
Farm size squared (ha)	-0.241	-0.285	0.001*	-0.001	0.001***	0.001**
	(0.231)	(0.659)	(0.001)	(0.001)	(0.000)	(0.000)
Wealth index (quintiles)	38.959***	9.467	-0.007	-0.011	0.029*	0.027*
	(11.018)	(22.878)	(0.023)	(0.042)	(0.015)	(0.014)
Own business (=1)	-11.332	102.631	0.023	0.073	-0.047	-0.068
	(33.826)	(65.527)	(0.056)	(0.117)	(0.054)	(0.057)
Number of adults	-4.377	-0.566	0.031	0.045	0.019	0.007
	(12.091)	(27.882)	(0.028)	(0.053)	(0.020)	(0.018)
Age of household head (years)	-0.414	1.233	0.003	0.004	-0.000	-0.002
	(1.451)	(3.207)	(0.004)	(0.007)	(0.003)	(0.002)
Female-headed household (=1)	-181.132**	-324.205	-0.246	-0.707*	-0.186*	-0.068
	(76.972)	(225.738)	(0.197)	(0.406)	(0.103)	(0.092)
Education (years of schooling)	2.652	26.751***	-0.011	-0.022	0.017*	0.020**
	(4.375)	(9.153)	(0.010)	(0.021)	(0.009)	(0.009)
Migrant (=1)	113.687***		-0.061		0.027	0.060
	(32.706)		(0.056)		(0.067)	(0.064)
Plot size (ha)	-7.491	-14.137	-0.104***	-0.063	-0.084***	-0.053***
	(9.024)	(21.056)	(0.021)	(0.038)	(0.017)	(0.014)
Age of rubber trees (years)	-32.052***	-33.473***	-0.014	-0.028	0.020**	0.011
	(5.586)	(10.745)	(0.009)	(0.018)	(0.010)	(0.009)
Age of trees (years squared)	0.542***	0.560**	0.000	0.001	-0.000*	-0.000
	(0.123)	(0.235)	(0.000)	(0.000)	(0.000)	(0.000)
Plot productive (=1)	191.446***	392.696***	3.393***	3.417***		
	(45.729)	(91.030)	(0.127)	(0.211)		
Employing sharecroppers (=1)	-62.861	-45.360	-0.077	-0.202	0.121**	0.136**
	(42.254)	(82.972)	(0.087)	(0.209)	(0.062)	(0.062)
Distance from residence (km)	-0.083	-0.308	0.002	-0.002	-0.001	-0.001
	(1.071)	(42.252)	(0.001)	(0.086)	(0.061)	(0.061)
Distance from road (km)	-20.854**	-2.569	0.029	0.074	0.005	0.002
	(9.577)	(21.924)	(0.024)	(0.054)	(0.016)	(0.014)
2012 (=1)	121.727***	178.450***	-0.170***	-0.222**	-0.124***	-0.071
	(27.185)	(51.524)	(0.060)	(0.102)	(0.046)	(0.047)
Non-random village (=1)	-67.208*	-261.588***	0.067	0.236**	-0.185***	-0.198***
	(36.386)	(67.676)	(0.080)	(0.114)	(0.065)	(0.058)
Material input (million IDR/ha)					0.000***	
					(0.000)	
Log of labor input (hours/ha)						0.334***
						(0.034)
Constant			3.784***	3.487***	7.096***	4.873***
			(0.291)	(0.539)	(0.199)	(0.287)
Chi2	139.889***	82.550***	4202.748***	482.462***	357.550***	1033.791***
Number of observations	1101	286	1015	269	850	846

Notes: All models were estimated with random effects panel estimators using data from 2012 and 2015. Coefficient estimates are shown with robust standard errors clustered at village level in parentheses. Due to left-censoring of the dependent variable, a Tobit specification was used in columns (1) and (2). IDR, Indonesian rupiah. * $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$.

