Biophysical and anthropogenic contributions to fire disturbance dynamics on the peat-swamp landscape, Indonesia

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ABSTRACT

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Fires have been increasing in size and frequency across the tropics in recent decades, particularly in tropical peatland areas. Indonesia has the largest amount of tropical peat carbon globally. Fires in fuel-rich tropical peatlands are a major source of carbon emissions, have serious consequences for human health, destroy or degrade habitat, and result in high economic costs. There have been many calls for a better understanding of the relative contributions of the biophysical and anthropogenic factors that drive fire, as this understanding would contribute to the success of efforts to reduce these fires. This dissertation uses remote sensing, fieldwork, and modeling to explore the dynamics of fire disturbance in Indonesia and investigates this disturbance from the framework of coupled human and natural systems, where complex interactions between the social and the biophysical are explicitly considered.

Chapters One and Two assess both the influence of various human and biophysical factors to fire probability (Chapter One) and ignitions (Chapter Two) on a peat-swamp forest area in Central Kalimantan, Indonesia, equivalent to a third of Kalimantan's peatland area. A Bayesian modeling approach is used in Chapter One to estimate the effects of atmospheric dryness, human access, vegetation, and hydrology on the probability of fire occurrence. The potential for peatland restoration to offset the impacts of climate on fire occurrence is also explored. I find that climate is the most important factor driving fire occurrence, which is consistent with the findings in many other parts of the tropics. However, two human-driven factors are almost as significant as

the influence of climate: drainage canals, which were put in place as part of a failed agricultural project and have lowered the water table; and woody vegetation, which has decreased over time. Chapter Two inspects the oft-asserted claim that escaped fires from oil palm concessions and smallholder farms near settlements are the primary sources of fire ignitions. We evaluate fire origin and spread, and find that most fires originate in non-forest, compared to oil palm concessions, and relatively few originate close to settlements. Moreover, most fires started within oil palm concessions and in close proximity to settlements stay within those boundaries. However, fire ignition density in oil palm concessions and close to settlements is high. Furthermore, increased anthropogenic activity in close proximity to oil palm concessions and settlements produces a detectable pattern of fire activity. These results refute the claim that most fires originate in oil palm concessions, and that fires escaping from oil palm concessions and settlements constitute a major proportion of fires in this study region. However, there is a potential for these land use types to contribute more substantially to the fire landscape if their area expands.

Chapter Three examines the potential for the financial incentive mechanism of Roundtable on Sustainable Palm Oil (RSPO) certification, which prohibits the use of fire on certified concessions, to reduce fire activity on oil palm concessions. We examine if RSPO-certified concessions have reduced fire activity in Sumatra and Kalimantan, the leading producers of oil palm both within Indonesia and globally. We also evaluate if this pattern changes with increasing likelihood of fires. These questions are particularly critical in fuel-rich peatland areas, of which approximately 46% was designated as oil palm concession as of 2010. We find that fire activity is significantly lower on RSPO certified concessions than non-RSPO certified concessions when the likelihood of fire is low (i.e., on non-peatlands in wetter years), but not when the likelihood of fire is high (i.e., on non-peatlands in dry years or on peatlands).

These chapters advance our understanding of how anthropogenic factors influence the controls of fire in Kalimantan and Sumatra, both directly (i.e., human-caused ignitions) and indirectly (i.e., changing the susceptibility of the landscape to ignitions and to burning). The findings presented in this dissertation indicate that oil palm concessions are associated with high fire probability (Chapter One) and a substantial amount of ignitions and relatively high ignition density (Chapter Two). One of the more pointed ways to target fire on oil palm concessions is through RSPO certification; however, we find that certification is only effective when fire likelihood is already low, suggesting that, in order for this mechanism to reduce fire, more assistance may be needed to control fires in dry years and on peatlands (Chapter Three). Non-forested, degraded areas contribute much more to fire activity than oil palm on this landscape; these areas experience the greatest number of ignitions, have highest ignition density, and are the primary source of forest fires (Chapter Two). Furthermore, the declines in vegetation and the hydrological alteration in these degraded areas contribute substantially to fire occurrence (Chapter One). Effective fire management in this area, including fire prevention and suppression efforts, should therefore target not just oil palm concessions and smallholdings around settlements, but should also focus strongly on non-forested, degraded areas – and in particular those near oil palm concession boundaries and outside the immediate vicinity of settlements – where fire probability is high and where ignitions and fires escaping into forest are most likely to occur. Rehabilitation of the degraded landscape through restoring hydrology and replanting will be key to fire reduction, and can offset the effects of climate on fire in this landscape.

The methodological approaches in this dissertation demonstrate ways in which remote sensing and analytical technologies can be used to answer complex questions about coupled human and natural systems that fuse social and environmental data, for both theoretical and management applications. Chapter One uses biophysical information from remotely sensed products and fieldwork with information about human access on the landscape and integrates them together with Moderate Resolution Imaging Spectroradiometer (MODIS) Active Fire detections under a Bayesian framework. Chapters Two and Three use a novel technique to cluster remotely sensed data on fire occurrence (MODIS Active Fire detections) into fire events so that ignitions can be isolated. This technique allows us to answer questions related to fire origin, spread, and impact that cannot be investigated by evaluating fire detections alone.

This dissertation addresses a gap in knowledge regarding the anthropogenic contributions to increased fire probability and to ignitions in peat swamp, and the approaches could be applied to other degraded peatland areas in Indonesia that are candidate sites for restoration (e.g., under the newly established Peatland Restoration Agency), and to degraded peatlands that experience a novel fire regime in other parts of the tropics. Furthermore, this dissertation evaluates the capacity for RSPO certification to reduce fire activity on oil palm concessions across Sumatra and Kalimantan, Indonesia, and the analyses conducted could be applied to landscapes in other parts of the tropics experiencing oil palm development. In conclusion, the research findings presented in this dissertation are a product of combining social and environmental data and evaluating this data with a suite of classic and novel modeling approaches. This dissertation is presented in the hope that it contributes to our understanding of fire dynamics in the globally important peat-swamp forest, Indonesia, and thus our capacity to manage these disturbances.

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This work has benefited from the support of family, friends, co-workers, and colleagues, and I am fortunate to say that there are too many to list individually here. However, I would like to mention a few. I can confidently say that my life is richer for having each of these people in it.

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DEDICATION

To my Grandmother, Dolores.

INTRODUCTION

The last few decades have been a time of unprecedented ecological change. Global change drivers, including large-scale land use / land cover (LULC) conversion, climate change, and other human-driven environmental impacts, are altering disturbance regimes at a rapid rate (Westerling, Hidalgo et al. 2006, Seidl, Rammer et al. 2014). Among these changing disturbance regimes is tropical fire disturbance. Fires in humid tropical forests, both natural and anthropogenic in origin, have been a source of disturbance over millennia (e.g., Goldammer 1990). However, fires have been increasing in size and frequency across the tropics in recent decades, largely as a result of anthropogenic LULC change (Goldammer 1991, Cochrane 2003, Cochrane 2009). Furthermore, biomass burning in the tropics releases carbon and other gases into the atmosphere, contributing to global climate change, air pollution, acid rain, and property damage (Crutzen and Andreae 1990, Hao, Liu et al. 1990, Hao and Ward 1993, Langmann and Graf 2002). Fire disturbance causes dramatic changes to the ecosystem where they are extrinsic to the system, such as many tropical areas (e.g., Cochrane and Schulze 1999, Ferry Slik, Verburg et al. 2002, Gerwing 2002, Shlisky, Waugh et al. 2007, Shilisky, Alencar et al. 2009), and fire in the tropics is one of the primary contemporary drivers of tropical forest loss and degradation. Because tropical zones host much of the world's biodiversity and are being lost at alarming rates, fires in the tropics are of special interest for scientists concerned with their conservation and ecology. Despite pervasive fire in the tropics, there have been few studies on fire in tropical ecosystems relative to other systems.

This dissertation focuses on fire in tropical peat-swamp forest in Indonesia. This ecosystem is characterized by peat soil types, which consist of partially decayed vegetation matter that has been accumulating over thousands of years. Tropical peatland occurs wherever rainfall and topography result in poor drainage, permanent waterlogging, and acidification of soil, and is distributed across the tropics in East and Southeast Asia, Africa, the Caribbean, and Central and South America. Indonesia has the largest volume and area of tropical peat globally (Rieley, Ahmad-Shah et al. 1996, Page, Rieley et al. 2006, Page, Rieley et al. 2011). Tropical peatlands are capable of storing substantial amounts of carbon in their natural condition; the tropical peatland carbon pool is estimated at 88.6 Gt, roughly 15-19% of the global peat carbon pool (Page, Rieley et al. 2011). Most of the peatland in Indonesia is located at low altitudes in coastal and subcoastal areas. These ombrogenous swamps form domes, and receive water and nutrient inputs entirely from rain, aerosols, and dust rather than from river or other groundwater inputs. In their natural condition, these lowland peat-swamp forest ecosystems are mid- to low-canopy forested peatland areas that are inundated at or close to the surface for most of the year. Fire and other types of disturbance can result in both hydrological degradation, resulting in areas with lowered water tables and dry peat, and / or and vegetative degradation, resulting in fern, bush, or grass dominated vegetation types.

Carbon emissions as a result of fires in tropical peatlands are particularly high, as peat is extremely rich in belowground organic carbon (Rieley, Ahmad-Shah et al. 1996, Page, Siegert et al. 2002, FRIM-UNDP/GEF 2006, Hooijer, Silvius et al. 2006, Page, Rieley et al. 2006, Page, Rieley et al. 2011, Harris, Minnemeyer et al. 2015). Over 90% of CO_2 emissions from decomposition of deforested and drained peatlands and associated fires in Southeast Asia come from Indonesia (Rieley, Ahmad-Shah et al. 1996, Page, Rieley et al. 2006, Page, Rieley et al. 2011). Peat fires in Southeast Asia, and Indonesia in particular, are consequently a major cause of smog and particulate air pollution (Hayasaka, Noguchi et al. 2014, Reddington, Yoshioka et al. 2014), with serious consequences for human health (Kunii 1999, Kunii, Kanagawa et al. 2002, Marlier, DeFries et al. 2012, Wooster, Perry et al. 2012) and local blocking of sunlight that can suppress plant photosynthesis (Davies and Unam 1999). In addition, peatland fires are responsible for forest habitat loss and degradation for flora and fauna, including those in marine systems (Yule 2010, Posa, Wijedasa et al. 2011, Jaafar and Loh 2014). Fire suppression efforts, lost timber and crop resources, missed workdays, and travel disruptions incur high economic costs (Ruitenbeek 1999, Barber and Schweithelm 2000, Tacconi 2003). In late 2015, Indonesia experienced an unusually severe fire season, resulting in a global environmental disaster. Fires burn in Indonesia nearly every dry season, but the 2015 dry season fires were the most severe since 1997. At the time of writing, peer-reviewed estimates for land area burned and emissions are not yet available, but emissions estimates are predicted to be about 1.75 billion metric ton of CO_2 equivalents, with substantial uncertainty, the highest since 1997 (GFED 2015). It is estimated that Indonesia lost US$8.5-20.1 billion during the 1997/98 fire season alone (ADB 1999, Varma 2003) and US$16.1 billion during the most recent fire crisis in 2015 (World Bank 2015).

Both national and international policy has been implemented in the past to attempt to reduce fire in Indonesia (e.g., ASEAN Agreement on Transboundary Haze Pollution, Singapore's Transboundary Haze Pollution Act, and Indonesia's national law (Act No 41/1999) banning corporations from using fire to clear land for palm-oil plantations), but with limited success.

However, as international attention is being directed toward Indonesian peat fires after the 2015 haze crisis, recent governmental action in Indonesia appears promising. The Indonesian president Joko Widodo banned clearing and converting peatlands, even on existing concessions, by presidential instructions (Indonesia 2015), which could be further strengthened by becoming legally binding law. In 2016, Widodo has also established a Peatland Restoration Agency, tasked with restoring about 2Mha of peatlands by 2020 in Sumatra, Kalimantan, and Papua (Indonesia 2016). Given the variety and severity of the consequences of tropical peatland fires in Indonesia, and the policy efforts to control these fires, it is of global interest to understand this changing disturbance regime and reduce fire occurrence.

Coincident with this time of increased anthropogenic change and altered fire disturbance regimes have been rapid technological advances that have greatly increased our ability to observe and evaluate earth processes. Progress in remote sensing technologies have made data collection more logistically and economically feasible, particularly for studies in remote areas. Increases in computer processing power have allowed researchers to model changes in ecological processes at a speed and intricacy unheard of even a few decades ago. As a result, the research community is able to answer questions associated with human-driven changes in Earth processes that require large spatio-temporal datasets and complex geospatial analysis.

This dissertation uses remote sensing, fieldwork, and modeling to explore the dynamics of fire disturbance in Indonesia and investigates this disturbance from the framework of coupled human and natural systems, where complex interactions between the social and the biophysical are explicitly considered. Simply, biomass fires can occur when there is sufficient heat applied to organic fuel with oxygen present: the traditional "fire triangle" concept (Countryman 1972, Pyne, Andrews et al. 1996). When heat is applied to a potential fuel load, before it combusts, it must first become dry. Additionally, for the fire to spread, it is not sufficient for combustion to occur in one location, it must also dry out potential fuel past the fire line. Human activity can interfere with fire controls at any scale, either directly (i.e., human ignitions) or indirectly (i.e., interacting with predisposing factors and sensitizing the landscape to those factors) (Bowman, Balch et al. 2011). The human contribution to changing fire regimes and our capacity to manage fire remains somewhat uncertain (Bowman, Balch et al. 2009, Bowman, Balch et al. 2011), and thus there have been many calls for a better understanding of the relative contributions of the biophysical and anthropogenic factors that drive fire (e.g., Eva and Lambin 2000). Evaluating the factors driving fire disturbance is a key component to understand changing fire regimes in the tropics and thus our capacity to manage these disturbances.

The following chapters evaluate how human-driven and biophysical landscape changes affect fire disturbance in Indonesia. Each chapter addresses an ecologically and socially relevant issue in the fuel-rich tropical peat-swamp forest in Indonesia, quantifies the relevant factors, and examines the implications for fire disturbance.

Chapters One and Two focus on a peat-swamp forest area in Central Kalimantan, Indonesia, and assess both the influence of various human and biophysical factors to fire probability (i.e., indirect anthropogenic contribution to fire) and ignitions (i.e., direct anthropogenic contribution to fire). The study area consists of the Sabangau-Katingan Forest and the recently degraded failed agricultural project called the Mega Rice Project (MRP), equivalent to around a third of

Kalimantan's total peat area. Both of these areas have historically experienced logging and hydrological alteration and continue to be exposed to anthropogenic activity. The Sabangau-Katingan Forest has been previously subjected to both concession and illegal logging throughout, and as a consequence of the latter is criss-crossed by small illegal logging timber extraction canals, on many of which canal damming initiatives are currently underway. Currently, the area is not open for human use apart from some small-scale activities, though enforcement capability is limited, and the forest remains relatively intact. The MRP is a failed and abandoned agricultural conversion project that was initiated in 1995 and aimed to convert 1 Mha of peat-swamp forest into rice plantations. Much of the area's forest was cleared and wide, deep irrigation canals totaling over 4,000 km in length have resulted in extreme drainage and subsequent fire susceptibility. The MRP has burned regularly since 1997, particularly during the dry seasons in El Niño phases, and it now contains patchy forest remnants surrounded by degraded fire-prone peat swamp. Currently, tens of thousands of families live along the rivers that border the area.

Chapter One analyzes how human-driven and biophysical landscape changes influence fire occurrence probability. A Bayesian modeling approach is used to estimate the effects of climate, human access, vegetation, and hydrology on the probability of fire occurrence, defined as the probability of burning at a 1km^2 spatial resolution and a monthly temporal resolution, from 2000 to 2010. These factors are known to contribute to fire in Indonesia. In terms of *climate*, during El Niño conditions of the ENSO, there is increased likelihood of drought in Southeast Asia and, thus, a well-established coupling of fires in Indonesia with El Niño conditions (e.g., Deeming 1995, Kita, Fujiwara et al. 2000, Siegert, Ruecker et al. 2001, Page, Siegert et al. 2002, Wang, Field et al. 2004, Fuller and Murphy 2006, Wooster, Perry et al. 2012, Spessa, Field et al. 2015). El Niño conditions are also favorable for escaped fires from shifting cultivation (Field, van der Werf et al. 2009). Fire probability is associated with *vegetation* type (Murdiyarso, Widodo et al. 2002), as sufficient fuel loads must be present for a fire to occur. *Human access* can result in increased ignitions; most land is cleared in Indonesia through the use fire (Stolle, Chomitz et al. 2003), including on agro-industrial concessions and smallholdings. Peat-swamp *hydrology* adds additional complexity to fire dynamics in those systems. In their natural condition, peat-swamps are inundated at or near the soil surface during the wet season and at about 20-40cm below the surface during the dry season drawdown, and thus peat in its natural state is not typically a major available fuel load. However, canals can drain the peat and lower the water table, causing the peat to become aerated and susceptible to fire (Hooijer 2006, Turetsky, Benscoter et al. 2015). In addition to evaluating the relevant influence of these factors on fire probability, the potential for peatland restoration to offset the impacts of climate on fire occurrence is explored.

