World Development 142 (2021) 105446

Contents lists available at ScienceDirect

World Development

journal homepage: www.elsevier.com/locate/worlddev

The effectiveness of protected areas in the context of decentralization

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ARTICLE INFO

Article history:
Available online 13 March 2021

JEL classification:
Q23
O13

Keywords:
Forest conservation
Protected areas
Decentralization
Impact evaluations
Indonesia
SE Asia

ABSTRACT

While protected areas (PA) remain a key conservation strategy globally, their performance is likely shaped by the socio-political context in which they exist. Although decentralization is a good example of such a contextual phenomenon in multiple locations globally, it is rare to find quantitative empirical analyses of how it moderates PA effectiveness. We evaluate how the decentralization in Indonesia (proxied by the introduction of direct elections, district head (*bupati*) change, and district splitting) influenced PA effectiveness between 2000 and 2008. Focusing on three outcomes - deforestation, forest fragmentation, and fires, we apply a quasi-experimental approach to a carefully constructed spatially explicit village-level panel dataset, combined with geospatial biophysical and physio-geographic data. We hypothesize that the moderating influence of decentralization on PA effectiveness depends on whether decentralization increased threats to forests, strengthened local accountability, or weakened enforcement. On average, we find *direct elections* improved the PA impact in terms of reducing deforestation in protected villages, but had no statistically significant effect on forest fragmentation, fires, or leakage. On average, we find *district splitting* increased forest fragmentation in the recently protected villages, but had no statistically significant impact on deforestation and fires. On average, we find *the bupati change* had no statistically discernible influence on PA impacts on deforestation, fragmentation or fires. Given the increasing threats to forests due to decentralization, these results imply that district splitting and the bupati change weakened enforcement inside PAs with regards to deforestation and forest fragmentation, in contrast to direct elections. By highlighting the potential channels through which decentralization in Indonesia impacted forests, we offer insights into the effectiveness of a common conservation policy in the country. Broadly, we contribute to the conservation impact evaluation literature by quantitatively examining how political economy influences the performance of conservation policies.

1. Introduction: protected areas and decentralization

While protected areas (PA) remain a key forest conservation strategy globally, their performance is shaped by the socio-political context in which they exist (Sills & Jones, 2018). Decentralization is one of the best examples of such context. Specifically, it is an administrative, political, fiscal, and economic process that transfers responsibilities from a central government to lower levels of government. For example, decentralization may strengthen the ability of the local government to monitor and enforce regulations (complementary 'moderation') (Lambin et al., 2014; Adam & Eltayeb, 2016). Alternatively, decentralization may weaken the ability of governments to monitor and enforce restrictions related to natural resource harvesting, may create incentives for increased timber harvesting locally, or limit the forest management expertise for PA management and, thus, contribute to weakened impact of PAs (antagonistic 'moderation') (Lambin et al., 2014; Adam & Eltayeb, 2016). Which effect dominates, however, likely varies depending on how decentralization is implemented (Resosudarmo & Pradnja, 2005; Hofman & Kaiser, 2006; Larson & Soto, 2008; Coleman & Fleishman, 2011; Wehkamp et al., 2018).

Recent literature has highlighted the need to understand the role of political economy factors in determining the performance of PAs (e.g., Pfaff & Robalino, 2012; Sills & Jones, 2018). While institutions are key in designing conservation interventions and shaping their effectiveness (Sills & Jones, 2018), generally, the literature on estimating the impact of decentralization policies on natural resources is thin (Miteva et al., 2012; Puri et al., 2016; Sills & Jones, 2018). Even

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https://doi.org/10.1016/j.worlddev.2021.105446
0305-750X/

fewer studies quantify the impact of political economy factors on conservation policy effectiveness. For example, although Burgess et al (2012) consider the political economy of deforestation in Indonesia, they leave out conservation policies from their analysis. In contrast, Engel et al. (2013) model the effectiveness of a national park in Indonesia as a bargaining game between park managers and local communities and examine the conditions under which co-management arises. However, their model focuses only on deforestation in a relatively small area (one national park in Sulawesi), has a small number of observations (50–80 communities) and, therefore, is not well placed to identify policy impacts. Pfaff et al. (2013) and Herrera et al. (2019) provide an indirect example by examining how state vs. federal vs. indigenous tenure shapes the effectiveness of PAs in reducing deforestation in Brazil. In other words, most rigorous empirical work has focused on either decentralization policies, or on the presence of PAs. Critically, only a few have considered how decentralization affects the performance of the conservation intervention directly. Our work addresses this gap.

Synthesizing theory on political economy and development economics, we highlight how decentralization moderates PA effectiveness in Indonesia. We extend previous analyses to test how decentralization (proxied by *direct elections*, *district splitting*, and *bupati (district head) change*), impacts the performance of PAs on three outcomes (deforestation, forest fragmentation, and the incidence of fires). We hypothesize that *direct elections* may improve PA effectiveness due to increased local accountability and matching to local preferences (Bardhan & Mookherjee, 2006). If the local population values protected areas (e.g., because of ecosystem services, tourism revenue etc), then direct elections may better align preferences and management, thereby improving PA performance. Conversely, we hypothesize *district splitting* weakens a governments' ability to enforce restrictions and, initially at least, facilitate corruption, thereby reducing PA effectiveness (e.g., Burgess et al., 2012). The *bupati change* creates uncertainty and incentives for short-run looting (e.g., Olson, 1993), which, we hypothesize, may result in weakened governance, and hence, PA effectiveness in the short run. Because of the hypothesized different channels through which the decentralization proxies affect PA effectiveness, we consider these three indicators as heterogeneous treatments.

We test the predictions with a very rich spatially explicit panel dataset from spanning almost 63,000 Indonesian villages between 2000 and 2008 using a combination of panel data estimators and matching. We perform the analyses on both the villages spanned by PAs as well as on the PA adjacent unprotected villages to test for direct impacts and spillovers, respectively. We find that, while decentralization spurred deforestation and forest degradation, but reduced the use of fires overall, it had a mixed impact on the PA effectiveness. On one hand, the introduction of *direct elections* decreased deforestation in protected villages, on average, but there was no discernible impact on fires and fragmentation of this interaction. However, *district splitting* resulted in more fragmented forests inside PAs established after 2000. The *bupati change* did not result in any statistically significant impacts on PA effectiveness, either in the villages inside PAs or those adjacent to them.

Our research makes two inter-related contributions to the existing literature, summarized in reviews such as Miteva et al. (2012) and Sills and Jones (2018). First, we attempt to move beyond aggregate deforestation as a proxy for forest conservation by considering fires and forest fragmentation. Second, our work is one of the few attempts to integrate impact evaluations with careful attention to political economy by empirically testing the impact of decentralization on the performance of a conservation policy (Miteva et al., 2012). Given Indonesia's importance to global efforts for biodiversity conservation and climate change mitigation (e.g., Parikesit et al., 2012; Griscom et al., 2017), our results provide insights into the factors affecting conservation interventions and into the design of effective conservation policies in Indonesia.

2. Background and hypothesis

2.1. Brief history of Indonesia's decentralization

In response to threats of secession by the Riau, Papua, and Aceh provinces, the Indonesian government carried out a series of rapid political, fiscal, and administrative reforms beginning in 2001 to transfer significant powers from the central to the district governments (Larson & Soto, 2008; Resosudarmo & Pradnja, 2005).[1] In order to attenuate separatist tendencies within provinces, decentralization circumvented the province governments in favor of the lower-tier district government structures (Bardhan & Mookherjee, 2006).

Following fears of increased separatism and demands from resource-rich districts for more of their revenue to be returned to them, the decentralization in Indonesia spurred district splitting: the number of districts increased from 292 in 1998 to 483 in 2008 (Burgess et al., 2012). With the onset of decentralization, the district governments received dramatically increased authority over almost all sectors of government and a larger share of the natural resource royalties originating from their district (Burgess et al., 2012). However, they also became responsible for expenditures that used to be covered by the national government (Duncan, 2007). The district (local) governments became responsible for providing health, education, infrastructure and environmental services (Bardhan & Mookherjee, 2006). Even though the responsibility for the management, financing and delineation of PAs lay with the central government, a ministerial decree gave the district officials the right to issue logging permits for areas smaller than 50,000 ha within the district (Resosudarmo & Pradnja, 2005). For example, in 2001 the district head of Bulungan district in East Kalimantan gave 618 such permits for 62,940 ha (Fox, Adhuri, & Resosudarmo, 2005). Furthermore, while the central government gave authorization for the conversion of forest land to other uses within conversion zones, the district office was responsible for the implementation; for production forests the district office developed management plans with the concession holder (Burgess et al., 2012). That decentralization also gave district offices the right to levy taxes on the timber transported through their boundaries (Resosudarmo & Pradnja, 2005) implies that no logging was possible without the complicity of the district office (Burgess et al., 2012). Furthermore, the district office became the point of control for authorizing and monitoring both legal and illegal logging within the district (Burgess et al., 2012; Resosudarmo & Pradnja, 2005). In short, one aspect of Indonesia's decentralization was to create incentives for districts to harvest natural resources, in order to increase district revenues.