Table S4: Historical forest coverage, land titles, and farm size

	Plot-level models (systematic land title =1)				Household-level models (log of farm size in ha)			
	(1) 2 km radius	(2) 5 km radius	(3) 10 km radius	(4) All plots	(5) 2 km radius	(6) 5 km radius	(7) 10 km radius	(8) All plots
Share of forested area in 1990	-0.180***	-0.128**	-0.180***		0.268*	0.337**	0.453**	
	(0.057)	(0.050)	(0.065)		(0.146)	(0.155)	(0.198)	
Deforestation (=1)				-0.060**				0.258***
				(0.028)				(0.086)
Age of household head (years)	-0.002	-0.001	-0.001	-0.001	0.011**	0.011**	0.011**	0.009*
	(0.002)	(0.002)	(0.001)	(0.001)	(0.005)	(0.005)	(0.005)	(0.005)
Education (years of schooling)	0.004	1.E-4	-0.001	-0.003	0.038***	0.037***	0.037***	0.039***
	(0.005)	(0.004)	(0.004)	(0.004)	(0.012)	(0.012)	(0.012)	(0.012)
Migrant (=1)	-0.042	-0.020	0.009	-0.014	0.137	0.135	0.132	0.148
	(0.035)	(0.030)	(0.025)	(0.029)	(0.101)	(0.101)	(0.101)	(0.101)
Wealth index (initial, quintiles)	0.003	0.009	0.018*	0.029**	0.142***	0.144***	0.146***	0.140***
	(0.015)	(0.012)	(0.010)	(0.011)	(0.034)	(0.034)	(0.034)	(0.034)
Non-random village (=1)	-0.030	-0.041	0.005	-0.008	0.169	0.144	0.105	0.177
	(0.054)	(0.048)	(0.044)	(0.051)	(0.137)	(0.136)	(0.137)	(0.136)
Share of migrants in village (%)	0.212***	0.197***	0.149**	0.184**	0.585***	0.596***	0.590***	0.578***
	(0.074)	(0.069)	(0.061)	(0.075)	(0.192)	(0.192)	(0.192)	(0.191)
Village wealth index (initial, quintiles)	-0.017	-0.004	-3.E-5	0.001	-0.105***	-0.107***	-0.111***	-0.104***
	(0.013)	(0.013)	(0.013)	(0.012)	(0.033)	(0.033)	(0.033)	(0.033)
Rubber plot (=1)	-0.059	-0.101***	-0.081***	-0.097***				
	(0.038)	(0.025)	(0.025)	(0.033)				
Duration of plot ownership (years)	0.005***	0.005***	0.004***	0.006***				
	(0.002)	(0.002)	(0.001)	(0.001)				
Distance from road (km)	-0.095**	-0.042**	-0.025**	-0.023**				
	(0.041)	(0.017)	(0.011)	(0.011)				
Age of household (years)					0.009*	0.009*	0.009*	0.008*
					(0.005)	(0.005)	(0.005)	(0.005)
Constant					-0.544*	-0.554*	-0.585*	-0.514*
					(0.301)	(0.300)	(0.301)	(0.298)
Regency dummies included	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Wald chi2 / squared correlation	74.830***	95.021***	77.205***	75.126***	0.208	0.210	0.211	0.217
Number of observations	433	660	750	594	462	462	462	462

Notes: Models in columns (1) to (4) were estimated as probit models. Rubber and oil palm plots are included. Average marginal effects are shown with robust standard errors clustered at village level in parentheses. Models in columns (5) to (8) were estimated as spatial lag models. The spatial lag coefficient ρ ranges from 0.231 to 0.24 significant at $p \leq 0.01$. The reported coefficients are the parameter estimates of β with standard errors reported in parentheses. Direct effects are calculated by $\left(\frac{3-\rho^2}{3(1-\rho^2)}\right) * \beta$). Indirect effects are calculated by $\left(\frac{3\rho+\rho^2}{3(1-\rho^2)}\right) * \beta$).The goodness of fit measure is the squared correlation. Coefficient estimates are shown with standard errors in parentheses. * $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$.

