Potential respiratory health benefits of tropical forest protection:

Do Indonesian deforestation restrictions reduce fires (and smoke)?

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Selected Paper prepared for presentation at the 2023 Agricultural & Applied Economics Association Annual Meeting, Washington DC; July 23-25, 2023

Potential respiratory health benefits of tropical forest protection: Do Indonesian deforestation restrictions reduce fires (and smoke)?

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July 10, 2023

Abstract: Challenged by high-rate deforestation, fire, and carbon emissions, the Indonesian government initiated a forest moratorium to curb deforestation and protect the peatland ecosystem. To understand whether the deforestation restriction has secondary effects on respiratory health through the pathway of land-clearing fires and air pollution, in this paper, I unpacked the first section of the chain and employed a difference-in-differences model to study whether the moratorium reduces land-clearing fire at the subdistrict level. The results suggest an unintended slow-down effect of the moratorium on fire reduction. Compared to the subdistricts with no protection, the moratorium-covered subdistricts missed an opportunity to reduce the number of fires by 77.5%. Evidence of the redistribution of fire and the accordingly variation in air pollution will be provided in the next step.

1 Introduction

With rising climate change, discussion on the compatibility of economic growth and environmental conservation becomes essential to achieve sustainable development goals. Many actions have been taken to curb deforestation and restore the damaged ecosystem, and a large body of literature has studied the effectiveness of anti-deforestation policies in reducing deforestation and carbon emissions (Busch et al., 2015; Chen et al., 2019; Soares-Filho et al., 2010; Arima et al., 2014; Börner et al., 2015). However, the link between these policies and human health is understudied. Fire is a common step in clearing tropical forests for alternative land uses, which not only deteriorates the ecosystem but also leads to smoke harmful to human health. It is important to understand whether and how policy interventions for ecosystem conservation may deliver co-benefits for human health.

In the chain from forest conservation to fire and air pollution and then to human health, the latter section as an independent topic has been well studied in the past literature. Substantial work has been done in estimating the impacts of fire on respiratory infections (Rangel & Vogl, 2019; Moeltner et al., 2013), and many have also shown that air pollution leads to considerable health consequences and high mortality (Jayachandran, 2009; Kim et al., 2017; He et al., 2020). However, few attempted to recover the entire chain or explored the association between forest conservation and health outcomes (Miteva et al., 2015; Garg, 2019; Rocha & Sant'Anna, 2022). To learn whether a policy targeting forest conservation affects human respiratory health and how much the variation in land-clearing fire transit to the variation in air quality and human health, understanding the association between forest conservation and fire is a critical precursor.

The high rate of deforestation and fires that raised public concern in the global community made Indonesia a suitable case to study. The Indonesian government initiated a moratorium in 2011 to prevent industrial plantations from expanding over the primary forests and peatlands. The policy has been out for a decade and it provides a good opportunity to learn lessons from a significant effort made by a developing country in battling adverse environmental factors while maintaining economic growth. The first stage of a broad research agenda is to start with the first section of the chain and comprehensively analyze the impact of the Primary Forest and Peat Moratorium in Indonesia on fire events. In the second stage, I plan to introduce the high-resolution satellite-based measure of air pollution and find the change in air pollution in response to the protection added by the moratorium. Lastly, I will leverage concentration-response functions following Hein et al. (2022) and calculate the potential effects of the moratorium on respiratory health.

In this paper, I will unpack the first section of the chain and only focus on the causal link between land-clearing fires and the moratorium. Besides building up for the next-step evaluation of the impacts on air pollution and human health, it is worth investigating as an independent research question for the following reasons. First, while many studies have revealed the adverse effects of crop residue burning on air pollution and human health, few have attention to the land-clearing fire, which highly concerns many tropical countries (Rangel & Vogl, 2019; He et al., 2020; Dipoppa & Gulzar, 2023). Second, existing literature had a mixed conclusion on the direct impact of the moratorium on deforestation though most point to the direction that forest loss and degradation were slowed down. Despite deforestation and fire often going hand-in-hand, a deforestation restriction has an uncertain influence on fire. Third, the complexity of fire and the motivation behind fire settings requires additional evidence that could be referenced to enhance fire management. Understanding the heterogeneity across economic units and landscapes in a country with different forest conversion dynamics across islands and provinces is essential for successfully coordinating multiple stakeholders and developing a compelling fire prevention agenda (Hergoualc'h et al., 2018).

Using the digitalized map of the moratorium combined with high spatial resolution satellite data of fire hotspots and other geographical characteristics, I employed a difference-in-differences (DID) model to study whether the moratorium reduces fire at the subdistrict level, where treatment is a binary indicator of the border overlaps across the moratorium and subdistrict units. To address the concern with the selection bias, a matching strategy was applied to balance the pre-treatment characteristics between the treatment and control groups. The results suggest an unintended slow-down effect of the moratorium on fire reduction. Compared to the subdistricts with no protection, the moratorium-covered subdistricts missed an opportunity to bring the number of fires down by 77.5%. The persistent fire trend among the moratorium subdistricts could be explained by a pathway through the decreasing demand for hired laborers in industrial plantations and the increasing demand for household farmland among smallholders (Xu et al., 2022). Sufficient evidence from variation in fire scale and smoke released from the burning will be provided to support this hypothesis in the next step.

The practice of the fire-centered analysis of the moratorium adds empirical evidence on land-clearing fire and shows diverse impacts on environmental outcomes beyond forest loss and degradation. More importantly, the results suggest a possibility of discerning the change in the agricultural sector and land distribution led by the moratorium using satellite data complementary to the low spatial and temporal resolution socio-economic data. Once the gap between fire and human health is closed, the study can join Rocha & Sant'Anna (2022) and provides insights into the health impacts of biomass burning in regions facing challenges of high-rate deforestation.

2 Background

2.1 Description of the moratorium

As the home to the world's third-largest span of tropical rainforest, Indonesia is also the fifth-largest emitter of greenhouse gases, and most emissions come from the forestry sector (Jong, 2019). From 2001 to 2020, Indonesia lost 27.7Mha of tree cover, equivalent to a 17% decrease in tree cover since 2000, 19.0Gt of CO emissions (Global Forest Watch, 2021).

To reduce emissions from deforestation and forest degradation, the Indonesian government and Norway government signed a Letter of Intent, according to which the Indonesian government should develop and implement policy instruments and enforcement capability. In May 2011, a Presidential Instructions (PI) was released, announcing a forest moratorium that suspended the granting of new concession licenses for logging and conversion of forest and peatland for the following two years (Murdiyarso et al., 2012). The moratorium was renewed every two years and was made a permanent law in 2019. It includes all agriculture, forestry, and mining business permits. However, it made exceptions for sectors vital to national development (oil and gas, geothermal, rice paddy, and sugar cane). Meanwhile, all the existing licenses would not be affected by the moratorium.

The moratorium covers many forests protected under Law No 41/1999 and its related regulations (Murdiyarso et al., 2012). Hence, the environmental gains due to the moratorium are smaller than expected. To reveal the additional coverage provided by the moratorium, CIFOR overlaid a digital map of primary forests in 2009 on a digital map of areas designated as conservation forests as of 2009. They also overlaid digital peatland maps provided in 2003, 2004 and 2006. In the end, they superimposed the most recent version of IMM. They concluded that the moratorium provides additional coverage to 22.5Mha (7.2Mha of primary forests, 11.2Mha of peatland and 4.1Mha that do not fall into either category). 5.8Mha of peatlands and 9.6Mha of primary forest are excluded from the IMM, which suggests that (i) they are likely under concessions granted prior to the moratorium yet have not been disturbed, (ii) they are allocated for activities that are not covered by the moratorium (e.g., rice paddy growing) (Murdiyarso et al., 2012). Although no public documents or data can explain the selection of forests for moratorium coverage, research evidence shows that dryland moratorium forests are significantly less accessible and valuable than non-moratorium forests or forests that were recently cleared (Sloan et al., 2012).

