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LETTER

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

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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 km^2). 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 (Koplitz *et al* 2016) and economic

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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 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 (Siegert *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 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 (Koplitz *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 ~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 Siegert 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

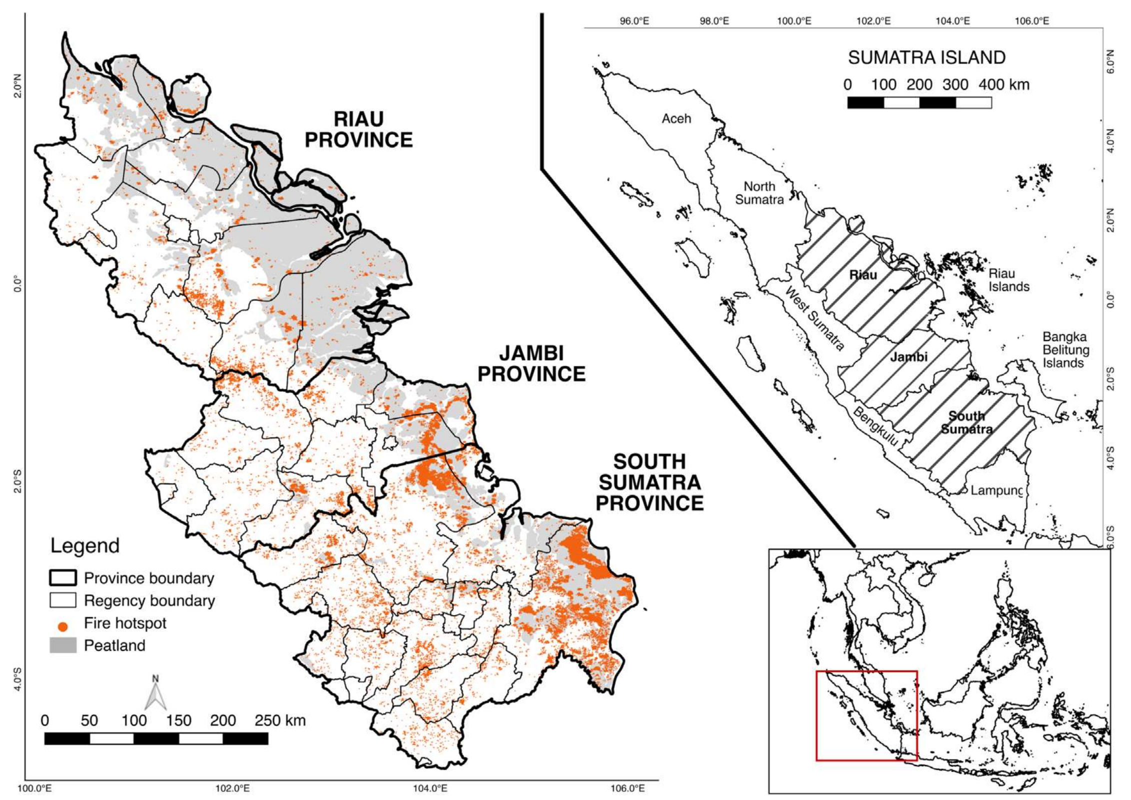

Figure 1. Distribution of active fire hotspots between 1 June–31 October 2015 from MODIS satellites (orange) and distribution of peatland extents (grey) in the three provinces of Indonesia (inset).

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
FireNo	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)
Conflict factors (C)				
LandConflict	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)
MultiEthnicity	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)
Brawl	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)
Economic factors (E)				
SmallPlant	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)
MedPlant	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)
LargePlant	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)
WFC	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)
OPC	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)
PracBurn	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)
Population factors (P)				
Pop	Population density from WorldPop gridded dataset of estimated people per pixel in 2010 adjusted to match United Nations population division estimates	Gaughan *et al* (2013), WorldPop (2014)	No. people per km^2 in regency (people per km^2)	Estimated no. people per pixel (no. people per pixel)
BurnTrash	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)
Forest Degradation factors (FD)				

Table 1. (Continued.)