Chapter Two inspects the oft-asserted claim that escaped fires from oil palm concessions and smallholder farms near settlements are the primary sources of fire from 2000-2010. Before large-scale anthropogenic land use change, the most common cause of ignition in tropical forests was natural, primarily lightning strikes (Baker and Bunyavejchewin 2009). Now, far more fires in the tropics are started by people than by natural sources (Stott 2000, Baker and Bunyavejchewin 2009). Ignitions in Indonesia, as in many parts of the tropics, are primarily of anthropogenic origin (Bompard and Guizol 1999, Bowen, Bompard et al. 2000), resulting in either accidental or deliberate fires. Who is responsible for ignitions in Indonesia is highly contested, and reports of the ignition sources are many and varied (Dennis, Mayer et al. 2005, Page, Hoscilo et al. 2009).

Because fires set for land clearing can 'escape' beyond their intended boundaries, both large and small holders have been held responsible (e.g., Stolle, Chomitz et al. 2003, Page, Hoscilo et al. 2009), as is often the case in rainforest fires more generally (Goldammer 1991). In this chapter, fire detections from the MODIS Active Fire product are grouped together into individual fire events using a novel approach - a hierarchical clustering algorithm - to discern the origin of fires. Fire origin and spread are evaluated, in particular for the longest and hottest fires and for fires that burn forest, on the LULC classes of legal, industrial oil palm concessions, non-forest, and forest, as well as in relation to settlement proximity. Fires that escape from oil palm concessions and settlements into other surrounding LULC classes are also identified. Additionally, because the sphere of influence of oil palm concessions and settlements extends beyond the immediate boundaries of those land use classes, whether fire ignitions occur disproportionately in proximity to oil palm concessions and settlements is analyzed.

Chapter Three examines the potential for the financial incentive mechanism of Roundtable on Sustainable Palm Oil (RSPO) certification to reduce fire activity on oil palm concessions from 2012-2015 for oil palm concessions developed prior to 2012 on Sumatra and Kalimantan, the leading producers of oil palm both within Indonesia and globally. This question is particularly critical in fuel-rich peatland areas, of which approximately 46% was designated as oil palm concession as of 2010 (WRI 2014). Oil palm (*Elaeis guineensis*), a major global commodity that dominates the vegetable oils market and is used for biofuel, is one of the world's most rapidly expanding crops. It is grown exclusively in the humid tropics. Production of oil palm and planted area have increased over the past few decades, especially in Indonesia, which is currently the largest oil palm producer (FAO 2015). Fire is a common tool for land conversion and management associated with oil palm production. However, the RSPO prohibits the use of fire on certified concessions. This chapter therefore examines if RSPO-certified concessions have a lower density of fire detections, fire ignitions, or 'escaped' fires compared with those concessions that are not certified, and if this pattern changes with increasing likelihood of fires in concessions located on peatland and in dry years. In order to identify fire ignitions and escaped fires, MODIS Active Fire Detections are clustered into unique fire events using the hierarchical clustering algorithm developed in Chapter Two.

With the ensuing chapters, I am pleased to contribute new information concerning the rapidly changing fire disturbance regime in the globally important peat-swamp forests of Indonesia with the hope that it will be meaningful for the scientific community. By increasing understanding about fire processes in the region, my desire is that this dissertation, united with the existing relevant body of work, will increase our capacity to manage fire in the region and ultimately to contribute to the conservation of this landscape and reducing the negative impacts associated with these fires.

CHAPTER ONE: Peatland restoration can mitigate impacts of climate on fires in Central Kalimantan, Indonesia

Megan E. Cattau, Benedicte Bachelot, María Uriarte, Mark E. Harrison, Iwan Shinyo, Sady Tungau, and Ruth DeFries

ABSTRACT

Fires in fuel-rich tropical peatlands are a major source of carbon emissions, have serious consequences for air quality that affect human health, destroy and degrade habitat, threaten wildlife, and result in high economic costs. Indonesia has the largest area of tropical peat carbon globally and experiences annual fire events, which in severely dry years result in a regional haze crisis. Understanding the relative contributions of the biophysical and anthropogenic factors that drive fire would contribute to the success of efforts to reduce these fires and their associated impacts. Using a Bayesian modeling approach, this work addresses the following questions for a peat-swamp forest landscape in Central Kalimantan, Indonesia that covers a third of Kalimantan's peatland area: 1) What are the relative effects of climate, human access, vegetation, and hydrology on the probability of fire occurrence in the peat swamp forest?, and 2) What is the potential for peatland restoration to reduce fire probability? We find that climate (strength of ENSO) is the most important factor driving fire occurrence. However, two human-driven factors are nearly as important as climate: distance from large drainage canals, which were put in place in the study area as part of a failed agricultural project and have lowered the water table; and woody vegetation cover (MODIS Vegetation Continuous Fields), which has decreased over time. We examine five restoration scenarios, and find that restoration of vegetation results in a 28.0 (25.0 – 30.1)% reduction in fire probability over the entire study area for all years, partial and complete restoration of hydrology (i.e., if hydrology were restored to the hydrologic equivalent of pixels at the mean value (8.1 km) and the third quartile value (11.6 km) from the nearest canal) results in a 22.9 (20.7 – 24.5)% and 33.6 (30.7-35.7)% reduction in fire probability, respectively, and restoration of vegetation paired with partial and complete restoration of hydrology results in a 44.5 (40.7 – 47.1)% and 52.2 (48.3-54.8)% reduction in fire probability,

respectively. These results demonstrate that rehabilitation of the landscape through restoring hydrology (e.g., damming canals to raise the water table) and replanting can help offset the influence of climate on fires.

INTRODUCTION

Tropical peatlands are a major source of carbon emissions during fire events because these areas are rich in belowground organic carbon (e.g., Page, Siegert et al. 2002, Hooijer, Silvius et al. 2006, Page, Rieley et al. 2011). This issue is particularly marked in Indonesia, which has the largest area of tropical peat carbon globally (Rieley, Ahmad-Shah et al. 1996, Page, Rieley et al. 2011). Smog and particulate matter emissions from peat fires have serious consequences for human health (Kunii 1999, Kunii, Kanagawa et al. 2002, Marlier, DeFries et al. 2012, Wooster, Perry et al. 2012). These fires also destroy or degrade habitat for both terrestrial and marine species (Yule 2010, Posa, Wijedasa et al. 2011, Jaafar and Loh 2014). Furthermore, there are high economic costs associated with fire suppression efforts, lost timber and crop resources, missed workdays, and travel disruptions (Ruitenbeek 1999, Barber and Schweithelm 2000, Tacconi 2003). In order to combat these fires, Indonesian President Widodo has recently established a Peatland Restoration Agency, tasked with restoring ~2Mha of peatlands by 2020 in Sumatra, Kalimantan, and Papua (Indonesia 2016). The factors that influence the probability of peatland fires in Southeast Asia - and in the tropics more generally - are complex, as fire is affected by land use conversion and other anthropogenic activity on the landscape, which interact with climate and other biophysical factors, leading to large spatio-temporal variations in fire occurrence. There have been many calls for a better understanding of the relative contributions of the biophysical and anthropogenic factors that drive fire probability in this area (e.g., Eva and Lambin 2000), which would inform the identification of degraded areas where fire probability is most likely and thus where restoration efforts could have the most impact on fire reduction.

Simply, biomass fires can occur when there is sufficient heat applied to organic fuel with oxygen present: the traditional "fire triangle" concept (Countryman 1972, Pyne, Andrews et al. 1996), and human activity can interfere with fire controls at any scale - either directly (i.e., human ignitions) or indirectly (i.e., interacting with predisposing factors and sensitizing the landscape to those factors) (Bowman, Balch et al. 2011). Land management activities can result in increased ignitions and can thus affect to what extent ignitions limit fire on the landscape. Most land is cleared in Indonesia through the use of fire (Stolle, Chomitz et al. 2003), including on agro-industrial concessions and smallholdings. Ignitions are necessary for fire, but will not necessarily result in fire unless the conditions are suitable. For example, fire probability is associated with vegetation type in this system as sufficient fuel loads must be present for a fire to occur after an ignition (Murdiyarso, Widodo et al. 2002). Furthermore, as most plant communities are up to 60% water, moisture is a common fire control in the humid tropics (Stott 2000). The drying of fuel, which can occur in tandem with or independently of climate, can remove the control of moisture on fire because it can prepare fuel for ignition and spread. In peatlands, the peat soil itself, which is composed of partially decayed vegetation material, adds additional complexity to fire dynamics in those systems, because the belowground biomass can be a potential fuel load in addition to vegetation. In their natural condition, peat-swamps are inundated at or near the soil surface, and thus peat in its natural state is not typically a major available fuel load. However, during El Niño conditions of the ENSO cycle, there is increased likelihood of drought in Southeast Asia, affecting both aboveground and belowground biomass, and, thus, a well-established coupling of fires in Indonesia with drought and El Niño conditions (e.g., Deeming 1995, Kita, Fujiwara et al. 2000, Wang, Field et al. 2004, Fuller and Murphy 2006, Wooster, Perry et al. 2012, Spessa, Field et al. 2015). There is some evidence that large fires do not occur unless precipitation falls below a particular threshold (Goldammer 2007, Field, van der Werf et al. 2009), and that the length and intensity of the dry season strongly affects fire (van der Werf, Randerson et al. 2008).

Although degraded or regenerating areas are much more susceptible to fire than mature forest due to a variety of biophysical differences from mature forest, less-disturbed forests can still be affected in instances when ignition events coincide with extreme drought (Guhardja, Fatawi et al. 2000, Langner, Miettinen et al. 2007, Wooster, Perry et al. 2012). Also, canals, which are often put in place for agricultural development or log removal drain the peat and lower the water table. Each dry season, particularly during El Niño phases, the peat can become aerated and susceptible to fire (Hooijer 2006, Turetsky, Benscoter et al. 2015), particularly if the groundwater depth drops below a critical threshold of 40 cm (Usup, Hashimoto et al. 2004, Wösten, Clymans et al. 2008). People also often use these canals for transportation, resulting in elevated ignitions near these infrastructural elements.

Here, we investigate the relative contribution of the factors controlling fires to the probability of fire occurrence. This research aims to evaluate how human-driven and biophysical landscape changes affect fire occurrence in a coupled human and natural peatland system. We address the following questions:

1) What are the relative effects of climate, human access, vegetation, and hydrology on the probability of fire occurrence in the peat swamp forest?

2) What is the potential for peatland restoration to reduce fire probability?

The study investigates these issues in a lowland tropical peat-swamp forest landscape in Central Kalimantan, Indonesia, on the site of a failed agricultural project called the Mega Rice Project (MRP) (Fig. 1), which covers roughly 1.5 Mha of the total 6.8 Mha of lowland peatland in Kalimantan. Development of the former MRP was initiated in 1995 (Presidential Decree RI/82-26, 1995), but the project failed, as predicted by peat experts, and was abandoned by 1999. An extensive irrigation canal network totaling over 4,000 km in length was developed in the former MRP, which lowered the water table, leaving the area susceptible to fire and causing considerable environmental damage (e.g., Aldhous 2004, Page, Hoscilo et al. 2009). The MRP now contains patchy forest remnants surrounded by degraded fire-prone peatland (e.g., Cattau, Husson et al. 2014), as well as several legal oil palm concessions. In 2000, less than half of the original peat-swamp forest remained in the MRP (Boehm and Siegert 2001). It is estimated that the carbon store of the MRP and the Sabangau Forest was 2.82-5.40 Gt C before the most destructive fire season in 1997-98, and that emissions totaling 0.19-0.23 Gt C from the peat and 0.05 Gt C from aboveground biomass occurred in this area during this period (Page, Siegert et al. 2002). From 2000-2010, 19.1% of the MODIS fire hotspots that occurred in all of the peatlands in Indonesia come from the Mega Rice Project.

We use a Bayesian modeling approach to estimate fire occurrence, defined as the probability of burning at a spatial resolution of $1km^2$ and at a monthly temporal resolution in the dry season months in the study area from 2000-2010. We built a spatial database of predictor variables related to climate, vegetation, human access, hydrology, and fire history (detailed in Table S1 in *Supplemental Information*, including source information), fit a generalized linear model (See Equation (1) in *Methods*), and retained the model with the lowest Bayesian Information Criterion

(BIC) (See *Fire probability model* in *Methods*), which included those related to climate (Sea surface temperature anomalies (3-month running average)), hydrology (Euclidean distance from nearest canal and Euclidean distance from nearest river), interactions between hydrology and human access (Euclidean distance from nearest populated place: Euclidean distance from nearest canal and Cost distance from city through roads: Euclidean distance from nearest river), human access (Euclidean distance from nearest populated place and Cost distance from city through roads), and vegetation (Percent woody vegetation and Percent woody vegetation - quadratic term) detailed in Table 2 in *Methods* (all candidate variables detailed in Table S1 in *Supplemental Information*) (See *Fire probability model* in *Methods* for further justification of the independent variables). Fire history variables were not included in the Bayesian model because they did not contribute significantly. This model was then fitted in a Bayesian framework (See *Fire probability model* in *Methods*). We compared fire probability within and outside of oil palm concessions. We also examined how fire probability would change in each administrative block A-E if vegetation and hydrology were restored, excluding areas already in oil palm concession, by predicting fire occurrence probability conditioned on VCF ≥55 (the threshold equivalent to a liberal definition of forest in this area, including mature, degraded, and regenerating forest (Cattau, Harrison et al. 2016)) and conditioned on two thresholds of distance from the nearest drainage canal (i.e., if hydrology were restored to the hydrologic equivalent of pixels at the mean value (8.1 km) and the third quartile value (11.6 km) from the nearest canal).

RESULTS

Nearly half of the study area (40.9% at the 1km^2 spatial resolution) experienced fire during at least one month over the course of the study period. Mean fire probability for all time periods, or the probability of fire in any given pixel in any dry-season month is 0.025 (95% credible interval (CI): 0.009 - 0.061) (Fig. 2), 0.002 (0.001-0.005) in La Niña phases, and 0.042 (0.015-0.103) in El Niño phases. Mean fire probability within oil palm concessions is 0.035 (0.013-0.082) and outside of oil palm concessions is 0.023 (0.008-0.057).

Standardized regression coefficients for the model predicting the probability of fire occurrence (Fig. 3) indicate that climate (3-month running average of the NINO4 Index) is most strongly correlated with fire occurrence (1.24; 95% CI: 1.16-1.32), followed by distance from canals (-1.00; -1.18- -0.82) and percent woody vegetation (MODIS Vegetation Continuous Fields, VCF) (-0.77; -0.87- -0.67). When conditionally predicting fire probability on VCF with climate at mean El Niño and La Niña values and all other variables at their mean value, fire probability as a function of percent woody vegetation follows a generally hump-shaped relationship with a positive skew in El Niño conditions, and is relatively flat in La Niña conditions (Fig. 4a). Fire probability is highest at 24 percent woody vegetation. Similarly, when conditionally predicting fire probability on distance from drainage canals with climate at mean El Niño and La Niña values and all other variables at their mean value, fire probability decreases exponentially with increasing distance from canals in El Niño conditions, and is relatively flat in La Niña conditions (Fig. 4b).