The existing literature generally supports that the forest moratorium is associated with less deforestation. Busch et al. (2015) conclude that the designation of concessions significantly increases local deforestation. Chen et al. (2019) quantify the effectiveness of the forest moratorium using data from 2011 to 2017 and find that deforestation rates outside the moratorium boundaries are higher than those within the boundaries. Groom et al. (2022) found that the moratorium led to a 0.65% increase in dryland forest cover but had no effects on peatland forests.

2.2 Fires and air pollution

Indonesia's vegetation and peat fires are mostly man-made (Heil, 2007). According to Carlson et al. (2012), 93% of forest loss are fire-related. Fires are employed in direct forest conversion and transitions from logged forests to agricultural fallows (Carlson et al., 2012). They are used systematically as part of the clearing process by firms because of the low cost of completing forest conversion. Among all concessions in Indonesia, 46% of fires are started in oil palm concessions, which drain and clear existing forests before planting oil palm (Balboni et al., 2021). Estimates from Riau province in 2000 suggest that burning primary forest is 44% cheaper than alternative clearance methods for oil palm plantations.

Deforestation rates are, therefore, closely associated with fires and emissions. Reddington et al. (2015) find a significant positive relationship between annual deforestation rates and annual particulate fire emissions for total fire emissions and emissions from deforestation fires. Similarly, Balboni et al. (2021) find that an increase in the share of forest loss leads to a significant increase in the probability of fire in the location where forest loss was observed in the previous year. In addition, ignitions are substantially less likely to occur in protected areas and more likely to occur in the production forest area. These findings suggest that the moratorium policy, which protects many forests from being converted to industrial plantations, may reduce deforestation rates and fire incidences in the protected area.

Smoke from vegetation or biomass burning has triggered respiratory infections and deaths, especially in El Niño. In 1997, wildfire smoke from the catastrophic fire in Indonesia decreased 15,600 births (Jayachandran, 2009). During the next worst El Niño event in 2015, smoke pollution led to an excess of 100,300 deaths (Koplitz et al., 2016). The most critical risk-related measure of smoke is particulate matter (PM) with an aerodynamic diameter 2.5 µm (PM2.5). (Naeher et al., 2007; Reid et al., 2005).

Besides dryland forests, Indonesia has a rich amount of peatlands that compose nearly 10% of national land masses. Peat fires mainly occur on deforested land (Kiely et al., 2019). Compared to vegetation fires, peat fires have higher emission factors for many atmospheric pollutants (Hu et al., 2018; Kiely et al., 2019). After peat fires start, they are very difficult to put out. They may last several months along with white and thick smoke filled with organic carbon, methane, carbon monoxide, and significant amounts of PM2.5. Hein et al. (2022) used satellite data of AOD to calculate the PM2.5 attributed to peatland fires based on the burned hectare in Sumatra and Kalimantan (Indonesian Borneo). They concluded 4390 additional hospital admissions related to respiratory diseases.

2.3 Links between pollutants and respiratory health

Mounting evidence shows that exposure to PM is associated with increases in the morbidity of respiratory diseases (Ostro, 2004; Nel, 2005). While PM in cities is primarily generated from fuel combustion in vehicles and industrial facilities, PM in rural areas is mostly from biomass burning (BB) (Ostro, 2004). Compared to PM from urban sources, the effects of PM from BB have been less extensively studied (Naeher et al., 2007; Johnston et al., 2012). According to a review and meta-analysis of 81 previous studies of human health impacts of BB exposure, the risk of respiratory admissions/ER visits increased by 4.10% and 4.83% per 10 µg m^{-3} increased in PM2.5 and PM10 respectively (Karanasiou et al., 2021).

Many economic studies have also proved the adverse effects of PM2.5 on human health. Leveraging on the wind direction, multiple pieces of evidence have confirmed that the population living downwind of a polluted center were exposed to higher PM2.5 and higher health risk (Schlenker & Walker, 2016; Anderson, 2015; Deryugina et al., 2019; He et al., 2020). With similar interests in deforestation-related air pollution shared in my study, Rocha and Sant'Anna (2022) used the municipality-level data in Brazilian Amazon and the wind instrument approach and found a 1.5% increase in the monthly hospitalization rate for respiratory conditions in response to one standard deviation increase in PM2.5.

The studies mentioned above primarily relied on ground-level air pollution measurements. However, recent research has compared satellite-based measurements of PM2.5 with ground-level data and incorporated them into economic studies covering a wide geographical scope (Fowlie et al., 2019; Gendron-Carrier et al., 2022). More recent studies examining air pollution in developing countries have also incorporated satellite-derived measures of air pollution into empirical analyses using a wind design. For instance, Pullabhotla and Souza (2022) utilized climate reanalysis data from MERRA-2 to validate the positive correlation between upwind agricultural fires and various pollutants in India. They discovered an increased risk of hypertension associated with air pollution caused by agricultural fires (Gelaro et al., 2017). The researchers employed a conversion factor derived from a previous atmospheric science study to generate a PM2.5 measurement based on pollutant components. They then compared the outcomes with ground-level PM2.5 measurements taken from sample locations. Similarly, Garg et al. (2023) used the same data sources and PM2.5 estimates from van Donkelaar et al. (2016) to investigate the impact of a nationwide rural road construction program on air pollution, specifically through the pathway of labor exits in agriculture and agricultural fires in India. By dividing the sample into two groups based on whether the villages were downwind or non-downwind of the treated areas, they discovered a significant increase in annual average PM2.5 levels in the downwind villages due to the road program. Connecting this information to national health survey data, they also observed a 5.5% rise in infant mortality in the downwind villages, suggesting the existence of environmental and health externalities associated with rural roads, which contributed to a shortage of agricultural labor.

3 Data

The moratorium border was extracted from the 8th revised version of Indicative Moratorium Maps (IMM) released by the Ministry of Environment and Forestry of Indonesia and digitalized by Greenpeace (Greenpeace, 2022).[1] In this study, the protection assigned by the moratorium in 2011 was assumed to be time-invariant.

The moratorium policy protects nearly 70% of the primary forests and peatlands in Indonesia. The protected areas are widely distributed in Sumatra, Kalimantan, Sulawesi, and Papua, among which Sumatra is the most populated island. The land included in the moratorium border can be divided into two groups: land protected under conservation programs initiated before the moratorium and land under newly added protection. For the newly protected land, there are two types of landscape, primary forest and peatland. Figure 1 shows the assignment of protection by the moratorium. Considering the unclear history of the protection status over the previously conserved land, in this empirical analysis in Sections 4 and 5, I will primarily focus on the newly added protection designated by the moratorium in 2011 and how the new protection status alters fire events.

