Supporting Information

Data Collection and Processing
All data were reprojected to WGS84/UTM Zone 48 South. Data were cleaned and processed using QGIS 2.18.9 (QGIS Development Team 2017), and R version 3.4.0 (R Core Team 2017) using packages rgdal, rgeos, raster, sp, and maptools (Bivand et al 2018, Bivand 2018, Hijmans et al 2017, 2018, Bivand et al 2017). Our final database used for the regency-level and pixel-level analysis and our R scripts are available from https://researchdata.ntu.edu.sg/dataverse/Sze-DriversFireSumatra

Administrative spatial boundaries
Administrative regency-level and village-level boundaries were obtained from the Indonesian Bureau of Statistics for Riau, Jambi and South Sumatra. Regency boundaries for the three provinces were dated at 2013, while village boundaries for Riau were dated at 2010 and Jambi and South Sumatra at 2003. Village-level spatial data for the three provinces were updated to agree with the names in PODES 2014 and with the boundaries on current Google maps (accessed between 1 December 2017 and 31 March 2018). Village boundaries for Riau were assumed to be updated to present, but some names with obvious spelling mistakes were corrected to match those recorded in PODES 2014. Village boundaries for Jambi and South Sumatra were entirely re-drawn according to village boundaries seen on Google maps, resulting in the creation of villages which were not present in 2003. However, Google maps is not entirely up to date. For example, some regency boundaries were changed in 2013 but were not reflected on Google maps. Where there were mismatches, the more recent regency boundaries were adhered to. This is particularly in Banyu Asin and Muara Enim regencies of South Sumatra. Further, several villages posed problems, especially for matching to PODES 2014 names (STable 2).

Socioeconomic data

Land conflict
We collated reports on land conflicts in the three provinces from both newspaper reports and Non-Governmental Organisations’ (NGOs) databases. Land conflict or dispute articles were searched for the time period between January 2010 and October 2015, resulting in results ranging from August 2010 to October 2015 using the terms ‘konflik lahan’ or ‘land conflict’ from nine Indonesian national or provincial newspaper websites: Kompas, The Jakarta Globe, The Jakarta Post, radar Palembang, Sumatera Ekspres (Sumeks), Tribun Sumsel, Riau Pos, Tribun Pekanbaru/Tribun Riau, and Tribun Jambi. The newspaper search was supplemented with land conflicts reported in three NGOs’ database (http://www.geodata-cso.org): Kelompok Konservasi Indonesia Warsi, Konsorsium Pendukung Sistem Hutan Kerakyatan, and Sawit Watch. This produced 180 land conflicts from the newspaper search and 165 land conflicts from the NGO database ranging from August 2010 to September 2015. With this combined dataset, for the regency analysis, we divided the number of land conflicts reported for each regency by the area and multiplied by 10,000 to obtain land conflict density per 10,000km².

For the pixel-level analysis, of the 345 conflicts reported in the three provinces, 99 were documented without village names. To identify the village where these conflicts occurred, we attempted a supplementary search using Google search engine with the names of the parties involved in the conflict and the regency or district. From newspaper articles in the search results, 24 more villages were added, 22 of them new conflicts and 2 that were also involved in conflicts already in our database. For conflicts with no information online, but the plantation involved was present in our wood fiber and oil palm concession maps, we identified the centroids of the concession polygons and chose the village that was in the center to be the village of conflict. Conflicts that were inferred to be duplicated and those that could not be identified to village level due to lack of information were omitted, resulting in 330 reported conflicts in 306 villages. The data was then made spatially explicit to village level and rasterized using QGIS gdal_rasterize tool with number of conflicts as the attribute, at 1000 map units (1km) per pixel resolution.

Multi-ethnicity, brawling incidents, practice of burning for agriculture and practice of burning waste
We used data from the Indonesian Bureau of Statistics (2016) Village Potential (Potensi Desa, PODES) survey for 2014. The PODES is a longstanding tradition of collecting data at the lowest administrivative level of local governments. Sub-district level agents from the Indonesian Bureau of Statistics who typically gather information from the village or urban neighborhood head collected information about Indonesia’s 82,190 villages and urban neighborhoods.
The following questions from PODES were used to extract information to village-level indicators of multi-ethnicity, brawling incidents, practice of burning for agriculture and practice of burning waste.