Decentralization also increased the role of the local voters, who could directly elect representatives to the district parliament (DPRD), which in turn elected the district head from closed party lists. The district heads (*bupati* in rural areas and *walikota* in urban) had significant powers to set the priorities of the district governments (Skoufias et al., 2011). However, they could be removed from office if they failed to provide accountability (Hofman & Kaiser, 2006). In addition, Law 32/2004 introduced direct elections of district heads; they were exogenously timed and depended on when the term of the previous district head came to an end (Burgess et al., 2012; Hofman & Kaiser, 2006; Skoufias et al., 2011). The reform was intended to make the district head more accountable to the local population.

[1] The major decentralization laws-Law 22 on regional governance and Law 25 on the balance of funds- were passed in 1999, but came into effect only in 2001 under President Habibie (Bardhan & Mookherjee, 2006; Resosudarmo & Pradnja, 2005).

2.2. Who is deforesting in Indonesia?

Typically, forest degradation and deforestation in the country depend on the agricultural suitability (e.g., slope and elevation), proximity to markets, ease of transportation (proximity to major roads and waterways), and the reliance of the local population on agriculture and natural resources (e.g., Pfaff & Robalino, 2012). In Indonesia, these factors implicate commercial firms and, to a smaller extent, communities as the primary actors of deforestation and forest degradation (Abood et al., 2015). However, the underlying causes of deforestation in Indonesia are complex and dynamic: they seem to be impacted by markets -both domestic and international, ineffective policies and regulations, lack of governance and monitoring capacity (Resosudarmo et al., 2012; Wheeler et al., 2011). One pathway to deforestation is related to the process of logging, which changes the forest structure, reduces the value of the forest as valuable trees are taken out and, thus, increases the probability of subsequent conversion to massive agricultural plantations like oil palm (Fuller, 2006). Even though clear felling is permitted only within permanent production forests, logging, legal or illegal, contributes to the removal of large quantities of timber over large areas within very short time horizons (Resosudarmo, 2004) . For example, Sintang district in West Kalimantan issued 409 small-scale timber licenses, which removed 1.2 million cubic meters of timber within one year (Resosudarmo, 2004). Removing the valuable timber species from the forest decreases its value and can facilitate the conversion to more profitable activities like agriculture (especially oil palm).

3. Hypotheses

Drawing on how decentralization was implemented in Indonesia, we formulate hypotheses about the PA effectiveness and the role of the political economy context. We consider PAs effective if they reduce deforestation, fires, and forest fragmentation, by reducing the forest edge area and/or by increasing the amount of core forest areas.

3.1. Deforestation

In line with previous studies (e.g., Pfaff & Robalino, 2012; Ferraro, Hanauer, & Sims, 2011), we posit that the effectiveness of PAs is determined by the threat to the forest, shaped by the opportunity cost of the land, and the ability to monitor and enforce restrictions, which is a function of institutions. That is, we expect PAs to have the greatest additional impact in areas with high background deforestation and high enforcement. If the forested land has properties that make it unfavorable for other uses like agriculture or large-scale timber harvesting, the threat of background deforestation is low, PAs will not be effective, *ceteris paribus*. If the deforestation threat is high, but the enforcement is low because of weak institutions, PAs are also not going to be effective, *ceteris paribus*.

Previous work showed that *district split*ting increased deforestation within districts (Burgess et al., 2012), likely for two main reasons: First, district splitting created incentives for district governments to issue additional permits for logging, in order to raise revenue (Burgess et al., 2012; Duncan, 2007). Second, because of the rapid district splitting, disrupting the institutional apparatus, decentralization resulted in weak formal institutions (Burgess et al., 2012; Resosudarmo and Pradnja, 2005; Duncan, 2007). Because district splitting increased the threats to forests and weakened the institutions responsible for the enforcement of regulations, we expect that district splitting adversely impacted the performance of PAs. That is, we expect to see higher deforestation inside PAs when districts split, *ceteris paribus.*

The change of the incumbent district head (*bupati change*) can create incentives to loot and, hence, lead to weak enforcement right before the new incumbent takes office (‘‘depletion effect”) (e.g., as in Olson, 1993; Ferreira & Vincent, 2010). For this reason, we expect that the *bupati change* will adversely moderate PA effectiveness, making PAs less effective around the time the bupati changes.

In line of the previous arguments, we could see a depletion effect and decreased enforcement during the transition period following *direct elections*. They could also lead to power grabs leading to the development of indigenous lands (Duncan, 2007). Thus, we expect *direct elections may spur deforestation.* However, direct elections also increase accountability of government officials to locals, matching practices to preferences (Bardhan & Mookherjee, 2006). If the local population value PAs either directly because of forest ecosystem services they provide, or indirectly because of the ecotourism revenues they generate, for example, *direct elections* can improve the PA performance in terms of reducing deforestation. To a large extent the answer lies in whether the election process increases the decision-making authority of lower-level bureaucrats vs. the local-level authority of local users (Larson and Soto, 2008). Indeed, when local users manage their forests, there is evidence that various forms of community concessions have positively impacted local forests and local livelihoods (Miteva et al., 2012; Putraditama et al., 2019; Santika et al., 2019).

3.2. Forest degradation

Deforestation and forest fragmentation are correlated, but not perfectly. Deforestation pertains to the aggregate forest lost, whereas our metric of forest fragmentation-to the configuration of the remaining forest across space. More complex shapes of forest patches are associated with more fragmentation (more edge and less core forest). While it is expected that deforestation increases fragmentation by potentially increasing the complexity of the shape of the remaining forest patches, it can also decrease fragmentation by removing complex forest shapes, thereby decreasing edge areas, *ceteris paribus*. There can also be no effect on our metric of fragmentation, if deforestation is driven by the clearing of small forest patches only or by the harvesting of large trees as these are not captured in either the edge, or core forest area calculations.

While we expect PAs to reduce fragmentation, *ceteris paribus,* the effect of the decentralization proxies and their interaction with PAs is not easily predicted. Without detailed spatial models of deforestation, it is not possible to predict which of effects above dominates. Therefore, the impact of decentralization and its effect on PAs with regards to reducing forest fragmentation is an empirical question.

3.3. Fires

District splitting, change in the district head, and the introduction of direct elections all create uncertainty about future enforcement and regulations. For this reason, we hypothesize they will decrease investment incentives (‘‘investment effect” as in Ferreira & Vincent, 2010). For this reason, if fires are used to clear land for agriculture (e.g., oil palm Cattau et al., 2016), which requires substantial investment in purchasing plants etc (Jelsma et al., 2017), we expect decentralization will reduce fires. Because previous studies have suggested that most fires in South East Asia are anthropogenic (Cattau et al., 2016), we expect that decentralization *decreased* the use of fires.

In terms of the impact of decentralization on PA performance with respect to anthropogenic fires, we expect that it lowered PA effectiveness, because of lowered background threats due to weakened enforcement and disincentives to clear land for agriculture.

4. Data & methods

4.1. Sample

Because of the data availability for a key decentralization variable - *direct election*, we limit our analysis to 2000–2008. We also limit our analysis to 342 districts (*kabupaten*) because this is the sample for which many critical district-level data are compiled (McCulloch & Malesky, 2011). Our unit of analysis is a village anchored to its 2003 boundaries. Our initial sample consists of 62,805 Indonesian villages, which span most of Indonesia. A village is considered protected if it is spanned partially or fully by any PA. The sample for the main analysis excludes unprotected villages that are adjacent to protected ones (n = 6339); we consider the impact of protection on adjacent villages separately.

Combining village and district-level data, our raw sample (prior to matching) contains 335 districts; post-matching, we retain 242 districts (using their 2000 boundaries) in the matched sample (the matching process is detailed below in the Empirical Model section). On average, a district in Indonesia in 2000 contained 161.46 villages (sd = 159.68, min = 1, max = 1,258, median = 119). Post-matching, our sample does not contain any districts with villages fewer than 10 (the minimum number of villages within a district in the matched sample is 13). Table 1 gives summary of the sample composition. Descriptive statistics for the matched sample are given in the Appendix (SI Tables 4–9). We apply frequency weights on the matched sample to account for control observations being used more than once in the matching.