Variable	Description	Source	Variable in regency-level analysis	Variable in pixel-level analysis
DegFor	Degraded primary forests in 2012 based on Margono *et al* (2014)	Margono *et al* (2014)	Proportion of degraded forests in regency (fraction)	Presence or absence of degraded forests (binary)
PrevFires	Repeated burns between June 2006 and May 2015 on peatlands derived from MODIS Burned Area product (MCD64A1)	Wahyunto *et al* (2003), Giglio *et al* (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)
SuscPeatCover	Land-cover over peatlands susceptible to fires based on Miettinen *et al* (2017)	Miettinen *et al* (2016)	Proportion of peatlands in regency with susceptible land-cover to fires (fraction)	Presence or absence of susceptible land-cover over peatland (binary)
Roads	Road density in regency	Minnemeyer *et al* (2009) , Center for International Earth Science Information Network–CIESIN (2013)	Road density in regency (road length per km^2)	Euclidean distance to roads (m)
Biophysical factors (BP)				
Rain	Mean rainfall for May and June 2015	Joyce *et al* (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)
Slope	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)
Peat	Area of peatland extent	Wahyunto *et al* (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).

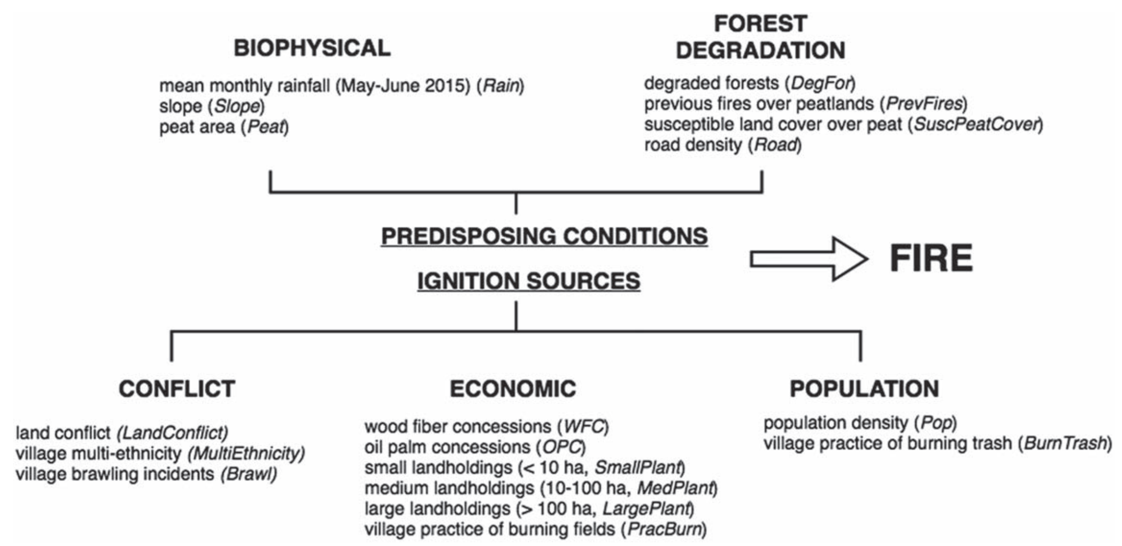

Figure 2. List of proxy variables under 'Ignition sources' and 'Predisposing conditions' considered under our analysis. See supporting information (STable 3) for justifications for selection of these variables and hypotheses.

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 Aikaike 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 km^2 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:

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

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, ΔAICc = 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 ^{2} = variance explained by the predictor variables and random variable (i.e. regency) in the model.

Model	Categories of variables	K	LogLik	AICc	ΔAICc	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

