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Evaluating the social and environmental factors behind the 2015 extreme fire event in Sumatra, Indonesia

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¹ Authors to whom any correspondence should be addressed.E-mail: jocelyne.sze@gmail.com and janicelee@ntu.edu.sg**Keywords:** peat, drought, socio-economic, haze, land-use, forest degradationSupplementary material for this article is available [online](#)**Abstract**

Fires in Indonesia release excessive carbon and are exacerbated during drier El Niño years. The recent 2015 fires were affected by an extended drought caused by a strong El Niño event. This led to severe haze conditions across Southeast Asia, resulting in adverse socioeconomic and health impacts. Here, we evaluate the social and environmental factors that contributed to the 2015 extreme fires in Riau, Jambi and South Sumatra. We developed proxy variables for plausible drivers of fire which contribute either as a predisposing condition or as an ignition source for fires. We evaluated how these variables influenced fire count at an administrative regency-level and fire occurrence at a pixel-level (1 km²). We used generalized linear mixed effect models to model fire count at the regency-level and boosted regression trees to model fire occurrence at the pixel-level. Rainfall, slope and population density were the most important variables predicting fires at both levels. Economic variables such as the proportion of small-scale (<10 ha) and medium-scale (10–100 ha) plantation landholdings, and the reported use of fires to clear agricultural lands in villages were important in explaining fire count at the regency-level. At the pixel-level, distance from roads and the number of recorded burns over peatlands were important in explaining fire occurrence. The main influence of rain on fires corroborates with previous studies, and highlights the importance of establishing an early warning system for droughts to better prevent and manage future extreme fire events. Mitigation efforts for future fires, especially during El Niño years, can focus on identifying high-risk areas using environmental data on rainfall, slope, peatlands, and previously burnt peat areas, as well as social data related to population density, access to roads, extents of small- and medium-plantation landholdings, and village-level propensity to burn land for agriculture.

1. Introduction

Fire is an inexpensive and convenient tool for agricultural land clearing in the rural tropics and is widely used across Indonesia by smallholders and companies (Ketterings *et al* 1999, Anderson and Bowen 2000, Carmenta *et al* 2011). Drought years associated with the El Niño Southern Oscillation (ENSO) and Indian Ocean Dipole exacerbate fires, resulting in extreme fire events in Indonesia in 1997, 2006 and 2015 (Field *et al* 2016). However, Indonesia's land-use policies, such as the logging and clear-cutting of tropical forests and

drainage of peatlands for industrial plantations (Miettinen *et al* 2012), have produced landscapes that are susceptible to extreme fires even in non-drought years (Siegert *et al* 2001, Field *et al* 2009, Gaveau *et al* 2014, Field *et al* 2016). These fires contribute to increasing atmospheric carbon dioxide concentrations (Huijnen *et al* 2016), and result in adverse socioeconomic and health impacts from haze (Marlier *et al* 2015a). In the most recent extreme fire event of 2015, the thick choking haze extended to Singapore, Malaysia and Thailand, and cost an estimated 100 000 deaths within Southeast Asia (Kopplitz *et al* 2016) and economic

losses of USD16.1 billion (World Bank 2015) in Indonesia alone.

Fires are a consequence of a combination of predisposing conditions, which define the vulnerability of the landscape to fires, and social causes, which result in fire ignitions (Stolle and Lambin 2003). Some proximate factors behind ignitions in Indonesia include land clearing (Gaveau *et al* 2014, Marlier *et al* 2015b), land conflict (Suyanto *et al* 2004), and the use of fire for household activities. Fires are used predominantly for land clearing as it is cheaper than manual clearing, and burnt land is of higher value to more actors compared to unburnt cleared land (Ketterings *et al* 1999, Purnomo *et al* 2017). Fires have been used as a weapon in times of land-use disputes either between local and migrant communities or between companies and communities (Suyanto *et al* 2004, Dennis *et al* 2005), and are also used by rural villagers for cooking and waste disposal.

Ignition sources are just part of the picture behind fires; the predisposing conditions of the landscape propagate fires and facilitate its spread (Stolle and Lambin 2003). The rapid conversion of forests and drainage of peatlands for oil palm and acacia plantations (Miettinen *et al* 2012, Carlson *et al* 2013, Abood *et al* 2015) made landscapes in Sumatra and Kalimantan more prone to extreme fires especially under strong ENSO conditions (Field *et al* 2016, Taufik *et al* 2017). The likelihood of major fires occurring increases sharply during prolonged dry conditions ($<4 \text{ mm day}^{-1}$ precipitation) (Field *et al* 2016) as a consequent of the subsurface hydrological drought (Taufik *et al* 2017). Ecosystem degradation through logging and canalization of peatlands results in higher amounts of dry biomass above- and below-ground respectively, increasing the fuel load for extreme fires to occur (Siebert *et al* 2001, Konecny *et al* 2016). Road development also enhances landscape fragmentation and increases access to forests and peatlands for conversion (Stolle *et al* 2003). Repeated fires over peatlands results in higher fern and scrub cover, increasing its susceptibility to future fires (Hoscilo *et al* 2011, Miettinen *et al* 2017). In addition, the slope of the landscape could influence the movement of fires while flatter lands correspond to where peatlands are located.

The 2015 extreme fires were unprecedented in scale and impact, and several studies have looked into understanding the environmental factors (Field *et al* 2016, Miettinen *et al* 2017) and the social factors (Carmenta *et al* 2017, Purnomo *et al* 2017) related to this event. However, none combined both social and environmental factors, or examined the influence of these drivers at different geographical scales. Evaluating how social and environmental factors influence fires at different scales could allow for more targeted responses to prevent and mitigate future fires (Schwartz *et al* 2015). We build on the conceptual model from Stolle *et al* (2003) which investigated fire

as a function of predisposing conditions that were mostly influenced by environmental factors, and ignition sources that were often influenced by social factors such as economic land-use. We present a mesoscale ($225\,000 \text{ km}^2$) assessment of the social and environmental factors of fire in three provinces of eastern Sumatra—Riau, Jambi and South Sumatra—which played an important role in the 2015 haze (Kopplitz *et al* 2016). Using a combination of spatially-explicit socioeconomic and geospatial datasets, we addressed the following research question: What were the major contributing social and environmental factors to fire counts in the eastern provinces of Sumatra in 2015 at a regency-level, and fire occurrence at a 1 km^2 pixel-level?