The restoration scenarios examined – restoration of vegetation, partial restoration of hydrology, complete restoration of hydrology, restoration of vegetation with partial restoration of hydrology, and restoration of vegetation with complete restoration of hydrology - result in a reduction of fire probability by 28.0 - 52.2% across the MRP, depending on the scenario (6.7- 60.3% when we examine each administrative block A-E separately) (Table 1). Restoration of vegetation, or predicted fire occurrence probability conditioned on VCF ≥55 (the threshold equivalent to a liberal definition of forest in this area, including mature, degraded, and regenerating forest (Cattau, Harrison et al. 2016)) and all other variables at their mean results in a 28.0 (25.0 – 30.1)% reduction in fire probability. Predicted fire occurrence probability conditioned on values greater than two thresholds of distance from drainage canals (i.e., if hydrology were restored to the hydrologic equivalent of pixels at the mean value (8.1 km) and the third quartile value (11.6 km) from canals) results in a 22.9 (20.7 – 24.5)% and 33.6 (30.7-35.7)% reduction in fire probability, respectively. Predicted fire occurrence probability conditioned on VCF ≥55 combined with each of the hydrologic thresholds results in a 44.5 (40.7 – 47.1)% and 52.2 (48.3-54.8)% reduction in fire probability. Across all restoration scenarios, Blocks A-D have a considerably higher reduction in fire probability relative to Block E, which was the least impacted area with the development of the MRP (i.e., not cleared outright and had fewer large canals dug). The percent reduction of fire probability as a result of the various restoration scenarios is comparable in El Niño phases, La Niña phases, and when all dates are included (Table S3 in *Supplemental Information*).

DISCUSSION AND CONCLUSION

Our results that a great potential for hydrological rehabilitation coupled with planting to reduce fire and thus offset effects of climate on fire occurrence in the area. Global climate is not amenable to management at the national or provincial level, while restoring hydrology of peat swamps and replanting are management strategies that could feasibly be implemented, such as through the Indonesian government's newly established Peatland Restoration Agency. In our restoration scenarios, we find that restoring both vegetation and hydrology together result in greater reductions in fire probability than restoring either alone. The magnitude of the standardized regression coefficient related to vegetation is greater than that for hydrology, but the confidence intervals overlap, suggesting that both hydrological restoration and replanting can make a similarly significant contribution to fire occurrence. Furthermore, restoring both in tandem is essential for maximum fire reduction, as the hydrology and vegetation in peat domes are strongly linked (Page, Rieley et al. 1999, Page, Hoscilo et al. 2009).

By evaluating the relative contribution of biophysical and anthropogenic factors on fire probability, this research contributes to the body of work on fire forecasting (e.g., Deeming 1995, Spessa, Field et al. 2015). We find that climate, coupled with human alteration of hydrology and changes in vegetation, alter fire probability on the peat-swamp landscape. Fire probability is positively correlated with atmospheric (and subsequently therefore peat) dryness and negatively correlated with distance from drainage canals and amount of woody vegetation. Climate is the most important factor driving fire probability, which interacts with land cover change. These results are consistent with findings in previous studies in both Indonesia (e.g., Kita, Fujiwara et al. 2000, Wang, Field et al. 2004, Fuller and Murphy 2006, Wooster, Perry et al. 2012) and many other parts of the tropics (e.g., Cochrane and Laurance 2008, Gutierrez-Velez, Uriarte et al. 2014). In this area, we find that the influence of canals and vegetation are almost as strong as the influence of climate.

Hydrological perturbation from the development of canals has a large effect on fire probability. The canals were put in place as part of a failed agricultural project and have lowered the water table. The relationships between fire probability and the distance from canals follows a negative exponential relationship. Although it is likely that ignitions are elevated along canals because people use these infrastructural elements as a means of transport, the interaction between distance from canals and distance from settlements, although significant, contributes relatively little to predicting fire probability. This result suggests that the main way in which canals contribute to fire probability is through the hydrological alteration itself rather than through increased access and thus increased ignitions.

The amount of woody vegetation, which has decreased over time, also has a large effect on fire probability. The relationships between fire probability and the amount of woody vegetation follows a generally hump-shaped relationship with a positive skew, with fire probability higher in the lower range of amount of vegetation than in the higher range. This relationship is further supported by the significant contribution of the quadratic term related to the amount of woody vegetation to the fire probability model. Fire probability is highest around 20% vegetation, as (moving from low vegetation to higher) regrowth post-disturbance accumulates biomass that is a potential fuel load and (moving from high vegetation to lower) as forest types transition from a fire break to a fuel load as biomass dies and degrades. Degraded and regenerating areas are often more susceptible to fire during drought due to a variety of biophysical differences from mature forest - for example, lower humidity, higher temperatures, greater wind speeds, higher fuel loads of dead wood and drier fuel. Additionally, independent of woody vegetation, non-woody vegetation types (e.g., invasive ferns associated with post-disturbance regrowth) and the peat substrate itself can serve as fuel loads. These results support previous research highlighting the interactions between deforestation and fire in Indonesia (van der Werf, Dempewolf et al. 2008, Spessa, Field et al. 2015). Because MODIS can miss fires under dense canopy, we likely underestimate fire probability in areas of high percent woody vegetation. However, we do not expect this to affect the overall trend, as fire probability continually decreases from ~25% woody vegetation, where fire detection rates would not be affected by canopy closure.

Increasing woody vegetation, including on tree plantations or oil palm concessions, could reduce fire occurrence relative to degraded land. However, any reduction in fire as a result of increased woody vegetation from maturing oil palm may be offset by the hydrological alteration that usually accompanies concession development or by fire ignitions that are often used to clear land prior to the initial planting, replanting after a complete crop cycle, or for maintenance. We find that, in this area, fire probability is approximately one and a half times higher inside oil palm concession boundaries as it is outside. Furthermore, ignition density in oil palm is on par with that in degraded areas, both of which are substantially higher than in forests (Cattau, Harrison et al. 2016).

We acknowledge several simplifications that we have made in our study that merit further research. First, we capture patterns of human activity on the landscape by evaluating the distance from populated places, the interaction between the distance from populated places and canals, the cost distance from major cities through roads, and the interaction between the cost distance from major cities through roads and rivers. Based on our extensive time in the area, we consider these reasonable proxies for patterns of movement on this landscape; however, spatially explicit information would improve the analysis and could perhaps increase the extent to which human access could predict fire probability on the landscape. Furthermore, social surveys examining local land management decisions related to fire surrounding individual population centers would be a strong complement to this study. Second, we use Euclidean distance from large canals as a proxy for hydrological disturbance. Hydrological disturbances in one part of a peat dome can have consequences for the entire dome (Page, Rieley et al. 1999), and thus the hydrology is likely to be altered even at great distances from the canals. Using distance from canals as a proxy for hydrological conditions is sufficient to demonstrate that the canals have a large effect on fire occurrence, but our estimates of fire reduction as a result of hydrological restoration are thus likely conservative. The complex effect that drainage canals have on the hydrology of the peat swamp could be more finely captured with detailed hydrological models (e.g., Wösten, Clymans et al. 2008, Ishii, Koizumi et al. 2016), including those that incorporate the feedbacks between hydrology and vegetation. Furthermore, we likely do not capture all of the canals in the study area, and thus likely further underestimate the effect of canals. Finally, we sufficiently demonstrate the large effect that vegetation has on fire occurrence using percent woody vegetation. However, biomass (e.g., captured with LiDAR and ground surveys) paired with percent moisture content could better represent potential fuel loads, and detailed information about species or trait composition of the vegetation could add further nuance to this pattern. Furthermore, we capture the spatial variability of woody vegetation across the landscape and the temporal changes at the annual timescale, but spatial information that explicitly captures the vegetation of proximate areas (e.g., average percent vegetation of neighboring pixels within a certain radius) and more finely resolved temporal data could yield additional information about fire spread across the landscape and intra-annual patterns of fire activity, respectively.

In late 2015, Indonesia experienced an unusually severe fire season, resulting in a global environmental disaster. Fires burn in Indonesia nearly every dry season, but the 2015 dry season fires were the most severe since 1997, resulting in emissions of 380 Tg C, or about 1.5 billion metric ton of CO_2 equivalents (Field, van der Werf et al. 2016). It is estimated that the 2015 fire crisis cost Indonesia US$16.1 billion (World Bank 2015), and smog from these fires affected people not just in Indonesia itself, but also across much of equatorial Asia (Koplitz, Mickley et al. 2016). Reducing fire occurrence through hydrological restoration paired with planting and supported by fire fighting could in turn contribute to mitigating climate change and improving air quality through reducing fire-related emissions. Given the severe consequences of peatland fires, targeting areas of high fire probability for restoration would be of great benefit to both local and international communities. The approach taken by this paper could be applied to other degraded peatland areas in Indonesia that are candidate sites for restoration, especially in Sumatra, Papua, and other parts of Kalimantan, and to degraded peatlands that experience a novel fire regime in other parts of the tropics.

METHODS

Fire Data

We obtain fire detections at the 1 kilometre^2 resolution from the Moderate Resolution Imaging Spectroradiometer (MODIS, 1 kilometre^2 resolution) Active Fire Product (Giglio, Descloitres et al. 2003) processed and quality checked by the University of Maryland (MCD14ML) and downloaded from the FIRMS MODIS Archive Download tool: https://firms.modaps.eosdis.nasa.gov/download/. This product includes, for each fire detected by either the Terra or Aqua MODIS sensor, among other information, the location of the centroid for the 1km^2 pixel in which the fire was detected and the date and time of detection. MODIS hotspots are considered the most accurate and complete among alternative methods for detecting fires (Langner and Siegert 2009). The fire detections were used to create burned-unburned binary rasters at the 1km^2 spatial resolution and a monthly temporal resolution from 2000-2010. Because fire activity peaks in the dry season, with 98% of fires detected between July and November (Fig. 5), we restrict the remainder of the analysis to dry season fires.

Correlations between the number of MODIS hotspots and the area burned on the ground is reasonably high in peatlands (R2 = 0.75 in Tansey, Beston et al. 2008). Although MODIS can miss fires that spread quickly or that are extremely short-burning because the sensor passes only one or twice a day, fires in peat are generally characterized by smoldering combustion, for which the rate of spread is quite slow (Rollins, Cohen et al. 1993, Wan Ahmad 2001, Rein 2013, Turetsky, Benscoter et al. 2015). MODIS can also miss ground fires under dense canopy or belowground fires if the fires do not produce sufficient heat (Ballhorn, Siegert et al. 2009, Langner and Siegert 2009), thus we may underestimate the number of fires in forest, or peat fires that smolder underground before resurfacing. MODIS can also miss fires that are masked by the smoke itself. In Kalimantan and Sumatra, the omission rate for MODIS active fire detections has been estimated from 34-60%, depending upon the LULC class (Liew, C. et al. 2003, Miettinen, Andreas et al. 2007, Tansey, Beston et al. 2008).

Fire probability model

We built a spatial database of predictor variables related to climate, vegetation, human access, hydrology, and fire history (all variables detailed in Table S1 in *Supplemental Information*, including source information), and fit a generalized linear model (logistic regression), assuming a binomial error, of the general form:

$$\log (p_{it} / 1\text{-}p_{it}) = \alpha C_{it} + \beta A_{it} + \gamma V_{it} + \delta H_{it} + \varepsilon F \qquad (1)$$

where p_{it} is the probability of fire occurrence in pixel *i* at time *t*, C_{it}, A_{it}, V_{it}, H_{it}, F_{it}, are covariates related to climate, human access, vegetation, hydrology, and fire history, respectively, at pixel *i* at time *t* (all variables detailed in Table S1 in *Supplemental Information*). A generalized linear model was chosen because it allows for non-normal distribution of the response variable. We fit several different models using various combinations of uncorrelated covariates and interactions, and retained the model with the lowest Bayesian Information Criterion (BIC). The final model included variables related to climate, hydrology, interactions between hydrology and human access, human access, and vegetation (detailed in Table 2). The climate variable, 3-month running average of sea surface temperature (SST) anomalies (NINO 4 Index), is related to ENSO and thus precipitation and temperature (and therefore peat dryness). Changes in SST can result in changes in convection and atmospheric circulation. Although SST anomalies in the Niño 3.4 region are often used, we use SST anomalies in the Niño 4 region because the SST anomaly required to meet the SST threshold for the development and persistence of deep convection is consistent throughout the year in this region, as opposed to the Niño 3.4 region, where the SST anomaly required to reach this threshold can vary throughout the year. The variables related to hydrology, Euclidean distance from nearest canal and Euclidean distance from nearest river, are proxies for water table depth; areas near rivers are often flooded, and ground surface levels decline toward drainage canals (Isbell, Calcagno et al. 2011). The human access variables

(Euclidean distance from nearest populated place and Cost distance from city through roads) are related to ignition sources, and interactions between hydrology and human access (Euclidean distance from nearest populated place: Euclidean distance from nearest canal and cost distance from city through roads: Euclidean distance from nearest river) are included because canals and rivers are used as transportation routes. Percent woody vegetation (MODIS Vegetation Continuous Fields (VCF)) is used to represent available potential fuel loads, and the quadratic term is included to determine if fire probability responds non-linearly to available biomass. The VCF product is currently available for 2000-2010, and so the analysis is constrained to this temporal window in order to capture a consistent measure of woody plant material. The variance inflation factor was under 2 for each variable included in the final model (Table S2 in *Supplemental Information)*. Fire history variables were not included in the Bayesian model because they did not contribute significantly.

This model was then fitted using a Bayesian framework with two intercepts indicating if the pixel is outside (μ_0) or within (μ_1) the boundaries of an oil palm concession and with a pixel random effect (γ_p):

$$Fire_{it} \sim dbern(p_{it}) \qquad (2)$$

$$p_{it} = invlogistic\ (\mu+\beta_1 * C_{it}+\beta_2 * H1_{it}+\beta_3 * H2_{it}+\beta_4 * HA1_{it} +\beta_5 * HA2_{it} +\beta_6 * A1_{it}+\beta_7 * A2_{it}+\beta_8 * V1_{it}+\beta_9 * V2_{it} +\gamma_p)$$

The covariates were z-transformed across all individuals prior to analyses to allow for comparison of their effect size (Gelman et al. 2013). Analyses were performed using R (http://www.r-project.org) and STAN statistical software (http://mc-stan.org/rstan.htlm). We used non-informative priors for each variable, and we ran two MCMC chains with 2,000 iterations. Significance of each parameter was assessed by non-overlap of the 95% credible intervals with 0. A credible interval, analogous to a confidence interval in frequentist statistics but treating the bounds as fixed and the parameter estimate as random because a Bayesian parameter estimate itself has a distribution of possible values, indicates the upper and lower bounds that the parameter has a given probability of lying between. We assessed convergence of the model using Brook and Gelman (2007). Goodness of fit was evaluated using Bayesian p values of the average (Bayesian p = 0.48) and standard deviation (Bayesian p = 0.49) fire occurrence (Fig. S1 in *Supplemental Information*) (Gelman et al. 2013) and posterior predictive checks, and r2 is estimated at 0.44 (CI: 0.22-0.66). To test how well the model captures spatial structure,

we split the dataset randomly and performed 1,000 bootstrapped mantel tests on 500 averaged fire occurrence per pixel locations between spatial and residual distance, each on with 100 repetitions. To correct for multiple tests, we use a False Discovery Rate and obtain an average p value =0.85, indicating there is no residual structure.

To evaluate the relationship between vegetation and fire probability and between hydrology and fire probability, the two most important variables after climate, we predicted fire occurrence for each of those variables (VCF and distance from large canals) with all other variables set at their mean values. We also predicted fire occurrence for VCF and for distance from large canals with climate set at the mean value for an El Niño phase (3-month running average of SST anomalies in the Niño 4 region above the threshold of +0.5°C) and again with climate set at the mean value for a La Nina phase (below the threshold of -0.5°C), with all other variables at their mean values (Fig. 4).

Finally, to examine how fire probability would change in each administrative block A-E with restoration, excluding areas already in oil palm concession, we predicted fire occurrence probability conditioned on VCF ≥55 (the threshold equivalent to a liberal definition of forest in this area, including mature, degraded, and regenerating forest (Cattau, Harrison et al. 2016)) and conditioned on two thresholds of distance from the nearest drainage canal (i.e., if hydrology were restored to the hydrologic equivalent of pixels at the mean value (8.1 km) and the third quartile value (11.6 km) from the nearest canal). The model was run 1) just restoring vegetation, 2) restoring hydrology to the lower threshold, 3) restoring hydrology to the upper threshold, 4) restoring vegetation and restoring hydrology to the lower threshold, and 5) restoring vegetation and restoring hydrology to the upper threshold (Table 1). We evaluate these estimates during El Niño phases and during La Niña phases (Table S3 in *Supplemental Information*).