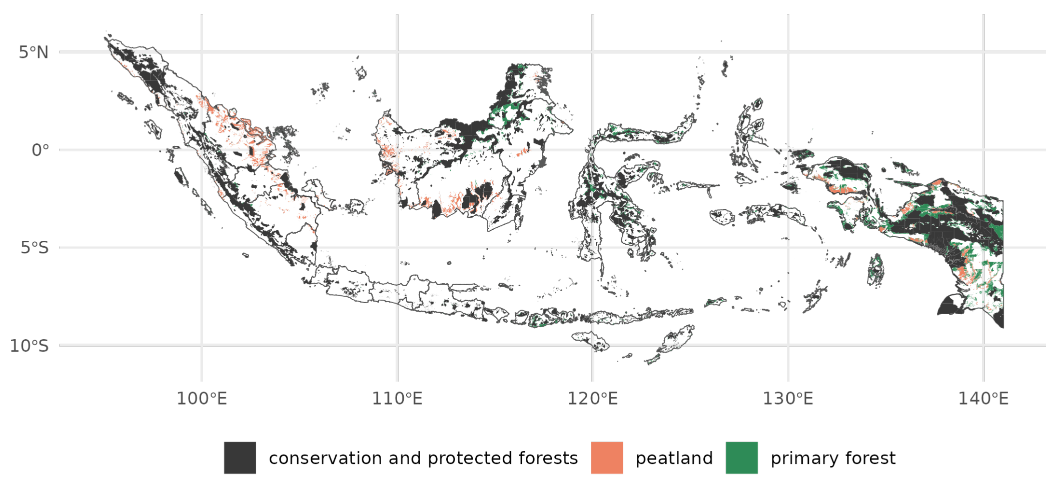

Figure 1: Map of the moratorium by land types

Notes: The black patches were under existing conservation programs before 2011, and the red and green are the newly added protection.

The daily fire hotspot data from 2001-2020 was collected by NASA'S Moderate Resolution Imag-

[1] Leijten et al. (2021) suggested that the change in the map in every edition was minor.

ing Spectroradiometer (MODIS) and downloaded from the Fire Information Management System (FIRMS). MODIS documents the coordinates of the center of the fire in a 1km pixel, the date and time of acquisition of fire records, brightness, fire radius power (FPR) and confidence. The daily hotspot data was processed based on four images captured by Terra and Aqua satellites at different time points of the day, and thus, for each pixel, it documents four hotspot observations at the maximum per day.

According to remote sensing studies on MODIS, the way that the satellite scans and maps fire to 1km pixels could cause a fire to be sensed in adjacent pixels (Freeborn et al., 2014). Hence hotspots in adjacent pixels could depict the same fire event. Moreover, a hotspot could be detected multiple times in a day from the different passes of the satellite at one location if the fire lasted for hours. In other words, a fire might be captured by multiple hotpots adjacent to each other multiple times daily. Therefore, the daily aggregated number of hotspots overestimates the number of fire events. To address this concern, I employed a 1.5km cutoff to implement a hierarchical clustering of hotspots on the same day. The number of fire events is measured by the number of fire clusters in subdistricts or villages. Considering that only 14%[2] of fires in Indonesia burn beyond one day, the choice of daily temporal resolution should not lead to a significant overestimation of fire events. From the 1,413,327 fire hotspots, 1,120,486 fire events were identified in Indonesia from 2001 to 2020. The maximum confidence of hotspots in a fire cluster was used as the measure of confidence of the fire event (cluster). Fire with confidence higher than 70% were classified as high-confidence fire.

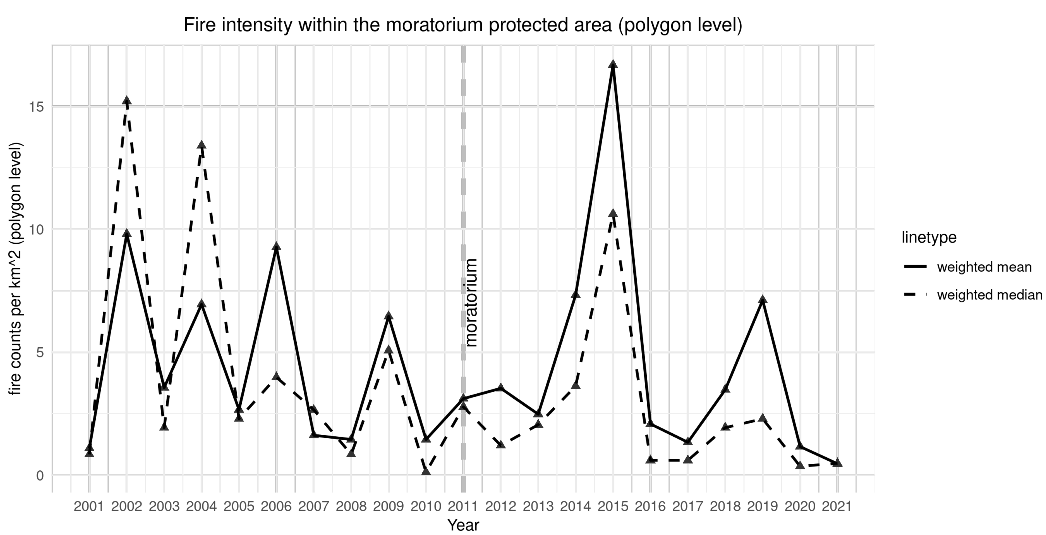

Figure 2: Fire intensity within the moratorium protected area
Notes: Statistics include all polygons covered by the moratorium regardless of whether the protection was newly added in 2011.

[2]The statistics were inferred from Balboni et al. (2021).

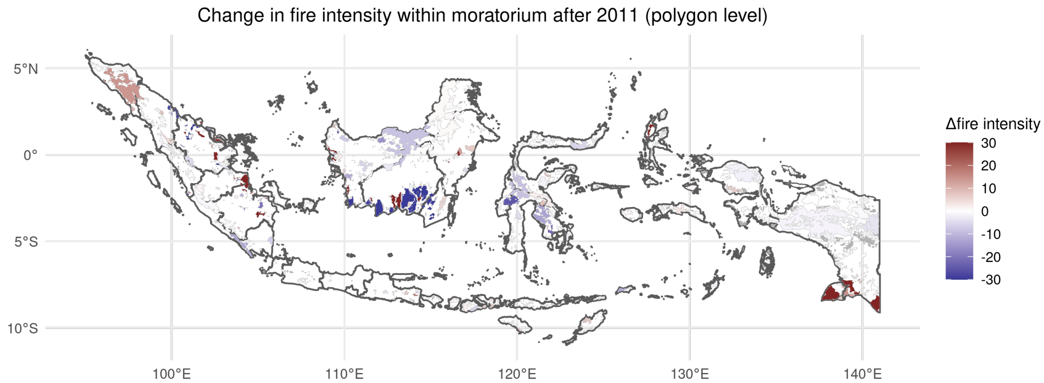

Figure 3: Change in remotely detected fires after the moratorium
Notes: Statistics include all polygons covered by the moratorium regardless of whether the protection was newly added in 2011.

Fires mainly concentrate in the dry season during July and October (Fig. A1). In El Niño years, due to the high temperature and low rainfall, fires become more frequent and massively increase in the dry season. During strong El Niño episodes, for example, from 2015 to 2016, annual fire incidences spiked to 37,000 in September, nearly two to three times the average year.

Figure 2 shows the trend of fire intensity within the moratorium-protected area at the polygon level, where fire intensity is measured by the number of fire events per square kilometer. Using the share of polygon size as weights, the weighted average of the polygon-level fire intensity fluctuates substantially by year. This could be due to the spatial heterogeneity of fire occurrences, where some outliers drive the average level. The conjecture is supported by the yearly change in the weighted median of fire intensity, where the effect of outliers is removed. Besides the abnormally high fire intensity in 2015, fire intensity tends to drop after the moratorium policy.

The map in Figure 3 shows that the moratorium policy may have differential impacts on fires across regions. The fire intensity dropped or remained at the same level in most protected areas (polygons) after the policy was enacted. In the meantime, fires tend to increase in peatlands or remote forests with low fire records throughout the past two decades.

Other geographical characteristics, such as the concession border, peat distribution, tree cover, land cover type, elevation and slope, came from multiple data sources. Details can be found in the Appendix in Table A5.