2. Data and methodology

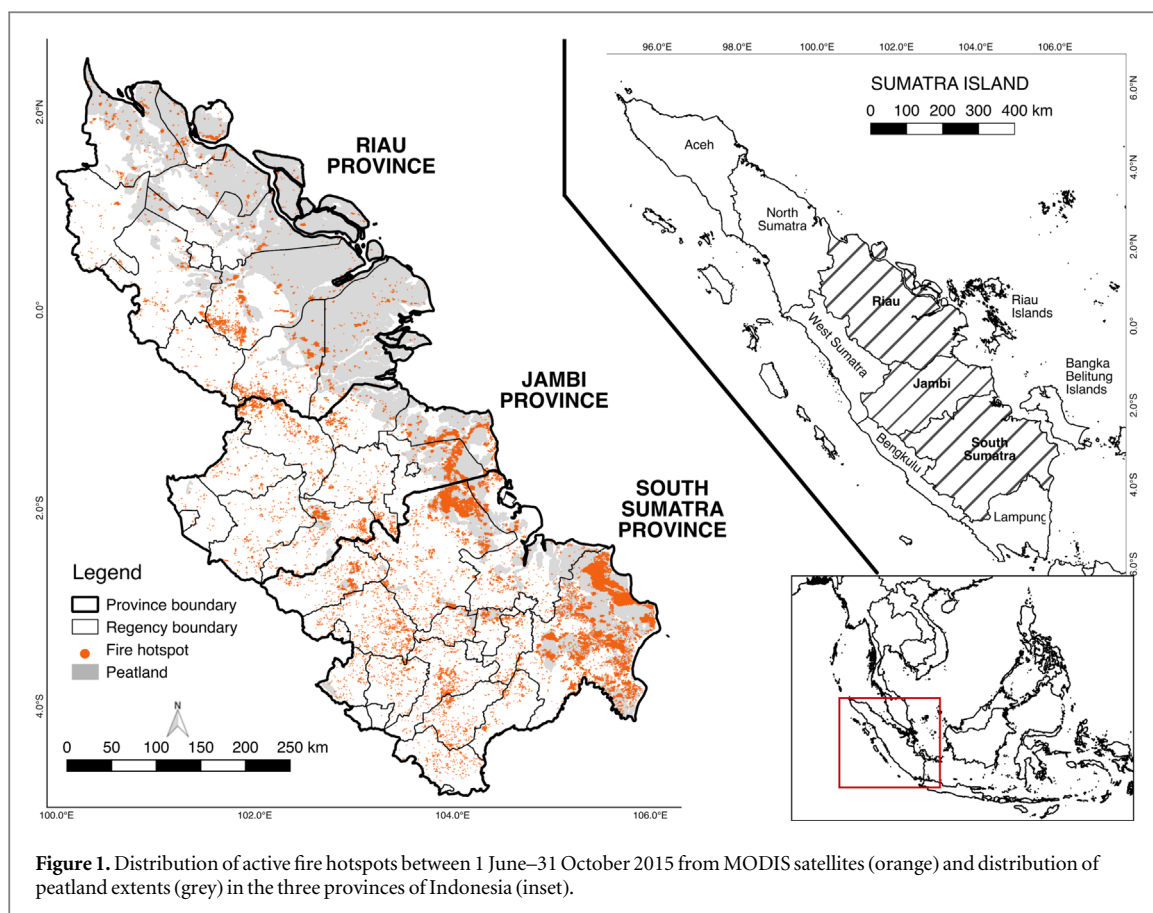
2.1. Study site

Our study sites are the provinces of Riau (0.5333°N , 101.4500°E), Jambi (1.5833°S , 103.6166°E) and South Sumatra (2.9789°S , 104.7584°E), with 40 regencies and $\sim 6\,000$ villages (figure 1, STable 1). These three provinces lie east of the Barisan mountain range, and cover an elevational gradient from 0 to 3 736 m. Approximately 27.8% of the land (STable 1) is underlain by peatland close to the eastern coast, with peat depth up to 8 m (Wahyunto *et al* 2003). These provinces were the epicenter of fire hotspots in Sumatra during the catastrophic 2015 fires. The dry season began in June with limited fire activity but reached its peak in Sumatra by September (Field *et al* 2016).

2.2. Data and processing

2.2.1. Fire data for 2015

We used the global monthly fire location product from the Moderate Resolution Imaging Spectroradiometer (MODIS) Active Fire Detections MCD14ML Collection 6 (NASA FIRMS 2017) to identify active fires (*FireNo*) between 1 June–31 October 2015 (table 1), corresponding with the major haze event. This product is derived from an active fire detection algorithm which utilizes 1 km resolution MODIS thermal bands from MODIS sensors on board the Terra and Aqua satellites (Giglio *et al* 2016). It is important to note that the sensors are unable to distinguish between one or more individual fires within a pixel, and that each detected fire hotspot is not always a separate individual fire but the same fire event detected multiple times a day as long as it keeps burning (Langner and Siebert 2009, Miettinen *et al* 2017). MODIS sensors are known to have detection errors due to the effect of sunglint and the challenges of detecting smoldering peat fires (Liew *et al* 2003, Tansey *et al* 2008). Despite its limitations, the MODIS hotspot dataset is commonly used to understand fire distribution in



Indonesia (Langner and Siegert 2009, Cattau *et al* 2016b, Miettinen *et al* 2017).

2.2.2. Proxy variables that influence fire

We derived 18 proxy variables grouped into five categories (*Conflict*, *Economic*, *Population*, *Forest Degradation* and *Biophysical*) to represent the social and environmental factors which influenced either ignition sources or predisposing conditions for fire spread in our study site (figure 2, table 1). The data sources for the derivation of these proxy variables include published sources of spatially-explicit datasets and the 2014 Village Potential Survey (*Potensi Desa* or PODES) from the Indonesian Central Bureau of Statistics (Indonesian Bureau of Statistics 2016) (table 1, supporting information is available online at stacks.iop.org/ERL/14/015001/mmedia). The derivation of each variable differs between the regency-level and the pixel-level analyses and these differences are described in greater detail in our supporting information. Here, we briefly introduce each proxy variable. Details on the hypothesized relationship between each variable and the outcome on fire count and occurrence are found in STable 3 under our supporting information.