TABLES AND FIGURES

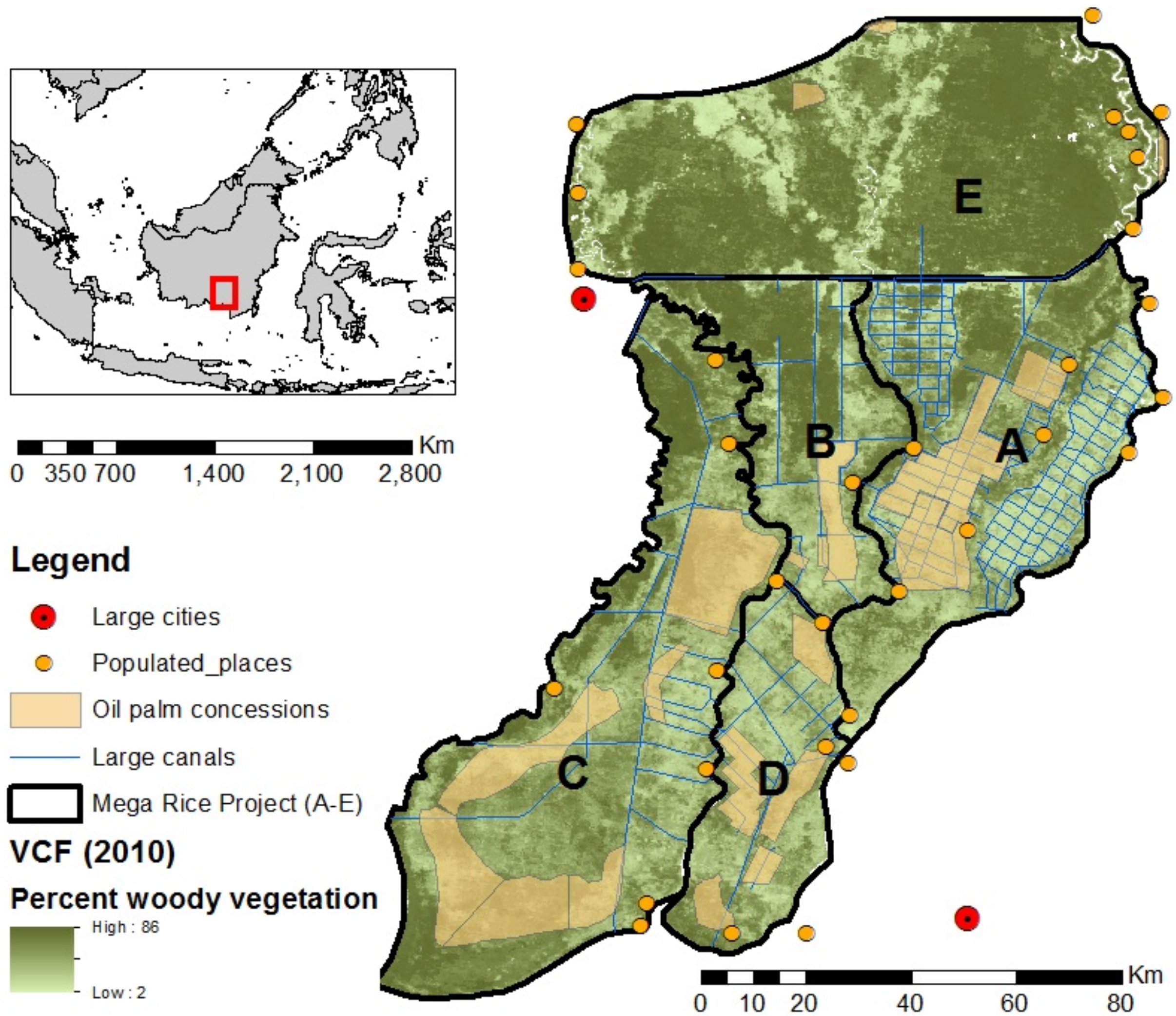


Fig. 1. The study area: a failed agricultural project called the Mega Rice Project, a lowland peat-swamp forest area in Central Kalimantan, Indonesia. Inset: Location within Indonesia.

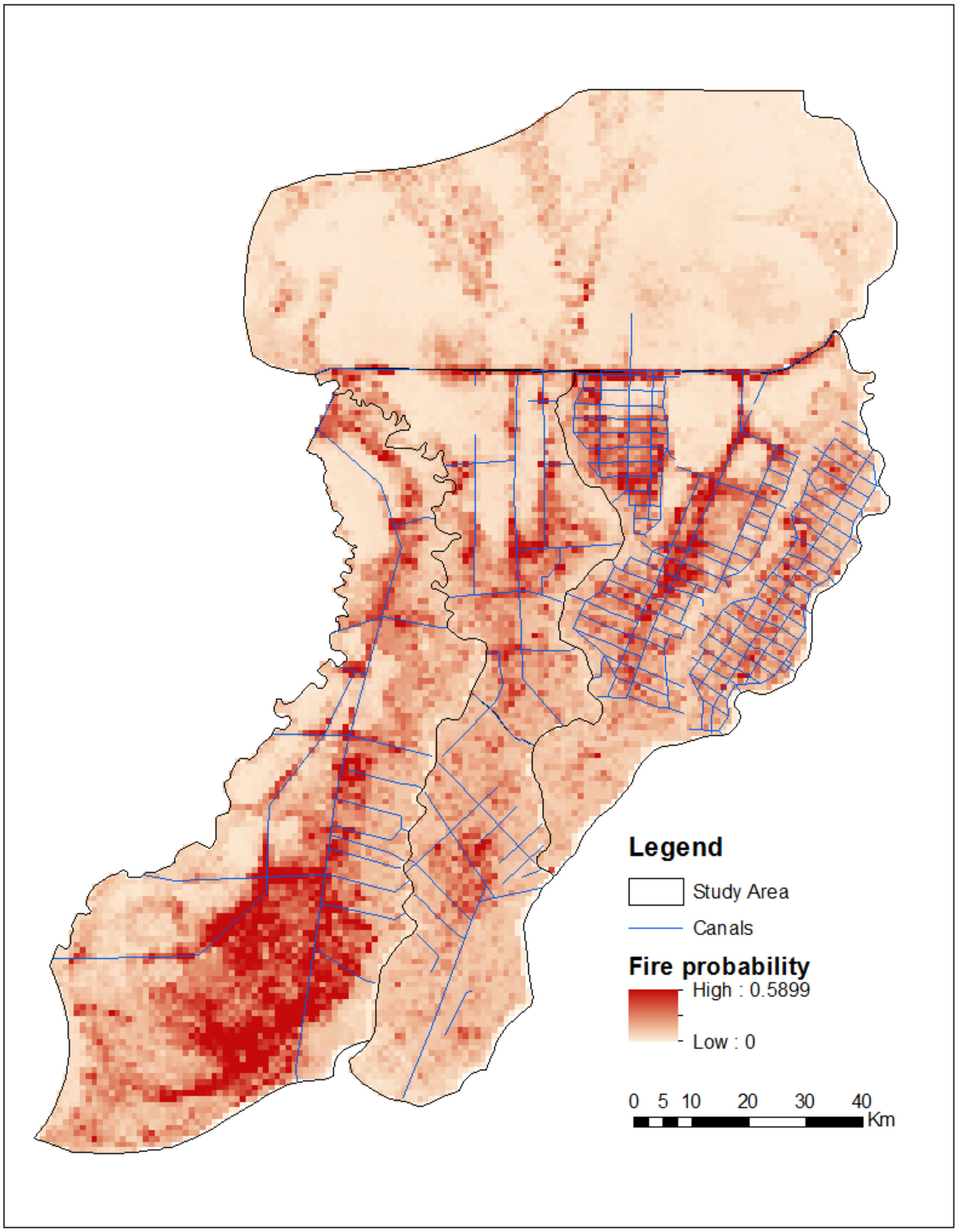


Fig. 2. Map of posterior mean fire occurrence probability at the pixel level.

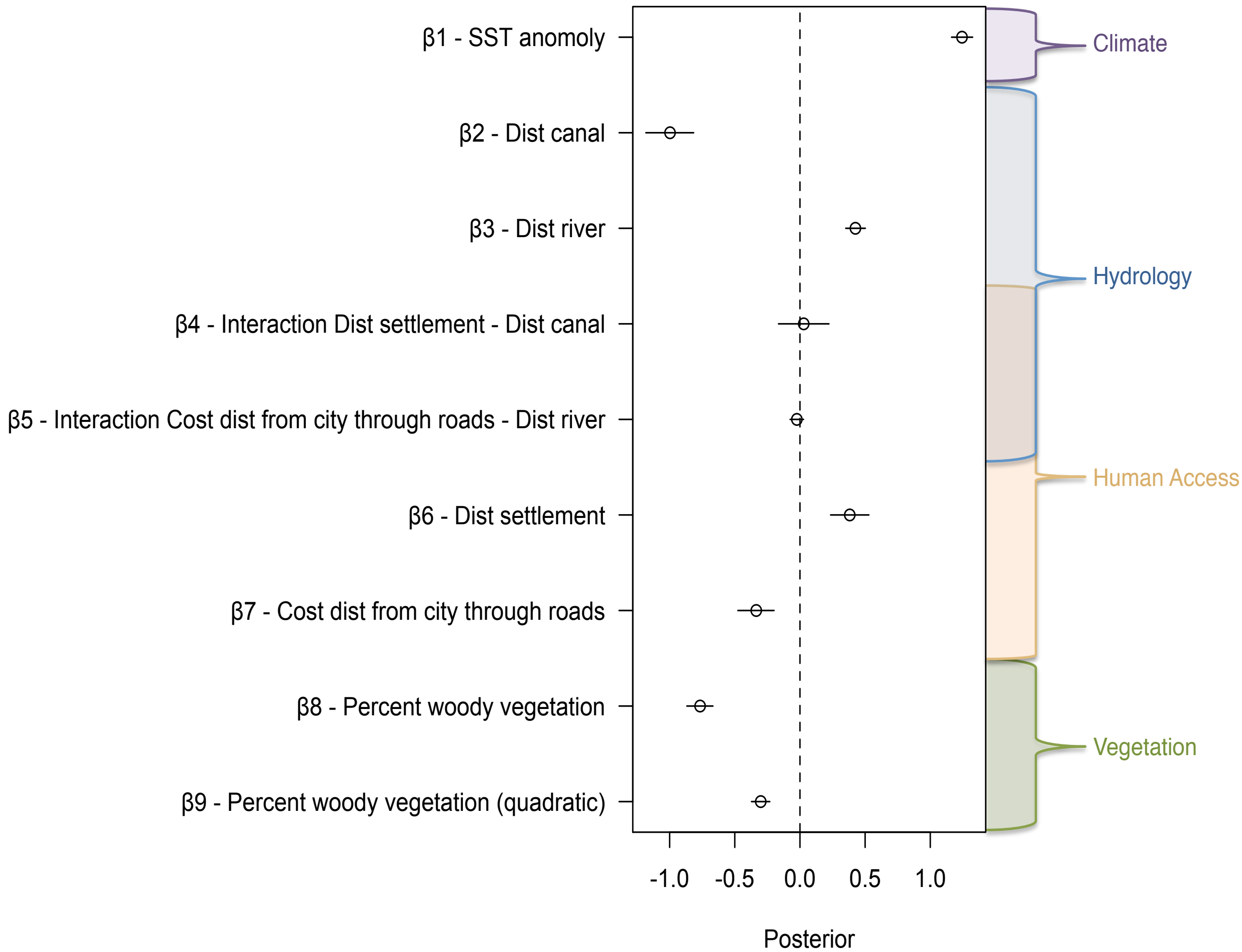
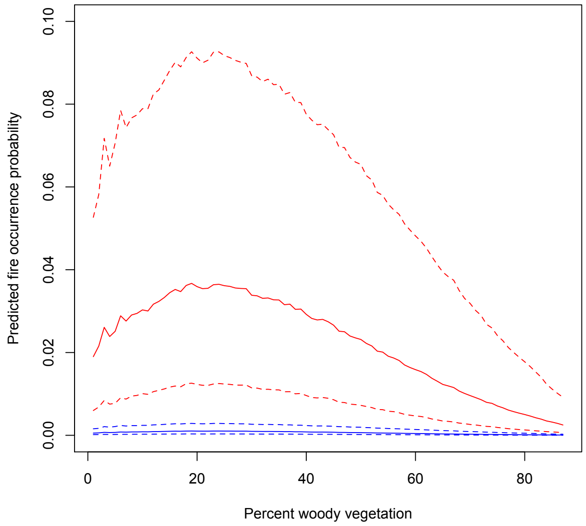


Fig. 3. Standardized regression coefficient estimates for the model predicting the probability of fire occurrence in the Sabangau catchment in Central Kalimantan, Indonesia.



a.

b.

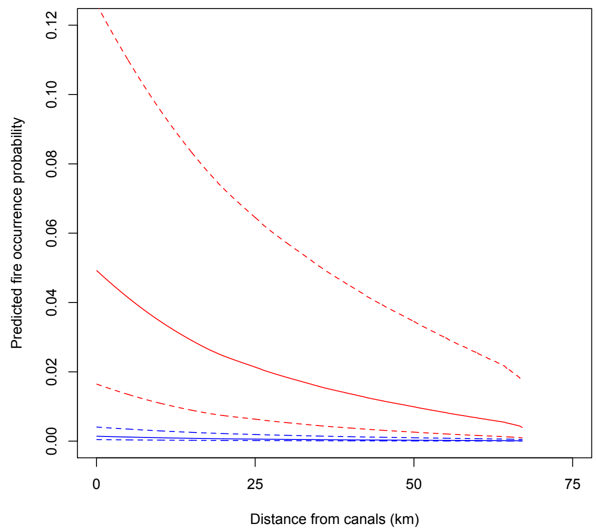


Fig. 4. Predictions for probability of fire in any pixel in any dry season month as a function of (a) percent woody vegetation and (b) distance from drainage canals (binned at 50m), with climate at mean El Niño and La Niña values and all other variables at their mean value. Mean predicted probability is shown with a solid line and the 95% credible interval with a dotted line, El Niño values in red and La Niña values in blue. Fire probability as a function of percent woody vegetation follows a hump-shaped relationship with a positive skew in El Niño phases. Fire probability decreases exponentially with increasing distance from canals in El Niño phases.

Table 1. Predicted mean fire occurrence probability under different restoration scenarios for each administrative Block in the former Mega Rice project area, excluding oil palm concessions. Numbers in parenthesis are 95% confidence interval.

	Restoration effort	No restoration	Restoration of vegetation	Restoration of hydrology (lower threshold)	Complete restoration of hydrology (upper threshold)	Restoration of vegetation with restoration of hydrology (lower threshold)	Restoration of vegetation with complete restoration of hydrology (upper threshold)
	Detail	No restoration	All pixels restored to VCF ≥ 55	All pixels restored to hydrologic equivalent of pixels at the mean value (8.1 km) from canals	All pixels restored to hydrologic equivalent of pixels at the third quartile value (11.6 km) from canals	All pixels restored to VCF ≥ 55 and ≥ 8.1 km from canals	All pixels restored to VCF ≥ 55 and ≥ 11.6 km from canals
Block A	Prediction for mean probability of fire	0.027 (0.009 – 0.068)	0.019 (0.006 – 0.049)	0.019 (0.006 – 0.049)	0.016 (0.005-0.041)	0.013 (0.004-0.035)	0.011 (0.004-0.029)
	Percent reduction	NA	30.5 (28.0 – 32.1)	30.2 (28.1 – 31.7)	42.0 (39.5 – 43.6)	51.8 (48.8 – 53.6)	60.0 (57.2 – 61.7)
Block B	Prediction for mean probability of fire	0.027 (0.010 – 0.067)	0.020 (0.007 – 0.052)	0.020 (0.007 – 0.049)	0.016 (0.006-0.042)	0.014 (0.005-0.038)	0.012 (0.004-0.031)
	Percent reduction	NA	26.3 (23.2 – 28.4)	28.8 (26.6 – 30.2)	40.9 (38.3 – 42.5)	47.8 (44.3 – 50.1)	56.8 (53.5 – 59.0)
Block C	Prediction for mean probability of fire	0.036 (0.013 – 0.082)	0.025 (0.009 – 0.060)	0.028 (0.010 – 0.066)	0.024 (0.009-0.057)	0.020 (0.007-0.048)	0.017 (0.006-0.041)
	Percent reduction	NA	30.0 (27.1 – 32.1)	21.2 (19.3 – 22.7)	32.3 (29.8-34.2)	45.1 (41.7 – 47.5)	53.0 (49.6 – 55.4)
Block D	Prediction for mean probability of fire	0.023 (0.007 – 0.060)	0.015 (0.005 – 0.041)	0.016 (0.005 – 0.045)	0.014 (0.004-0.037)	0.011 (0.003-0.030)	0.009 (0.003-0.025)
	Percent reduction	NA	33.7 (31.8 – 34.7)	27.3 (25.8 – 28.4)	39.8 (37.8 – 41.1)	52.0 (49.7 – 53.3)	60.3 (58.1 – 61.6)
Block E	Prediction for mean probability of fire	0.009 (0.003 – 0.029)	0.008 (0.002 – 0.024)	0.009 (0.002 – 0.027)	0.008 (0.002-0.026)	0.007 (0.002-0.023)	0.007 (0.002-0.022)
	Percent reduction	NA	16.6 (14.8 – 17.8)	6.7 (6.1 – 7.2)	12.1 (11 - 12.8)	22.5 (20.1 – 24.2)	27.3 (24.6 – 29.1)