- **Multi-ethnicity [PODES Q804]:** if the villagers are made up of several tribes/ethnicities (yes – 1, no – 2).
- **Brawling incident [PODES Q1301]:** if there was an incidence of mass fights in the village during the last year (have – 1, none – 2).
- **Practice of burning for agriculture [PODES Q513]:** if the villagers had a habit of burning fields/gardens in the village for the process of agricultural business during the last year (have – 1, none – 2).
- **Practice of burning waste [PODES Q505]:** how waste disposal was carried out in the village (Dumpster then transported – 1, dumped or burned – 2, river, irrigation canals, lakes or sea – 3, drainage (sewer) – 4, others – 5)

At the regency level, for multi-ethnicity, brawling incident and practice of burning for agriculture, we calculated the fraction of villages that responded affirmatively (response ‘1’) within each regency as a variable. For the practice of burning waste, we calculated the fraction of villages that reported to burn their waste (response ‘2’) within each regency. This variable also included villages that reported dumping their waste only.

For the pixel analysis, data from PODES 2014 was made spatially explicit to village level and rasterized using QGIS gdal_rasterize tool at 1000 map units (1km) per pixel resolution for a binary response.

### Spatial data

**Fire hotspots**

We downloaded MODIS active fire hotspots (MCD14ML) from NASA FIRMS (2017) for 1 June 2015 to 31 October 2015, accessed on 21 March 2017. For the regency analysis, we counted the number of fires within each regency. For the pixel analysis, the active fire shapefile was rasterized at 1000 map units (1km) per pixel resolution using QGIS gdal_rasterize tool for a binary response.

**Oil Palm Concessions and Wood Fiber Concessions**

We downloaded oil palm concession and wood fiber concession datasets from the Global Forest Watch (GFW) data portal (Indonesia Ministry of Forestry 2017, Indonesia Ministry of Forestry et al 2017), accessed on 21 April 2017. The oil palm concession dataset is dated at 2014, while the wood fiber concession dataset is dated at 2017. To obtain a wood fiber concession dataset for 2014, we referred to the Greenpeace wood fiber concession dataset (Greenpeace 2014) which was dated at 2014 to remove concessions from 2015 to 2017. For the regency analysis, we calculated the concession area in each regency using the intersect function in R to obtain the fraction of concession within each regency. For the pixel analysis, we rasterized the shapefiles using QGIS gdal_rasterize tool at 1000 map units (1km) per pixel resolution for a binary response.

**Small landholdings, medium landholdings and large landholdings**

We downloaded tree plantation by type dataset from the GFW data portal (Transparent World 2015), accessed on 13 April 2017. We dissolved the plantations by type (large industrial plantation; mosaic of medium-sized plantations; mosaic of small-sized plantations; Clearing/very young plantations) and rasterized the vector data using GRASS v.to.rast tool for each plantation type in QGIS, with a resolution of approximately 900m² per pixel. For the regency analysis, we calculated the number of pixels of each plantation type in each regency in R and multiplied this number by the area of pixel (899.98 m²) to obtain the area of each plantation type. The fraction of these three landholding classes within each regency was then used as an explanatory variable. The fractions of the three landholding classes do not sum to one since the land could also be used for other purposes than tree plantations. For the pixel analysis, we obtained three separate raster layers (30m) for the large landholdings, medium landholdings and small landholdings. We used the aggregate function in R (factor = 33, function = mean) to form larger pixels that contained values between 0 and 1. To obtain a binary variable, we rounded values between 0-0.5 to 0, and 0.5-1 to 1, and used the resample function in R (method = ngb or ‘nearest neighbour’) to obtain pixels at 1km² resolution. We acknowledge there exist overlaps between our large-scale landholding (> 100 ha) and our wood fiber and oil palm industrial concessions (37.9% and 53.2% respectively).