4.2. Outcomes

We consider three outcomes – *deforestation area as a fraction of the remaining forest*, *edge to core forest ratio*, and *the frequency of fires per hectare ("fire density")*. In the appendix, we present robustness checks using the forest area and the area of core and edge forests (in ha) as the outcomes.

To obtain the deforestation outcome, we employ a fine-resolution panel dataset of tree cover at the 30-by-30 m pixel level (Hansen et al., 2013), which we refine by allowing deforestation to take place only on pixels that have at least 80% tree cover in 2000 (Sexton et al., 2015). By setting a high threshold to define forests, we are likely to exclude small disturbed forest patches and degraded forest with low tree density. Thus, our estimates are conservative. Further, because this dataset contains only deforestation events and no comparable reforestation data exist, we focus on deforestation only. Because trees take a significant time to grow and ecosystems need time to recover (e.g., Blackham et al., 2014), deforestation is more important from a conservation standpoint.

Because the forest configuration is a proxy for forest health, we examine changes in the edge forest to core forest ratio in addition to aggregate deforestation (Turner et al., 2001). To do that, we use the MODIS Vegetation Continuous Fields (MODIS VCF) dataset, which presents the percent tree cover within each grid cell within each year, thus capturing the effects of both deforestation and reforestation (DiMiceli et al., 2011). The high computational burden associated with the fine resolution Hansen data precluded us from using the dataset for the fragmentation analysis. For this reason, we chose MODIS VCF, which is available at a lower resolution instead of us aggregating the Hansen data to an arbitrary larger unit of analysis. Because of the two different datasets for the forest variables, the number of observations are not the same.

Using a 50% cutoff to define forests, we first convert each MODIS VCF raster file into a binary forest-no forest layer. Then we run the Landscape Fragmentation Tool that classifies each forested pixel into edge, core, perforated, and patch forest areas; this classification is based on the distribution of the forest in the landscape, regardless of village boundaries (Vogt et al., 2007). Using the zonal statistics tool in ESRI ArcGIS, we calculate the areas of core and edge forests per village for each year.

For the main analysis, we calculate the edge to core forest ratio. The ratio decreases if the area of edge forest decreases or the area

Table 1
Sample composition (full sample prior to matching) Panel A; Panel B-matched sample. All values pertain to villages (unit of analysis). A similar table for the PA adjacency analysis is located in the Appendix (Table SI 2).

Panel A. Full sample prior to matching for PA sample								
Year	Protected		District split		District direct elections		Bupati (change)	
	No	Yes	No	Yes	No	Yes	No	Yes
2000 or prior	52,287	4,207	56,822	0	54,944	0	No data	
2001	52,213	4,281	56,822	0	54,944	0	No data	
2002	52,124	4,370	50,712	6,110	54,944	0	49,170	2,385
2003	52,079	4,415	42,187	14,635	54,944	0	44,461	8,614
2004	51,604	4,890	42,187	14,635	54,944	0	52,015	3,711
2005	51,543	4,951	42,187	14,635	54,944	0	42,369	12,638
2006	51,430	5,064	42,187	14,635	20,760	35,432	48,257	6,687
2007	51,354	5,140	37,282	19,540	16,999	39,004	54,049	1,954
2008	51,334	5,160	36,388	20,434	No data		No data	
Panel B. Matched PA sample								
Year	Protected		District split		District direct elections		Bupati (change)	
	No	Yes	No	Yes	No	Yes	No	Yes
2000 or prior	3,341	3,408	6,749	0	6,749	0	No data	
2001	3,281	3,468	6,749	0	6,749	0	No data	
2002	3,205	3,544	5,497	1,252	6,749	0	5,903	315
2003	3,171	3,578	3,868	2,881	6,749	0	5,854	488
2004	2,770	3,979	3,868	2,881	6,749	0	6,045	553
2005	2,711	4,038	3,868	2,881	6,639	0	5,160	1,481
2006	2,614	4,135	3,868	2,881	2,878	3,825	6,221	418
2007	2,550	4,199	3,056	3,693	2,521	4,093	6,410	204
2008	2,542	4,207	2,731	4,018	No data		No data	

of core forest increases. Thus, high values of the ratio indicate more disturbed forests, and low values indicate less disturbed forests (Krebs, 2001). To address the right skewed distribution of the variable, we apply a square root transformation. As a robustness check, in the appendix, we present the results of the analysis using the core and edge areas as separate outcomes as well as the fraction of forest that is considered edge or core (SI Tables 16–18).

Additionally, as fire is often used to clear land for agriculture (specifically, oil palm), we calculated the total number of fire events occurring within a village in a given year. Because larger villages are likely to have more fires, *ceteris paribus*, we use the fire density, calculated as the annual sum of fire events per hectare in the estimation. To address the right skewness of the distribution, again we apply a square root transformation.

4.3. Protected areas (PA)

To generate the protection (PA) variable, we combine the village geospatial boundaries available from the Indonesian census with the boundaries of the protected areas in Indonesia obtained from the World Database on Protected Areas (http: https://www.protectedplanet.net; Accessed July 2017). In this analysis, we lump all protection together, regardless of the type of PAs. We use lagged values for both the protection and PA adjacent variables. A village is considered protected if any part of it falls under a PA.

PAs could also impact forests indirectly through spillovers in the villages adjacent to the protected area (Miteva, Kramer, Brown, & Smith, 2017; Pfaff & Robalino, 2017). Thus, we conduct the analysis separately for the protected villages (defined above) and the unprotected-but-PA adjacent villages.

4.4. Decentralization proxies

To proxy for decentralization, we use (a) whether or not a *district split* during our study period; (b) whether or not there were *direct elections* of the district head, and (c) whether or not the district had a *bupati change* in a given year, regardless of the presence of elections. The district split variable we constructed using data from the Indonesian census. The data on the type of bupati and the introduction of direct elections were obtained from the Indonesian Growth and Governance dataset (McCulloch & Malesky, 2011). Based on previous studies, we use lagged values of the district splitting and direct elections (Burgess et al., 2012). The variables take a value of 1 in a village if a *district split* or *direct elections* were introduced in the previous year and remain as 1 for all subsequent years. Because we expect the effects in the *bupati change* to be limited to the time around the end of the governor's term, for the *bupati change* term we used contemporaneous values. That is, the variable takes a value of 1 if the bupati changed in a given year and 0 otherwise. Thus, we treat the *bupati change* as a shock that we predict led to increased incentives for looting and weakened enforcement of restrictions (e.g., Olson, 1993).

4.5. Covariates

In order to preprocess the sample and ensure overlap in the covariate distributions for the PA and unprotected villages, we collect data on a wide range of covariates. Following the established empirical approach in the literature, these covariates are chosen because of their correlation with the placement of PA and with the outcomes. These include suitability for agriculture and logging (slope, elevation, forest area in 2000, area under peatland in 2000, annual precipitation) and proximity to markets (proximity to ports, cities, roads, length of the river network inside the village, length of the road network inside a village, whether or not a village is rural). In addition, to proxy for the village dependence of forests, we include the 2000 values for the population density, the share of poor households, and the share of agricultural households within a village. Finally, we include the village area and whether or not a populated part of the village was inside the forest in 2000.

In order to address concerns that district-level characteristics other than decentralization may be driving the forest outcomes at the village level, we also collect data on district-level indicators (district income, share of agricultural workers, population, unemployment, degree of ethnolinguistic fractionalization, and crime levels). These variables are used in the matching analysis, where a village is the unit of analysis. The descriptions and data sources of the variables used in the analysis are given in Table SI 2 in the Appendix.

We treat the year 2000 as the baseline as it is the year before decentralization took place. However, we do not have all relevant baseline values for the affected villages because many PAs were established prior to that year (e.g., some as early as 1913-see SI Table 1). This is one of the limitations in our dataset.

5. Empirical model

5.1. Panel data estimators

To test how the decentralization variables influence the impact of protected areas, we estimate the following model:

$$y_{idt} = \alpha + \beta_1 PA_{idt-1} + \beta_2 Z_{dt-1} + \beta_3 PA_{idt-1} Z_{dt-1} + \beta_4 X_{idt} + \alpha_d + \alpha_t + \varepsilon_{idt}, \quad (1)$$

where i indicates village, d-district and t-year. y indicates the outcome; PA_{idt-1} is a binary variable that indicates whether a village was protected in a given year; Z_{dt-1} is a set of lagged district level decentralization variables, X_{idt}-a set of baseline characteristics and exogenous time-varying variables like annual precipitation. α_d and α_t are district and year fixed effects, respectively.