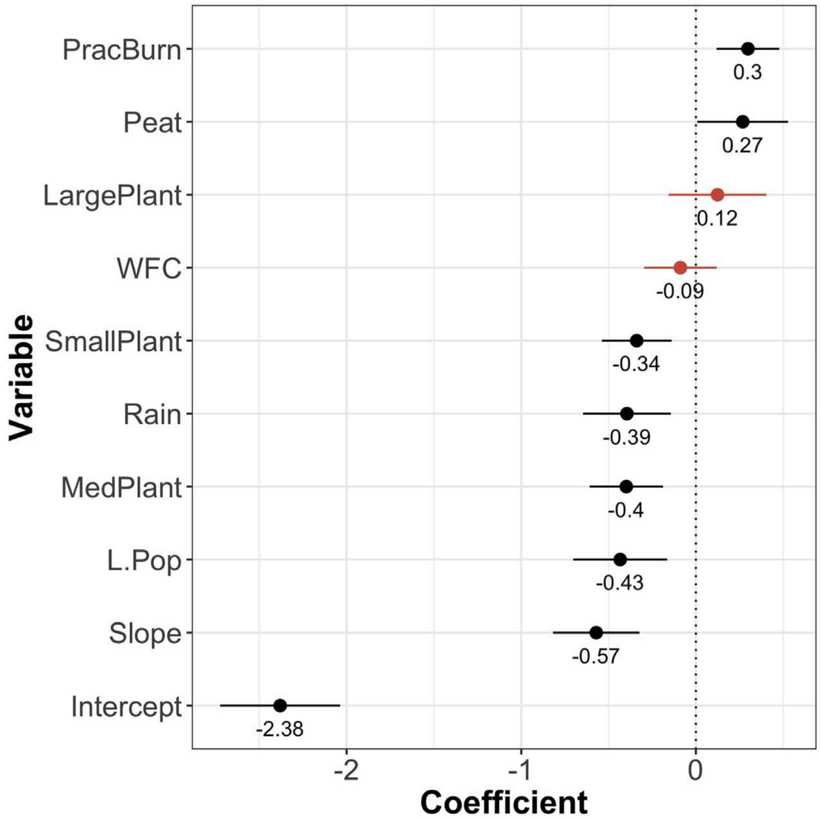

Figure 3. Standardized coefficient estimates and 95% confidence intervals for the top regency generalized linear mixed effect model. Dot-whisker points in black represent model coefficient confidence intervals that did not overlap with zero, while dot-whisker points in red represent model coefficient confidence intervals that overlap with zero.

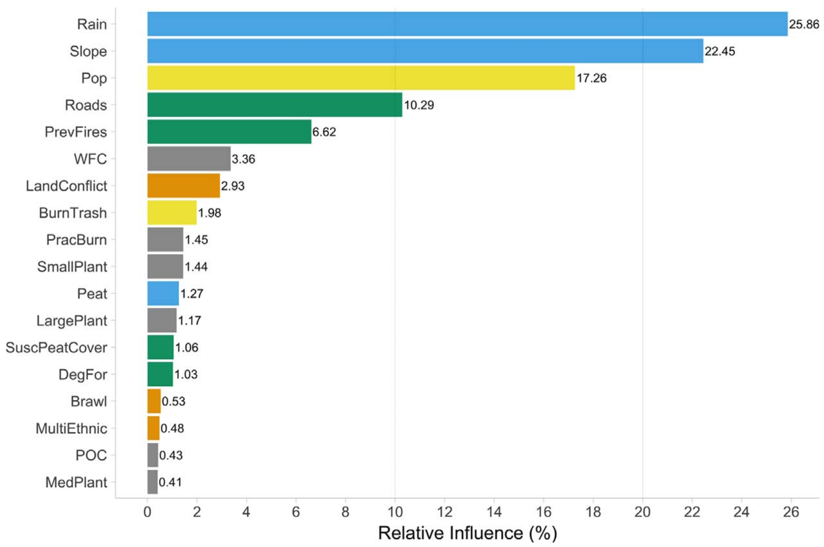

Figure 4. Relative influence of biophysical (shown in blue), population (shown in yellow), forest degradation (shown in green), economic (shown in grey) and conflict (shown in orange) factors on fire distribution based on the BRT model. Values on the right of the bar represent the relative influence value (%) of the variable.