**Population density**

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2
We downloaded Indonesia’s population data from WorldPop (WorldPop 2014, Gaughan et al 2013), accessed on 16 May 2017, which is a gridded dataset indicating estimated people per pixel at 100m resolution using Random Forest method. For the regency analysis, we calculated the mean people per pixel in each regency in R. For the pixel analysis, we used the aggregate function (factor = 11, function = sum) and resample function (method = bilinear) in R to obtain 1km² pixels.

Degraded forest

We downloaded data from Global Land Analysis and Discovery (Margono et al 2014), accessed on 4 April 2017. We reclassified the 16 classes to 5 classes representing the state of forests in 2012 (in brackets):

(i) Out of area study (no data)
(ii) No change of primary degraded forest from 2000-2012 (primary degraded forest)
(iii) No change of primary intact forest from 2000-2012 (primary intact forest)
(iv) No change of non-primary from 2000-2012 (non-primary forest)
(v) Primary intact, cleared 2005 (cleared forest)
(vi) Primary intact, cleared 2010 (cleared forest)
(vii) Primary intact, cleared 2012 (cleared forest)
(viii) Primary intact, degraded 2005 (primary degraded forest)
(ix) Primary intact, degraded 2010 (primary degraded forest)
(x) Primary intact, degraded 2012 (primary degraded forest)
(xi) Primary degraded, cleared 2005 (cleared forest)
(xii) Primary degraded, cleared 2010 (cleared forest)
(xiii) Primary degraded, cleared 2012 (cleared forest)
(xiv) Primary intact, degraded 2005, cleared 2010 (cleared forest)
(xv) Primary intact, degraded 2005, cleared 2012 (cleared forest)
(xvi) Primary intact, degraded 2010, cleared 2012 (cleared forest)

We reclassified the 16 classes to 5 classes representing no data, degraded primary forests, intact primary forests, non-primary forests, and cleared forests in 2012 using GRASS r.reclass tool in QGIS. Margono et al. (2014) defined primary tree cover as having a minimum height of 5 m, a canopy cover of at least 30% at the Landsat pixel scale, has not been cleared in recent history, and consists of a contiguous block of 5 ha or more. Primary degraded forests were defined as “mature natural forests of 5 ha or more in extent that retain their natural composition and structure, and have not been completely cleared and re-planted in recent history” but that have been “fragmented or subjected to forest utilization, for example, by selective logging or other human disturbances that have led to partial canopy loss and altered forest composition and structure”, and were identified using roads, settlements and other signs of human landscape alteration in Margono et al. (2014).

For the regency analysis, we counted the number of pixels in each of the 5 classes using R, then multiplied the count by area of pixel (885.34m²) to obtain the area of degraded forest in each regency. The fraction of degraded forest area over regency area in each regency was used as an explanatory variable. For the pixel analysis, the reclassified raster data (30m) was converted to a binary absence/presence of degraded forest in 2012 pixels. We used the aggregate function in R (factor = 33, function = mean) to form larger pixels that contained values between 0 and 1. To obtain a binary variable, we rounded values between 0-0.5 to 0, and 0.5-1 to 1, and used the resample function in R (method = ngb) to obtain pixels at 1km² resolution.

Susceptible peatland cover

We obtained the 2015 peatland land-cover map (Miettinen et al 2016) from the author (Miettinen, J.) and reclassified the 11 land-cover classes to the following 4 land-cover classes, following Miettinen et al., (2017):

(i) Non-Peatlands: Water and Mangrove
(ii) Undeveloped-degraded Peatlands: Seasonal water, Ferns/low shrub, Cleared/burnt are and Tall shrub/Secondary forest
(iii) Managed Peatlands: Industrial plantation, Small-holder area, and Built-up area
(iv) Peatswamp Forest: Peatswamp Forest and Degraded Peatswamp forest

The Undeveloped-degraded and Managed Peatland land-cover classes were considered to be susceptible to fires based on Miettinen et al. (2017) assessment of fire occurrence. We combined these two land-cover classes and renamed it ‘Susceptible Peatland Cover’.