Our three proxy variables under *Conflict* included the number of reported land conflicts from January 2010–October 2015 (*LandConflict*), the reported status on multi-ethnicity in the village (*MultiEthnicity*), and the reported status of brawling incidents in the

village (*Brawl*). We assumed that multi-ethnic villages would have a higher likelihood of local conflict. Brawling incidents reported under PODES are not specific to land conflicts and can refer to any mass fights that occurred in the village. Since fires are used as weapons in conflict, we hypothesize that higher occurrences of conflict would result in more fires.

We included six proxy variables related to land-use under *Economic factors*—wood fiber concessions (WFC), oil palm concessions (OPC), non-species specific plantations (e.g. mix of rubber, oil palm, acacia plantations) with different size classes including small-scale (<10 ha; *SmallPlant*), medium-scale (10–100 ha; *MedPlant*), and large-scale (>100 ha; *LargePlant*) landholdings, and the reported practice of burning to clear agricultural lands in the past year within the village (*PracBurn*). The variables *SmallPlant*, *MedPlant*, and *LargePlant* were calculated based on the proportion of plantation area over the regency area, and these proportions do not sum to one. Fires are often used in land clearing, and we chose these proxies to elucidate associations between economic actors and fires.

Our two *Population factors* included population density (*Pop*) and the reported use of fires to remove wastes in the village (*BurnTrash*). We hypothesize that higher population density is likely to correlate with more fires (Cochrane 2003), and increased use of fires for waste disposal is likely to result in greater probability of accidental fires breaking out.

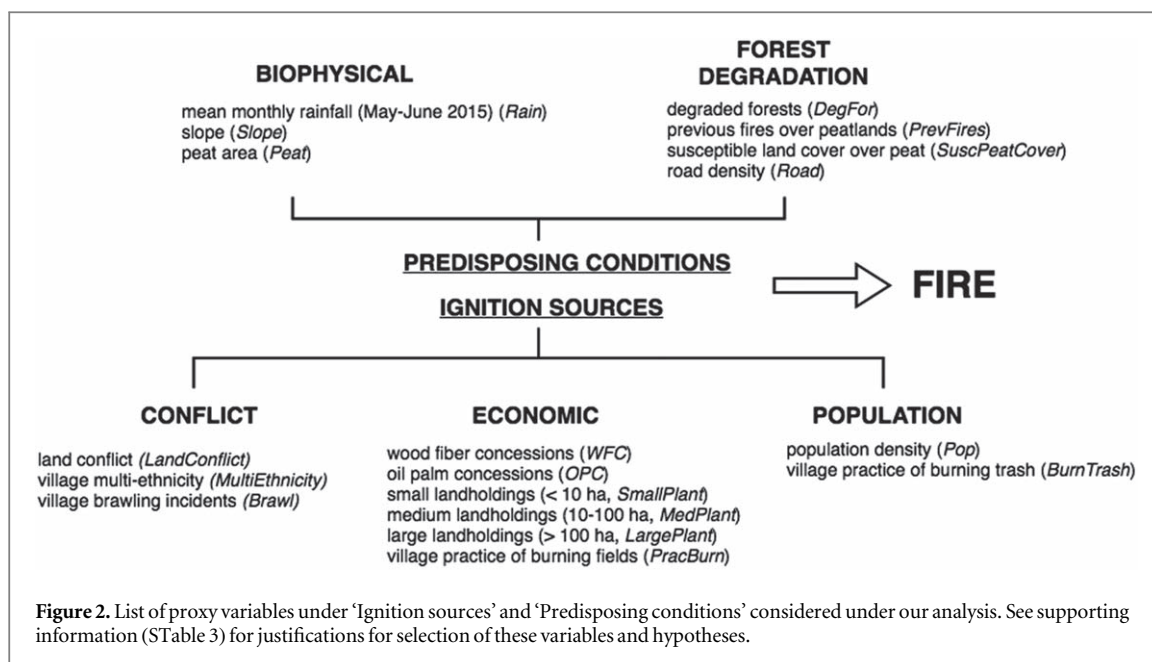
Table 1. Variables used as proxies for social and environmental factors related to 2015 fires (see supporting information for a detailed description of our variables).

Variable	Description	Source	Variable in regency-level analysis	Variable in pixel-level analysis
<i>FireNo</i>	MODIS Active fires (MCD14ML) from 1 June 2015 to 31 Oct 2015	NASA FIRMS (2017)	No. fires in regency (no. fires)	Presence or absence of fires (binary)
<i>Conflict factors (C)</i>				
<i>LandConflict</i>	Land conflicts from Jan 2010 to Oct 2015 based on newspaper articles and social NGO reports	Authors' compilation (supporting information)	No. land conflicts per 10 000 km ² in regency (no. land conflicts per 10 000 km ²)	Number of land conflicts reported in pixel (no. land conflicts)
<i>MultiEthnicity</i>	Reported status of multi-ethnicity of village from 2014 PODES	Indonesian Bureau of Statistics (2016)	Proportion of villages in regency that are multi-ethnic (fraction)	Presence or absence village multi-ethnicity (binary)
<i>Brawl</i>	Reported status of brawling incidents in village from 2014 PODES	Indonesian Bureau of Statistics (2016)	Proportion of villages in regency that reported brawling incidents (fraction)	Presence or absence village brawling incident (binary)
<i>Economic factors (E)</i>				
<i>SmallPlant</i>	Small landholdings with mixed-species plantations (<10 ha) in 2013–2014	Transparent World (2015)	Proportion of small landholdings in regency (fraction) ^a	Presence or absence of small landholding (binary)
<i>MedPlant</i>	Medium landholdings with mixed-species plantations (10–100 ha) in 2013–2014	Transparent World (2015)	Proportion of medium landholdings in regency (fraction) ^a	Presence or absence of medium landholding (binary)
<i>LargePlant</i>	Large landholdings with mixed-species plantations (>100 ha) in 2013–2014	Transparent World (2015)	Proportion of large landholdings in regency (fraction) ^a	Presence or absence of large landholding (binary)
<i>WFC</i>	Industrial wood fiber concessions in 2014	Indonesia Ministry of Forestry (2017a)	Proportion of wood fiber concessions in regency (fraction)	Presence or absence of wood fiber concession (binary)
<i>OPC</i>	Industrial oil palm concessions in 2014	Indonesia Ministry of Forestry (2017b)	Proportion of oil palm concessions in regency (fraction)	Presence or absence of oil palm concession (binary)
<i>PracBurn</i>	Reported use of burning as a method for agricultural land clearing over the past year in village from 2014 PODES	Indonesian Bureau of Statistics (2016)	Proportion of villages that practice burning for agriculture in regency (fraction)	Presence or absence of village practice of burning for agriculture (binary)
<i>Population factors (P)</i>				
<i>Pop</i>	Population density from WorldPop gridded dataset of estimated people per pixel in 2010 adjusted to match United Nations population division estimates	Gaughan <i>et al.</i> (2013), WorldPop (2014)	No. people per km ² in regency (people per km ²)	Estimated no. people per pixel (no. people per pixel)
<i>BurnTrash</i>	Reported use of fires to remove waste in village from 2014 PODES	Indonesian Bureau of Statistics (2016)	Proportion of villages that practice burning trash in regency (fraction)	Presence or absence of village burning trash (binary)
<i>Forest Degradation factors (FD)</i>				

Table 1. (Continued.)