(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

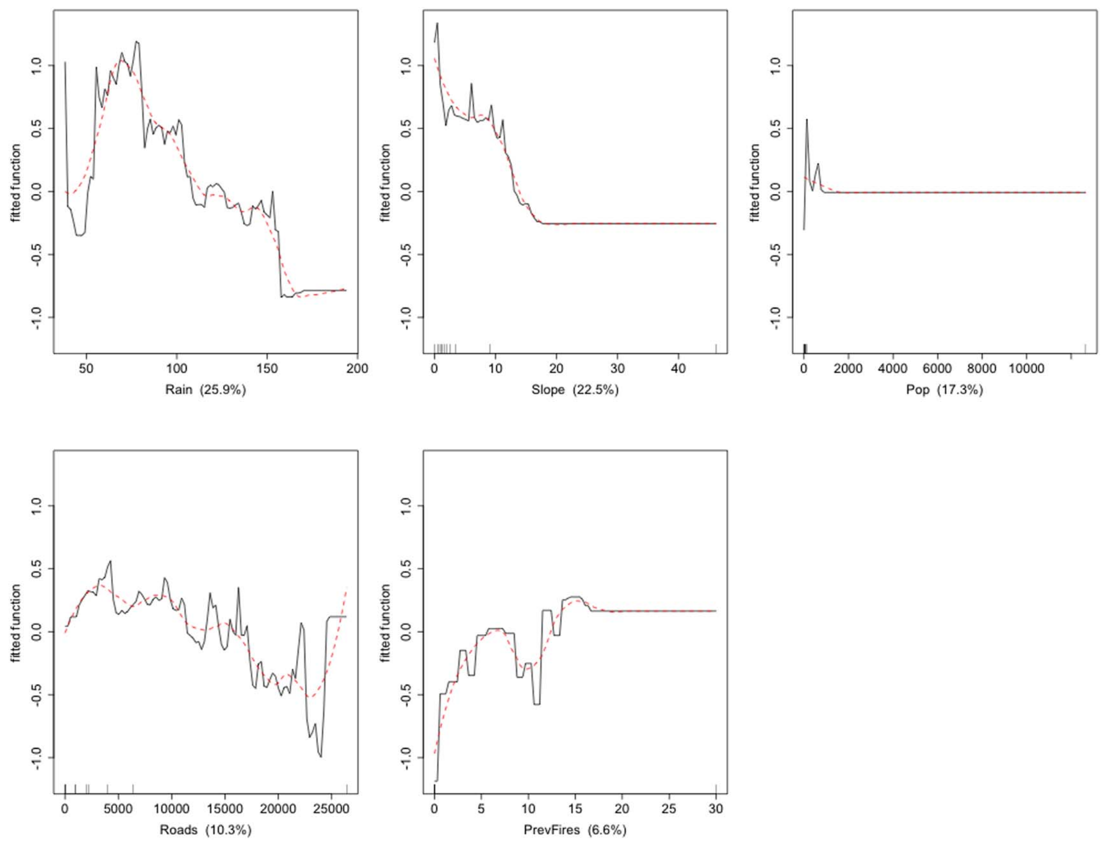

Figure 5. Partial dependence plots for predictor variables with relative influence values greater than the randomness threshold of 5.56%. The red dotted line represents a smoothing trend line for the model.

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 km^2) 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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References

Abood S A, Lee J S H, Burivalova Z, Garcia-Ulloa J and Koh L P 2015 Relative contributions of the logging, fiber, oil palm, and mining industries to forest loss in indonesia *Conserv. Lett.* **8** 58–67

Abram N K *et al* 2017 Oil palm-community conflict mapping in Indonesia: a case for better community liaison in planning for development initiatives *Appl. Geogr.* **78** 33–44

Anderson I P and Bowen M R 2000 *Fire Zones and the Threat to the Wetlands of Sumatra, Indonesia* (Palembang) (http://www.fire.uni-freiburg.de/se_asia/projects/ffpcp/FFPCP-14-Firezone-Threat-Wetlands-Sumatra.pdf)

Bates D, Maechler M, Bolker B and Walker S 2015 Fitting linear mixed-effects models using lme4 *J. Stat. Softw.* **67** 1–48

Burnham K P and Anderson D R 2002 *Model Selection and Multi-model Inference* (New York: Springer)

Carlson K M, Curran L M, Asner G P, Pittman A M, Trigg S N and Marion Adeney J 2013 Carbon emissions from forest conversion by Kalimantan oil palm plantations *Nat. Clim. Change* **3** 283–7

Carmenta R, Zabala A, Daeli W and Phelps J 2017 Perceptions across scales of governance and the Indonesian peatland fires perceptions across scales of governance and the Indonesian peatland fi res *Glob. Environ. Change* **46** 50–9

Carmenta R, Parry L, Blackburn A, Vermeylen S and Barlow J 2011 Understanding human-fire interactions in tropical forest regions: a case for interdisciplinary research across the natural and social sciences *Ecol. Soc.* **16** art53

Cattau M E, Harrison M E, Shinyo I, Tungau S, Uriarte M and Defries R 2016a Sources of anthropogenic fire ignitions on the peat-swamp landscape in Kalimantan, Indonesia *Glob. Environ. Chang.* **39** 205–19

Cattau M E, Marlier M E and DeFries R 2016b Effectiveness of roundtable on sustainable palm oil (RSPO) for reducing fires on oil palm concessions in Indonesia from 2012 to 2015 *Environ. Res. Lett.* **11** 105007