3
We rasterized the vector data using the GRASS v.to.rast tool at 900m² per pixel. For the regency analysis, we calculated the number of ‘Susceptible Peatland Cover’ pixels and multiplied by area of pixel (900m²) to obtain the area of peatlands which was considered susceptible to fires. We used the fraction of peatlands susceptible to fires in each regency as an explanatory variable. For the pixel analysis, the rasterized data was reclassified to binary presence/absence of Susceptible Peatland Cover to fires. We used the aggregate function (factor = 33, function = mean) on the raster layer (30m) to form larger pixels that contained values between 0 and 1. To obtain a binary variable, we rounded values between 0-0.5 to 0, and 0.5-1 to 1, and used the resample function in R (method = ngb) to obtain pixels at 1km² resolution.

Previous fire occurrence on peatlands
We downloaded monthly Burned Area covering the study region from MODIS Collection 6 (MCD64A1) (Giglio et al 2015) in GeoTIFF format for June 2006 to May 2015, accessed on 11 May 2017. The data was then summed to produce a raster layer with pixels identifying number of times it was burned. We used the World Resources Institute’s (WRI) Interactive Atlas of Indonesia’s Forest peatland map (Wahyunto et al 2003) to identify burned areas over peatlands. For the regency analysis, we reclassified the raster layer into binary pixels of 0 = not burned and 1 = burned at least once in R. We then calculated the number of repeated burn pixels and multiplied by area of pixel (237,654 m²) to obtain the area of peatlands which suffered at least one burn between 2006 and 2015. The fraction of peatland in each regency which suffered at least one burn was used as an explanatory variable. For the pixel analysis, we used the aggregate function (factor = 2, function = sum) on the raster layer of number of burned pixels over peatlands (500m) to form larger pixels and resample function (method = ngb) to 1km² pixels.

Road network
We downloaded the gROADS dataset from the Socioeconomic Data and Applications Centre (CIESIN, 2013) accessed on 13 April 2017 and obtained the JALAN dataset from WRI’s Interactive Atlas of Indonesia’s Forests (Minnemeyer et al 2009). We then merged the two datasets to obtain a road network of the study area. For the regency analysis, we calculated the sum length of the roads (kilometers) and divided this by the area of the regency to obtain the density of roads in each regency in QGIS. For the pixel analysis, the road network was rasterized to binary 1km² pixels then the Proximity (raster distance) tool in QGIS was used to calculate the distance (meters) each pixel was to the nearest road pixel.

Mean rainfall in May and June 2015
We obtained rainfall data covering the study region from the International Research Institute Data Library (IRIDL, 2017) for May and June 2015, accessed on 17 November 2017. We chose the months May and June as it is the month preceding and the first month of the fire season for 2015, given Gaveau et al. (2014) finding that monthly Fire Radiative Power (FRP) correlated with rainfall over the month of FRP measurements and the month before during the mega-fire event of 2013. The Climate Prediction Center Morphing Technique was used to aggregate daily precipitation estimates to monthly values on a 0.25x0.25 degree grid, from passive microwave satellite scans (Joyce et al 2004). We used the disaggregate function (factor = 27, method = bilinear) in R to obtain a higher pixel resolution. For the regency analysis, we split the raster layer by regency polygons and calculated the mean rainfall for May and June 2015 for each regency in R. For the pixel analysis, the mean rainfall raster layer was resampled (method = bilinear) to 1km² pixels.

Slope
We downloaded Digital Elevation Model data covering the study region (United States Geological Survey 2017), accessed on 5 May 2017, and mosaicked the raster files that cover the study area into one file. We calculated slope from the elevation data using the terrain function (option = ‘slope’, unit = ‘degrees’, neighbors = 8) in R. For the regency analysis, we split the raster layer by regency polygons to calculate mean slope for each regency. For the pixel analysis, we used the aggregate (factor = 11, function = mean) and resample functions (method = bilinear) to obtain 1km² pixels.