Variable	Description	Source	Variable in regency-level analysis	Variable in pixel-level analysis
<i>DegFor</i>	Degraded primary forests in 2012 based on Margono <i>et al</i> (2014)	Margono <i>et al</i> (2014)	Proportion of degraded forests in regency (fraction)	Presence or absence of degraded forests (binary)
<i>PrevFires</i>	Repeated burns between June 2006 and May 2015 on peatlands derived from MODIS Burned Area product (MCD64A1)	Wahyunto <i>et al</i> (2003), Giglio <i>et al</i> (2015)	Proportion of peatlands in regency which suffered at least one burn between June 2006 and May 2015 (fraction)	No. times recorded as burnt area between June 2006 and May 2015 (no. burns)
<i>SuscPeatCover</i>	Land-cover over peatlands susceptible to fires based on Miettinen <i>et al</i> (2017)	Miettinen <i>et al</i> (2016)	Proportion of peatlands in regency with susceptible land-cover to fires (fraction)	Presence or absence of susceptible land-cover over peatland (binary)
<i>Roads</i>	Road density in regency	Minnemeyer <i>et al</i> (2009), Center for International Earth Science Information Network–CIESIN (2013)	Road density in regency (road length per km ²)	Euclidean distance to roads (m)
<i>Biophysical factors (BP)</i>				
<i>Rain</i>	Mean rainfall for May and June 2015	Joyce <i>et al</i> (2004), International Research Institute for Climate and Society Data Library-IRIDL 2017	Mean rainfall in May and June 2015 for regency (mm)	Mean rainfall in May and June 2015 (mm)
<i>Slope</i>	Slope calculated from United States Geological Service Shuttle Radar Topography Mission Digital Elevation Model 2014	United States Geological Survey 2017	Mean slope for regency (degree)	Slope (degree)
<i>Peat</i>	Area of peatland extent	Wahyunto <i>et al</i> (2003)	Proportion of peat area in regency (fraction)	Presence or absence of peatland (binary)

^a Refers to the particular size class over the regency, not the proportion of the particular size class over all plantation landholding classes for the regency, hence they do not sum to one, e.g. SmallPlant/Regency, not SmallPlant/(SmallPlant + MedPlant + LargePlant).



We included four proxy variables related to forest and peatland degradation under *Forest Degradation factors*—spatial data on primary degraded forests (*DegFor*), previous recorded burns from June 2006–May 2015 over peatlands (*PrevFires*), peatland-cover that are susceptible to fires (*SuscPeatCover*) and spatial data on roads (*Roads*). Degraded ecosystems are more susceptible to fire disturbance (Siegert *et al* 2001, Konecny *et al* 2016); here we include degraded primary forests (*DegFor*) and susceptible peatland cover (*SuscPeatCover*) to encompass both non-peat and peat ecosystems. We included previous recorded burns over peatlands as a separate variable as the burn history of peatlands has been shown to influence its susceptibility to fires (Hoscilo *et al* 2011). Fragmentation of the landscape by roads increases human access and exacerbates degradation (Stolle *et al* 2003, Laurance *et al* 2009), which we hypothesize to correlate with increased likelihood of fires.

Our three *Biophysical factors* included mean monthly rainfall from May–June 2015 (*Rain*), spatial data on slope (*Slope*), and peat area (*Peat*). Drought rainfall is a known predictor of fires, while steeper slopes facilitate fire spread in fire behavioral studies (Rothermel 1983), though in our study site, flatter lands are more accessible to fire ignitions. Peat ignites more easily than mineral soils and has been shown to be an important predictor of fire distribution (Miettinen *et al* 2011).

2.3. Data analysis

2.3.1. Fire count at regency-level

To analyze the social and environmental factors of fire counts among regencies in eastern Sumatra ($n = 40$, SFigure 1), we used generalized linear mixed effect models (GLMMs) which allow response variables

from different distributions and account for correlations between observations and nested data structures by including random factors (Zuur *et al* 2009). Fire count was modelled using a negative binomial distribution to account for overdispersion and the logarithmic link function. Province (*Prov*) was specified as a random effect and the log area (*L.Area*) of the regency as an offset variable to account for regency area differences. We log-transformed population density (*L.Pop*) and standardized all our variables for analysis. Since our aim was to evaluate the relative contribution of predictors instead of assessing the predictive power of our model, we removed variables *OPC* and *BurnTrash* which were highly collinear with *LargePlant* and *L.Pop* respectively ($\rho > 0.70$). We adopted the information-theoretic approach for statistical inference, using the Akaike Information Criterion (AICc) adjusted for small sample size to select the best model out of our set of candidate models (i.e. the model with the highest weighted AICc) (Burnham and Anderson 2002). The set of candidate models included individual variables and every combination of the five categories, as well as three interaction terms which we hypothesized will have an effect on fires: rainfall with degraded forests, rainfall with previously burnt areas, and rainfall with susceptible peatland-cover ($n = 67$, STable 4 and 5). We hypothesized that models with both social and environmental factors perform better at explaining fire counts at the regency-level. We quantified the goodness-of-fit (R^2) of the top three models, comprising marginal and conditional R^2 (variance explained by fixed factors, and both fixed and random factors respectively) (Nakagawa and Schielzeth 2013). GLMMs were constructed using *lme4* and *MASS* packages (Venables and Ripley 2002, Bates *et al* 2015) in R version 3.4.0 (R Core Team 2017).