4 Research design

In the empirical analysis, I hope to answer the question: Does the moratorium reduce fire? If so, by how much? To perform the analysis, I restricted the analysis to two major islands, Sumatra and Kalimantan, because they were at the frontier of the deforestation and land-clearing fire problem in the past two decades and included the majority of the newly added land to be protected by the moratorium. Since fires have been closely associated with economic activities and compliance with the moratorium policy could be determined by the local administration, I started the analysis with low-level administrative units, namely subdistricts (*kecamantan*). In total, there are 2,455 subdistricts in Sumatra and Kalimantan, and each subdistrict consists of 12 villages on average.

A unit was assigned to the new-protection group if it contained a positive share of land under the newly added protection by the moratorium in 2011. Suppose it also contained land under the existing protection before 2011. In that case, it was assigned with new protection status only if the land under the newly added protection was the majority share of land under any form of protection; otherwise, if the majority of the protected land were credited by the moratorium but under existing conservation programs before 2011, the unit would be listed under the existing-protection group. If a unit did not cut the moratorium border, it was left in the no-protection group[3].

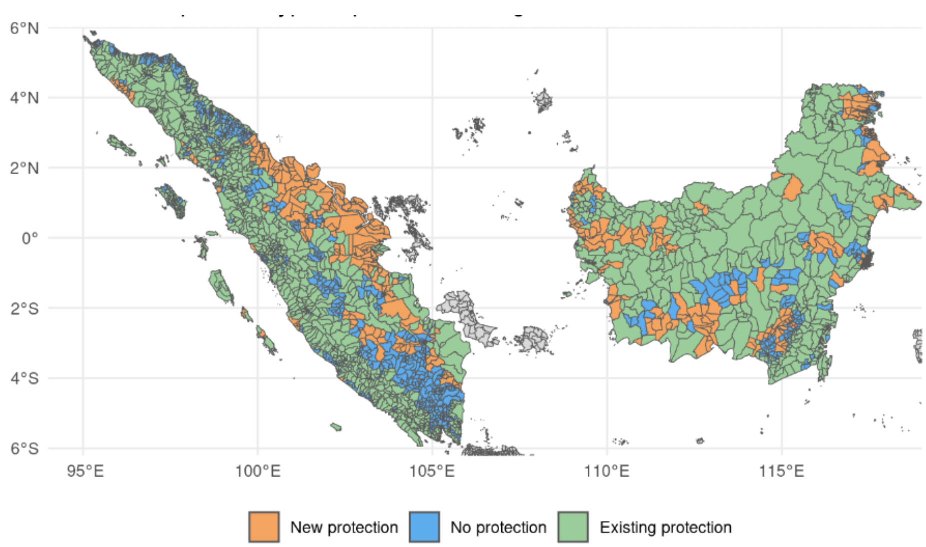

Figure 4: Map of the protection status at the subdistrict level

Figure 4 shows the three protection status of subdistricts in Sumatra and Kalimantan. Most subdistricts were under the existing protections because the moratorium covered a significant portion of the two islands. Within the moratorium border, nearly 85% of the land was under existing protection.

[3]Subdistricts under existing protection refer to those overlapped with the black patches in Figure 1; if they also covered land under the newly added protection (the red and green), the coverage under the black patches must have been the majority of all protected land in this subdistrict.

Considering the interest of the study is in the moratorium, these pre-protected subdistricts

Table 1: Summary statatistics of the subdistrict panel

	New Protection		No protection	
Var names	Mean	SD	Mean	SD
Num.fire before	6.50	11.06	2.22	5.19
Num.fire after	5.11	11.72	1.38	3.80
Num.fire dryseason before	4.83	9.73	1.88	4.78
Num.fire dryseason after	3.68	10.05	1.09	3.34
Num.fire high confidence before	2.85	5.39	1.08	2.82
Num.fire high confidence after	2.28	5.75	0.64	2.02
Num.fire dry-season high CI before	2.19	4.75	0.94	2.63
Num.fire dry-season high CI after	1.66	4.89	0.52	1.81
Mor. newly added protection share %	18.27	18.56	0.00	0.00
Mor. peat share %	17.92	18.71	0.00	0.00
Mor. primiry forest share %	0.35	2.60	0.00	0.00
Mor. pre-protected forest share %	1.40	4.15	0.00	0.00
Area included %	0.67	0.26	0.73	0.27
Treecover % 2010	50.17	16.26	41.81	21.43
Treecover % (low-land) 2010	47.09	18.45	28.90	23.92
Peat %	29.62	25.50	0.12	1.31
Elevation (m)	51.10	171.07	121.89	230.35
Slope	0.43	0.62	0.87	1.20
Size (km^2)	323.40	328.71	115.87	140.51
Concession %*	30.58	27.47	10.55	20.64
Cropland %*	0.68	4.50	8.15	18.10
Cropland mosaic %*	1.51	7.59	7.33	17.84
Urbanland %*	4.55	10.94	17.06	24.69
Num. subdistrict	237	237	782	782

Note: Statistics of all variables but the * ones were measured based on the adjusted area of subdistricts excluding the concessions and irrelevant landcover types. The variable 'Area included %' describes the proportion of land of a subdistrict after the adjustment.

Table 2: Summary statistics of pre-treatment characteristics: After entropy balancing

	New Protection		No protection	
Var names	Mean	SD	Mean	SD
Treecover % (low-land) 2010	47.09	18.45	47.09	20.05
Elevation (m)	51.10	171.07	51.10	61.14
Slope	0.42	0.62	0.42	0.28
Size (km^2)	323.40	328.71	323.40	264.35
Concession %*	30.58	27.47	30.58	27.95
Cropland %*	0.68	4.50	0.68	3.74
Cropland mosaic %*	1.51	7.59	1.51	7.53
Urbanland %*	4.55	10.94	4.55	12.59

Note: The selected variables correspond to the variables in the last block of variables in Table 1.

were excluded from the principal analysis. In this analysis, treatment is defined as being assigned to the new-protection group. Subdistricts with the new protection status are the treatment group, and those with the no protection status are the comparison group. Those under the existing-protection group were not used in the analysis.

The treatment group concentrates on the east coast of Sumatra, west and central Kalimantan. Table 1 shows the summary statistics of the fire counts before and after the moratorium, the share of moratorium protection by landscapes, and the pre-treatment characteristics. As the moratorium neither directly altered the fire settings over the established concessions nor farmers' burning practices on the cropland, I excluded the area of the concessions and irrelevant landcover types such as cropland, cropland mosaics, urban land, and waterbody, and focused on fire in the area after the adjustments - the land on which the moratorium could have direct impacts. Compared to the subdistricts that had no overlap with the moratorium border, the treatment group had higher fire frequency, a larger unit size, a higher level of low-land treecover share, and more peat and concessions. The differences suggest selection issues with the place of the protection designated by the moratorium.

To address this concern, I used Entropy Balancing Weights (EBW) to achieve a covariate balance between the treatment and control groups (Hainmueller, 2012). The method was designed with an easy implementation attraction for observational studies with binary treatments. It can impose the equality of the first, second, or possibly higher moments of the selected covariates in the treatment and control group by reweighting the units from the control group. Table 2 shows the selected pre-treatment characteristics after EBW adjustments. The first moment (i.e., the mean) was precisely balanced.