Peatland area
We used the World Resources Institute’s (WRI) Interactive Atlas of Indonesia’s Forest peatland map (Wahyunto et al 2003) to identify peat areas. For the regency analysis, we calculated the area of peatland within each regency. For the pixel analysis, we rasterized the shapefile using QGIS gdal_rasterize tool at 1000 map units (1km) per pixel resolution for a binary response.
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Supporting Tables & Figures

**Table 1.** Description of the three provinces, Riau, Jambi and South Sumatra. The number of regencies and villages were obtained from PODES, an estimate of 2010 population size was derived from WorldPop (WorldPop 2014) and the extent of peat in each province was derived from Wetlands International (Wahyunto et al 2003).

| Province        | Area (km²) | No. of regencies | No. of villages | Population in 2010 (,000 people) | Peat area (km²) (% of province composed of peat) |
|-----------------|------------|------------------|-----------------|----------------------------------|-----------------------------------------------|
| Riau            | 89,975     | 12               | 1,837           | 5,074                            | 41,099 (45.7)                                |
| Jambi           | 48,987     | 11               | 1,551           | 2,838                            | 7,056 (14.4)                                 |
| South Sumatra   | 86,930     | 17               | 3,237           | 6,826                            | 14,661 (16.9)                                |
| Total           | 225,893    | 40               | 6,623           | 14,739                           | 62,817 (27.8)                                |
| Problem village on Google maps                          | Comment                                                                 | Solution                                                                 |
|---------------------------------------------------------|--------------------------------------------------------------------------|--------------------------------------------------------------------------|
| Muara Air Dua, Sitinjau Laut, Kerinci, Jambi             | Village was incorporated into Betung Kuning village in 2011 (Kementerian Dalam Negeri) | Renamed as Betung Kuning                                                 |
| Taman Asri, Semendawai Suku III, East Ogan Komering Ulu, South Sumatra | Village was not recorded in PODES 2014                                  | Renamed as Taraman Jaya which is recorded in PODES 2014 but whose spatial location is unknown |
| Pagar Alam and Beruge Tengah in Pendopo, Empat Lawang, South Sumatra | Villages were not recorded in PODES 2014                                | Merged and renamed as Pagar Tengah which is recorded in PODES 2014 but whose spatial location is unknown |
| Sukaraya, Suku Tengah Lakitan Ulu, Musi Rawas, South Sumatra | Village appears twice on Google maps                                   | One was deduced through elimination and comparison with PODES 2014 to be Sukakarya village |
| Keban Agung, South Kikim, Lahat, South Sumatra          | Village appears twice on Google maps                                   | Larger one renamed as Keban Agung Sp I                                  |
| Villages in Muara Belida, Muara Enim, South Sumatra     | Village locations on Google maps are known to be erroneous              | Boundaries are drawn theoretically based on Peta Administrasi Wilayah Kabupaten Muara Enim Tahun 2012-2032 |
| Variable             | Expected effect on fire count and occurrence | Justification                                                                                                                                 |
|----------------------|----------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------|
| **Conflict Factors** |                                              |                                                                                                                                            |
| LandConflict         | Positive                                     | Land conflicts have been shown to be an underlying cause for fires (Suyanto et al 2004, Dennis et al 2005).                               |
| MultiEthnic          | Positive                                     | Conflicts between locals and migrants within villages have been recorded, with some resulting in fire ignitions (Suyanto 2007). However we acknowledge that higher multi-ethnicity does not necessarily correlate with higher community conflict |
| Brawl                | Positive                                     | Conflicts within the village over land-use might be recorded here and could result in fire ignitions.                                         |
| **Economic Factors** |                                              |                                                                                                                                            |
| SmallPlant           | Positive or negative                         | Small and medium landholdings may have more fires as they lack resources to control fires and are less regulated/inspected, but may also have fewer fires since it is easier to manage a smaller area of land and there is higher personal motivation to protect the land. |
| MedPlant             | Positive or negative                         |                                                                                                                                            |
| LargePlant           | Positive or negative                         | Conversely, large landholdings/concessions may have fewer fires since they have the means to use mechanical clearing and resources to control fire outbreaks, but larger areas are harder to manage and monitor, and fires might also be used illegally to clear and prepare land. |
| OPC                  | Positive or negative                         |                                                                                                                                            |
| WFC                  | Positive or negative                         |                                                                                                                                            |
| PracBurn             | Positive                                     | Villages where more people practice burning of agricultural land have a higher chance of fires escaping accidentally                           |
| **Population Factors** |                                             |                                                                                                                                            |
| Pop                  | Positive                                     | Fires are mostly anthropogenic in origin, hence where there are more people, it is likely that more fires would be started (Cochrane 2003). |
| BurnTrash            | Positive                                     | Villages which dispose of their waste by burning are more likely to have fires escaping accidentally                                         |
| **Forest Degradation Factors** |                                          |                                                                                                                                            |
| DegFor               | Positive                                     | Degraded forests are more open which make them more likely to dry out (Siegert et al 2001), which then makes them more susceptible to fires. Where land has been burnt at least once, the vegetation that returns is often scrub and ferns which are more susceptible to fires (Hoscio et al 2011). |
| PrevFires            | Positive                                     |                                                                                                                                            |
| SuscPeatCover        | Positive                                     | Peatland cover which are drained, degraded, undeveloped or managed are more likely to be susceptible to fires (Miettinen et al 2017, Gaveau et al 2016). |
| Roads                | Positive                                     | Roads fragment the landscape and help fires spread more easily (Laurance et al 2009, Stolle and Lambin 2003).                               |
| **Biophysical Factors** |                                             |                                                                                                                                            |
| Rain                 | Negative                                     | Low rainfall results in lowering of the water table and above ground vegetation to dry out, making the landscape more susceptible to fires (Sloan et al 2017, Field et al 2016, Taufik et al 2017). |
**Slope**  | Positive or negative  | Steeper areas more likely to have fires due to the heat intensity burning the land (Rothermel 1983) however less steep areas correspond to flatlands which are more likely to be cultivated and thus be at a higher risk of burning.