Entire MRP	Prediction for mean probability of fire	0.023 (0.008 – 0.057)	0.016 (0.006 – 0.043)	0.018 (0.006-0.045)	0.015 (0.005-0.040)	0.013 (0.004-0.034)	0.011 (0.004-0.030)
	Percent reduction	NA	28.0 (25.0 – 30.1)	22.9 (20.7 – 24.5)	33.6 (30.7-35.7)	44.5 (40.7-47.1)	52.2 (48.3 – 54.8)

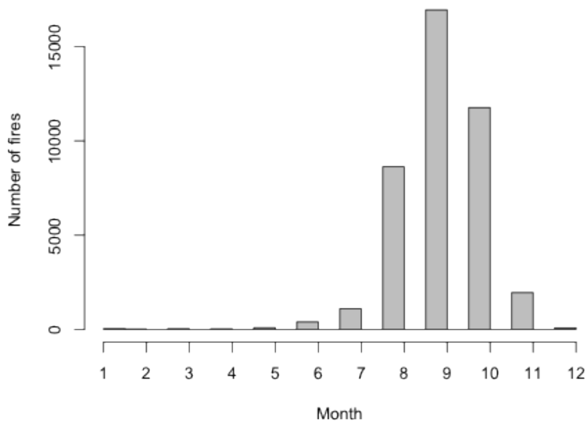
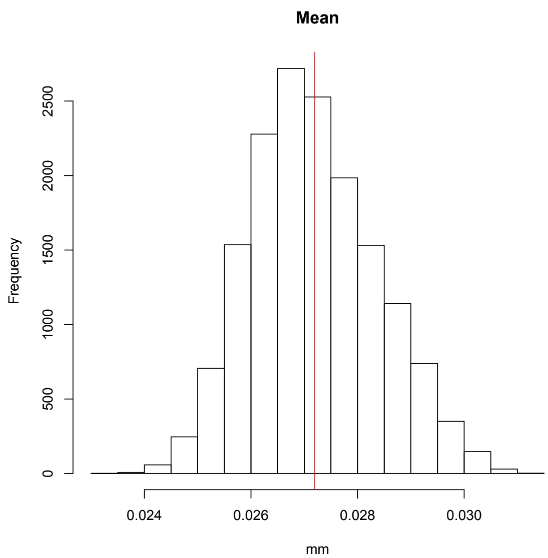


Fig. 5. Total number of MODIS fire detections 2000-2010 per month in the study area. The majority of fires (98%) take place in dry season months July - Nov.

Table 2. Variables included in final Bayesian model

Parameter	Variable abbreviation	Predictor Variables	Resolution (Temporal and spatial)	Category
β_1	C	Sea surface temperature anomalies (3-month running average)	monthly, entire area	Climate
β_2	H1	Euclidean distance from nearest canal	entire study period, $1km^2$	Hydrology
β_3	H2	Euclidean distance from nearest river	entire study period, $1km^2$	Hydrology
β_4	HA1	Interaction: Euclidean distance from nearest populated place and Euclidean distance from nearest canal	entire study period, $1km^2$	Human Access / Hydrology
β_5	HA2	Interaction: Cost distance from city through roads and Euclidean distance from nearest river	entire study period, $1km^2$	Human Access / Hydrology
β_6	A1	Euclidean distance from nearest populated place	entire study period, $1km^2$	Human Access
β_7	A2	Cost distance from city through roads	entire study period, $1km^2$	Human Access
β_8	V1	Percent woody vegetation	yearly, $1km^2$	Vegetation
β_9	V2	Percent woody vegetation - quadratic term	yearly, $1km^2$	Vegetation

SUPPLEMENTAL INFORMATION



a. **b.**

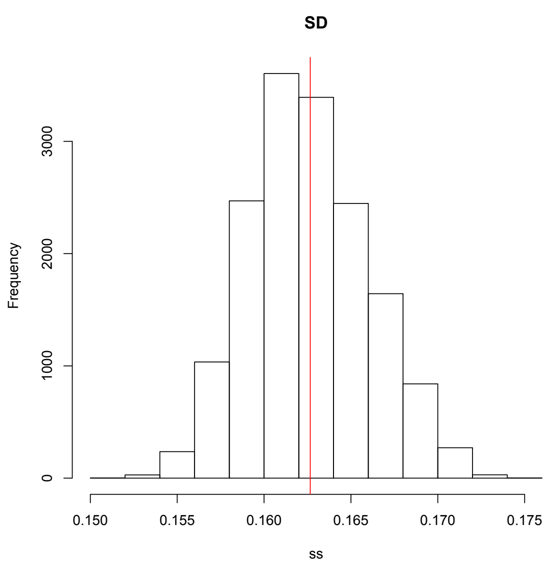


Fig. S1. Distribution of the a. average predicted presence of fire with a red line indicating the observed average, Bayesian p = 0.48, and b. standard deviation for predicted presence of fire with a red line indicating the observed standard deviation, Bayesian p = 0.49.

Table S1. Variables used in the prospective models to predict fire occurrence.

Predictor Variables	Source / Derived from	Resolution (Temporal and spatial)	Category
Sea surface temperature anomalies (3-month running average)	NINO4 Index from HadISST1, NOAA	monthly, entire area	Climate
Euclidean distance from nearest river	(Minnemeyer, Boisrobert et al. 2009)	entire study period, $1km^2$	Hydrology
Euclidean distance from nearest canal	Agata Hoscillo (Pers. comm)	entire study period, $1km^2$	Hydrology
Density of canals	Agata Hoscillo (Pers. comm)	entire study period, $1km^2$	Hydrology
Euclidean distance from nearest road	(Minnemeyer, Boisrobert et al. 2009)	entire study period, $1km^2$	Human Access
Density of roads	(Minnemeyer, Boisrobert et al. 2009)	entire study period, $1km^2$	Human Access
Euclidean distance from nearest city	Simon Husson (Pers. comm)	entire study period, $1km^2$	Human Access
Cost distance from any city through roads	Simon Husson (Pers. comm) and (Minnemeyer, Boisrobert et al. 2009)	entire study period, $1km^2$	Human Access
Euclidean distance from nearest populated place	Simon Husson (Pers. comm)	entire study period, $1km^2$	Human Access
Percent woody vegetation	Vegetation Continuous Field (VCF) Collection 5 (Townshend, Carroll et al. 2011)	Annual, $1km^2$	Vegetation
Euclidean distance from mature forest	Vegetation Continuous Field (VCF) Collection 5 (Townshend, Carroll et al. 2011)	Annual, $1km^2$	Vegetation
Age of woody forest	Vegetation Continuous Field (VCF) Collection 5 (Townshend, Carroll et al. 2011)	Annual, $1km^2$	Vegetation
Time since last fire	MODIS	Annual, $1km^2$	Fire History
Burn intensity of most recent burn: Fire radiative power (FRP)	MODIS	Annual, $1km^2$	Fire History
Burned in previous year (binary)	MODIS	Annual, $1km^2$	Fire History

Table S2. Variance inflation factor for each variable included in the final model.

Variable	VIF
Sea surface temperature anomalies (3-month running average)	1.01
Euclidean distance from nearest canal	1.44
Euclidean distance from nearest river	1.88
Euclidean distance from nearest populated place	1.53
Cost distance from city through roads	1.98
Percent woody vegetation	1.65

Table S3. Predicted mean fire occurrence probability under different restoration scenarios for each administrative Block in the former Mega Rice project area, excluding oil palm concessions for El Niño and La Niña phases. Numbers in parenthesis are 95% confidence interval.

		Restoration effort	No restoration	Restoration of vegetation	Restoration of hydrology (lower threshold)	Complete restoration of hydrology (upper threshold)	Restoration of vegetation with restoration of hydrology (lower threshold)	Restoration of vegetation with complete restoration of hydrology (upper threshold)
	ENSO Phase	Detail	No restoration	All pixels restored to VCF ≥ 55	All pixels restored to hydrologic equivalent of pixels at the mean value (8.1 km) from canals	All pixels restored to hydrologic equivalent of pixels at the third quartile value (11.6 km) from canals	All pixels restored to VCF ≥ 55 and ≥ 8.1 km from canals	All pixels restored to VCF ≥ 55 and ≥ 11.6 km from canals
Block A	El Niño	Prediction for mean probability of fire	0.047 (0.016 – 0.115)	0.033 (0.011 – 0.084)	0.033 (0.011 – 0.084)	0.027 (0.009 – 0.071)	0.023 (0.008 – 0.060)	0.019 (0.006 – 0.050)
		Percent reduction	NA	30.4 (27.6-32.1)	29.9 (27.5-31.5)	41.7 (38.9-43.5)	51.5 (48.2-53.5)	59.8 (56.6-61.7)
	La Niña	Prediction for mean probability of fire	0.002 (0.001 – 0.006)	0.001 (0.000 – 0.004)	0.001 (0.000 – 0.004)	0.001 (0.000 – 0.003)	0.001 (0.000 – 0.003)	0.001 (0.000 – 0.002)
		Percent reduction	NA	31.2 (30.5-31.7)	31.9 (31.4-32.5)	43.9 (43.3-44.5)	53.1 (52.2-53.8)	61.4 (60.6-62.0)
Block B	El Niño	Prediction for mean probability of fire	0.047 (0.017 – 0.114)	0.035 (0.012 – 0.088)	0.034 (0.012 – 0.084)	0.028 (0.010 – 0.071)	0.025 (0.008 – 0.064)	0.020 (0.007 – 0.054)
		Percent reduction	NA	26.2 (22.9-28.4)	28.5 (26.0-30.1)	40.6 (37.3-42.3)	47.5 (43.7-50.0)	56.6 (52.9-58.9)
	La Niña	Prediction for mean probability of fire	0.002 (0.001 – 0.005)	0.001 (0.000 – 0.004)	0.001 (0.000 – 0.004)	0.001 (0.000 – 0.003)	0.001 (0.000 – 0.003)	0.001 (0.000 – 0.002)
		Percent reduction	NA	26.8 (25.5-27.9)	30.9 (30.2-31.3)	43.2 (42.5-43.7)	49.3 (50.4-47.9)	58.3 (57.1-59.4)
Block C	El Niño	Prediction for mean probability of fire	0.060 (0.023 – 0.137)	0.042 (0.016 – 0.100)	0.048 (0.018 – 0.111)	0.041 (0.015 – 0.097)	0.033 (0.012 – 0.081)	0.029 (0.010 – 0.070)

		Percent reduction	NA	29.8 (26.6-32.1)	20.8 (22.5-18.7)	31.9 (34.0-29.1)	44.8 (41.0-47.4)	52.7 (48.9-55.3)
	La Niña	Prediction for mean probability of fire	0.003 (0.001 – 0.007)	0.002 (0.001 – 0.005)	0.002 (0.001 – 0.005)	0.002 (0.001 – 0.004)	0.001 (0.000 – 0.004)	0.001 (0.000 – 0.003)
		Percent reduction	NA	27.9 (27.2-28.6)	23.8 (23.3-24.5)	35.6 (34.9-36.4)	44.7 (43.8-45.6)	53.2 (52.2-54.1)
Block D	El Niño	Prediction for mean probability of fire	0.039 (0.012 – 0.102)	0.026 (0.008 – 0.070)	0.028 (0.009 – 0.076)	0.023 (0.007 – 0.064)	0.019 (0.006 – 0.052)	0.015 (0.005 – 0.043)
		Percent reduction	NA	33.8 (31.8-34.9)	27.2 (28.3-25.4)	39.6 (37.4-41.0)	52.0 (49.5-53.4)	60.3 (57.9-61.7)
	La Niña	Prediction for mean probability of fire	0.002 (0.000 – 0.005)	0.001 (0.000 – 0.003)	0.001 (0.000 – 0.003)	0.001 (0.000 – 0.003)	0.001 (0.000 – 0.002)	0.001 (0.000 – 0.002)
		Percent reduction	NA	32.1 (31.6-32.6)	28.5 (28.2-29.0)	41.2 (40.8-41.8)	51.4 (50.8-52.1)	60.1 (59.4-60.7)
Block E	El Niño	Prediction for mean probability of fire	0.016 (0.005 – 0.049)	0.013 (0.004 – 0.042)	0.015 (0.004 – 0.046)	0.014 (0.004 – 0.044)	0.012 (0.003 – 0.040)	0.012 (0.003 – 0.037)
		Percent reduction	NA	16.4 (14.5-17.6)	6.8 (6.1-7.2)	12.2 (11.0-13.0)	22.4 (24.1-19.9)	27.2 (24.1-29)
	La Niña	Prediction for mean probability of fire	0.001 (0.000 – 0.002)	0.001 (0.000 – 0.002)	0.001 (0.000 – 0.002)	0.001 (0.000 – 0.002)	0.000 (0.000 – 0.002)	0.000 (0.000 – 0.002)
		Percent reduction	NA	17.3 (18.2-16.1)	6.7 (7.0-6.3)	11.9 (11.3-12.5)	23.1 (21.6-24.3)	27.6 (25.9-28.9)
Entire MRP	El Niño	Prediction for mean probability of fire	0.039 (0.014 – 0.097)	0.028 (0.010 – 0.073)	0.030 (0.010 – 0.077)	0.026 (0.009 – 0.067)	0.022 (0.007 – 0.058)	0.019 (0.006 – 0.050)
		Percent reduction	NA	27.8 (24.6-30.1)	22.6 (20.2-24.4)	33.3 (30.1-35.5)	44.2 (40.1-47.0)	51.9 (47.7-54.7)
	La Niña	Prediction for mean probability of fire	0.002 (0.001 – 0.005)	0.001 (0.000 – 0.003)	0.001 (0.000 – 0.003)	0.001 (0.000 – 0.003)	0.001 (0.000 – 0.003)	0.001 (0.000 – 0.002)
		Percent reduction	NA	27.5 (28.4-26.4)	24.9 (24.0-25.8)	36.0 (34.7-37.2)	45.1 (43.5-46.4)	53.1 (51.4-54.5)

CHAPTER TWO: Sources of anthropogenic fire ignitions on the peat-swamp landscape in Kalimantan, Indonesia

Megan E. Cattau, Mark E. Harrison, Iwan Shinyo, Sady Tungau, María Uriarte, and Ruth DeFries

ABSTRACT

Fire disturbance in many tropical forests, including peat swamps, has become more frequent and extensive in recent decades. These fires compromise a variety of ecosystem services, among which mitigating global climate change through carbon storage is particularly important for peat swamps. Indonesia holds the largest amount of tropical peat carbon globally, and mean annual CO_2 emissions from decomposition of deforested and drained peatlands and associated fires in Southeast Asia have been estimated at ~2,000 Mt y-1. A key component to understanding and therefore managing fire in the region is identifying the land use / land cover classes associated with fire ignitions. We assess the oft-asserted claim that escaped fires from oil palm concessions and smallholder farms near settlements are the primary sources of fire in a peat-swamp forest area in Central Kalimantan, Indonesia, equivalent to around a third of Kalimantan's total peat area. We use the MODIS Active Fire product from 2000-2010 to evaluate the fire origin and spread on the land use / land cover classes of legal, industrial oil palm concessions (the only type of legal concession in the study area), non-forest, and forest, as well as in relation to settlement proximity. We find that most fires (68-71%) originate in non-forest, compared to oil palm concessions (17%-19%), and relatively few (6-9%) are within 5 km of settlements. Moreover, most fires started within oil palm concessions and in close proximity to settlements stay within those boundaries (90% and 88%, respectively), and fires that do escape constitute only a small proportion of all fires on the landscape (2% and 1%, respectively). Similarly, a small proportion of fire detections in forest originate from oil palm concessions (2%) and within close proximity to settlements (2%). However, fire ignition density in oil palm (0.055 ignitions km^{-2}) is comparable to that in non-forest (0.060 km^{-2} ignitions km^{-2}), which is approximately ten times that in forest (0.006 ignitions km^{-2}). Ignition density within 5 km of settlements is the highest at

0.125 ignitions km^{-2}. Furthermore, increased anthropogenic activity in close proximity to oil palm concessions and settlements produces a detectable pattern of fire activity. The number of ignitions decreases exponentially with distance from concessions; the number of ignitions initially increases with distance from settlements, and, from around 7.2 km, then decreases with distance from settlements. These results refute the claim that most fires originate in oil palm concessions, and that fires escaping from oil palm concessions and settlements constitute a major proportion of fires in this study region. However, there is a potential for these land use types to contribute substantially to the fire landscape if their area expands. Effective fire management in this area should therefore target not just oil palm concessions, but also non-forested, degraded areas where ignitions and fires escaping into forest are most likely to occur.