2.3.2. Fire occurrence at pixel-level

We modelled the occurrence of fires among pixels using boosted regression tree (BRT) models, which combine multiple simple regression trees to form an ensemble model. Individual regression trees (each relating a response to predictors using a ‘tree’ of recursive binary split) are added sequentially that best reduces a loss function using a stochastic gradient boosting algorithm to improve model accuracy and predictive performance (De’ath 2007, Elith *et al* 2008). We used BRTs to fit fire distribution (binary indicator of presence or absence) to the 18 predictor variables (STable 6) using the *dismo* package in R (Hijmans *et al* 2017). BRTs can handle different types of error distribution, loss functions and predictor variables, and allow for non-linear relationships between response and predictor variables (Elith *et al* 2008). Social variables (*LandConflict*, *MultiEthnic*, *Brawl*, *PracBurn*, and *BurnTrash*) were first made spatially-explicit to the village administrative level (see supporting information). All vector data were rasterized, and with other raster data, resampled to 1 km² grids ($n = 225\,710$ pixels). We ran a training set of models with 10% of the data ($n = 22\,571$ pixels) to develop the model and set aside the remaining 90% ($n = 203\,139$ pixels) as test data for independent evaluation of model robustness and optimal settings. We used default bag fraction of 0.5 (fraction of samples drawn at random to fit trees at each step) with bernoulli distribution for the response. We ran the models using a range of learning rates (0.005, 0.01, 0.02 and 0.05) which assessed the contribution of each tree to the growing model, and tree complexities (4, 5 and 6) which determined the maximum number of splits for fitting each regression tree (Elith *et al* 2008). We selected the model that minimized the deviance and maximized the area under the receiver operating characteristic curve (AUC). Outputs include the relative influence of predictor variable plot (measured based on the number of times a variable was selected for splitting, weighted by the squared improvement to the model as a result of each split, and averaged over all trees), and partial dependence plots for each variable (which demonstrate the effect of a variable on the response after accounting for the average effects of all other variables in the model) (Elith *et al* 2008). Following Müller *et al* (2013), we did not consider variables with a relative influence value smaller than expected due to chance (100 divided by the number of variables); 5.56% in this evaluation.

We used two different methods to assess the drivers of fire counts at the regency-level and fire occurrence at the pixel-level primarily due to differences in the sample size for these two analyses. Fire count is a continuous variable, with 40 regencies as units for analysis. Fire occurrence is a binary variable, with 225 710 pixels as units for analysis. The use of GLMMs was not feasible for our fire occurrence pixel-level analysis due to its large sample size. Likewise, we could not apply

BRTs to our fire count regency-level analysis which had too few data points. As our main objective was to identify the contributing variables to fire counts and fire occurrence at different geographical scales, we applied models that were most appropriate at handling the outcome variables with its associated number of sample units used for analyses.

3. Results

Between 1 June 2015–31 October 2015, 50 325 active fires were recorded by MODIS Aqua and Terra satellites, with ~61% of active fires (30 924) over peatlands. Most fires were concentrated in South Sumatra ($n = 33\,085$, 0.38 fires km⁻²), followed by Jambi ($n = 9318$, 0.19 fires km⁻²) and Riau ($n = 7922$, 0.09 fires km⁻²).

3.1. Regency analysis

The most parsimonious model out of our candidate set of models included economic, population and biophysical variables as important predictors for the expected log count of fires at the regency-level (wAICc = 0.871, marginal $R^2 = 0.216$, table 2), and is represented by the following equation:

$$\begin{aligned} \text{Log}(\text{FireNo}) = & -2.38 + 0.12*\text{LargePlant} \\ & - 0.40*\text{MedPlant} - 0.34*\text{SmallPlant} \\ & + 0.30*\text{PracBurn} - 0.09*\text{WFC} - 0.43* \\ & \times \text{L.Pop} - 0.57*\text{Slope} - 0.39*\text{Rain} + \\ & \times 0.27*\text{Peat}. \end{aligned}$$