After adjusting the sample with EBW, I employed a linear DID model to explore the effect of the moratorium on fire. Using the subdistrict-level data, I estimate the following equation:

$$Y_{i,g,t} = \beta_1 + \beta_2 D_i * I_t + X_{i,t}\eta + \alpha_i + \theta_{g,t} + \varepsilon_{i,g,t} \tag{1}$$

where $Y_{i,g,t}$ is the number of fire events in subdistrict i, province g, and in year t. D is a binary indicator of a subdistrict being assigned to the new protection group. $I_t = 1\{t \geq 2011\}$ indicates the post-moratorium time period. X is a vector of the time-variant covariates, including the share of low-land treecover (elevation $\leq$ 100m), the size of the subdistrict after adjustments[4], the share of cropland, cropland mosaics, and urban land in subdistrict i at the beginning of year t. Although the land of concession, cropland, and urban use was excluded when counting the fire, the share of these land cover types partially reflects the structure of the economy of the subdistrict and they could be relevant

[4]The adjusted size of subdistrict depends on the yearly variant land cover types. For example, in a subdistrict i, an area could be converted from broadleaf land cover to cropland from year t-1 to year t. Hence, this area was included in the fire counting practice in year t-1 but not in year t, and the size of the subdistrict i shrank accordingly from year t-1 to year t. The yearly size adjustment should be minor.

to the fire-setting decisions. Hence they were included as controls. α_i and $\theta_{g,t}$ are the subdistrict fixed effect and the province-by-year fixed effect interaction. β_2 is the coefficient of interest.

Another concern with the biasedness of the DID estimate is unobserved factors that might cause the trend of fire events to develop differently between the treatment and comparison group For example, some fire prevention programs were developed for the non-protected area but were absent in the protected area. To ensure the unobserved factors did not affect the fire trend before the moratorium and to comprehensively understand the effect of the moratorium, I employed a dynamic difference-in-difference model in response to Eq. (1). using the equation below:

$$Y_{i,g,t} = \tau + \sum_{r} \zeta_r D_i * 1_{r=t-2011 \& r \neq -1} + X_{i,t}\eta + \alpha_i + \theta_{g,t} + \varepsilon_{i,g,t} \tag{2}$$

where $1_{r=t-2011\&r\neq-1}$ describes a year dummy with the lag year of the moratorium 2010 omitted. The coefficients ζ_r capture the effect of the moratorium compared to the baseline in 2010 as if the moratorium was enacted $-r$ years lag of 2011 or r years leading to 2011. The results can verify the parallel trend assumption as well as reveal the dynamics of the treatment effect after the initial year when the policy was rolled out. For $r < 0$, ζ_r should not be statistically different from zero if the fire trend is linear and holds parallel across the treatment and control group before the moratorium. For $r \geq 0$, ζ_r reflects the effect of the moratorium at different time points.

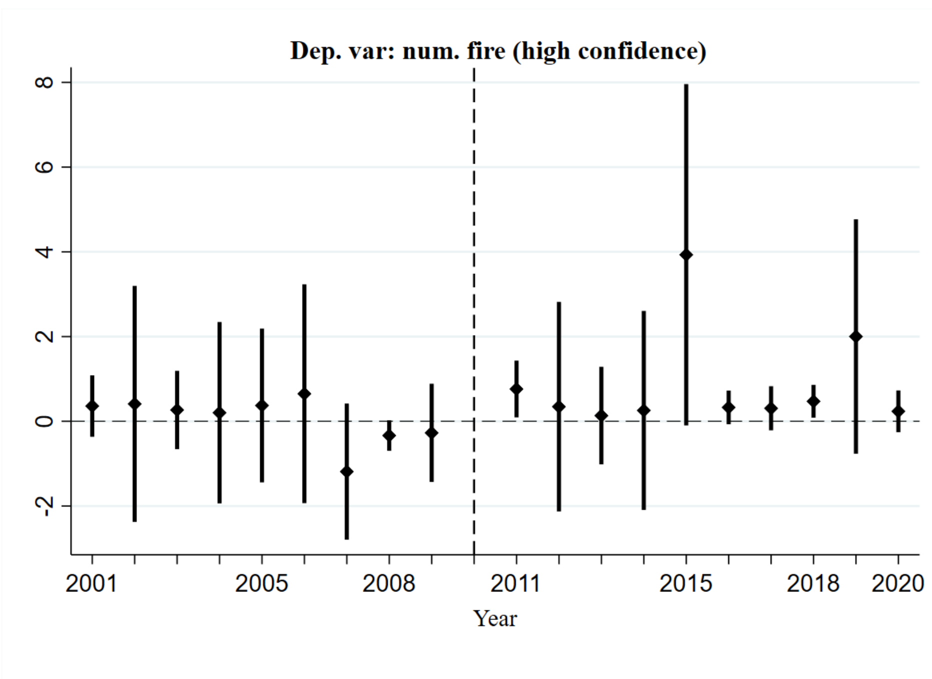

Figure 5: Event Study - EBW adjusted

5 Preliminary Results

Figure 5 plots the coefficients of the treatment-year interaction term, ζ_r, from Equation (2) using EBW adjusted sample. The difference in fire counts across the moratorium-protected and non-protected subdistricts was constant before 2011. The effect of the moratorium on the number of high-confidence fires appeared shortly in 2011 and then faded away. Until 2016, the moratorium showed a steady positive effect on the fire, which means the difference in high-confidence fire counts between the protected and non-protected units increased due to the moratorium. Combining it with the decreasing fire counts revealed in Table 1 means that the moratorium slowed down the reduction in fires.

The average effects of the moratorium on fire in subdistricts with new protections are reported in Table 3. The positive effects hold consistently across different measurements of fire counts. Column (3) shows that due to the moratorium, the number of high-confidence fires in subdistricts with new protection status reduces 0.837 less than in subdistricts without protection. That says the moratorium causes a missing opportunity of 77.5% reduction of high-confidence fires, relative to the average number of high-confidence fires of the pre-moratorium control group[5].

Admittedly, the EBW-adjusted DID estimates are not free from the concern with unbiasedness because peat share as an important covariate was not balanced due to the violation of the overlap assumption. The failure of fire reduction compared to the subdistricts with no protection might be attributed to the dynamics of peatland encroachment or peat fire instead of the moratorium. Since the moratorium already covered the majority of peatland in Indonesia and only left little outside the moratorium border, it is not impossible that unobserved factors triggered an increase in peatland encroaching and peat fire after 2015 and such effect was confounded with the moratorium.

Besides using a data pre-processing method to adjust the balance of the treatment and the control, I experimented with another way to improve the proximity of the counterfactual of the treatment group by constructing a control group with a sample of units with no protection but shared borders with the treated unit and excluded units not geographically adjacent to a treated unit. Figure A1 in Appendix shows the map of the sample distributions, and summary statistics of the adjacent sample pairs are reported in Table A1. The discrepancies in the covariates are much smaller than before the sample adjustments though the pre-treatment characteristics are still unbalanced. Figure 6 shows the dynamics effects of the moratorium using the adjacent sample units. There is an increasing trend in fires after the enaction of the moratorium. However, the pre-trend is ambiguous over the 10-year window from 2001-2010. Table 4 show that the DID estimates using the adjacent sample of subdistricts are positively significant on dry-season and high-confidence fires.

To check the robustness of the results, and also to investigate fire displacement and redistribution,

[5]The average number of high confidence fire of the control group can be found in Table 1

I experimented with the analysis at the 1km x 1km pixel level using the specification presented in Equation (1). The fine pixels allow high accuracy of the fire locations relative to the moratorium border to be identified. The outcome variable is a binary variable documenting whether a fire hotspot was observed at pixel i, year t. Pixels falling in the new protection (i.e., the red and green patches in Figure 1) are the treatment group and pixels in the no protection group are the control.

There are a few minor adjustments on the vector of covariates in the pixel-level analysis. First, the unit size was identical for all observations, and thus, size was no longer included as a covariate. Second, the treecover share in each year was included rather than the low-land treecover share because it was impossible to stratify tree cover by elevations at the pixel level. Third, the land cover type share of pixel i was measured by the mean value within a 9km x 9km kernel centered at the pixel. Because the selected sample pixels used for the fire analysis only included those outside concessions and were not classified as particular land cover types, there was no variation in the cropland and urban land indicator. The mean of land cover share in a buffer zone is proximate to the distance to the land cover, which could be relevant for the fire-setting decisions.