INTRODUCTION

Fires in humid tropical forests, both natural and anthropogenic in origin, have been a source of disturbance over millennia (e.g., Goldammer 1990), but large, intense fires have been relatively infrequent prior to anthropogenic land use change. Fire has been increasing across the tropics both in size and in frequency in recent decades (Goldammer 1991, Cochrane 2003, Cochrane 2009). In that time, both the largest and greatest number of fires have occurred in the tropics relative to other regions (Cochrane 2003, Cochrane and Ryan 2009). Tropical and subtropical moist broadleaf forests are considered the most fire-sensitive of the major ecoregions (Shlisky, Waugh et al. 2007, Shilisky, Alencar et al. 2009), and thus the ecological consequences for increased fire in the tropics are far-reaching, including changes in forest composition (Cochrane and Schulze 1999) and structure (Gerwing 2002) that are potentially long-term in nature (e.g., Ferry Slik, Verburg et al. 2002). Furthermore, biomass burning in the tropics releases carbon and other gases into the atmosphere, contributing to global climate change, air pollution, acid rain, and property damage (Crutzen and Andreae 1990, Hao, Liu et al. 1990, Hao and Ward 1993, Langmann and Graf 2002).

Trends of fire activity in Southeast Asia follow pantropical trends (Taylor, Saksena et al. 1999, Field, van der Werf et al. 2009), and peatland fires in Indonesia have been increasing in frequency, number, and severity since the 1980's (Meijaard and Dennis 1997). Consequently, tropical peatlands, the majority of which are found in Southeast Asia (57% of the tropical peatland area and 77% of the volume) (Page, Rieley et al. 2011), are at heightened fire risk. During El Niño phases of the El Niño Southern Oscillation (ENSO), there is increased likelihood of drought in Southeast Asia and, thus, a well-established coupling of fires in Indonesia with El

Niño conditions and precipitation, including in Kalimantan (e.g., Deeming 1995, Kita, Fujiwara et al. 2000, Siegert, Ruecker et al. 2001, Page, Siegert et al. 2002, Wang, Field et al. 2004, Fuller and Murphy 2006, Wooster, Perry et al. 2012, Spessa, Field et al. 2015). There is some evidence that large fires do not occur unless precipitation falls below a particular threshold (Goldammer 2007, Field, van der Werf et al. 2009). However, fire is increasing in tandem with land use change and increased population density (Field, van der Werf et al. 2009) and, without anthropogenic influence on the landscape, extreme fire events would not exist.

Carbon emissions as a result of fires in peatlands are particularly high, as peat is extremely rich in belowground organic carbon; peat-swamp forest with a depth of 10 m can store 12-19 times the amount of carbon as other tropical forest types (FRIM-UNDP/GEF 2006). Mean annual CO_2 emissions from decomposition of deforested and drained peatlands and associated fires in Southeast Asia are estimated at ~2,000 Mt y^{-1} (Hooijer, Silvius et al. 2006). However, there is annual variability in emissions, and emissions during El Niño phases of ENSO far exceed those from non-El Niño periods (van der Werf, Dempewolf et al. 2008). Over 90% of these peat emissions come from Indonesia, which has the largest amount of tropical peat carbon globally (Rieley, Ahmad-Shah et al. 1996, Page, Rieley et al. 2006, Page, Rieley et al. 2011). It is estimated that 0.81-2.57 Gt C were released from Indonesia's peatlands during the 1997/98 fire season alone due to peat and vegetation combustion (Page, Siegert et al. 2002). Fires in the 2015 dry season were the most severe since 1997/98, but, at the time of writing, peer-reviewed estimates for land area burned and emissions are not yet published. Indonesia has become the world's fourth largest emitter of CO_2, largely as a result of emissions from the 2015 fires, which have reached 1.62 billion tons of CO_2 (Harris, Minnemeyer et al. 2015).

Peat fires in Southeast Asia, and Indonesia in particular, are consequently a major cause of smog and particulate air pollution (Hayasaka, Noguchi et al. 2014, Reddington, Yoshioka et al. 2014), with serious consequences for human health (Kunii 1999, Kunii, Kanagawa et al. 2002, Marlier, DeFries et al. 2012, Wooster, Perry et al. 2012) and local blocking of sunlight that can suppress plant photosynthesis (Davies and Unam 1999). In addition, peatland fires are responsible for forest habitat loss and degradation for flora and fauna, including those in marine systems (Yule 2010, Posa, Wijedasa et al. 2011, Jaafar and Loh 2014). Fire suppression efforts, lost timber and crop resources, missed workdays, and travel disruptions incur high economic costs (Ruitenbeek 1999, Barber and Schweithelm 2000, Tacconi 2003), and it is estimated that Indonesia lost US$20.1 billion during the 1997/98 fire season alone (Varma 2003). Both national and international policy has been implemented to attempt to reduce fire in Indonesia prior to the 2015 fire season (e.g., ASEAN Agreement on Transboundary Haze Pollution, Singapore's Transboundary Haze Pollution Act, and Indonesia's national law (Act No 41/1999) banning corporations from using fire to clear land for palm-oil plantations), but with limited success. Given the variety and severity of the consequences of tropical peatland fires, particularly those in Indonesia, it is of global interest to understand this changing disturbance regime and reduce fire occurrence (Harrison, Page et al. 2009).

Before large-scale anthropogenic land use change, the most common cause of ignition in tropical forests was natural, primarily lightning strikes (Baker and Bunyavejchewin 2009). Now, far more fires in the tropics are started by people than by natural sources (Stott 2000, Baker and Bunyavejchewin 2009). Ignitions in Indonesia, as in many parts of the tropics, are primarily of anthropogenic origin (Bompard and Guizol 1999, Bowen, Bompard et al. 2000), resulting in either accidental or deliberate fires. The human contribution to changing fire regimes and our capacity to manage fire remains somewhat uncertain (Bowman, Balch et al. 2009, Bowman, Balch et al. 2011). Thus, a key component to understand changing fire regimes in the tropics is to identify the sources of fire ignitions and the land use / land cover (LULC) classes associated with fire ignitions.

Who is responsible for ignitions in Indonesia is highly contested, and reports of the ignition sources are many and varied (Dennis, Mayer et al. 2005, Page, Hoscilo et al. 2009), often resulting in a chain of finger-pointing (e.g., Suyanto 2000). Although some large-holders do clear land mechanically, most land is cleared in Indonesia through use of fire (Stolle, Chomitz et al. 2003). Because fires set for clearing can 'escape' beyond their intended boundaries, both large and small holders have been held responsible (e.g., Stolle, Chomitz et al. 2003, Page, Hoscilo et al. 2009), as is often the case in rainforest fires more generally (Goldammer 1991). Burning to clear land has been the traditional practice of smallholders and indigenous groups, and there is some evidence that smallholders' use of fire has been historically relatively small-scale and well-managed (Seavoy 1973, Dove 1985, Wibowo, Suharti et al. 1997, G√∂nner 1998, Nicolas 1998, Tomich, Fagi et al. 1998, Bowen, Bompard et al. 2000). However, this is likely not the case today. The scale of land cleared by fire has expanded with increased use of burning by both smallholders and larger-scale rubber and oil palm concessions (Brauer and Hisham-Hashim 1998, Potter and Lee 1998, Stolle, Chomitz et al. 2003). Originally, the Indonesian government blamed smallholder shifting cultivators for fire, but later publically claimed that it was more likely larger-scale companies opening land on commercial plantations for palm oil, pulpwood, and timber, some of which was promoted by government policies themselves (Brown 1998, Page, Hoscilo et al. 2009). There is evidence that high-impact fires often originate on plantations, logging concessions, and large land-clearing projects (Hoffmann, Hinrichs et al. 1999) and that wildfires escaping from oil palm concessions contribute to deforestation (Carlson, Curran et al. 2012). However, much evidence still points to small- and mid-scale farmers outside of large concessions as the main contributors to fire. For example, although concessions do contribute substantially to emissions, particularly in peatlands and non-forested areas, the majority of emissions can be attributed to fires outside of concessions in both Sumatra and Kalimantan (Marlier, DeFries et al. 2015). Additionally, it is often complicated to attribute ignitions to agro-industrial plantations or to local communities because communities can be given land to plant within concession boundaries (Gaveau, Salim et al. 2014). Furthermore, fire is used in social conflicts over forest conversion and land tenure, which may include fires started inside concessions by people from outside of the concession (Tomich, Fagi et al. 1998). However, the argument can also be made that large companies should be responsible for activities occurring within the boundaries of their concessions, especially considering the financial resources available to them to do so.

Because many studies using satellite data to evaluate fire consider individual fire detections at the 1 km^2 resolution (e.g., Langner and Siegert 2009) and not individual fire events (i.e., a fire with a common ignition source, which may consist of multiple fire detections), it is often difficult to pinpoint the LULC classes on which ignitions occur rather than the LULC classes associated with fire or that are predisposed to burning. This issue complicates efforts to determine who should be blamed for fires and the associated pollution and damage, particularly if fires quickly escape a LULC boundary and burn into another LULC class. In this study, for what we believe to be the first time, we disentangle fire detections from individual fire ignitions to discern the origin of fires in a peat-swamp forest landscape in Central Kalimantan, Indonesia. We focus on ignition sources in this study area because of the global importance of peatland areas in Indonesia and the consequences of peatland fires.

In so doing, we assess the oft-asserted claim that escaped fires from oil palm concessions and from smallholder farms near settlements are the primary sources of fire, through addressing the following questions:

1) In which LULC classes do fires, in particular the longest and hottest fires, originate and to which LULC classes do they spread?
2) What proportion of fires, in particular the longest and hottest fires, escape from oil palm concessions and settlements into other surrounding LULC classes?
3) Do fire ignitions occur disproportionately in proximity to oil palm concessions and settlements? Are these fires longer in duration or hotter than fires occurring away from oil palm concessions and settlements?

MATERIALS AND METHODS

Study Site

We analyze fire ignitions in an area of lowland tropical peat-swamp forest in Central Kalimantan, Indonesia (Fig. 1). The study area consists of the Sabangau-Katingan Forest and the recently degraded failed agricultural project called the Mega Rice Project (MRP), representing a combined total of ~2.5 Mha of the total 6.8 Mha of lowland peatland in Kalimantan. The

630,000 ha Sabangau-Katingan Forest consists of the now-protected Natural Laboratory of Peat Swamp Forest and the Sebangau National Park. It has been previously subjected to both concession and illegal logging throughout, and as a consequence of the latter is criss-crossed by small illegal logging timber extraction canals, on many of which canal damming initiatives are currently underway. Some parts of the forest have suffered fire damage. Currently, the area is not open for human use apart from some small-scale activities, but enforcement capability is limited. There are several villages located along the Katingan and Sabangau Rivers.

The MRP is a failed and abandoned agricultural conversion project that was initiated in 1995 and aimed to convert 1 Mha of peat-swamp forest into rice plantations. Much of the area's forest was cleared and wide, deep irrigation canals totaling over 4,000 km in length have resulted in extreme drainage and subsequent fire susceptibility. The MRP has burned regularly since 1997, particularly during the dry seasons in El Niño phases, and it now contains patchy forest remnants surrounded by degraded fire-prone peat swamp. In 2000, less than half of the original peat-swamp forest remained in the MRP (Boehm and Siegert 2001), and fire has been identified as a primary factor of forest cover loss in the area (Hoscilo, Page et al. 2011). Currently, tens of thousands of families live along the Kahayan, Kapuas, and Barito Rivers that border the area. Many of these people rely upon forest resource extraction for their livelihoods, some in combination with smallholdings. There are no wood fiber, rubber, or logging concessions in the study area, but there are several oil palm concessions located throughout the MRP and on the southeastern edge of the Sabangau basin. There are still several large transmigration settlements in the study area, many of which are located adjacent to the oil palm concessions.

It is estimated that the carbon store of the MRP and the Sabangau Forest was 2.82-5.40 Gt C before the most destructive fire season in 1997-98, and that emissions totaling 0.19-0.23 Gt C from the peat and 0.05 Gt C from aboveground biomass occurred during this period (Page, Siegert et al. 2002). The Sabangau Forest is home to the largest remaining population of Bornean orangutans (Wich, Meijaard et al. 2008) and southern Bornean gibbons (Cheyne, Thompson et al. 2008), and the adjacent portion of the Mega Rice Project also hosts a substantial population of Bornean orangutans (Cattau, Husson et al. 2014). As is typical for the region, more fires occur in the study area during the dry season and particularly El Niño phases (Fig. 2).

Data

Fire detections at the 1 km^2 resolution across the study area from 2000-2010 are obtained from the Moderate Resolution Imaging Spectroradiometer (MODIS) Active Fire Detections, extracted from MCD14ML and distributed by NASA FIRMS. The MODIS Active Fire Product includes, for each fire detected by either the Terra or Aqua MODIS sensor, the location of the center of the 1 km^2 pixel in which the fire was detected, the date and time of detection, the Fire Radiative Power (FRP, a measure of fire heat output), and the detection confidence. MODIS hotspots are considered the most accurate and complete among alternative methods for detecting fires (Langner and Siegert 2009) and correlations between the number of MODIS hotspots and the area burned on the ground is reasonably high, especially in peatlands (R2 = 0.75 in Tansey, Beston et al. 2008). However, MODIS can miss fires that spread quickly or that are extremely short-burning, as the sensor passes only one or twice a day, and it can also miss ground fires in dense canopy if they do not produce sufficient heat (Ballhorn, Siegert et al. 2009, Langner and Siegert 2009). We therefore focus here on persistent fires, which are more likely to be detected as they emit heat during at least one satellite pass. Additionally, fires in peat are generally characterized by smoldering combustion, for which the rate of spread is quite slow, thus increasing their chances of detection over a multi-day period (Rollins, Cohen et al. 1993, Wan Ahmad 2001, Rein 2013, Turetsky, Benscoter et al. 2015). However, smoke from fires can prevent their detection, and it is possible that we also miss ground fires under dense canopy, thus underestimating the number of fires in forest, or peat fires that smolder underground before resurfacing. In Kalimantan and Sumatra, the omission rate for MODIS active fire detections has been estimated from 34-60%, depending upon the LULC class (Liew, C. et al. 2003, Miettinen, Andreas et al. 2007, Tansey, Beston et al. 2008).

We create a LULC layer at the annual temporal resolution consisting of oil palm concessions, forest, and non-forest classes. Oil palm concession boundaries according to the Indonesian Ministry of Forestry are obtained from the Global Forest Watch portal (WRI 2014). Oil palm plantations almost certainly exist outside of these official concession boundaries, particularly small-scale plantations or plantations immediately adjacent to concessions, but these have not been mapped and so we focus on legal concessions in this analysis. According to these data, there are no wood fiber, rubber, or logging concessions in the study area. The forest and non-forest classes are based upon tree cover derived from the MODIS Vegetation Continuous Fields (VCF) Collection 5 product, which contains proportional estimates of woody vegetation at the 250 m^2 resolution (DiMiceli, Carroll et al. 2011). VCF is aggregated to the 1 km^2 resolution, and a forest binary layer is created by thresholding VCF at 55 percent woody vegetation to designate tree cover. This classification is based upon the range of VCF values of areas known to be tree cover in the study area. Classification accuracy of the forest binary layer is assessed using GPS points collected in the field in forest (50 points) and non-forest (50 points) in 2009, and accuracy is over 95%. Because this classification is based on woody vegetation, it is possible that the forest class also includes some mature illegal plantations, particularly if trees are present. We use a relatively coarse non-forest class because degraded LULC classes can be highly spectrally variable and LULC verification points are not available for all possible degraded LULC classes. This non-forest class includes a relatively heterogeneous mixture of non-forest LULC classes, including fern-dominated, shrub/bushland, bare peat, and possibly even young plantations and some highly degraded forest. We assign non-forest conservatively to reduce classification error. Furthermore, land use policy for degraded areas in Indonesia is targeted at non-forest broadly (e.g., national policy to develop oil palm plantations on degraded land rather than primary forest or peatland) and more precise definitions of 'degraded land' vary between the relevant government institutions (e.g., Ministry of Environment and Forestry, Ministry of Agriculture, Land Agency). Finally, settlement locations, or points indicating the center of major villages and cities, are used to calculate distance from settlement across the study area.