The parameter capturing the impact of protected areas is given by β_1;the impact of the decentralization proxies by β_2; and the moderating impact of the decentralization on the effectiveness of protected areas by β_3. Note, because we have three proxies for decentralization, β_3 is a vector, not a single parameter.

Given villages as the unit of analysis, the use of district-level variables implies a hierarchical model. Because of the large number of districts, we cannot estimate Eq. (1) as a simple random effects model. Instead, we model that as a mixed effects model with a random intercept dependent on the district. Specifically, we estimate Eq. (1) as a two-level mixed-effects linear regression, with the district as the grouping random variable (using Stata 16 and the *xtmixed* toolset) and year fixed effects. With this approach, the district effects are included but not estimated directly. A key benefit of the mixed-level approach is that it allows us to include a large number of time-invariant characteristics, which influence the outcomes. To further account for the hierarchical nature of the data, we cluster the standard errors at the district level (Angrist & Pischke, 2009).

To examine the impact of decentralization on the established PAs after 2000, we estimate the following fixed effects model as well (the notation is the same as for Eq. (1)):

$$y_{idt} = \alpha_i + \beta_1 PA_{idt-1} + \beta_2 Z_{dt-1} + \beta_3 PA_{idt-1} Z_{dt-1} + \beta_4 X_{idt} + \varepsilon_{idt}, \quad (2)$$

In contrast to the mixed effects model, Eq. (2) exploits only the time-varying village and district characteristics; that is, identification is based only on the villages inside the PAs established after 2000, the decentralization variables, and the average annual precipitation within a village. All other covariates from the mixed effects model are collinear with the village fixed effects. While the fixed effects model allows us to control for any time-invariant linear potential omitted variable at the village-level, it does not allow us to model the effect time-invariant characteristics that also affect the outcomes. Because a large majority of the villages in our sample were protected prior to 2000 (Table 1), we would be discarding most of the data and basing identification on only using a very small set of villages that saw a change in protection after 2000. Thus, our preferred specification is the mixed effects specification [Eq. (1)], but we also report the results on the recently established PAs.

5.2. Endogeneity of PA placement

The placement of PAs is endogenous (e.g., Ferraro, Hanauer, & Sims, 2011). To address this endogeneity issue, prior to the panel data estimation, we use nearest neighbor matching with a Mahalanobis distance matrix, trimming based on the propensity score, replacement, and exact matching *within each major island group*, to pre-process the sample (e.g., Ho et al., 2007; Imbens & Wooldridge, 2009; Ferraro & Miranda, 2017). We use the village- and district-level characteristics in the matching to preprocess the sample (see section on Covariates). The descriptive statistics for each covariate in the matching by each major island group before and after matching are given in SI Tables 3–15. We adjust Eqs. (1) and (2) using frequency weights to correct for some control observations being used more than once. By matching to preprocess the sample, we ensure overlap in the covariate distributions of the treatment and control groups (Imbens & Wooldridge, 2009). This approach allows us to treat protected areas as exogenous for the matched sample (Imbens & Wooldridge, 2009; Ho et al., 2007).

5.3. Endogeneity of the decentralization variables

The timing of *direct elections* of the district head is exogenous by nature of the process of setting elections, the timing of which depended on when the previous term ended (Burgess et al., 2012; Hofman & Kaiser, 2006). For the *district split* and the *bupati change* variables, we contend the decentralization proxies we use are conditionally exogenous (see Burgess et al., 2012 for similar reasons). First, while one could argue that unobservables (e.g., booming economy) maybe correlated with the *district split* and the *bupati change*, the districts are orders of magnitude larger than any one village – our unit of analysis - the split and the *bupati change* are exogenous at the village level (Fig. 1). For example, the average number of villages per district in our dataset is 139 and the median-106. Second, because we are using panel data, we can difference out any time-invariant linear unobservable characteristics that are correlated with *district split* and *bupati change*. Third, through the matching to preprocess the sample, we ensure covariates like the district level revenue, the unemployment rate, and the degree of ethnolinguistic fractionalization (potential drivers of *district split* and *bupati change*) are balanced at the baseline between the treated and control groups. Fourth, we examine pairwise correlations within year with time varying factors such as the state of the local economy (proxied by the annual real district revenue and the share of the population that is unemployed) with the outcomes. For the most part, these pairwise correlations are insignificant. In sum, all of these considerations reduce our concern about the correlation between an unobservable time-variant factor and decentralization that might confound our finding.

However, in Eqs. (1) and (2) we do not consider endogeneity in the timing of protection, *district split*, or the *bupati change*. While we conduct a robustness check ignoring the timing of decentralization and the protected areas (see below), this remains a limitation of our analysis. Since the timing of the *direct election* proxy is exogenous, the skeptical reader and reviewer could focus only on those sets of results.

6. Additional analyses

6.1. Potential leakage (spillovers)

To capture the effect of PAs on unprotected but immediately adjacent to protected villages, we repeat the matching and panel-data estimation outlined above for a second sample, comprised of the unprotected adjacent villages as the "treatment" and the unprotected non-adjacent villages as control. This analysis allows us to detect spillovers and capture the net effect of protection.

6.2. Potential channel

Critically, to gain further insights behind the observed patterns of deforestation, fragmentation, and fire density, we examine one of the primary channels in the literature– what happened to the population density in these treated areas. For example, if decentralization reduces the enforcement capabilities of district governments, then the population density inside protected areas is likely to increase. Similarly, increases in the population density inside protected areas are likely due to indigenous peoples migrating after land grabs and the development of indigenous territories, which some have suggested was a corollary of decentralization in Indonesia (Duncan, 2007). Essentially, we use population density (log-transformed) as the outcome variable and estimate the same models as reported above.

6.3. Robustness checks

We perform robustness checks varying the way we quantify deforestation and forest fragmentation. Specifically, we estimate Eqs. (1) and (2) by using the annual forest area, core, and edge areas (in hectares) as the outcomes.

To address concerns related to the potential endogeneity of the timing of decentralization and protection, we estimate a difference-in-difference model that ignores the timing of decentralization and protection. That is, we estimate a version of Eq. (1) with 2000 as the baseline year and 2007 as the end year, by assigning a value of 1 to a village if it was "treated" (i.e., spanned by or adjacent to a PA established prior to 2008 for the analysis of protection and spillovers, respectively) and 0 otherwise. Similarly, for each of the decentralization proxies, we assign a value of 1 to a village if it was in a decentralized district before 2008 and 0 otherwise. We repeat the estimation for the sample, using PA adjacency as the treatment.

7. Results

The full random effects model (Eq. (1)) estimates give us the average impact of the protection and decentralization on the forest (*i.e.*, deforestation, fragmentation, and fires) variables for all treated villages in the sample. The FE specification (Eq. (2)) gives us the average impact on forest and fires for only the PAs established after 2000. While the two models are consistent in terms of the signs of the coefficients, they vary in the statistical significance. We discuss the estimates of both below.

7.1. On average, were protected areas effective?

On average, we find no statistically significant impact of PAs on deforestation, forest fragmentation, or fire density inside the protected villages (Model [5] Table 2). The results are consistent with the fixed effects models in terms of signs (Model [6] Table 2). However, the latter suggests that PAs significantly reduced forest frag-