Table A3 reports the results of the EBW-adjusted estimates of the moratorium's effects on fires. Besides the pre-treatment variables listed in Table 2, the peat dummy was added when estimating the weights. Currently, only pixels in the sample of adjacent subdistricts (see Figure A1). The results show that the fire probability inside the moratorium border is not significantly higher than outside. Combining them with the results from the subdistrict-level analysis shown in Table 3 implies possible fire displacements to the area outside and close to the moratorium borders. This finding agrees with the evidence of displaced forest loss near the moratorium border shown by Leijten et al. (2021).

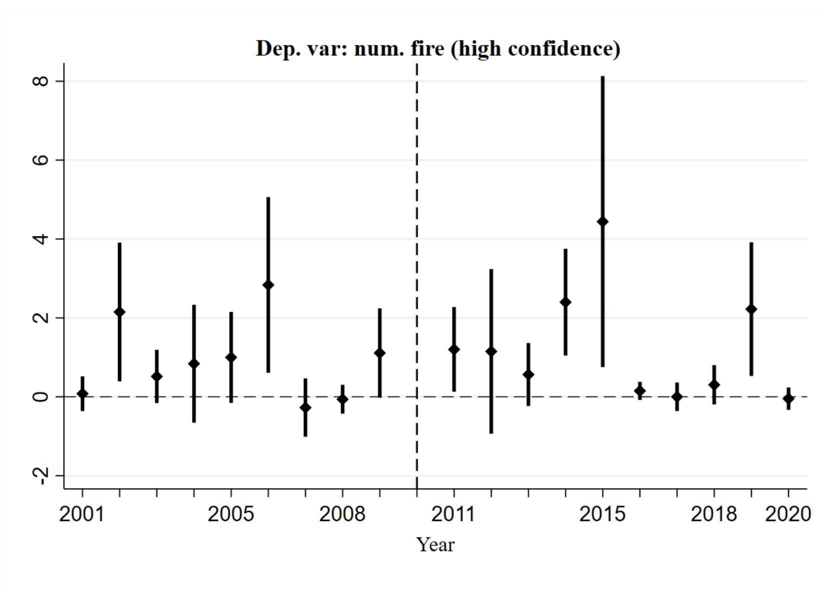

Figure 6: Dynamic difference-in-difference estimates using the adjacent sample units

Table 3: EBW adjusted DID - the effect of new protection on fire

	#fire	#fire dry	#fire high CI	#fire high-dry
new protection × post	1.359*	1.451*	0.837*	0.872*
	(0.720)	(0.696)	(0.435)	(0.423)
post	3.202**	2.447**	0.913	0.610
	(1.169)	(1.003)	(0.585)	(0.498)
low-land treecover share	0.0590**	0.0526**	0.0205*	0.0193*
	(0.0213)	(0.0237)	(0.00978)	(0.0107)
size	-0.00630	0.00134	0.00177	0.00540
	(0.0246)	(0.0131)	(0.0134)	(0.00831)
cropland %	0.0222	0.00959	0.00999	0.00657
	(0.0218)	(0.0166)	(0.0139)	(0.0114)
cropland mosaic %	0.159***	0.155***	0.0814***	0.0823***
	(0.0480)	(0.0355)	(0.0262)	(0.0222)
urbanland %	0.0531	0.0401*	0.0254	0.0193
	(0.0303)	(0.0210)	(0.0164)	(0.0126)
Subdistrict FE	Y	Y	Y	Y
Province × Year FE	Y	Y	Y	Y
Observations	20320	20320	20320	20320
R^2	0.387	0.397	0.363	0.370

Standard errors were clustered by province and presented in the parenthesis.
Time-variant variables listed in Table 2, low-land treecover share before a year began, and the share by cropland, cropland mosaic and urbanland are included.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Using the adjacent sample only - the effect of new protection on fire

	#fire	#fire dry	#fire high CI	#fire high-dry
new protection × post	0.560	0.549*	0.425*	0.354*
	(0.416)	(0.304)	(0.233)	(0.186)
Subdistrict FE	Y	Y	Y	Y
Province × Year FE	Y	Y	Y	Y
Observations	10640	10640	10640	10640
R^2	0.308	0.323	0.272	0.284

Standard errors were clustered by province and presented in the parenthesis.
Time-variant variables listed in Table 2, low-land treecover share before a year began, and the share by cropland, cropland mosaic and urbanland are included.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6 Discussion

In this study, I provided empirical evidence on the effect of a national forest conservation policy on fire events in Indonesia, where the prevalent deforestation and land-clearing fire were highly concerned with environmental management. Contradicted with the expectation of positive effects in terms of achievements in environment conservation, the preliminary results indicate that the moratorium slowed down the fire reduction in the protected area and resulted in a missing opportunity of saving bills in fire prevention and also possibly in air quality improvement.

At this stage, two concerns that might compromise the credibility of the results have not been fully addressed. One is the concern with selection bias created by the landscape targeted by the moratorium that the entropy balancing could not address. It was not impossible that the encroachment on peatlands became out of control after 2015, such that fire over peatlands was harder to abate than fire over the dryland after 2015. Another is the concern with unobserved factors that alter the trend of fire in the control group but not the treatment group. After the catastrophic fire in 2015, the Indonesian government faced pressure from the international community to act on fire controls. One of the preventative measures for the fire was reinforcing fire prevention in 664 fire-prone villages by supporting community-based fire patrol and socialization, and it has appeared to be effective in reducing fire activities during 2016-2019 (Sloan et al., 2021). Hypothetically, if many of the targeted villages belong to the subdistricts with no moratorium protection and perhaps an adjacent unit to the protected subdistricts, then it leads to an omitted variable bias to the DID estimates and explains the deviation of fire trend in the treatment group after 2015.

On the other hand, the unintended slow-down effect on fire reduction could be achieved by the moratorium through an obscure pathway of labor supply in the agricultural sector. A conjecture is that the moratorium increased smallholders' demand for household farmland since hiring agricultural labor decreased when fewer large concessionaires were developing their plantations. It is supported by Xu et al. (2022), who used the labor outcomes from 2007 and 2015 and found an increase in smallholder agricultural labor supply in the districts that cut the moratorium borders.

It is challenging to prove that the agents behind the persistent fire events in the moratorium-protected subdistricts were smallholders and they burned to expand their farms. However, three observations were consistent with this conjecture. First, fire settings could be motivated by the demand for small-scale cropland. Table 3 implies a positive correlation between fire counts over non-croplands and cropland mosaics. A subdistrict with a heavy portion of fragmented land might have more incentives to expand the small croplands. Second, the moratorium did not significantly change forest loss (See Appendix Table A2). The ambiguous effects on deforestation at the administrative unit level were consistent with the results from Table 7 in Xu et al. (2022). If the agents behind the fire were large plantation companies, the forest loss could have been more noticeable. Third, the timing of the slow-down effect on fire reduction being observed was four years after the moratorium. The labor market response to the moratorium was likely to be delayed because the development of concessions granted in the late 2010s was still under development and required a considerable number of laborers in the initial 4-5 years after the enactment of the moratorium. Following the agricultural labor market's transformation, the demand for household farmland increased, and so did the land-clearing fire.

The next step is to investigate the rescaling or redistribution effect of the moratorium on fire events. Did the suspension in concession granting replace the would-have-happened large-scale fire with many small-scale fires? The answer could help unveil the change in economic incentives and human activities behind the subtle change in fire settings. With high spatial and temporal resolution data, the evidence from fire variations can complement the evidence directly from the socio-economic outcomes. In addition, although the impacts on deforestation had been evaluated in the past literature, given the complexity of the environmental impact of the moratorium policy, the impacts on fire might have decoupled with the impacts on forest loss and need to be carefully evaluated.