Analysis

Data analysis covers the period from 2000-2010. We group multiple fire detections into single fire events, identify high-impact fires based upon fire duration and heat, and trace the LULC class on which that ignition occurs and to which that fire spreads. We also evaluate if increased anthropogenic activity in close proximity to oil palm concessions and settlements results in a detectable pattern of fire activity. Data processing is conducted in ArcGIS (ESRI 2011) and the R programming environment (Team 2012), and statistical analyses are conducted in R.

Grouping fire detections into single fire events and identifying high-impact fire events

The MODIS Active Fire Product indicates the presence of a fire within a 1 km^2 area, but not the exact location or size of a particular fire (Langner, Miettinen et al. 2007, Miettinen, Andreas et al. 2007, Langner and Siegert 2009). Thus, it is challenging to determine if proximal fire detections are spatially contiguous or if they represent isolated fires. We assign all fire detections to a particular fire event using two methods (Fig. 3). In the more conservative single-pixel technique, fire detections that occur within a given pixel are assigned to the same fire and fire detections in neighboring pixels are not included. Thus, fires are restricted to a 1km^2 area, and fires are not allowed to spread beyond their pixel of origin. In the neighborhood-pixel technique, fire detections that occur within a given pixel or the eight adjacent pixels (3 x 3 window) are assigned to the same fire using hierarchical clustering with the 'dplyr' package in R (Wickham and Francois 2014). Fires are not confined to one 3 x 3 window; they are allowed to spread provided there is a fire detection in a pixel adjacent to any pixel already within a given fire.

Because the MODIS Active Fire Product has a relatively high and variable rate of omission, we allow for fire detections that do not occur on consecutive days to be considered the same fire, to account for missed detections or subterranean fires that resurface. We use a variety of temporal thresholds (1, 2, 4, 6, 8, 10, 12, and 14 days) to define the temporal window in which fire detections are considered to originate from the same ignition event. We run all further analyses using the various temporal thresholds to designate fires. Thus, we use a relatively conservative four-day fire detection temporal threshold for all figures and tables in the remainder of the manuscript; this threshold is sufficiently high to account for the 60% upper omission rate for MODIS active fire detections and also the possibility of subsurface fires. Lower thresholds are even more conservative in terms of fire spread. We include results using the full range of temporal thresholds in *Supporting Information*.

Fires with a duration (determined by the difference in days between the earliest and latest fire detection date in each fire) and/or maximum heat (determined by the fire detection with the highest fire radiative power (FRP) in each fire) within the top decile of fires are considered "high-impact". This distinction is made because these factors affect the fires' potential environmental damage - for example, burning the seed bank in the soil (Van Nieuwstadt, Sheil et al. 2001). Additionally, the fire detections with high-FRP and the long-duration fires tend to have consistently average to high detection confidence (Fig. S1 in *Supporting Information*). We isolate the 'high-impact' fires for fires identified using both the single- and neighborhood-pixel techniques.

We evaluate the agreement between fire events identified with our model and finer spatial resolution data. We acquire Normalized Burn Ratio (NBR) data at the 30 m resolution based on surface reflectance generated by the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) for every Landsat 5 TM and Landsat 7 ETM+ scene (WRS 2 Path 118 row 62, covering 83.5% of the study region) with less than 10% cloud cover available from 2000-2010 from USGS Earth Resources Observation and Science (EROS) Center Science Processing Architecture (ESPA) On Demand Interface. For any two images fewer than 90 days apart, we calculate the differenced NBR (dNBR), for a total of 4 scene-pairs consisting of 6 scenes. We do not include image pairs with longer periods in between acquisition dates in order to avoid the confounding effects of seasonal changes. We create a binary burned - unburned raster by thresholding dNBR layers at 1500, based on on-the-ground knowledge of the study area and visual inspection of burn scars seen in composite images of surface reflectance in the green, near infrared, and short-wave infrared parts of the spectrum (i.e., Landsat 5 TM and Landsat 7 ETM+ bands 2, 4, and 7), and also include results from using thresholds of 1000 and 2000 (Fig. S3 in *Supporting Information*). Because thresholding dNBR excludes areas that burn between the acquisition dates of the two scenes if that area is also burned in the first scene, we also include areas that were burned in the first scene (NBR is 2000 or lower). To compute a pixel-based error matrix (Table S2 in *Supporting Information*), we sample our MODIS-derived fire layer and the Landsat-derived fire layer at approximately 2,000 random points stratified by burn status as predicted by our algorithm. We also evaluate the polygon-based output of our algorithm by calculating the percent of the burned area predicted by our MODIS-derived fire layer that is predicted as burned by the Landsat-derived fire layer (Table S3 in *Supporting Information*).

In which LULC classes do fires originate and to which LULC classes do they spread?

We consider the earliest fire detection in each fire event to be the ignition for that fire event. In some cases, fire events can have multiple ignitions if there are multiple fire detections with the same time stamp associated with that fire (Fig. 4). On the other hand, if the fire event consists of only one detection, ignition and detection are the same. We calculate the percentage of fire ignitions located on the different LULC categories, plus the percentage of fire ignitions in close proximity to settlements (within 1, 2, 3, 4, and 5 km, which could include oil palm concessions, forest, or non-forest). Analyses of fire spread between LULC classes are restricted to fires identified using the neighborhood-pixel technique, as fires using the single-pixel technique were restricted to one pixel and, thus, cannot indicate fire spread. For each fire detection, we identify the LULC class in which the fire originates (i.e., the location of the earliest fire detection in the fire detection cluster) and calculate how many fire detections are associated with fires whose ignitions are located on the different LULC categories. We determine the density of ignitions per LULC class by dividing the number of ignitions in each LULC class by the area of that LULC class in the entire study region for each year and taking the mean.

What proportion of fires escape from oil palm concessions and settlements into other surrounding LULC classes?

We identify fires that escape from oil palm concessions by isolating fires that start within oil palm concessions and burn outside the concession boundaries at some point during the burn (i.e., have at least one fire detection outside of the concession boundaries). Similarly, we identify fires that escape from settlements by isolating fires that start near settlements (we use a 5km threshold, following Stolle, Chomitz et al. 2003) and burn outside that boundary at some point during the burn. We determine if the mean duration in days and mean maximum FRP of these escaped fires are significantly different from all other fires in the study area using Welch's t-tests. We also test whether the difference is significant for all other fires that start on the same LULC class but are not escaped.

Do fire ignitions occur disproportionately in proximity to oil palm concessions and settlements?

To analyze the influence of increased anthropogenic activity around settlements and outside of oil palm concessions on fire activity, we evaluate if the number of ignitions and the severity of fires (i.e., fire duration or the maximum FRP) varies as a function of the fire ignitions' distance from oil palm concessions or from settlements. After assessing exploratory plots, we fit models of the number of fire ignitions as a function of distance from oil palm concessions and from settlements using the MASS package in R (Venables and Ripley 2002). Because we find no relationship between distance from oil palm concession and distance from settlement (e.g., most settlements are not necessarily found only within close distances to oil palm concessions), these factors are evaluated separately. We fit exponential regression models for distance from oil palm concessions (binned into 50m increments) because we expect anthropogenic ignitions to be highest near concession borders (due to expansion of the concession itself, clearing for smallholder plots, or accidental fires where workers are regularly frequenting) and then decrease as distance from concession increases (due to increased cost of travel from the concession). We fit a Ricker function of the form $y \sim ax \exp(-bx)$, where y is the number of ignitions and x is the distance from settlements binned into 50m increments, and estimate the parameters a and b using the 'nls' package in R. We select a Ricker model, which has been commonly used to model density-dependent population growth, because we expect the number of ignitions to start at zero due to an aversion to burn very close to the village, increase to a peak, and then decrease back to zero as the cost of travelling from the settlement increases with distance. This function allows us to estimate $1/b$, or the distance from settlements at which ignitions peak. We also evaluate the relationship between both fire duration and maximum FRP with distance from both oil palm concessions and settlements after examining exploratory plots. We apply linear, second order polynomial, third order polynomial, forth order polynomial, and exponential regressions. We use fires detected using both the single-pixel and neighborhood techniques, using all fires and all high-impact fires.

RESULTS

Grouping fire detections into single fire events and identifying high-impact fire events

For fires identified using the single-pixel and neighborhood detection techniques, mean fire duration is 1.6 (± 1.6) days and 2.1 (±3.3) days, respectively, and mean maximum FRP is 45.7 (±65.0) MW_{th} and 43.8 (±79.6) MW_{th}, respectively. For both detection techniques, ~80% of fires burn for just one day (Fig. 5) The lower bound of high-impact fires, or the threshold above which a fire is considered high-impact, is 3 days or 95.1 MW_{th} using the single-pixel technique, and 4 days or 87.0 MW_{th} using the neighborhood-pixel technique, resulting in 19% and 18% of the fires being classified as 'high-impact,' respectively. See Fig. S2 and Table S1 in *Supporting Information* for characteristics of fires identified across the range of temporal thresholds. Overall pixel-based accuracy of fires identified by our algorithm is 73 (±3)% (see Table S2 in *Supporting Information* for overall accuracy of fires identified by our algorithm broken down by each time period, as well as producer's and user's accuracy for burned and unburned land cover classes broken down by each time period). Polygon-based comparisons show that 34 (±4)% of the total area of fires identified by our algorithm is also identified as burned by Landsat-derived dNBR thresholded at 1500 (see Table S3 in *Supporting Information* for percent broken down by each time period).

In which LULC classes do fires originate and to which LULC classes do they spread?

Fires ignited in non-forest areas have the biggest impact on the landscape. By far the majority of ignitions occur in non-forest (Table 1; Table S4 in *Supporting Information*). The same pattern is found for 'high-impact' fires, and results are consistent when using both the single- and neighborhood-pixel detection techniques and across the temporal thresholds chosen to identify fires. When we evaluate fire spread between and among LULC classes, we find that the majority of fire detections are associated with fires that start on non-forest (Fig. 7; Fig. S4 in *Supporting*

Information). Fires that start on non-forest are also the primary ignition source for fires that burn non-forest itself and for fires that burn forest (Table 2 and Fig. 7; Table S5 and Fig. S4 in *Supporting Information*).

Fires that begin on oil palm concessions constitute approximately 20% of all fires and 20% of high-impact fires (Table 1; Table S4 in *Supporting Information*). Fire detections from fires started on oil palm constitute 18% of all detections and 16-18% of detections associated with high-impact fires (Fig. 7; Fig. S4 in *Supporting Information*). Most fires that burn oil palm concessions are started on the concessions. Fires that begin on oil palm concessions, however, are not the main source of ignition for fires on any other LULC class. The fewest fires originate in forest (Table 1; Table S4 in *Supporting Information*). Fire detections from fires starting on forest constitute 7-13% of all detections and 7-12% of detections associated with high-impact fires (Fig. 7; Fig. S4 in *Supporting Information*). The number of fires that are started close to settlements, which could occur on oil palm concessions, non-forest, or forest, are low in comparison (6-9%). A very low percentage of fires and high-impact fires are ignited close to settlements (Table 1; Table S4 in *Supporting Information*).

Non-forest has the highest density of ignitions followed by oil palm concessions, and these LULC classes have an identical density of ignitions for high-impact fires (Table 1 and Fig. 6; Table S4 in *Supporting Information*). For both all fires and high-impact fires, this is about ten times the density of ignitions in forest. The density of ignitions near settlements is just over twice that of non-forest and oil palm for all fires, and approximately 1.5 times that of non-forest and oil palm for high-impact fires. This density is higher than can be explained by LULC near the settlements alone. So, the density of fires near human settlements is high, but the overall contribution of fires near settlements is low.

What proportion of fires escape from oil palm concessions and settlements into other surrounding LULC classes?

Most fires that are started within oil palm concessions stay on the concession, and most fires that are started near settlements stay near settlements (Table 3; Table S6 and Table S7 in *Supporting Information*). However, high-impact fires that begin on oil palm concession and near settlements are more likely to escape than non-high impact fires. Although some fires, and particularly high-impact fires, do escape from oil palm concessions and from settlements, they constitute only a small percent of total fires in the study area. Furthermore, these escaped fires do not serve as a notable ignition source for forest fires; a low percentage of forest fires are associated with fires that were ignited in oil palm concessions or close to settlements (Table 2; Table S5 in *Supporting Information*). However, fires that escape from oil palm concessions or from settlements are higher impact than other fires, and have both a longer mean duration and a higher mean maximum FRP than both other fires that start in oil palm concessions or near settlements but do not escape and all other fires in the landscape (Table 4; Table S8 in *Supporting Information*).

Do fire ignitions occur disproportionately in proximity to oil palm concessions and settlements?

Using both the single-pixel and neighborhood techniques, the number of ignitions of all fires and high-impact fires decreases exponentially with increasing distance from oil palm concessions, but fire duration and heat do not have a clear relationship with distance from oil palm concessions (Fig. 8; Fig. S5 in *Supporting Information*). Although regressions between both fire duration and maximum FRP with distance from oil palm concessions are significant, they explain less than 1% of the variation in the duration of fires and the maximum FRP of fires identified using both the single-pixel and neighborhood techniques.

When we explore the relationship between the number of ignitions and distance from settlements, we find that the Ricker model fits the data well, including at the extremes, and that the number of ignitions increases farther from settlements, peaks, and then decreases (Fig. 8; Fig. S6 in *Supporting Information)*. Fire duration and maximum heat do not follow this trend. The distance from settlements at which the number of ignitions is at its maximum is 7.2 km (±0.2). Again, although regressions between fire severity and distance from settlements are significant, they explain very little of the variation in the duration of fires and the maximum FRP of fires.

DISCUSSION

Our results provide only limited support to the claim that fires occurring on or escaping from oil palm concessions and settlements are major contributors to fire in this study region during our study period. The vast majority of ignitions occurs in non-forested areas, a relatively heterogeneous mixture that includes fern-dominated, shrub/bushland, bare peat, plantations including very young oil palm (outside legal concession boundaries), and degraded forest. A relatively low but still substantial percentage of ignitions occur on oil palm concessions, and very few ignitions occur in close proximity to settlements. The majority of fires started within concessions or near settlements are confined to those boundaries, and a very low percentage of fires on the landscape are escaped fires from oil palm concessions or settlements into other LULC classes.

While there is potential for oil palm concessions from converted degraded land to reduce fire prevalence on the landscape if ignitions on oil palm concessions can be reduced relative to degraded areas, this is not currently the case; ignition density in oil palm was on par with that in degraded areas, both of which were substantially higher than in forests. Although fires that have escaped from oil palm currently constitute a small percentage of fires in the study area relative to fires on degraded non-forest areas, our findings nevertheless support concerns about the contribution of the oil palm industry to emissions and hazardous smog in the region (e.g., Stuart 2012, Marlier, DeFries et al. 2015). Furthermore, our results likely underestimate the number of ignitions attributable to oil palm companies and overestimate the contribution from other LULC classes, as our oil palm category includes only those plantations found within the reported boundaries of legal oil palm concessions.

Our findings that there is a detectable pattern in the number of fire ignitions as a function of distance from oil palm concessions and settlements suggest that these LULC classes influence the fire regime through increased anthropogenic activity around them, plus escaped fires from these LULC classes. The extent to which these ignitions will result in high-impact fires depends upon both the flammability of the landscape and the capacity for management interventions (e.g., Uriarte, Pinedo-Vasquez et al. 2012). If the peat is relatively undrained and inundated close to the surface, the forest is intact, and fire-fighting resources are available, an ignition is much less likely to turn into a high-impact fire than if the land is degraded from canal development and unmanaged. We find that increased anthropogenic activity around oil palm concessions and settlements increases the number of high-impact fires, indicating that fire reduction efforts are needed in these areas through both capacity building and awareness raising to increase the success of management interventions, establishment of effective fire-fighting teams, plus landscape restoration to reduce the predisposition of the landscape to burning. Additionally, because the density of ignitions in oil palm is nine times that in forest, and the density of ignitions within 5km of settlements is over twenty times that in forest, it is clear that anthropogenic activity within oil palm concessions and settlements has the potential to contribute substantially to the fire landscape if these land use types continue to expand, and peat and fire management practices do not improve, particularly if fragmentation and/or climate change leave the landscape more predisposed to burning. Furthermore, these fires are not only well-managed fires that burn low-heat for a short period of time; the density of ignitions of high-impact fires in concessions and near settlements are 10 and 15 times that in forest, respectively.