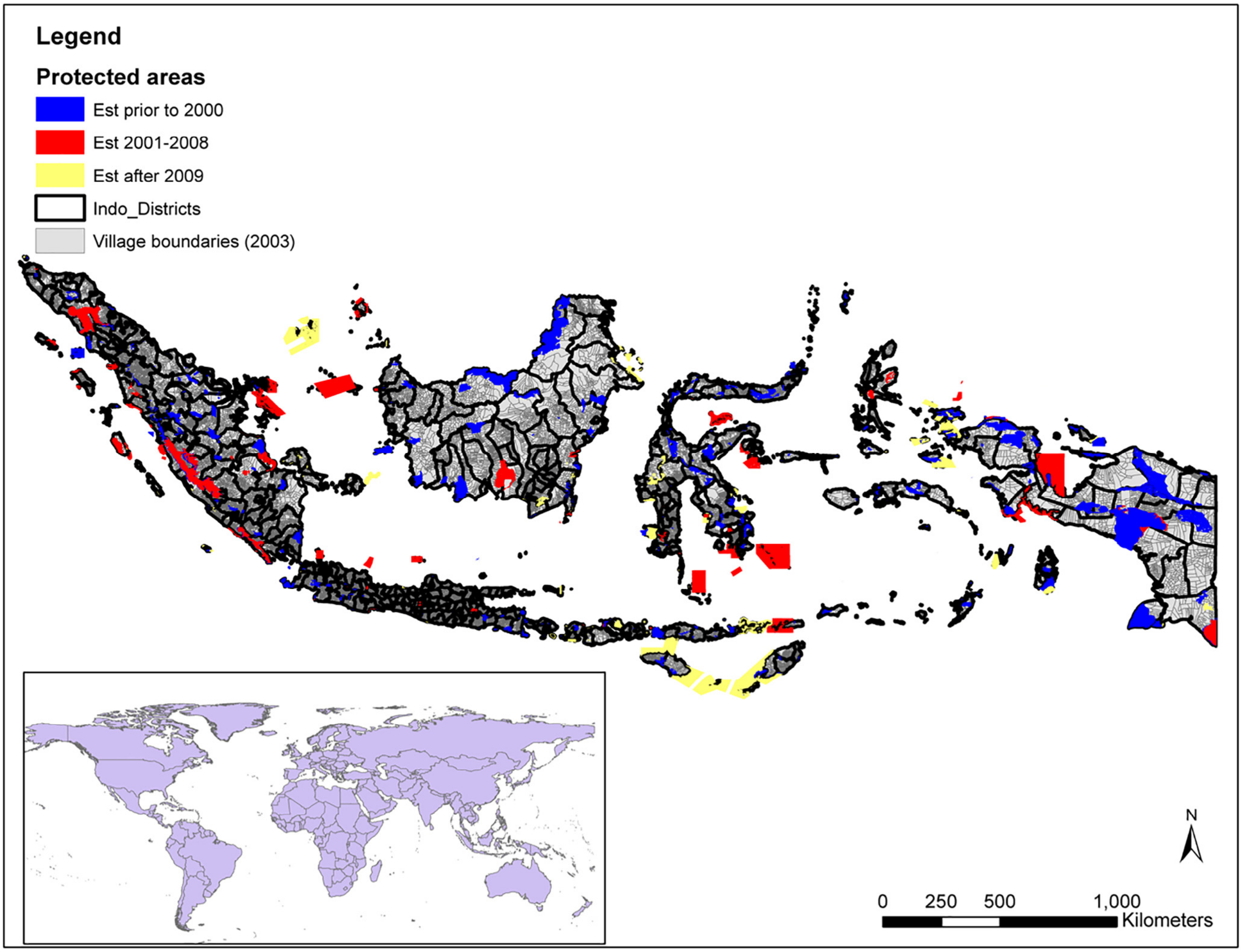

Fig. 1. District sizes relative to villages and protected areas.

mentation, by reducing the forest edge and increasing the forest core (SI Tables 16–17). PAs had no statistically significant impact on fires during our study period. However, the results from the spillover analysis indicate the deforestation and the incidence of fires was higher in the PA adjacent villages relative to observationally similar controls (Model [5] in Table 3).

7.2. On average, what was the impact of decentralization?

We hypothesize that district splitting, direct elections, and the *bupati change* should increase deforestation, *ceteris paribus*. While our results indicate a positive coefficient for the three proxies on deforestation, only the *direct elections* significantly increased deforestation, *ceteris paribus* (Model [5] Table 2). In the FE models, the introduction of *direct elections* increased deforestation for the samples using the protected and the unprotected PA-adjacent villages as the treatment (Model [6] in Tables 2 and 3).

In the FE models (Model [6] in Table 2), we find *direct elections* also decreased fragmentation by increasing core forests relative to edge forests (SI Tables 16–17). Collectively, these results imply that the *direct elections* created incentives for clearing small patches of existing forest or increasing forest loss due to small openings in the canopy due to logging, while leaving the larger forest patches preserved (i.e., with less edge and more core areas). The impact of *direct elections* on forest fragmentation in the PA-adjacent unprotected villages was not statistically significant.

The impact of *district splitting* on deforestation and forest fragmentation was only significant in the FE specifications, where we find that it resulted in increased deforestation in both PA and PA-adjacent villages (Model [6] in Tables 2 and 3), *ceteris paribus*. However, it also resulted in degreased fragmentation (Model [6] in Table 2 and Model [5] in Table 3). This is due to increasing the core forest relative to all other forests (SI Tables 17–18) and no statistically significant impact on edge areas. Similar to the results for direct elections, our interpretation here is that district splitting resulted in reduced complexity of the shape of the remaining forests, in small forest patches being cleared as well as in potential increases in perforated forest areas indicative of logging (e.g., Miteva et al., 2015b). The *bupati change* did not have a statistically significant impact on deforestation and forest fragmentation in any of the specifications.

We hypothesize that the uncertainty due to *district splitting*, *direct elections*, or *bupati change* decreased investment incentives, specifically with regards to clearing forests for oil palm. That is, we expect anthropogenic fires to decrease in the presence of decentralization, *ceteris paribus*. Our results are consistent with the hypothesis: We find direct elections and the *bupati change*

Table 2
Results from the panel data models for the matched sample (standard errors in parentheses). A square root transformation has been applied to all outcomes.

Deforestation calculated as forest loss area in year t/forest area in year t-1						
Variable	[1] RE	[2] RE	[3] RE	[4] RE	[5] RE	[6] FE
Protected	−0.004**	−0.003	−0.003	−0.004	−0.002	−0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)
District split		−0.0001			0.0002	0.010**
		(0.003)			(0.004)	(0.004)
Protected × District split		−0.004*			−0.003	−0.003
		(0.002)			(0.003)	(0.003)
Direct elections			0.008*		0.011**	0.007*
			(0.005)		(0.006)	(0.004)
Protection × Direct elections			−0.006**		−0.007**	−0.005*
			(0.003)		(0.003)	(0.003)
Bupati (change)				0.002	0.003	0.002
				(0.003)	(0.003)	(0.003)
Protection × bupati change				−0.001	−0.001	−0.001
				(0.003)	(0.003)	(0.003)
N	83,510	75,159	58,056	48,243	48,243	48,266
Edge forest to core forest ratio						
Variable	[1] RE	[2] RE	[3] RE	[4] RE	[5] RE	[6] FE
Protected	−0.014	−0.023	−0.009	−0.007	−0.015	−0.032**
	(0.012)	(0.016)	(0.013)	(0.013)	(0.016)	(0.017)
District split		−0.014			−0.026	−0.038*
		(0.018)			(0.025)	(0.022)
Protected × District split		0.021			0.020	0.034**
		(0.020)			(0.022)	(0.015)
Direct elections			−0.031		−0.007	−0.036*
			(0.020)		(0.024)	(0.020)
Protection × Direct elections			0.001		−0.010	0.009
			(0.017)		(0.024)	(0.024)
bupati change				0.001	0.001	−0.007
				(0.022)	(0.023)	(0.021)
Protection × bupati change				−0.019	−0.021	−0.0005
				(0.031)	(0.030)	(0.026)
N	65,165	58,672	45,127	37,428	37,428	39,431
Fire density per ha= #fires in year t/village area (in ha)						
Variable	[1] RE	[2] RE	[3] RE	[4] RE	[5] RE	[6] FE
Protected	−0.00005	−0.00001	0.00001	−0.0001	0.0001	0.0005
	(0.0004)	(0.001)	(0.0004)	(0.0005)	(0.001)	(0.001)
District split		−0.0002			−0.001	−0.0005(0.001)
		(0.0005)			(0.001)	
Protected × District split		−0.0002			−0.0002	0.00003
		(0.001)			(0.001)	(0.001)
Direct elections			−0.001		−0.001	−0.002***
			(0.001)		(0.001)	(0.001)
Protection × Direct elections			−0.0003		−0.001	−0.001
			(0.0004)		(0.0005)	(0.001)
Bupati change				−0.001	−0.001	−0.001**
				(0.001)	(0.001)	(0.001)
Protection × bupati change				0.0002	0.0001	−0.0002
				(0.001)	(0.001)	(0.0005)
N	75,120	66,156	52,252	43,399	43,399	48,598

Significance levels: ***1%, **5%, *10%.

decreased the incidence of fires in the FE model (Model [6] in Tables 2 and 3). Similarly, the district splitting also reduced the incidence of fires (Model [5] in Table 3).

7.3. How did decentralization impact protected area effectiveness?

We hypothesize a few different channels through which our three decentralization proxies could moderate the impacts protected areas with regards to forest and fires. While decentralization could weaken the monitoring and enforcement of PA regulations, it could be a positive influence if there is greater local accountability and aligning with local preferences. Further, it also expected to increase the threat to forests. *Ceteris paribus*, an increasing threat to forests could improve the effectiveness of PAs.