Meanwhile, in the next stage, I plan to introduce air pollution data and provide evidence of the moratorium on air quality and health. The evidence from the variation in the amount and distribution of air pollution could reflect the heterogeneity in fire locations and scale, which was challenging to measure using only the hotspot data. More importantly, it will connect the moratorium, an environmental policy targeting deforestation, to human health. Understanding the quantity of benefits or damages translated into human health could inform policymakers of the co-benefits of the moratorium that had been overlooked or the quantity of the underestimated loss from an ineffective forest conservation policy. The results will shed light on the balance between environmental conservation and economic development in rural areas in developing countries and could be referenced in future legislation on fire and forest management.

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Appendix

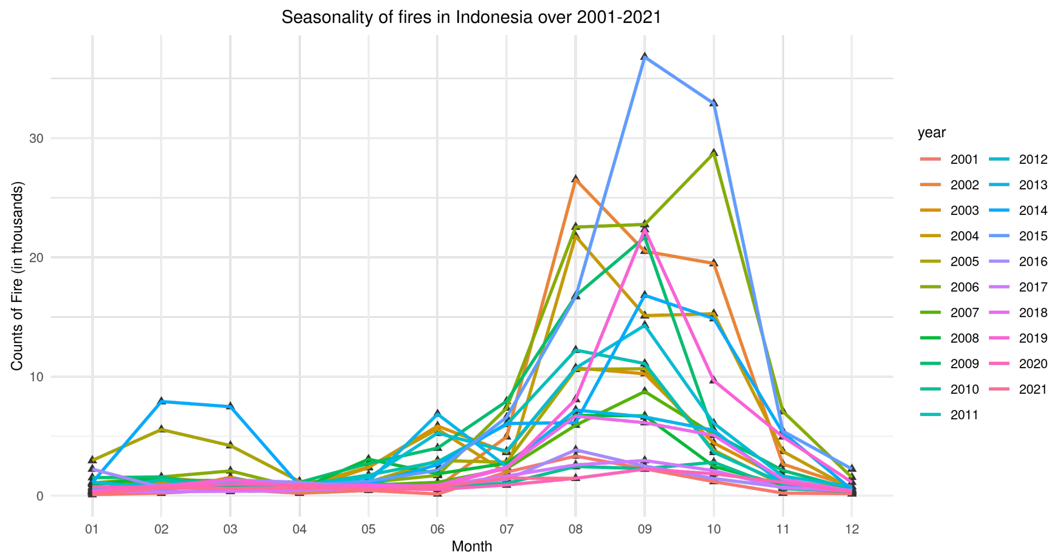

Figure A1: Seasonality of fire

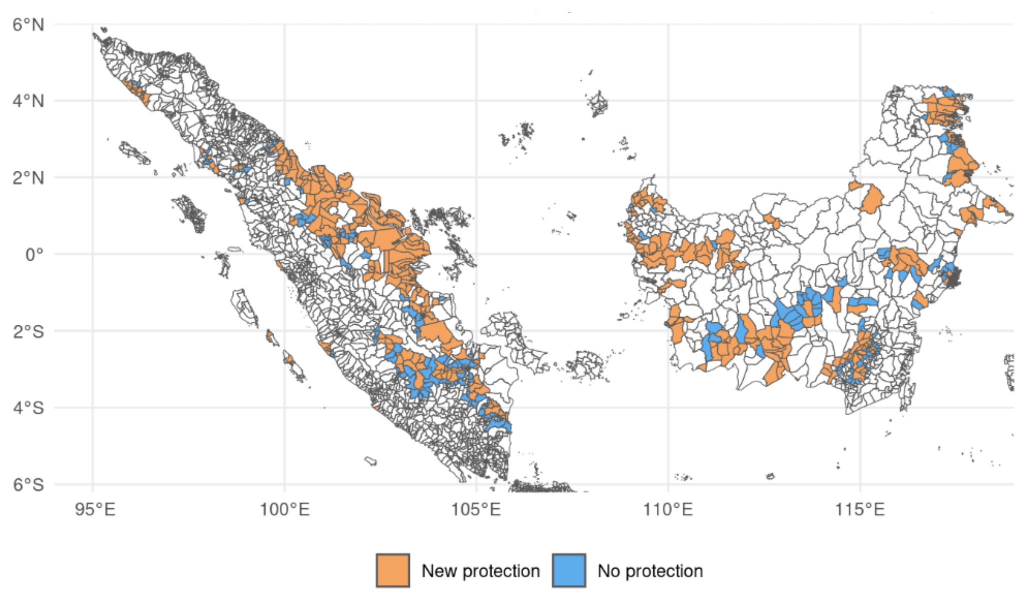

Figure A2: Map of the adjacent sample

Table A1: Summary statatistics of the subdistrict panel

	New Protection		No protection	
Var names	Mean	SD	Mean	SD
Num.fire before	6.50	11.06	4.80	7.90
Num.fire after	5.11	11.72	3.02	5.86
Num.fire dryseason before	4.83	9.73	4.20	7.47
Num.fire dryseason after	3.68	10.05	2.52	5.29
Num.fire high confidence before	2.85	5.39	2.33	4.25
Num.fire high confidence after	2.28	5.75	1.42	3.14
Num.fire dry-season high CI before	2.19	4.75	2.08	4.05
Num.fire dry-season high CI after	1.66	4.89	1.21	2.89
Mor. newly added protection share %	18.27	18.56	0.00	0.00
Mor. peat share %	17.92	18.71	0.00	0.00
Mor. primiry forest share %	0.35	2.60	0.00	0.00
Mor. pre-protected forest share %	1.40	4.15	0.00	0.00
Area included %	0.67	0.26	0.72	0.26
Treecover % 2010	50.17	16.26	47.15	17.95
Treecover % (low-land) 2010	47.09	18.45	41.10	20.40
Peat %	29.62	25.50	0.48	2.56
Elevation (m)	51.10	171.07	59.44	148.51
Slope	0.43	0.62	0.57	0.72
Size (kmˆ2)	323.40	328.71	200.40	184.53
Concession %*	30.58	27.47	20.87	26.58
Cropland %*	0.68	4.50	1.03	3.37
Cropland mosaic %*	1.51	7.59	3.86	12.63
Urbanland %*	4.55	10.94	10.13	20.27
Num. subdistrict	237	237	199	199

Note: Statistics of all variables but the * ones were measured based on the adjusted area of subdistricts excluding the concessions and irrelevant landcover types. The variable 'Area included %' describes the proportion of land of a subdistrict after the adjustment.