**Peat**  | Positive  | Peat is more susceptible to burning than mineral soils (Miettinen et al 2011).

*Fire ignition attribution using satellite-derived data is particularly tricky in Indonesia due to overlapping and conflicting land use and land ownership claims (Suyanto et al 2004, Gaveau et al 2016, Miettinen et al 2017, Sloan et al 2017). Here we include possible actors based on satellite-derived data to attempt elucidating any associations, bearing in mind the above caveat.*
## STable 4. Variables used to model fire prevalence at the regency level

| Variable   | Description                                                                 | Mean ± sd (2dp)          | Range (2dp)      |
|------------|-----------------------------------------------------------------------------|--------------------------|------------------|
| FireNo     | No. active firest in regency (no. fires)                                    | 1258.12 ± 3005.62       | 2 - 18104        |
| Area       | Area of regency (km$^2$)                                                    | 5644.97 ± 4259.00       | 171.40 – 17931.20|
| Conflict Factors (C) | | | | |
| LandConflict | No. land conflicts per 10,000 km$^2$ in regency (no. land conflicts per 10,000 km$^2$) | 14.59 ± 19.83           | 0 – 104.93       |
| MultiEthnic | Proportion of villages in regency that are multiethnic (fraction)          | 0.89 ± 0.12             | 0.61 - 1         |
| Brawl      | Proportion of villages in regency that reported brawling incidents (fraction) | 0.02 ± 0.02             | 0 - 0.10         |
| Economic Factors (E) | | | | |
| SmallPlant | Proportion of small landholdings in regency (fraction)                    | 0.08 ± 0.12             | 0 – 0.47         |
| MedPlant   | Proportion of medium landholdings in regency (fraction)                    | 0.11 ± 0.17             | 0 – 0.85         |
| LargePlant | Proportion of large landholdings in regency (fraction)                     | 0.17 ± 0.14             | 0 – 0.47         |
| WFC        | Proportion of wood fiber concessions in regency (fraction)                 | 0.13 ± 0.12             | 0 – 0.38         |
| PracBurn   | Proportion of villages that practice burning for agriculture in regency (fraction) | 0.34 ± 0.21             | 0.01 – 0.97      |
| Population Factors (P) | | | | |
| Pop        | No. people per km$^2$ in regency (people per km$^2$)                        | 2.64 ± 7.36             | 0.24 – 38.57     |
| Forest Degradation Factors (FD) | | | | |
| DegFor     | Proportion of degraded forests in regency (fraction)                       | 0.14 ± 0.11             | 0 - 0.48         |
| PrevFires  | Proportion of peatlands in regency which suffered at least one burn between June 2006 and May 2015 (fraction) | 0.11 ± 0.15             | 0 - 0.51         |