Center for International Earth Science Information Network–CIESIN 2013 Columbia University and Information Technology Outreach Services—ITOS—University of Georgia Global Roads Open Access Data Set (version 1) (gROADSv1) (https://doi.org/10.7927/H4VD6WCT)

Cochrane M A 2003 Fire science for rainforests *Nature* **421** 913–9

De'ath G 2007 Boosted trees for ecological modeling and prediction *Ecology* **88** 243–51

Dennis R A *et al* 2005 Fire, people and pixels: linking social science and remote sensing to understand underlying causes and impacts of fires in indonesia *Hum. Ecol.* **33** 465–504

Elith J, Leathwick J R and Hastie T 2008 A working guide to boosted regression trees *J. Animal Ecol.* **77** 802–13

Fernandes K, Verchot L, Baethgen W, Gutierrez-velez V, Pinedo-vasquez M and Martius C 2017 Heightened fire probability in Indonesia in non- drought conditions : the effect of increasing temperatures *Environ. Res. Lett.* **12** 054002

Field R D *et al* 2016 Indonesian fire activity and smoke pollution in 2015 show persistent nonlinear sensitivity to El Niño-induced drought *Proc. Natl Acad. Sci. USA* **113** 9204–9

Field R D, van der Werf G R and Shen S S P 2009 Human amplification of drought-induced biomass burning in Indonesia since 1960 *Nat. Geosci.* **2** 185–8

Fire Free Alliance 2016 Fire Free Alliance (http://firefreealliance.org/)

Gaughan A E, Stevens F R, Linard C, Jia P and Tatem A J 2013 High resolution population distribution maps for Southeast Asia in 2010 and 2015 *PLoS One* **8** e55882

Gaveau D L A, Pirard R, Salim M A, Tonoto P, Yaen H, Parks S A and Carmenta R 2017 Overlapping land claims limit the use of satellites to monitor *no-deforestation* commitments and *no-burning* compliance *Conserv. Lett.* **10** 257–64

Gaveau D L A *et al* 2014 Major atmospheric emissions from peat fires in Southeast Asia during non-drought years: evidence from the 2013 Sumatran fires *Sci. Rep.* **4** 6112

Giglio L, Justice C O, Boschetti L and Roy D P 2015 MCD64A1 MODIS/Terra+Aqua Burned Area Monthly L3 Global 500m SIN Grid V006 MCD64A1 (https://doi.org/10.5067/MODIS/MCD64A1.006)

Giglio L, Schroeder W and Justice C O 2016 The collection 6 MODIS active fire detection algorithm and fire products *Remote Sens. Environ.* **178** 31–41

Hijmans R J, Phillips S, Leathwick J and Elith J 2017 Package 'dismo' (https://cran.r-project.org/web/packages/dismo/dismo.pdf)

Hoscilo A, Page S E, Tansey K J and Rieley J O 2011 Effect of repeated fires on land-cover change on peatland in southern Central Kalimantan, Indonesia, from 1973 to 2005 *Int. J. Wildl. Fire* **20** 578–88

Huijnen V, Wooster M J, Kaiser J W, Gaveau D L A, Flemming J, Parrington M, Inness A, Murdiyarso D, Main B and Van Weele M 2016 Fire carbon emissions over maritime southeast Asia in 2015 largest since 1997 *Sci. Rep.* **6** 26886

Indonesia Ministry of Forestry 2017a Oil Palm Concessions (http://data.globalforestwatch.org/datasets/f82b539b9b2f495e853670ddc3f0ce68_2)

Indonesia Ministry of Forestry 2017b Asia Pulp and paper and APRIL Indonesia wood fiber concessions V1.1 (http://data.globalforestwatch.org/datasets/indonesia-wood-fiber-concessions)

Indonesian Bureau of Statistics 2016 Village Potential Statistics (https://library.duke.edu/data/sources/podes)

International Research Institute for Climate and Society Data Library – IRIDL 2017 Indonesia Monthly Rainfall Analysis Tool (http://iridl.ldeo.columbia.edu/maproom/Fire/Regional/Indonesia/Monthly_Rainfall.html?region=bb%3A90%3A-12%3A155%3A10%3Abb)