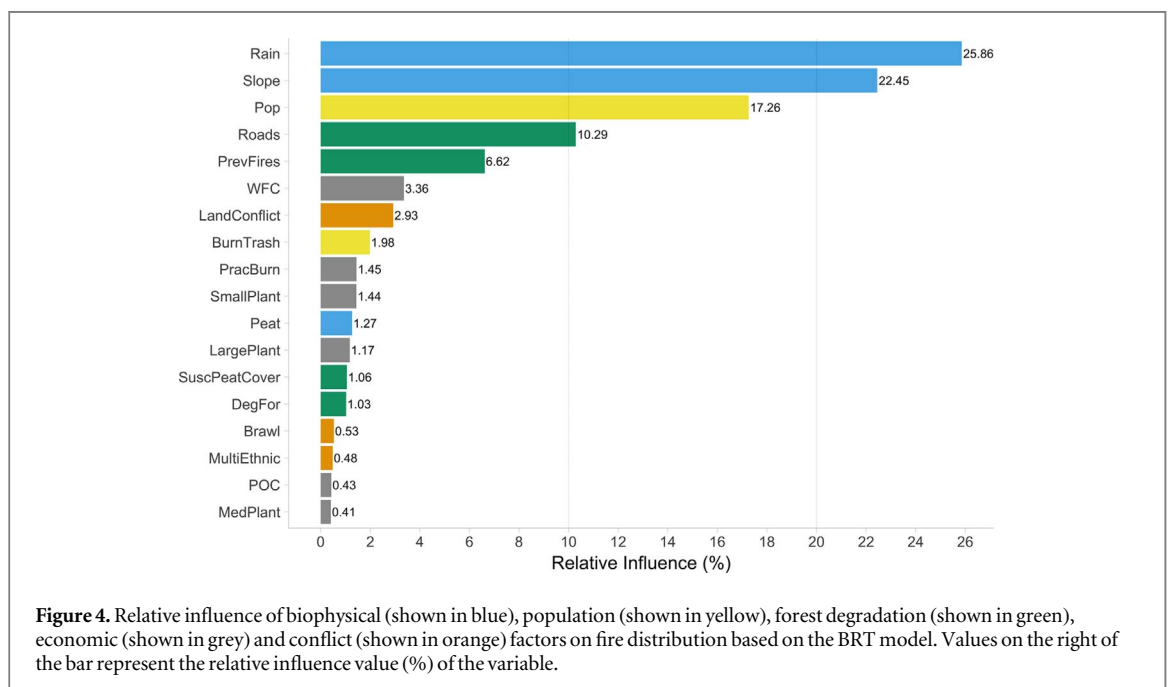
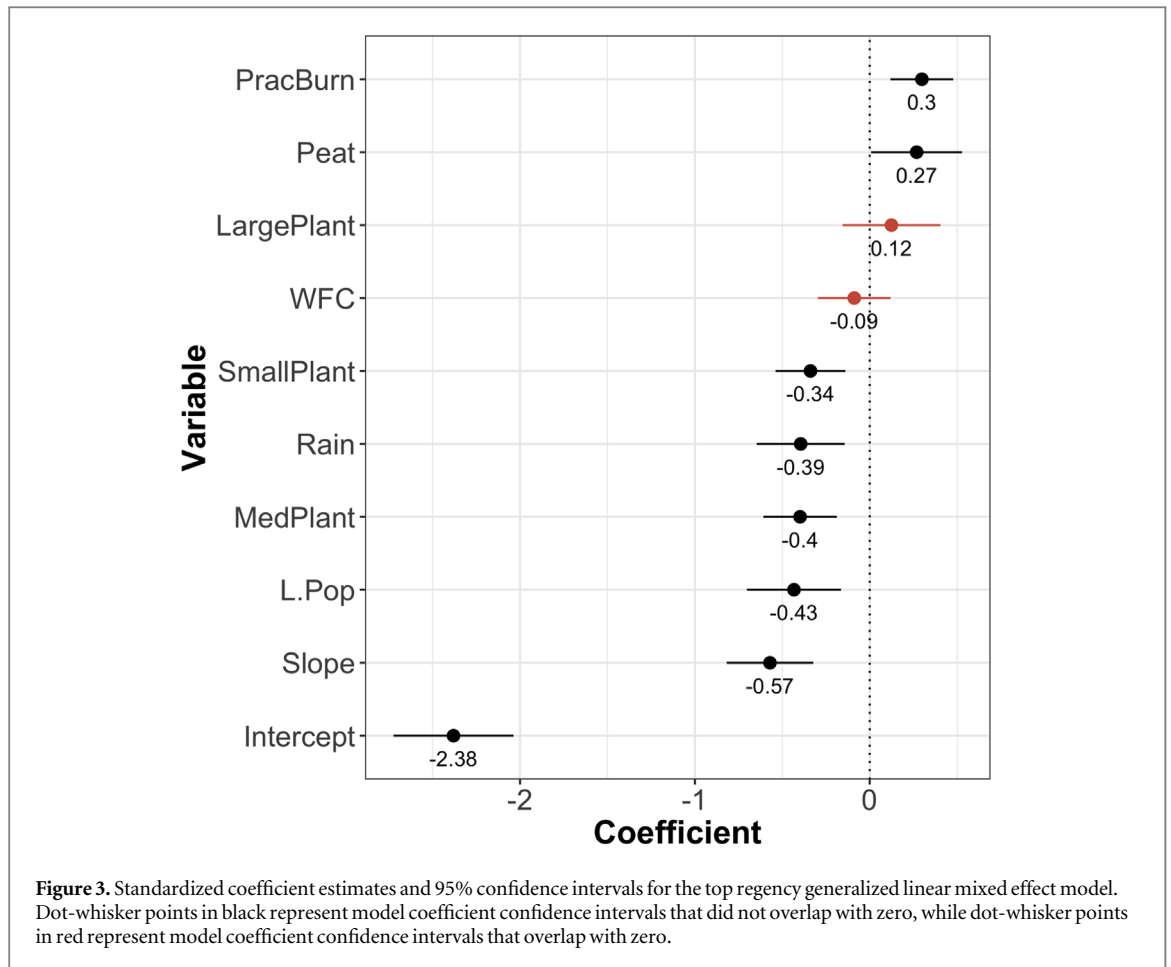
Forest degradation variables (*DegFor*, *PrevFires*, *SuscPeatCover*, *Roads*), conflict variables (*LandConflict*, *MultiEthnic*, *Brawl*) and the three interaction terms of rainfall (*DegFor*Rain*, *PrevFires*Rain*, *SuscPeatCover*Rain*) had no influence on fires. The 95% confidence intervals of model coefficients for all variables in our most parsimonious model (figure 3) did not include zero, except for the variables large landholdings ($\beta_{\text{LargePlant}} = 0.12$, 95% Confidence Interval = [-0.16, 0.40]) and WFC ($\beta_{\text{WFC}} = -0.09$ [-0.30, 0.12]), (figure 3). Hence, the effect of these two variables on fires were indeterminate. The practice of burning for agriculture and proportion of peat area were associated with an increase in fires ($\beta_{\text{PracBurn}} = 0.30$ [0.12, 0.48]; $\beta_{\text{Peat}} = 0.27$ [0.01, 0.53]). More rainfall ($\beta_{\text{Rain}} = -0.40$ [-0.65, -0.14]), steeper slopes ($\beta_{\text{Slope}} = -0.57$ [-0.82, -0.32]), and higher log population density ($\beta_{\text{Pop}} = -0.43$ [-0.70, -0.16]) were associated with a decrease in fires. Surprisingly, an increase in the proportion of medium plantation landholdings ($\beta_{\text{MedPlant}} = -0.40$ [-0.61, -0.19]) and small plantation landholdings ($\beta_{\text{SmallPlant}} = -0.39$ [-0.54, -0.14]) within the regency were associated with a decrease in expected log count of fires.

3.2. Pixel-level analysis

The BRT model with the highest independently-validated AUC score (0.799) and lowest deviance