Our results indicate that the introduction of *direct elections* reduced deforestation inside protected villages (Model [5] in Table 2), but had no statistically significant impact on forest fragmentation and fires or deforestation in PA adjacent unprotected villages (Tables 2 and 3). In the FE specifications, we also find *district splitting* increased fragmentation inside protected villages (Table 2 Model [6]), due to a reduction in the core forest area (Model [6] in SI Tables 14–15). None of the other interaction terms are statistically significant in either the RE or FE models for any of the three outcomes - deforestation, fragmentation or fires.

Table 3
Results from the spillover analysis (standard deviations in parentheses). A square root transformation has been applied to all outcomes.

Deforestation = forest loss area in year t/forest area in year t-1						
Variable	[1] RE	[2] RE	[3] RE	[4] RE	[5] RE	[6] FE
1 if PA Adjacency	0.002 (0.001)	0.002 (0.001)	0.002* (0.001)	0.003** (0.001)	0.003* (0.001)	0.002 (0.003)
1 if District split		0.004 (0.004)			0.002 (0.005)	0.017*** (0.005)
1 if bupati change				0.001 (0.003)	0.001 (0.003)	−0.001 (0.003)
1 if Direct elections			0.006 (0.005)		0.008 (0.006)	0.008* 0.005
PA Adjacency × District split		0.0001 (0.002)			−0.001 (0.003)	0.0005 (0.003)
PA Adjacency × bupati change				−0.004 (0.003)	−0.003 (0.002)	−0.003 (0.003)
PA Adjacency × Direct elections			0.001 (0.003)		0.003 (0.003)	0.005 (0.003)
N	85,482	85,482	65,903	54,818	54,818	54,818
Edge forest to core forest ratio						
Variable	[1] RE	[2] RE	[3] RE	[4] RE	[5] RE	[6] FE
1 if PA Adjacency	−0.006 (0.005)	−0.011* (0.006)	−0.004 (0.006)	−0.005 (0.006)	−0.011 (0.007)	−0.037 (0.024)
1 if District split		−0.033** (0.013)			−0.036* (0.021)	−0.034 (0.021)
1 if bupati change				−0.004 (0.014)	−0.004 (0.014)	−0.007 (0.013)
1 if Direct elections			−0.020 (0.016)		−0.010 (0.017)	−0.012 (0.012)
PA Adjacency × District split		0.016* (0.008)			0.018 (0.012)	0.006 (0.009)
PA Adjacency × bupati change				0.009 (0.013)	0.008 (0.012)	0.014 (0.011)
PA Adjacency × Direct elections			−0.006 (0.008)		−0.002 (0.011)	0.013 (0.013)
N	56,291	56,291	43,495	36,269	36,269	38,790
Fire density per ha= #fires in year t/village area (in ha)						
Variable	[1] RE	[2] RE	[3] RE	[4] RE	[5] RE	[6] FE
1 if PA Adjacency	0.001** (0.0003)	0.001** (0.0003)	0.001** (0.0003)	0.001* (0.0003)	0.001* (0.0004)	−0.0001 (0.001)
1 if District split		−0.001 (0.0004)			−0.001* (0.001)	−0.0003 (0.001)
1 if Bupati change				−0.0005 (0.001)	−0.0005 (0.0006)	−0.001** (0.001)
1 if Direct elections			−0.001 (0.001)		−0.001 (0.001)	−0.002*** (0.001)
PA Adjacency × District split		−0.0001 (0.0004)			−0.0001 (0.001)	−0.0005 (0.0004)
PA Adjacency × bupati change				0.0003 (0.001)	0.0001 (0.001)	0.0004 (0.0005)
PA Adjacency × Direct elections			−0.0004 (0.0004)		−0.001 (0.001)	−0.0002 (0.0005)
N	70,236	70,236	54,235	45,165	45,165	55,319

Significance levels: ***1%, **5%, *10%.

To summarize these findings, in Fig. 2 we plot the average marginal effects based on Model [5] in Tables 2 and 3. The average marginal effects should be interpreted as the instantaneous change in the outcome (that is, the derivative) due to the treatment (either PA or PA-adjacency), which is evaluated at the two discrete levels of each of the decentralization variables. Statistical significance of the impacts is identified by whether the 90% CI cross the horizontal 0 line. These figures reaffirm the findings on the direct impacts of PAs, adjacent PAs and decentralization, and of the interaction terms Model [5] of Tables 2 and 3, as summarized above.

The results from the robustness checks are consistent with the main results (SI Tables 16–21).

7.4. Are changes in population density a potential channel for the observed patterns?

Here we focus on the interaction terms for PA and each of the three decentralization proxies (SI Table 22). We find that on average the population density decreased in PA adjacent unprotected villages in the *bupati change* case, only. The positive coefficients on the rest of the interaction terms for the protected villages, while consistent with weak enforcement or local land grabs, are not statistically significant. The results imply that the changes in forest and fire outcomes are unlikely driven by changes in the population density. However, because we do not explicitly model migration or

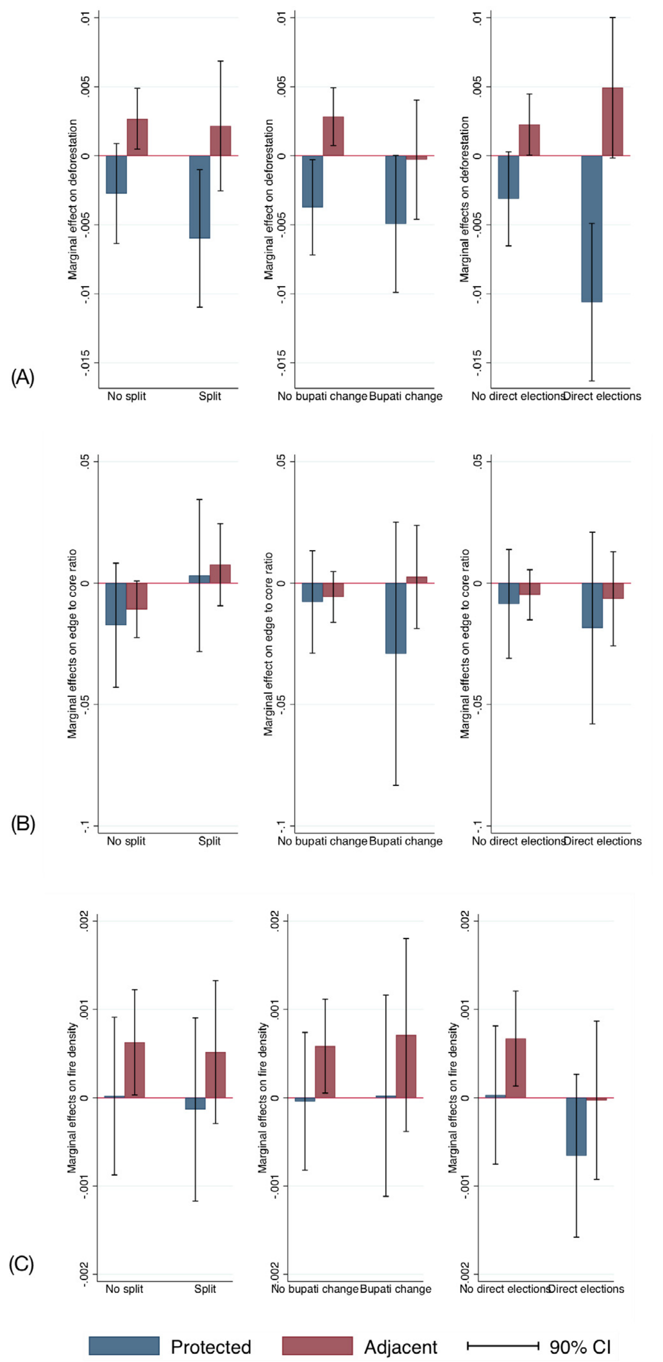

Fig. 2. Marginal effects from the main random effects model for deforestation, edge to core ratio, and fire density outcomes (Panels A, B, and C, respectively).

account for potential non-random attrition, these results are suggestive only.

8. Discussion

8.1. Decentralization had a mixed impact on conservation

We examine how decentralization (e.g., *district split*, *bupati change*, and *direct elections*) impacted the performance of PAs along multiple indicators for forest health (deforestation, fragmentation, and fires) between 2000 and 2008 in Indonesia. We hypothesize that the moderating influence of decentralization on PA effectiveness depends on whether decentralization increased the threats to forests, strengthened local accountability, or weakened enforcement. On average, we find *direct elections* improved the PA impact in terms of reducing deforestation in protected villages, but had no statistically significant effect on forest fragmentation, fires, or leakage. On average, we find *district splits* increased forest fragmentation in the recently protected villages (FE model), but the results are not statistically significant for deforestation and fires. On average, we find *bupati change* had no statistically discernible influence on PA impacts on deforestation, fragmentation or fires. Given the increasing threats to forests due to decentralization, these results imply *district splitting* and the *bupati change* weakened enforcement inside PAs with regards to deforestation and forest fragmentation.