Joyce R J, Janowiak J E, Arkin P A and Xie P 2004 CMORPH: a method that produces global precipitation estimates from passive microwave and infrared data at high spatial and temporal resolution *J. Hydrometeorol.* **5** 487–503

Ketterings Q M, Wibowo T T, van Noordwijk M, Penot E, Tri Wibowo T, van Noordwijk M and Penot E 1999 Farmers' perspectives on slash-and-burn as a land clearing method for small-scale rubber producers in Sepunggur, Jambi Province, Sumatra, Indonesia *Forest Ecol. Manage.* **120** 157–69

Konecny K, Ballhorn U, Navratil P, Jubanski J, Page S E, Tansey K, Hooijer A, Vernimmen R and Siegert F 2016 Variable carbon losses from recurrent fires in drained tropical peatlands *Glob. Change Biol.* **22** 1469–80

Koplitz S N *et al* 2016 Public health impacts of the severe haze in Equatorial Asia in September–October 2015: demonstration of a new framework for informing fire management strategies to reduce downwind smoke exposure *Environ. Res. Lett.* **11** 094023

Langner A and Siegert F 2009 Spatiotemporal fire occurrence in Borneo over a period of 10 years *Glob. Change Biol.* **15** 48–62

Laurance W F, Goosem M and Laurance S G W 2009 Impacts of roads and linear clearings on tropical forests *Trends Ecol. Evol.* **24** 659–69

Lee J S H, Jaafar Z, Tan A K J, Carrasco L R, Ewing J J, Bickford D P, Webb E L and Koh L P 2016 Toward clearer skies: challenges in regulating transboundary haze in Southeast Asia *Environ. Sci. Policy* **55** 87–95

Liew S C, Shen C, Low J, Lim A and Kwoh L K 2003 Validation of MODIS fire product over Sumatra and Borneo using High Resolution SPOT Imagery *Proc. 24th Asian Conf. on Remote Sensing & 2003 Int. Symp. on Remote Sensing*

Margono B A, Potapov P V, Turubanova S, Stolle F and Hansen M C 2014 Primary forest cover loss in Indonesia over 2000–2012 *Nat. Clim. Change* **4** 730–5

Marlier M E, DeFries R S, Kim P S, Gaveau D L A, Koplitz S N, Jacob D J, Mickley L J, Margono B A and Myers S S 2015a Regional air quality impacts of future fire emissions in Sumatra and Kalimantan *Environ. Res. Lett.* **10** 054010

Marlier M E, DeFries R S, Kim P S, Koplitz S N, Jacob D J, Mickley L J and Myers S S 2015b Fire emissions and regional air quality impacts from fires in oil palm, timber, and logging concessions in Indonesia *Environ. Res. Lett.* **10** 085005

Miettinen J, Hooijer A, Shi C, Tollenaar D, Vernimmen R, Liew S C, Malins C and Page S E 2012 Extent of industrial plantations on Southeast Asian peatlands in 2010 with analysis of historical expansion and future projections *GCB Bioenergy* **4** 908–18

Miettinen J, Shi C and Liew S C 2017 Fire distribution in peninsular malaysia, sumatra and borneo in 2015 with special emphasis on peatland fires *Environ. Manage.* **60** 747–57

Miettinen J, Shi C and Liew S C 2011 Influence of peatland and land cover distribution on fire regimes in insular Southeast Asia *Reg. Environ. Change* **11** 191–201

Miettinen J, Shi C and Liew S C 2016 Land cover distribution in the peatlands of Peninsular Malaysia, sumatra and Borneo in 2015 with changes since 1990 *Glob. Ecol. Conserv.* **6** 67–78

Milner L, Boom A, Page S E and Matthews R Effects of fire on the organic matter composition of a tropical peatland in Central Kalimantan, Indonesia (in preparation)

Minnemeyer S, Boisrobert L, Stolle F, Muliastra Y I K D, Hansen M, Arunarwati B, Prawijiwuri G, Purwanto J and Awaliyan R 2009 Interactive Atlas of Indonesia's Forests (CD-ROM)

Müller D, Leitão P J and Sikor T 2013 Comparing the determinants of cropland abandonment in Albania and Romania using boosted regression trees *Agric. Syst.* **117** 66–77

Nakagawa S and Schielzeth H 2013 A general and simple method for obtaining R^2 from generalized linear mixed-effects models *Methods Ecol. Evol.* **4** 133–42