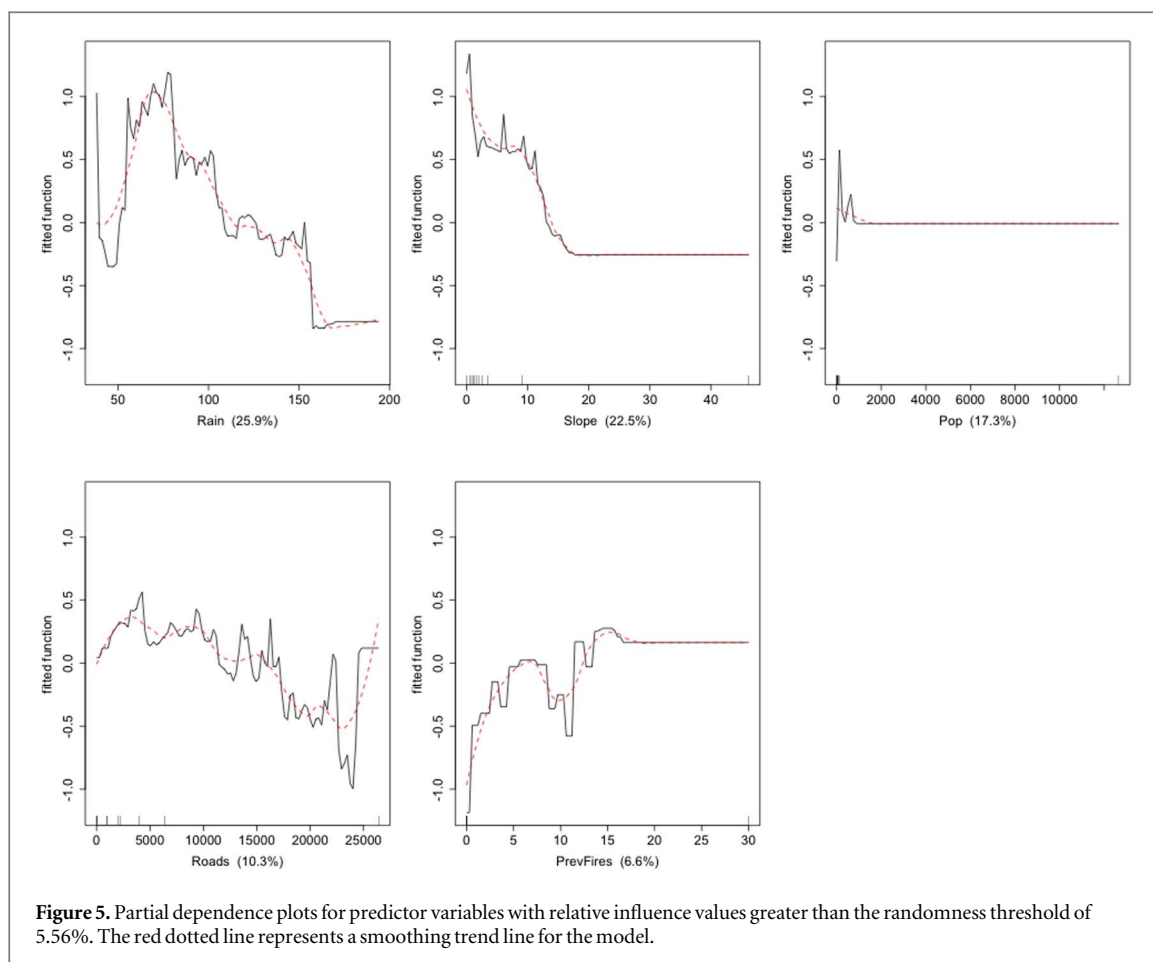
Table 2. Top 3 GLMM with variables from Economic (E), Population (P) and Biophysical (BP) categories of factors. K = number of parameters, LogLik = log-likelihood, AICc = AIC corrected for small sample size, $\Delta AICc$ = difference in AICc between the given model and the model with the lowest AICc, wAICc = relative weight of the given model, marginal R^2 = variance explained by the predictor variables in the model, conditional R^2 = variance explained by the predictor variables and random variable (i.e. regency) in the model.

Model	Categories of variables	K	LogLik	AICc	$\Delta AICc$	wAICc	Marginal R^2	Conditional R^2
FireNo ~ offset(L.Area) + LargePlant + MedPlant + SmallPlant + PracBurn + WFC + Pop + Slope + Rain + Peat + (1 Province)	E + P + BP	12	-256.9	549.4	0	0.871	0.216	0.234
FireNo ~ offset(L.Area) + LargePlant + MedPlant + SmallPlant + PracBurn + WFC + Slope + Rain + Peat + (1 Province)	P + BP	11	-261.6	554.6	5.18	0.065	0.196	0.230
FireNo ~ offset(L.Area) + Pop + Slope + Rain + Peat + (1 Province)	E + BP	7	-268.8	555.0	5.66	0.051	0.185	0.224



(0.504) had a learning rate of 0.01 and tree complexity of 6, giving an optimal tree number of 4,850 (SFigure 2). The relative influence of each predictor variable in this model is shown in figure 4. Only 5 out of 18 variables had relative influence values above 5.56%: Rainfall (25.86%), Slope (22.45%), Population density (17.26%),

Roads (10.29%) and Previous Fires (6.62%). The partial dependence plots in figure 5 further show the influence of each of these five variables on fire occurrences. Overall, this suggests that fires are more likely to occur in areas where there has been low rainfall, gentler slopes and lower population density, corroborating the results



from our regency-level analysis (figure 3). Fires were also likely to occur closer to roads and over peatlands which have been burnt repeatedly.

4. Discussion

We found that biophysical and population variables strongly influenced fire count and occurrence at the regency- and pixel-level respectively (figures 3; 4). However, economic and forest degradation variables had varying impact, with economic drivers being more important at explaining fire count at the regency-level whilst forest degradation factors were more relevant at explaining fire occurrence at the pixel-level. Conflict variables showed no effect on the 2015 fires at both spatial scales. This suggests that mitigation efforts for future fires, especially during ENSO years, can focus their campaigns in high-risk areas that can be identified using updated data on recent rainfall, population density, roads and data on specific land-use or land-cover types.

The strong effect rainfall has on fire at both scales is unsurprising. Both analyses showed lower mean monthly rainfall in the preceding two months are likely to result in more fires or higher fire occurrence, concurring with previous studies where a fall in rainfall induced by the El Niño in 2015 had a major contribution to the extreme fires (Field *et al* 2016,

Fernandes *et al* 2017, Sloan *et al* 2017). Our BRT model showed an increase in fire occurrence below a mean monthly rainfall of 150 mm/month. This value is close to the critical rainfall threshold of 200 mm/month based on a study on fire activity from 1982–2010 in Borneo (Sloan *et al* 2017). Low rainfall leads to less recharge in groundwater levels in peatlands, rendering peat soils highly flammable, which facilitates fire ignition and spread (Page and Hooijer 2016, Taufik *et al* 2017). The effect of slope on fires is also clearly negative at both scales of analyses, which showed that more fires occurred on flat ground. This is likely due to the ease of accessibility compared to steep areas for agricultural activities or resource extraction and also corresponds with the distribution of peatlands in our study site.