| SuscPeatCover | Proportion of peatlands in regency with susceptible land cover to fires (fraction) | 0.57 ± 0.44             | 0 - 1            |
| Roads      | Road density in regency (road length per km$^2$)                            | 0.55 ± 0.25             | 0.19 – 1.27      |
| Biophysical Factors (BP) | | | | |
| Rain       | Mean rainfall in May and June 2015 for regency (mm)                        | 108.91 ± 28.57          | 58.03 – 162.89   |
| Slope      | Mean slope for regency (degree)                                            | 4.04 ± 3.65             | 0.78 – 15.92     |
| Peat       | Proportion of peat area in regency (fraction)                              | 0.19 ± 0.26             | 0 – 0.91         |
Candidate models for regency analysis. Model formula is ‘FireNo ~ offset(L.Area) + … + (1|Province)’, where … should be filled in with the variable(s) below.

| No. | Model Specification |
|-----|----------------------|
| 1   | LandConflict + MultiEthnic + Brawl (Conflict) |
| 2   | LandConflict |
| 3   | MultiEthnic |
| 4   | Brawl |
| 5   | SmallPlant + MedPlant + LargePlant + WFC + PracBurn (Economic) |
| 6   | SmallPlant |
| 7   | MedPlant |
| 8   | LargePlant |
| 9   | WFC |
| 10  | PracBurn |
| 11  | L.Pop (Population) |
| 12  | DegFor + PrevFires + SuscPeatCover + Roads (Forest Degradation Properties) |
| 13  | DegFor |
| 14  | PrevFires |
| 15  | SuscPeatCover |
| 16  | Roads |
| 17  | Rain + Slope + Peat (Biophysical) |
| 18  | Rain |
| 19  | Slope |
| 20  | Peat |
| 21  | DegFor*Rain (Interaction 1) |
| 22  | PrevFires*Rain (Interaction 2) |
| 23  | SuscPeatCover*Rain (Interaction 3) |
| 24  | C + E + P + FD + BP (Full model) |
| 25  | Full model + Interaction 1 |
| 26  | Full model + Interaction 2 |
| 27  | Full model + Interaction 3 |
| 28  | C + BP |
| 29  | E + BP |
| 30  | P + BP |
| 31  | FD + BP |
| 32  | FD + BP + Interaction 1 |
| 33  | FD + BP + Interaction 2 |
| 34  | FD + BP + Interaction 3 |
| 35  | C + E |
| 36  | C + P |
| 37  | C + FD |
| 38  | C + E + P |
| 39  | C + P + FD |
| 40  | C + E + FD |
| 41  | C + E + FD + P |
| 42  | C + E + BP |
| 43  | C + P + BP |
| 44  | C + FD + BP |
| 45  | C + FD + BP + Interaction 1 |
| 46  | C + FD + BP + Interaction 2 |
| 47  | C + FD + BP + Interaction 3 |
| 48  | C + E + FD + BP |
| 49  | C + E + FD + BP + Interaction 1 |
| 50  | C + E + FD + BP + Interaction 2 |
| 51  | C + E + FD + BP + Interaction 3 |
| 52  | E + P |
| 53  | E + FD |
|   | Formula |
|---|---------|
| 55 | E + P + BP |
| 56 | E + P + FD |
| 57 | E + P + FD + BP |
| 58 | E + P + FD + BP + Interaction 1 |
| 59 | E + P + FD + BP + Interaction 2 |
| 60 | E + P + FD + BP + Interaction 3 |
| 61 | P + FD |
| 62 | P + FD + BP |
| 63 | P + FD + BP + Interaction 1 |
| 64 | P + FD + BP + Interaction 2 |
| 65 | P + FD + BP + Interaction 3 |
**Table 6. Variables used to model fire presence at pixel level (1km²).**