8.2. Caveats

A few caveats remain, however. First, we consider the short term impacts of decentralization (impacts only within the first 7 years); longer term impacts remain to be seen. Second, we do not distinguish between different types of PAs that may vary in their effectiveness in protecting forests (e.g., Pfaff, Robalino, Lima, Sandoval, & Herrera, 2013; Ferraro et al., 2013; Miteva et al., 2015a). Because our analysis treats the different types of protected areas as a homogenous group, the standard errors of the estimates tend to be large. Third, we consider any village spanned by any fraction of a PA to be protected. Therefore, it is possible that the insignificant results are driven by spillovers to the unprotected parts of protected villages (e.g., Miteva et al., 2019). Finally, because of the high tree cover cutoffs to define forests, our results present conservative estimates; impacts may be more pronounced at lower cutoffs of tree cover. In general, any analysis by the subgroups (e.g., for interaction terms in our paper) lowers statistical power, in the sense that the cells are small.

8.3. Ways forward

In sum, our paper represents an attempt to quantify the impacts of decentralization in shaping the effectiveness of protected areas to conserve forest ecosystems. We find that overall that the moderating influence of decentralization on PA effectiveness depends on whether decentralization strengthened local accountability (e.g., through direct elections) or weakened enforcement. In villages in districts with *direct elections*, PAs were more effective in conserving forests between 2000 and 2008. In villages experiencing *district splits*, the opposite was true. While we detect general patterns that are consistent with decentralization increasing logging, land clearing of small forest patches, thereby increasing the pressure on PAs, we need data and models on these intermediate channels and processes to confirm these hypotheses. Our analysis is a small step in this direction. Translation of empirical results directly into policy is challenging partly because there is a disconnect between context underlying interventions like protected areas (PAs), on one hand, and how impact evaluations consider such contextual factors on the other hand (Heckman, 2010; Deaton, 2010; Ravallion, 2008; Sills & Jones, 2018). We present a starting point for how to organize data and consider questions that respond to recent calls for expanding the connection between policies and the process by which they achieve outcomes.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.worlddev.2021.105446.

References

Abood, S. A., Lee, J. S. H., Burivalova, Z., Garcia-Ulloa, J., & Koh, L. P. (2015). Relative contributions of the logging, fiber, oil palm, and mining industries to forest loss in Indonesia. *Conservation Letters, 8*(1), 58–67. https://doi.org/10.1111/conl.12103.

Adam, Y. O., & Eltayeb, A. M. (2016). Forestry decentralization and poverty alleviation: A review. *Forest Policy and Economics, 73*, 300–307. https://doi.org/10.1016/j.forpol.2016.05.009.

Angrist, J. D., & Pischke, J. S. (2009). *Mostly harmless econometrics: an empiricist's companion*. Princeton: Princeton University Press.

Bardhan, P., & Mookherjee, D. (2006). Reviewed work(s): "decentralisation and accountability in infrastructure delivery in developing countries". *The Economic Journal, 116*(508), 101–127.

Blackham, Grace V., Edward L. Webb, & Richard T. Corlett. Natural Regeneration in a Degraded Tropical Peatland, Central Kalimantan, Indonesia: Implications for Forest Restoration. Forest Ecology and Management 324 (July 15, 2014): 8–15. https://doi.org/10.1016/j.foreco.2014.03.041.

Burgess, R., Hansen, M., Olken, B. A., Potapov, P., & Sieber, S. (2012). The political economy of deforestation in the tropics. *Quarterly Journal of Economics, 127*(4).

Cattau, M. E., Harrison, M. E., Shinyo, I., Tungau, S., Uriarte, M., & DeFries, R. (2016). Sources of anthropogenic fire ignitions on the peat-swamp landscape in Kalimantan, Indonesia. *Global Environmental Change, 39*, 205–219. https://doi.org/10.1016/j.gloenvcha.2016.05.005.

Coleman, E. A., & Fleischman, F. D. (2012). Comparing forest decentralization and local institutional change in Bolivia, Kenya, Mexico, and Uganda. *World Development, 40*(4), 836–849. https://doi.org/10.1016/j.worlddev.2011.09.008.

Deaton, A. (2010). Understanding the mechanisms of economic development. *Journal of Economic Perspectives, 24*(3), 3–16. https://doi.org/10.3386/w15891.

DiMiceli, C. M., Carroll, M. L., Sohlberg, R. A., Huang, C., Hansen, M. C., Townshend, J. R. G., et al., 2011. Annual Global Automated MODIS Vegetation Continuous Fields (MOD44B). 250 m Spatial Resolution for Data Years Beginning Day 65, 2000–2010, Collection 5, Percent Tree Cover. Available: http://glcf. umd.edu/data/vcf/.).

Duncan, C. R. (2007). Mixed outcomes: The impact of regional autonomy and decentralization on indigenous ethnic minorities in Indonesia. *Development and Change, 38*(4), 711–733. https://doi.org/10.1111/j.1467-7660.2007.00430.x.

Engel, S., Palmer, C., & Pfaff, A. (2013). On the endogeneity of resource comanagement: Theory and evidence from Indonesia. *Land Economics, 89*(2), 308–329.

Ferraro, Paul J., Merlin M. Hanauer, Daniela A. Miteva, Gustavo Javier Canavire-Bacarreza, Subhrendu K. Pattanayak, & Katharine R. E. Sims. More Strictly Protected Areas Are Not Necessarily More Protective: Evidence from Bolivia, Costa Rica, Indonesia, and Thailand. Environmental Research Letters 8, no. 2 (June 2013): 025011–025011. https://doi.org/10.1088/1748-9326/8/2/025011.

Ferraro, P. J, Hanauer, M. M., & Sims, K. R. E. (2011). Conditions Associated with Protected Area Success in Conservation and Poverty Reduction. *Proceedings of the National Academy of Sciences, 108*(34), 13913–13918. https://doi.org/10.1073/pnas.1011529108.

Ferreira, S., & Vincent, J. R. (2010). Governance and Timber Harvests. *Environmental and Resource Economics, 47*(2), 241–260. https://doi.org/10.1007/s10640-010-9374-5.

Ferraro, P. J., & Miranda, J. J. (2017). Panel data designs and estimators as substitutes for randomized controlled trials in the evaluation of public programs. *Journal of the Association of Environmental and Resource Economists, 4*(1), 281–317.

Fuller, D. O. (2006). Tropical forest monitoring and remote sensing: A new era of transparency in forest governance? *Singapore Journal of Tropical Geography, 27* (1), 15–29. https://doi.org/10.1111/j.1467-9493.2006.00237.x.

Fox, J., Adhuri, D. S., & Resosudarmo, I. P. (2005). Unfinished Edifice or Pandora's Box? Decentralization and Resource Management in Indonesia. In Budy Resosudarmo (Ed.), *The Politics and Economics of Indonesia's Natural Resources*. Singapore: Institute of Southeast Asian Studies.

Griscom, B. W., Adams, J., Ellis, P. W., Houghton, R. A., Lomax, G., Miteva, D. A., et al. (2017). Natural climate solutions. *Proceedings of the National Academy of Sciences, 6*. https://doi.org/10.1073/pnas.1710465114.

Hansen, M. C., Potapov, P. V., Moore, R., Hancher, M., Turubanova, S. A., & Tyukavina, A. High-resolution global maps of 21st-century forest cover change. Science 342, no. 6160 (2013): 850–53. https://doi.org/10.1126/science.1244693.

Heckman, James J. Building Bridges between Structural and Programme Evaluation Approaches to Evaluating Policy. Journal of Economic Literature 48, no. June (2010): 1–66. https://doi.org/10.1257/jel.48.2.356.

Herrera, Diego, Alexander Pfaff, & Juan Robalino. Impacts of protected areas vary with the level of government: comparing avoided deforestation across agencies in the Brazilian Amazon. Proceedings of the National Academy of Sciences 116, no. 30 (July 23, 2019): 14916–25. https://doi.org/10.1073/pnas.1802877116.

Ho, D. E., Imai, K., King, G., & Stuart, E. A. (2007). Matching as nonparametric preprocessing for reducing model dependence in parametric causal inference. *Political Analysis, 15*(3), 199–236. https://doi.org/10.1093/pan/mpl013.