Our results from both regency- and pixel-level analyses also revealed that areas with low (but not zero) population densities contribute to fires. This is contrary to what was expected since fires in these landscapes are predominantly anthropogenic and a higher population density is likely to increase the probability of fires (Cochrane 2003, Dennis *et al* 2005). The inverse relationship between fires and population pressure could indicate that more fires occur in remote areas where land is available for agricultural activities and resource extraction. As population densities increase towards city levels, fires are less likely to

occur. This relationship between fires and population corroborates with Cattau *et al* (2016a) which found that fire ignition first increased, then decreased as distance from settlement increases. Our finding that low population densities have higher fire likelihoods might suggest that prioritizing villages in remote areas in the training of fire prevention awareness and interventions, such as the Fire-Free Village Program, are important in combatting fires (Fire Free Alliance 2016).

When the regency was used as a unit for analysis of fire counts, economic variables were included as important factors in addition to biophysical and population variables. Of the economic variables that were included in our results, the proportion of small-scale (< 10 ha) and medium-scale (10–100 ha) plantation landholdings within a regency showed a negative association with log count of fires. This corroborates with Miettinen *et al* (2017) where fire hotspot density was found to be lower in small-holder areas compared to industrial plantations. Unsurprisingly, the reported use of fires for clearing agricultural lands in villages showed a positive association with fires, indicating the persistence use of fires for agricultural land-clearing and the importance of managing fire use at the village-level. The role of agency in Indonesia's fires is a contentious issue due to serious ramifications of extreme fire events such as the 2015 fires. Determining who is accountable for Indonesia's fires is complex due to overlapping land claims between industrial plantation companies, medium landholdings and small farmers (Gaveau *et al* 2014, 2016). While cross-sectional studies like ours and Miettinen *et al* (2017) show less fires within small to medium landholdings, Sloan *et al* (2017) focused on long-term trends of fires in Borneo and showed how fires resulted from interactions between large plantation concessions and economic land-use activity by small and medium landholdings. Longitudinal studies on fire patterns and land-use in Sumatra could reveal a more in-depth understanding of shifting drivers of fire activity which could be an area for future work.

When the pixel (1 km²) was used as a unit for analysis of fire occurrence, forest degradation, in addition to biophysical and population variables were included as important factors. Roads have been known to contribute to forest degradation (Laurance *et al* 2009) and provide access for lighting fires (Stolle *et al* 2003). Our BRT model demonstrated that fire occurrence increased between 0–2.5 km from roads, before decreasing as distance to roads increases up until 25 km before rising again. This suggests that proximity to roads increases the probability of fires being lit. At greater distances from roads, accessibility could be restricted and the likelihood of fire occurrence decreases. However, remote fires such as that recorded under our BRT model at >25 km from roads could still be lit, and access to such sites could be through rivers or

drainage canals which were not included in our analyses.

The proportion of peatlands in the regency showed a positive association with fires under our regency-level analysis but fell below the randomness threshold under our pixel-level analysis. Instead, peatlands which experienced repeated burns from June 2006–May 2015 was identified as an important variable for fire occurrence at the pixel-level. Our BRT model demonstrated that fire occurrence increased in peatlands which have been burnt between one and six times before plateauing at 15 burn events. The relationship behind fire occurrence and burn history may be related to post-fire changes in vegetation cover over peatlands, relative peat depth and chemical properties of peat soils. Peatswamp forests that were burnt in an initial fire could result in intense fires due to the consequent woody vegetation cover. These initial fires leave behind standing and fallen timber which contribute as above-ground fuel for subsequent fires. As the vegetation cover of peatlands transitions from woody to non-woody vegetation through repeated burning, the volume of woody fire fuels decreases, possibly leading to less fire occurrences (Hoscilo *et al* 2011). Konecny *et al* (2016) also found that the frequency of fires over peatlands decreased the relative burned area depth of peat soils, potentially influencing the mass of peat soil available for burning. Past fires could also alter the chemistry of peat soils, reducing the amount of labile, easily-combustible carbon constitutes and increasing the resistance of peat soils to fires (Milner *et al* in prep.) Our results suggest that burn history of peatlands should be considered when monitoring Sumatra's fire landscape, since peatlands with few burn events show a higher risk of being burnt in the next fire.

Although conflict has been found to be an underlying cause of fires in Indonesia (Suyanto 2007, Dennis *et al* 2005), our results suggest, similar to Stolle and Lambin (2003), that social conflicts did not play a major role in the 2015 fires. Clear land ownership and tenure in Indonesia has always been lacking, where *adat* or customary laws are often overlooked when granting land concessions (Shivakumar *et al* 2015). Combined with the lack of a transparent system for redress and compensation when conflict arises, fires are started as retaliation to destroy crops and reclaim land, both between smallholders and companies, and between locals and transmigrants (Suyanto *et al* 2004, Dennis *et al* 2005, Suyanto 2007). Conflict, however, is an inherently social phenomenon with all its accompanying complexities, and relying on reports of land conflicts from newspaper articles risk simplifying this issue due to the bias of under-reporting or selective reporting in the media (Abram *et al* 2017). We attempted to reduce this bias by obtaining information from three national newspapers, six provincial newspapers, and supplementary reporting from three local non-governmental organizations. We also included

variables such as village-level multi-ethnicity and brawl incidents as proxy variables for conflict but these were also unimportant in influencing fire count and occurrence in our analyses. While our proxies for conflict could be inadequate, the unimportance of conflict relative to other variables in explaining fire count and fire occurrence in the 2015 extreme fires could be a result of the overwhelming influence of the El Niño-related drought in that year.

5. Conclusion

Our study aimed to gain a better understanding of the variables that had the greatest influence on the 2015 extreme fire event in Sumatra. We showed that rainfall, slope and population density were the most important variables predicting fires. The main influence of rain corroborates with previous studies, and highlights the importance of establishing an early warning system for droughts to better prevent and manage future extreme fire events (Field *et al* 2016, Tacconi 2016, Lee *et al* 2016, Miettinen *et al* 2017). Economic variables such as the proportion of small-scale and medium-scale plantation landholdings and the reported use of fires to clear agricultural lands in villages were important factors in explaining fire count at the regency-level. Distance from roads and the number of recorded burns over peatlands were important contributors to fire occurrence at the pixel-level. Mitigation efforts for future fires, especially during ENSO years, can be focused on high-risk areas identified using environmental data on rainfall, slope, peatlands, and previously burnt peat areas, as well as social data related to population density, access to roads, extents of small- and medium-plantation landholdings, and village-level propensity to burn land for agriculture.

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