NASA FIRMS 2017 MCD14ML Active Fires (https://firms.modaps.eosdis.nasa.gov/download)

Page S E and Hooijer A 2016 In the line of fire: the peatlands of Southeast Asia *Phil. Trans. R. Soc.* B **371** 20150176

Purnomo H, Shantiko B, Sitorus S, Gunawan H, Achdiawan R, Kartodihardjo H and Dewayani A A 2017 Fire economy and actor network of forest and land fires in Indonesia *Forest Policy Econ.* **78** 21–31

R Core Team 2017 R: A language and environment for statistical computing (http://r-project.org)

Rothermel R C 1983 How to Predict the Spread and Intensity of Forest and Range Fires *General Technical Report* INT-143 USDA Forest Service, Intermountain Forest and Range Experiment Station, Utah

Schwartz N B, Uriarte M, Gutiérrez-Vélez V H, Baethgen W, DeFries R, Fernandes K and Pinedo-Vasquez M A 2015 Climate, landowner residency, and land cover predict local scale fire activity in the Western Amazon *Glob. Environ. Change* **31** 144–53

Shivakumar S, Bell K C, Toha K, Zaenal A and Collier W 2015 A Review of Indonesian Land-based Sectors with Particular Reference to Land Governance and Political Economy. *Annual World Bank Conf. on Land and Poverty 2015: Linking Land Tenure and Use for Shared Prosperity (Washington, DC, 23–27 March 2015)* (Washington, DC: World Bank Group)

Siegert F, Ruecker G, Hinrichs A and Hoffmann A A 2001 Increased damage from fires in logged forests during droughts caused by El Niño *Nature* **414** 437–40

Sloan S, Locatelli B, Wooster M J and Gaveau D L A 2017 Fire activity in Borneo driven by industrial land conversion and drought during El Niño periods, 1982–2010 *Glob. Environ. Change* **47** 95–109

Stolle F, Chomitz K M, Lambin E F and Tomich T P 2003 Land use and vegetation fires in Jambi Province, Sumatra, Indonesia *Forest Ecol. Manage.* **179** 277–92

Stolle F and Lambin E F 2003 Interprovincial and interannual differences in the causes of land-use fires in Sumatra, Indonesia *Environ. Conserv.* **30** S0376892903000390
Suyanto S 2007 Underlying cause of fire: different form of land tenure conflicts in Sumatra *Mitig. Adapt. Strateg. Glob. Change* **12** 67–74
Suyanto S, Applegate G, Permana R P, Khususiyah N and Kurniawan I 2004 The role of fire in changing land use and livelihoods in Riau-Sumatra *Ecol. Soc.* **9** 15
Tacconi L 2016 Preventing fires and haze in Southeast Asia *Nat. Clim. Change* **6** 640–3
Tansey K, Beston J, Hoscilo A and Kalimantan S E 2008 Relationship between MODIS fire hot spot count and burned area in a degraded tropical peat swamp forest in Central Kalimantan, Indonesia *J. Geophys. Res.* **113** 23112
Taufik M, Torfs P J J F, Uijlenhoet R, Jones P D, Murdiyarso D and Van Lanen H A J 2017 Amplification of wildfire area burnt by hydrological drought in the humid tropics *Nat. Clim. Change* **7** 428–31
Transparent World 2015 Tree Plantations (http://transparentworld.ru/en/resources/plantation/)
United States Geological Survey 2017 Shuttle Radar Topography Mission Non-Void Filled Digital Elevation Model (https://earthexplorer.usgs.gov)
Venables W N and Ripley B D 2002 *Modern Applied Statistics with S* (New York: Springer)
Wahyunto, Ritung S and Subagjo H 2003 *Maps of Area of Peatland Distribution and Carbon Content in Sumatra 1990–2002* (Bogor) (http://wetlands.or.id/PDF/buku/Atlas Sebaran Gambut Sumatera.pdf)
World Bank 2015 *Indonesia Economic Quarterly: Reforming amid uncertainty* (Jakarta) (http://pubdocs.worldbank.org/en/844171450085661051/IEQ-DEC-2015-ENG.pdf)
WorldPop 2014 Indonesia Population (https://doi.org/10.5258/SOTON/WP00114)
Zuur A, Ieno E N, Walker N, Saveliev A A and Smith G M 2009 *Mixed Effects Models and Extensions in Ecology with R* (New York: Springer)