Hofman, B., & Kaiser, K. (2006). Decentralization, democratic transition, and local governance in Indonesia. In P. K. Bardhan & D. Mookherjee (Eds.), *Decentralization and local governance in developing countries: A comparative perspective* (pp. 81–124). Cambridge, Mass: MIT Press.

Imbens, Guido W., &Jeffrey M. Wooldridge. Recent developments in the econometrics of program evaluation. Journal of Economic Literature 47, no. 1 (2009): 5–86. https://doi.org/10.1257/jel.47.1.5.

Jelsma, I., Schoneveld, G. C., Zoomers, A., & van Westen, A. C. M. (December 2017). Unpacking Indonesia's independent oil palm smallholders: An actor-disaggregated approach to identifying environmental and social performance challenges. *Land Use Policy, 69*, 281–297. https://doi.org/10.1016/j.landusepol.2017.08.012.

Krebs, C. J. (2001). *Ecology: The experimental analysis of distribution and abundance* (5th ed.). San Francisco, CA: Benjamin Cummings.

Lambin, Eric F., Patrick Meyfroidt, Ximena Rueda, Allen Blackman, Jan Börner, Paolo Omar Cerutti, Thomas Dietsch, et al. Effectiveness and synergies of policy instruments for land use governance in tropical regions. Global Environmental Change 28 (2014): 129–40. https://doi.org/10.1016/j.gloenvcha.2014.06.007.

Larson, Anne M, & Fernanda Soto. Decentralization of Natural Resource Governance Regimes. Annual Review of Environment and Resources 33, no. 1 (2008): 213–39. https://doi.org/10.1146/annurev.environ.33.020607.095522.

McCulloch, N., & Malesky, E.. Does Better Local Governance Improve District Growth Performance in Indonesia? IDS Working Papers 2011, no. 369 (2010). https://doi.org/10.1111/j.2040-0209.2011.00369_2.x.

Miteva, Daniela A., Subhrendu K. Pattanayak, Paul J. Ferraro. Evaluation of Biodiversity Policy Instruments: What Works and What Doesn't? Oxford Review of Economic Policy 28, no. 1 (March 2012): 69–92. https://doi.org/10.1093/oxrep/grs009.

Miteva, D. A., Murray, B. C., & Pattanayak, S. K. (2015a). Do protected areas reduce blue carbon emissions? A quasi-experimental evaluation of mangroves in Indonesia. *Ecological Economics, 119*, 127–135. https://doi.org/10.1016/j.ecolecon.2015.08.005.

Miteva, Daniela A., Colby Loucks, and Subhrendu K. Pattanayak. Social and environmental impacts of forest management certification in Indonesia. PLoS ONE 10, no. 7 (2015b): e0129675–e0129675. https://doi.org/10.1371/journal.pone.0129675.

Miteva, Daniela A., Peter W. Ellis, Edward A. Ellis, & Bronson W. Griscom. The role of property rights in shaping the effectiveness of protected areas and resisting forest loss in the Yucatan Peninsula. Edited by Laura C. Schneider. PLOS ONE 14, no. 5 (May 8, 2019): e0215820. https://doi.org/10.1371/journal.pone.0215820.

Miteva, D. A., Kramer, R. A., Brown, Z. S., & Smith, M. D. (2017). Spatial Patterns of Market Participation and Resource Extraction: Fuelwood Collection in Northern Uganda. *American Journal of Agricultural Economics, 99*(4), 1–19. https://doi.org/10.1093/ajae/aax027.

Olson, M. (son, September 1993). Dictatorship, democracy, and development. *The American Political Science Review, 87*(3), 567–576. https://doi.org/10.2307/2938736.

Pfaff, Alexander, & Juan Robalino. Spatial variation in policy impacts on tropical deforestation. Oxford Review of Economic Policy 28, no. 2 (2012).

Pfaff, A., & Robalino, J. (2017). Spillovers from Conservation Programs. *Annual Review of Resource Economics, 9*(1), 299–315. https://doi.org/10.1146/annurev-resource-100516-053543.

Pfaff, A., Robalino, J., Lima, E., Sandoval, C., & Herrera, L. D. (2013). Governance, location and avoided deforestation from protected areas: Greater restrictions can have lower impact, due to differences in location. *World Development, 55*, 7–20. https://doi.org/10.1016/j.worlddev.2013.01.011.

Puri, Jyotsna, Megha Nath, Raag Bhatia, & Louise Glew. Examining the Evidence Base for Forest Conservation Interventions, Evidence Gap Map Report 4. New Delhi, 2016. https://www.researchgate.net/publication/316430471_Examining_the_evidence_base_for_forest_conservation_interventions.

Putraditama, A., Kim, Y. S., & Meador, A. J. S. (2019). Community forest management and forest cover change in Lampung, Indonesia. *Forest Policy and Economics, 106* 101976.

Parikesit, P., Okubo, S., Husodo, T., Takeuchi, K., Muhamad, D., & Iwasa, Y. (2012). Biodiversity Issues in Indonesia, with Special Reference to Biodiversity in Human-Dominated Landscapes. In Shin-ichi Nakano, Tetsukazu Yahara, & Tohru Nakashizuka (Eds.), *The Biodiversity Observation Network in Asia-Pacific Region: Toward Further Development of Monitoring* (pp. 93–110). Tokyo: Springer. https://doi.org/10.1007/978-4-431-54032-8_8.

Ravallion, Martin. Evaluating Anti-Poverty Programs. In Handbook of Development Economics, edited by T Paul Schultz and A Strauss John, Volume 4:3787–3846. Elsevier, 2008. https://doi.org/10.1016/S1573-4471(07)04059-4.

Resosudarmo, Ida Aju Pradnja. Closer to People and Trees: Will Decentralization Work for the People and the Forests of Indonesia. In Democratic Decentralization through a Natural Resource Lense, edited by Anne M Larson and Jesse C Ribot, 110–32. London ; New York: Routledge, 2005. http://search.library.duke.edu/search?id=DUKE003439065.

Resosudarmo, Ida Aju Pradnja (2004). Closer to People and Trees: Will Decentralisation Work for the People and the Forests of Indonesia?. *The European Journal of Development Research, 16*(1), 110–132. https://doi.org/10.1080/09578810410001688761.

Resosudarmo, Budy P, Ani A Nawir, Ida Aju P Resosudarmo, & Nina L Subiman. Forest Land Use Dynamics in Indonesia, 2012. http://ideas.repec.org/p/pas/papers/2012-01.html.

Santika, T., Wilson, K. A., Budiharta, S., Kusworo, A., Meijaard, E., Law, E. A., et al. (2019). Heterogeneous impacts of community forestry on forest conservation

and poverty alleviation: Evidence from Indonesia. *People and Nature, 1*(2), 204–219.
Sexton, J. O., Noojipady, P., Song, X.-P., Feng, M., Song, D.-X., Kim, D.-H., ... Townshend, J. (2015). Conservation Policy and the Measurement of Forests. *Nature Climate Change, 6*, 1–6. https://doi.org/10.1038/nclimate2816.
Sills, E. O. & Jones, K.. 2018. Causal Inference in Environmental Conservation: The Role of Institutions. Chapter IX in P Dasgupta, SK Pattanayak and VK Smith (eds.) Handbook of Environmental Economics. Volume 4. Elsevier, North Holland. Pages 395 – 438.
Skoufias, E., Narayan, A., Dasgupta, B., & Kaiser, K. (2011). Electoral Accountability, fiscal decentralization and service delivery in Indonesia. *World Bank Policy Research Working Paper Series*.
Turner, M., Gardner, R. H., & O'Neill, R. V. (2001). *Landscape ecology in theory and practice: Pattern and process*. New York: Springer Verlag.
Vogt, P., Riitters, K. H., Estreguil, C., Kozak, J., Wade, T. G., & Wickham, J. D. (August 2007). Mapping spatial patterns with morphological image processing. *Landscape Ecology, 22*(2), 171–177. https://doi.org/10.1007/s10980-006-9013-2 (http://clear.uconn.edu/tools/lft/lft2/).
Wehkamp, J., Koch, N., Lübbers, S., & Fuss, S. (February 2018). Governance and deforestation — A meta-analysis in economics. *Ecological Economics, 144*, 214–227. https://doi.org/10.1016/j.ecolecon.2017.07.030.
Wheeler, D., Hammer, D., Kraft, R., Dasgupta, S., & Blankespoor, B. (2011). Economic dynamics and forest clearing: A spatial econometric analysis for indonesia. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2009400.