Table A2: DID - the effect of new protection on forest loss

	DID	EBW adjusted	adjacent sample
new protection × post	-0.108	-0.0235	-0.0648
	(0.0892)	(0.0895)	(0.129)
Subdistrict FE	Y	Y	Y
Year FE	Y	Y	Y
Province × Year FE	Y	Y	Y
Observations	20310	20305	8660
R^2	0.418	0.383	0.383

Standard errors were clustered by province and presented in the parenthesis.
Time-invariant variables listed in Table 2, low-land treecover share before a year began, and the El Nino year group dummy are included.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

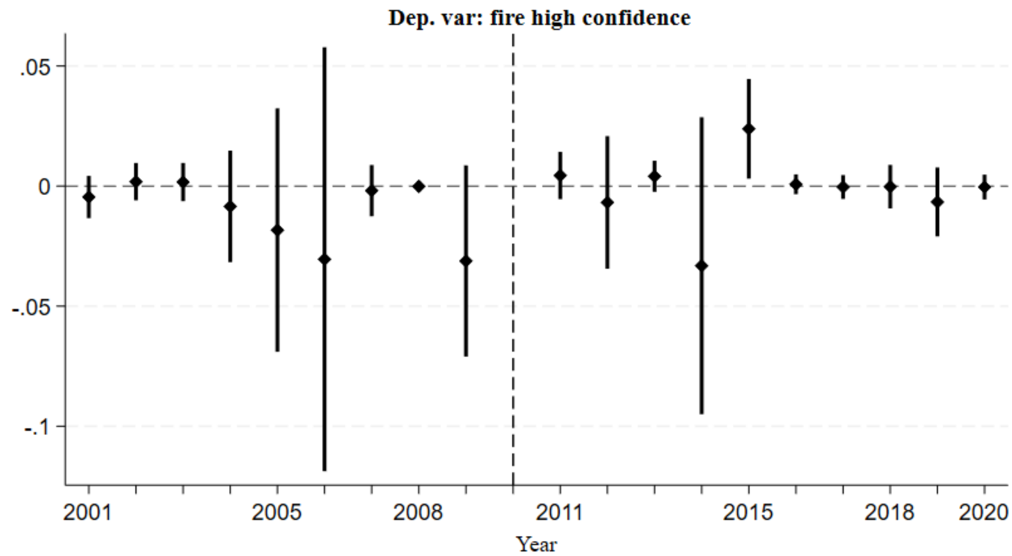

Figure A3: EBW-adjusted DID - using grids in the adjacent subdistrict sample

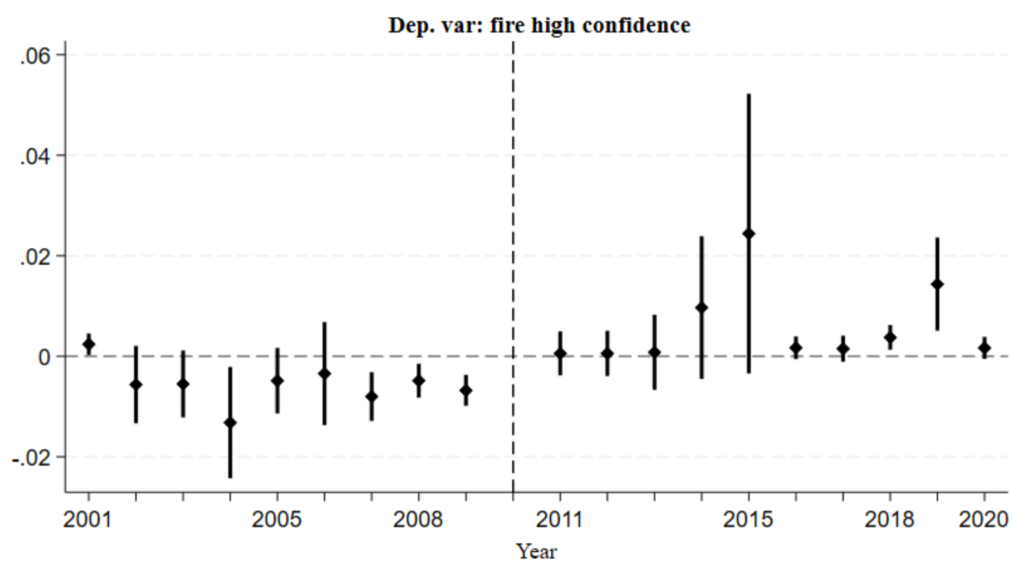

Figure A4: DID - using grids in the adjacent subdistrict sample

Table A3: EBW adjusted DID from the pixel-level analysis - the effect of new protection on fire

	hotspot	hotspot dry	hotspot high CI	hotspot high-dry
new protection × post	0.00794	0.000881	0.00773	0.00211
	(0.0119)	(0.00397)	(0.00906)	(0.00334)
post	-0.0114**	-0.0157***	-0.00793**	-0.0101***
	(0.00473)	(0.00171)	(0.00357)	(0.00128)
lag treecover share	-0.000633***	-0.000440***	-0.000259***	-0.000135***
	(0.0000934)	(0.000140)	(0.0000671)	(0.0000177)
cropland	0.0347	0.0102	0.0598**	0.0396***
	(0.0536)	(0.0463)	(0.0247)	(0.0104)
cropland mosaic	-0.308	-0.347	-0.278	-0.268
	(0.482)	(0.457)	(0.341)	(0.319)
urbanland	0.0891**	0.0407	0.0338*	0.0146
	(0.0292)	(0.0267)	(0.0176)	(0.00971)
Subdistrict FE	Y	Y	Y	Y
Province × Year FE	Y	Y	Y	Y
Observations	1543038	1543038	1543038	1543038
R^2	0.054	0.056	0.031	0.032

Standard errors were clustered by province and presented in the parenthesis.
The average probability of fire in the no-protection area before the moratorium is around 0.01.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A4: DID estimates from the pixel-level analysis - the effect of new protection on fire

	hotspot	hotspot dry	hotspot high CI	hotspot high-dry
new protection × post	0.0163***	0.0145***	0.0105***	0.00908***
	(0.00318)	(0.00257)	(0.00195)	(0.00166)
post	-0.0368***	-0.0169***	-0.0203***	-0.00641***
	(0.00389)	(0.00163)	(0.00246)	(0.000980)
lag treecover share	-0.000370***	-0.000168***	-0.000213***	-0.0000999***
	(0.000105)	(0.0000296)	(0.0000662)	(0.0000193)
cropland	0.0204	0.00811	0.00649	0.00281
	(0.0362)	(0.0302)	(0.0175)	(0.0136)
cropland mosaic	0.240***	0.194***	0.135***	0.127***
	(0.0596)	(0.0401)	(0.0370)	(0.0333)
urbanland	0.0439***	0.0311***	0.0233***	0.0164***
	(0.0138)	(0.00972)	(0.00721)	(0.00534)
Subdistrict FE	Y	Y	Y	Y
Province × Year FE	Y	Y	Y	Y
Observations	1549758	1549758	1549758	1549758
R^2	0.019	0.017	0.011	0.010

Standard errors were clustered by province and presented in the parenthesis.
The average probability of fire in the no-protection area before the moratorium is around 0.01.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A5: Data descriptions of characteristics included as covariates

Data	Description:
Concessions	The digitalized map of oil palm and wood fiber concessions were updated by Global Forest Watch in 2019. The time when the concessions were granted, however, was not fully disclosed to the public (Global Forest Watch, 2019a, 2019b)
Treecover & forest loss	The 30m x 30m high-resolution data of treecover in 2000 and the annual forest loss during 2000-2020 was gained from Global Forest Watch. It was used to generate the yearly treecover share at the 1km pixel level and then was aggregated by subdistrict (Hansen et al. 2013)
Peat	The map of peat was provided by Global Forest Watch (Global Forest Watch, 2019)
Land cover type	The data of land cover type was from MODIS Land Cover Type product where the land cover scheme incorporates 17 classes of land cover defined by the IGBP. The satellite images on the first day of each calendar year during 2001-2020 were exported from Google Earth Engine at the 1km x 1km resolution. This allows me to identify whether the pixel of land was in the human-altered class or vegetation class. (Friedl & Sulla-Menashe, 2022)
Elevation & slope	Digital elevation dataset was from the Shuttle Radar Topography Mission (SRTM) and exported from Google Earth Engine at the 1km x 1km resolution (Jarvis et al., 2008)
Administration boundaries	The georeferenced map of subdistricts were accessed and downloaded from https://data.humdata.org/dataset/cod-ab-idn May 2020. (BIG, 2017)