Table S5: Historical forest coverage and land titles (spatial error and spatial lag models)

	Spatial error models				Spatial lag models			
	(1) 2 km radius	(2) 5 km radius	(3) 10 km radius	(4) All plots	(5) 2 km radius	(6) 5 km radius	(7) 10 km radius	(8) All plots
Share of forested area in 1990	-0.160***	-0.113**	-0.150***		-0.164***	-0.107**	-0.146***	
	(0.050)	(0.048)	(0.057)		(0.053)	(0.046)	(0.056)	
Deforestation (=1)				-0.068**				-0.068**
				(0.027)				(0.027)
Rubber plot (=1)	-0.056	-0.096***	-0.078**	-0.105***	-0.057	-0.095***	-0.077**	-0.105***
	(0.042)	(0.034)	(0.031)	(0.032)	(0.042)	(0.033)	(0.031)	(0.031)
Duration of plot ownership (years)	0.007***	0.006***	0.005***	0.006***	0.007***	0.006***	0.005***	0.006***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
Distance from road (km)	-0.086***	-0.041***	-0.025**	-0.020**	-0.085***	-0.042***	-0.025**	-0.021**
	(0.030)	(0.013)	(0.010)	(0.008)	(0.030)	(0.013)	(0.010)	(0.008)
Age of household head (years)	-0.002	-0.001	-0.001	-0.000	-0.002	-0.001	-0.001	-0.000
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Education (years of schooling)	0.005	0.000	0.001	0.000	0.004	0.000	0.001	0.001
	(0.005)	(0.004)	(0.003)	(0.004)	(0.005)	(0.004)	(0.003)	(0.004)
Migrant (=1)	-0.028	-0.013	0.012	-0.014	-0.030	-0.013	0.012	-0.013
	(0.042)	(0.034)	(0.031)	(0.030)	(0.042)	(0.034)	(0.031)	(0.030)
Wealth index (initial, quintiles)	0.008	0.012	0.017	0.028***	0.007	0.012	0.018*	0.029***
	(0.015)	(0.012)	(0.011)	(0.011)	(0.015)	(0.012)	(0.011)	(0.011)
Total farm size (ha)	-0.001	-0.003	-0.002	-0.004*	-0.001	-0.003	-0.002	-0.004*
	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
Non-random village (=1)	-0.066	-0.056	-0.007	-0.013	-0.066	-0.055	-0.007	-0.015
	(0.052)	(0.043)	(0.040)	(0.042)	(0.055)	(0.042)	(0.039)	(0.039)
Share of migrants in village (%)	0.195**	0.190***	0.126**	0.128**	0.202**	0.183***	0.123**	0.117*
	(0.078)	(0.070)	(0.060)	(0.065)	(0.083)	(0.068)	(0.059)	(0.061)
Village wealth index (quintiles)	-0.025*	-0.011	-0.005	-0.003	-0.026*	-0.011	-0.005	-0.004
	(0.014)	(0.012)	(0.010)	(0.011)	(0.015)	(0.011)	(0.010)	(0.011)
Constant	0.276**	0.297***	0.198*	0.141	0.287**	0.287***	0.191*	0.135
	(0.132)	(0.110)	(0.102)	(0.110)	(0.134)	(0.109)	(0.101)	(0.107)
Regency dummies included	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sigma								
Constant	0.314***	0.306***	0.304***	0.279***	0.314***	0.306***	0.304***	0.279***
	(0.011)	(0.009)	(0.008)	(0.008)	(0.011)	(0.009)	(0.008)	(0.008)
Lambda and rho								
Constant	-0.079	0.062	0.039	0.122	-0.050	0.068	0.032	0.148
	(0.104)	(0.095)	(0.091)	(0.103)	(0.099)	(0.092)	(0.087)	(0.096)
Squared correlation	0.088	0.074	0.057	0.099	0.089	0.075	0.058	0.104
Number of observations	405	620	734	573	405	620	734	573