| Variable      | Description                                                                 | Mean ± sd | Range    |
|---------------|------------------------------------------------------------------------------|-----------|----------|
| **FirePresence** | Presence or absence of fires (binary)                                        | 0.09 ± 0.29 | 0 or 1   |
| **Conflict Factors** |                                                                               |           |          |
| LandConflict  | Number of land conflicts reported in pixel (no. land conflicts)               | 0.14 ± 0.43 | 0 - 4    |
| MultiEthnic   | Presence or absence village multi-ethnicity (binary)                          | 0.91 ± 0.28 | 0 or 1   |
| Brawl         | Presence or absence village brawling incident (binary)                        | 0.03 ± 0.18 | 0 or 1   |
| **Economic Factors** |                                                                               |           |          |
| SmallPlant    | Presence or absence of small landholding (binary)                             | 0.22 ± 0.41 | 0 or 1   |
| MedPlant      | Presence or absence of medium landholding (binary)                            | 0.11 ± 0.31 | 0 or 1   |
| LargePlant    | Presence or absence of large landholding (binary)                             | 0.29 ± 0.45 | 0 or 1   |
| OPC           | Presence or absence of oil palm concession (binary)                           | 0.12 ± 0.32 | 0 or 1   |
| WFC           | Presence or absence of wood fiber concession (binary)                          | 0.17 ± 0.37 | 0 or 1   |
| PracBurn      | Presence or absence of village practice of burning for agriculture (binary)   | 0.44 ± 0.50 | 0 or 1   |
| **Population Factors** |                                                                               |           |          |
| Pop           | Estimated no. people per pixel (no. people per pixel)                         | 74.36 ± 311.51 | 0 - 16293.67 |
| BurnTrash     | Presence or absence of village burning trash (binary)                         | 0.67 ± 0.47 | 0 or 1   |
| **Forest Degradation Factors** |                                                                               |           |          |
| DegFor        | Presence or absence of degraded forests (binary)                              | 0.15 ± 0.36 | 0 or 1   |
| PrevFires     | No. times recorded as burnt area between June 2006 and May 2015 (no. burns)   | 0.30 ± 1.36 | 0 - 32   |
| SuscPeatCover | Presence or absence of susceptible land cover over peatland (binary)          | 0.25 ± 0.43 | 0 or 1   |
| **Biophysical Factors** |                                                                               |           |          |
| Roads         | Euclidean distance to roads (m)                                               | 2442.50 ± 3478.16 | 0 - 27459 |
| Rain          | Mean rainfall in May and June 2015 (mm)                                       | 111.59 ± 32.22 | 38.13 – 197.86 |
| Slope         | Slope (degree)                                                                | 3.22 ± 4.44 | 0 - 46.13 |
| Peat          | Presence or absence of peatland (binary)                                      | 0.27 ± 0.45 | 0 or 1   |
SFigure 1. Regencies of Riau, Jambi and South Sumatra
**SFigure 2.** Boosted Regression Tree model results for testing range of tree complexity values and learning rates for (a) minimum predictive deviance and (b) maximum AUC. We selected the BRT model with a tree complexity of 6 and learning rate of 0.01, based on the lowest predictive deviance and highest AUC score.