Notes: The dependent variable in all models is a dummy that take a value of 1 if the plot was systematically titled in 2015, and 0 otherwise. The reported coefficients are the parameter estimates of β with standard errors reported in parentheses. In column (1) to (4) β equals the average marginal effect. In column (5) to (8): Direct effects are calculated by $\left(\frac{3-\rho^2}{3(1-\rho^2)}\right)*\beta$) and indirect effects are calculated by $\left(\frac{3\rho+\rho^2}{3(1-\rho^2)}\right)*\beta$). $^{*}p \leq 0.10$, $^{**}p \leq 0.05$, $^{***}p \leq 0.01$.

Table S6: Historical forest coverage and farm size (spatial error and ordinary least square models)

	Spatial error model				Ordinary least squares			
	(1) 2 km radius	(2) 5 km radius	(3) 10 km radius	(4) All plots	(5) 2 km radius	(6) 5 km radius	(7) 10 km radius	(8) All plots
Share of forested area in 1990	0.325*	0.406**	0.535**		0.321*	0.412**	0.551**	
	(0.178)	(0.187)	(0.240)		(0.164)	(0.177)	(0.233)	
Deforestation (=1)				0.236***				0.283***
				(0.089)				(0.086)
Age of household head (years)	0.012**	0.012**	0.012**	0.009*	0.011***	0.011***	0.011***	0.008**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
Education (years of schooling)	0.038***	0.038***	0.038***	0.038***	0.038**	0.037**	0.037**	0.039***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.014)	(0.014)	(0.014)	(0.013)
Migrant (=1)	0.112	0.112	0.110	0.128	0.155	0.152	0.149	0.169
	(0.106)	(0.106)	(0.106)	(0.105)	(0.133)	(0.131)	(0.130)	(0.131)
Age of household (years)	0.009*	0.009*	0.008*	0.008*	0.009**	0.009**	0.009**	0.008**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
Wealth index (initial, quintiles)	0.142***	0.144***	0.146***	0.141***	0.144***	0.147***	0.149***	0.142***
	(0.035)	(0.035)	(0.035)	(0.035)	(0.036)	(0.036)	(0.037)	(0.036)
Share of migrants in village (%)	0.757***	0.763***	0.751***	0.733***	0.701**	0.710**	0.702**	0.691**
	(0.227)	(0.225)	(0.224)	(0.221)	(0.299)	(0.295)	(0.294)	(0.278)
Village wealth index (initial, quintiles)	-0.122***	-0.124***	-0.129***	-0.121***	-0.127***	-0.129***	-0.134***	-0.126***
	(0.039)	(0.039)	(0.039)	(0.038)	(0.038)	(0.038)	(0.038)	(0.037)
Non-random village (=1)	0.214	0.183	0.137	0.212	0.218*	0.186	0.140	0.224*
	(0.163)	(0.161)	(0.162)	(0.158)	(0.128)	(0.130)	(0.139)	(0.119)
Constant	-0.307	-0.325	-0.354	-0.246	-0.237	-0.262	-0.298	-0.204
	(0.312)	(0.310)	(0.311)	(0.304)	(0.317)	(0.319)	(0.326)	(0.291)
Regency dummies included	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sigma								
Constant	0.818***	0.817***	0.817***	0.816***				
	(0.027)	(0.027)	(0.027)	(0.027)				
Lambda								
Constant	0.253***	0.243***	0.240***	0.226***				
	(0.084)	(0.084)	(0.084)	(0.086)				
F-stat. / squared correlation	0.186	0.190	0.191	0.196	8.354	8.589	8.621	8.152
Number of observations	462	462	462	462	462	462	462	462

Notes: The dependent variable in all models is log of farm size in 2015 measured in hectares. Coefficient estimates are shown with standard errors in parentheses (clustered at village level in columns 5-8). Goodness of fit measure for the spatial error models is the squared correlation. * $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$.