Our results support previous research that most fires occur in non-forest or degraded areas (including oil palm in Miettinen, Andreas et al. 2007, Gaveau, Salim et al. 2014) and that emissions from fire are associated with highly degraded areas (Marlier, DeFries et al. 2015), by showing both that the majority of fires are ignited in non-forest and highlighting that fires actually start in non-forest rather than merely just occur in non-forest (with the possibility that ignition started there or elsewhere). Management to reduce ignitions in degraded non-forest areas, in addition to reducing the probability of continued burning when ignitions do occur, will be pivotal in reducing fire across the landscape. This strategy is also key to preventing forest fires and the associated loss of habitat, as we found that the majority of forest fires start in non-forest. Achieving this goal among numerous smallholders is likely to prove even more difficult than reducing fire ignition and burning in oil palm concessions, however, as the latter have much greater capacity to implement consistent management policies over large areas and provide necessary management resources, and are under higher pressure to do so. There are some existing village-level fire teams (Regu Pemadam Kebakaran = RPK) and community groups for fire management (Kelompok Masyarakat Pengendali Kebakaran = KMPK1) operating in degraded, non-forest areas, but these groups are small-scale and under-funded. It is also easier to identify actors of illegal burning within concessions and bring prosecutions against a single concession holder, compared to numerous smallholders operating illegally in areas with ill-defined land ownership. This approach is likely to be even more challenging in very remote areas that are not being frequented or cultivated by smallholders, as much of this land is discarded wasteland. In these areas, regeneration efforts, including reforestation and hydrological restoration, will be key for fire reduction on the landscape. In making this recommendation, we recognize that some previous projects focusing on restoration in this area appear to have failed due to a combination of insufficient or inconsistent funding, land tenure concerns, misinformation between project organizers and local people, etc. (e.g., Atmadja, Indriatmoko et al. 2014). However, there are currently active restoration efforts on the ground. Based on our field experience, these efforts, much like the local fire teams, are effective but small-scale and underfunded. Indonesia has recently established a Peatland Restoration Agency with the goal of preventing peatland fires and restoring about 2 million ha of fire-damaged peatland across the nation. Although specific spatially-explicit targets areas have not yet been identified, this agency could make peatland restoration more feasible by providing funding and capacity beyond that which is currently available in the region.

The low percentage of and density of ignitions in forest are consistent with the thesis that mature forest has low flammability due to lower levels of peat drainage, increased moisture conditions within a closed canopy and decreased anthropogenic activity (e.g., Langner, Miettinen et al. 2007). One limitation to our methods is that it is possible that small, low-heat fires, particularly those burning under a forest canopy, were missed from detection by MODIS. Thus, we may have underestimated the number of fire ignitions that occur in forest, but notwithstanding the fact that they are in forests, these small, low-heat fires are likely of lower importance in terms of ecological impact. On the other hand, because the forest class may include mature illegal plantations in addition to mature forest, some of the fire ignitions that we attribute to forest will actually have occurred on mature illegal plantations. In the case of tree plantations, low fire occurrence is likely related to more careful management to minimize the risk of damage to valuable mature crop resources.

While we cannot definitively identify the exact source or location of fire ignitions without extensive fieldwork on the ground, including fire forensics (e.g., fire-scene investigations or fire path reconstructions), this was beyond the scope of this study. Because we are assessing trends in fire activity over a large area of inaccessible terrain in which there are potential legal repercussions for igniting fire, fire activity detected empirically through satellite data provides a more comprehensive and unbiased picture than through interviews or empirical observations on the ground. Furthermore, the results of our analysis were not sensitive to the temporal threshold chosen to cluster fire detections into fires, showing that missed detections due to subsurface fires or smoke do not affect the trends in our results. When we compare the output of our algorithm with burned area products derived from satellite data with a finer spatial scale (Landsat dNBR), the overall accuracy of 73(±3)% is reasonably high. However, because only 34 (±4)% of the total area of fires identified by our algorithm is also identified as burned by Landsat-derived dNBR, we are overestimating fires compared with the Landsat-derived dNBR data, meaning that we may overestimate fire spread. However, how long it takes post-fire regrowth to mask a fire scar from detection by Landsat in this study area is unknown and likely variable, and the Landsat scenes we use for validation are 32-80 days apart; thus, our algorithm, which uses data with a finer temporal resolution, may detect fires that the Landsat-derived dNBR data does not.

While it may be possible to pinpoint ignitions locations reasonably reliably with the methods that we developed, we do not recommend that these methods be used to assign responsibility to specific land owners or other actors for fire occurrence. Additionally, the underlying causes of fire can be both complex and site-specific (Bowen, Bompard et al. 2000, Applegate, Chokkalingam et al. 2001, Dennis, Mayer et al. 2005), and so management and policy actions need to take into account the diverse needs of all stakeholders. Important and complementary information that we cannot deduce through satellite data could be ascertained through interviews (e.g., motivations for lighting fires, willingness or ability to adapt alternative land clearing strategies, etc.). Institutional issues are also relevant to this conversation, as national and regional policies affect land use zoning (Stolle, Chomitz et al. 2003), and how these policies are implemented affects the behavior of stakeholders (e.g., communities and government agencies) on the ground. For example, when the customary laws under the *marga* system, which gave rights to forest resources to local communities, were replaced with current forest laws, local communities were left feeling marginalized, with little incentive to engage in fire-fighting efforts outside the boundaries of their plots (Bompard and Guizol 1999). Recent law changes are now giving more forest rights back to communities, but there is concern that this too will lead to more forest destruction (Handadhari 2015).

There has been an Indonesian national law banning corporations from using fire to clear land for palm-oil plantations since 1999 (Act No 41/1999), but it is unclear if the Indonesian government has the capacity to monitor or enforce burning bans or other fire reduction efforts, particularly since decentralization. In 2006, the provincial government in Central Kalimantan banned households and community plantations from using fire to clear land (Someshwar, Boer et al. 2010). After much resistance from local communities, the ban was softened in 2008 to incorporate seasonal forecasts informed by the Seasonal Fire Early Warning Tool developed by an international partnership (Wong, Marshall et al. 2010); farmers are allowed to burn if climatic conditions indicate low fire risk. However, adherence to the ban in high-risk years would likely be low if local people were to feel that they had no choice but to burn to clear land or were unaware of official designated fire risk. Furthermore, the capacity to enforce the ban is limited, particularly in remote areas. Community outreach activities that not only inform local people about the importance of alternative land management strategies but enable them to adopt those strategies will be pivotal in restoration and fire prevention efforts on this degraded landscape (Page, Hoscillo et al. 2009). The ASEAN Agreement on Transboundary Haze Pollution sets the groundwork for international cooperation in fire monitoring and prevention, calls for national efforts, and also resulted in the development of a joint monitoring system. However, haze problems in the region have persisted since the Agreement came into effect in 2003. Additionally, Singapore enacted a Transboundary Haze Pollution Act in 2014, which places criminal and civil liability for haze pollution that reaches Singapore on the responsible agri-business entities. Responses to the recent fire crisis in the region will reveal how effective transboundary, national, and sub-national policy initiatives are in reducing fire in Indonesia. As of yet, efforts do not appear promising, as the haze problem continues to worsen and efforts on the ground have been largely inadequate despite the serious economic and health consequences of these fires.

Fire regimes are dictated by ignition source, the conduciveness of meteorological conditions for burning, and fuel availability (Stolle, Chomitz et al. 2003). Thus, while ignition is a key component to the fire regime because it is necessary for either an open or a smoldering self-sustaining fire, ignition *per se* does not necessarily lead to fire; there must also be sufficient fuel loads, appropriate air temperature and moisture, etc. We focus on ignitions themselves, following the recommendations of (Vayda 2006) who makes a call for a distinction between research approaches addressing factors responsible for ignition versus fire occurrence. However, understanding the factors that predispose the landscape to burning is also critical to understanding the fire regime, including altered hydrology from drainage canals for agricultural development, logging history and other vegetation changes, climate change, and fire history itself, all of which can alter the probability of fire occurrence and spread. Certainly more research is needed on the relative influence of various biophysical and anthropogenic factors on increasing fire probability. Because ignition will not turn into a fire if there are sufficient biophysical or spatial controls, management or policy interventions focused on ignitions should be focused on reducing the prevalence of conditions under which fires can and do result (i.e., where ignitions could potentially lead to fire because they are not constrained biophysically), in addition to behavior change leading to reduced ignitions. Additionally, promoting less-flammable LULC classes that may help buffer ignitions could also reduce fire on the landscape (e.g., allowing degraded or logged-over forest to recover or even actively restoring it rather than allocating it for conversion).

Conclusions

Fires in Indonesia have consequences from the local to global scale, including burning forest that is home to endemic and endangered flora and fauna, emitting haze that compromises human health and impacts economies across the region, and converting peatlands from a major carbon sink to a major source of CO_2. Identifying the sources of fire ignitions and LULC classes associated with fire ignitions is a key factor for reducing fire on this landscape, as this will allow us to more pointedly target management and policy interventions. Results of this research, which uses remotely sensed data and modeling to analyze ignition sources and fire spread in tropical peat-swamp forest in Central Kalimantan from 2000-2010, indicate that most fires (68-71%) originate in non-forest areas, and refute the claim that fires occurring on or escaping from oil palm concessions and settlements constitute the major proportion of fires in this study region during 2000-2010. We find that only 17%-19% of fires are ignited on oil palm concessions, and that most fires that start on oil palm concessions stay on the concession (90%), with the relatively few escaped fires from concessions constituting a very low percentage of fires on the landscape (2%). Similarly, few fires start within 5km of settlements (6-9%), most stay within those boundaries (88%), and fires escaping from settlements constitute only 1% of fires on the landscape. However, we do find a detectable pattern of fire ignitions around oil palm concessions and settlements, and a high density of ignitions within them (0.055 ignitions km^{-2} and 0.125 ignitions km^{-2}, respectively), suggesting that increased anthropogenic activity around these land use classes contributes to fire activity, and that the expansion of settlements or concession areas could substantially increase fire on the landscape, if peat and fire management is not improved. Effective fire management should therefore target not just oil palm concessions or areas around settlements, but should also focus strongly on non-forested, degraded areas –and in particular those near oil palm concession boundaries and outside the immediate vicinity of settlements – where ignitions are most likely to occur. Addressing these issues within degraded, unmanaged, or illegally planted non-forest areas is likely to prove even more challenging than addressing them within oil palm concessions.

TABLES AND FIGURES

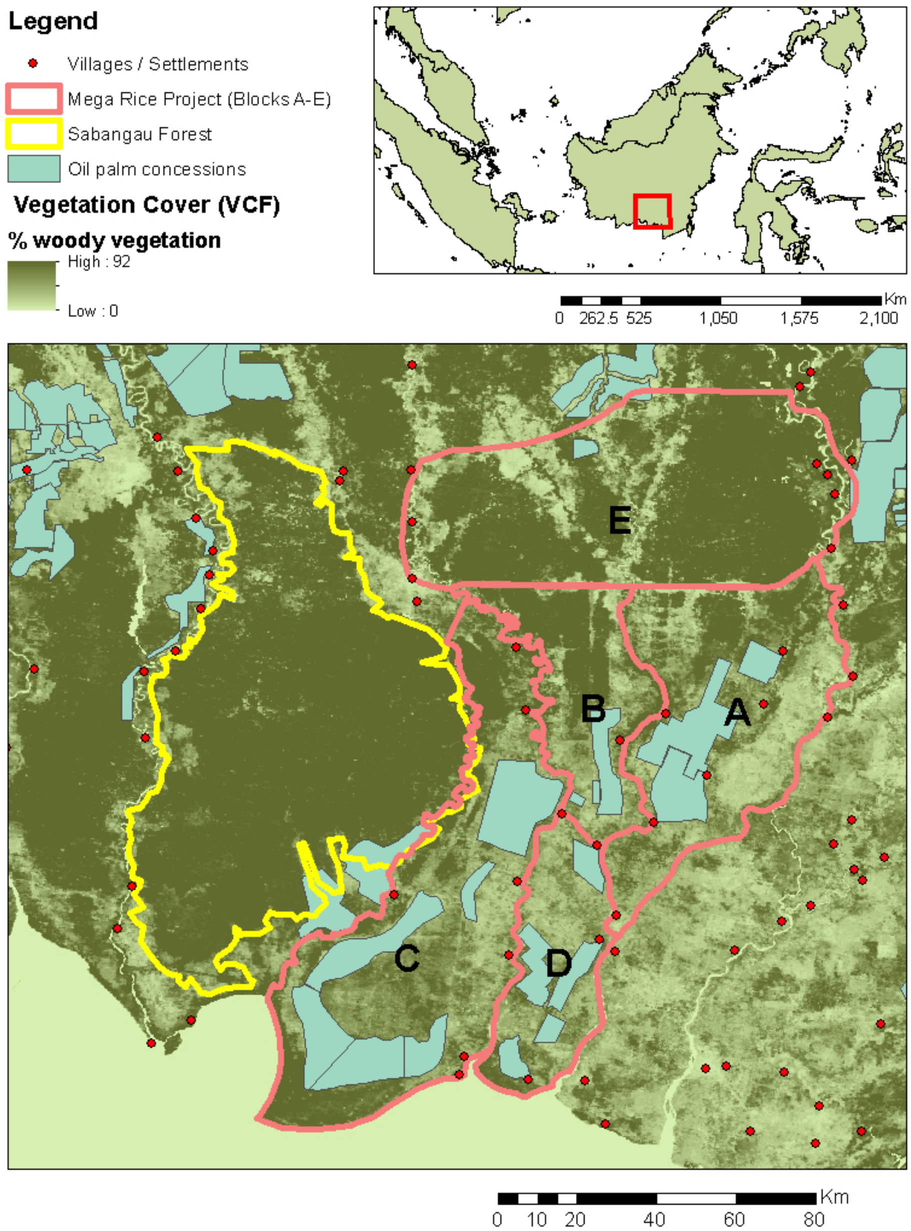
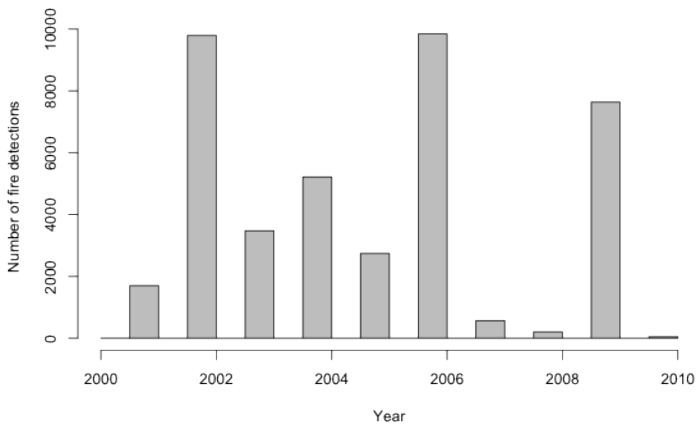
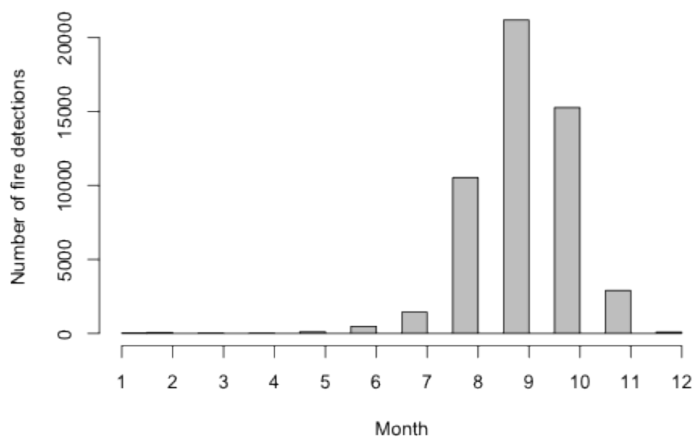


Figure 1. The study area: lowland peat-swamp forest in Central Kalimantan, Indonesia, consisting of the failed Mega Rice Project (pink borders; letters indicate administrative zones) and the adjacent Sabangau Forest (yellow border), including the percent woody vegetation, legal oil palm concession boundaries, and major villages and settlement locations. Inset: Location within Indonesia.



a.



b.

Figure 2. Temporal pattern of fire in the study area 2000-2010: the number of MODIS fire detections per year and per month within the study area. Fire activity peaks during a. El Niño phases (2002, 2004, 2006, and 2009) and b. during the dry season months (August-October). Data source described below in *Data*.

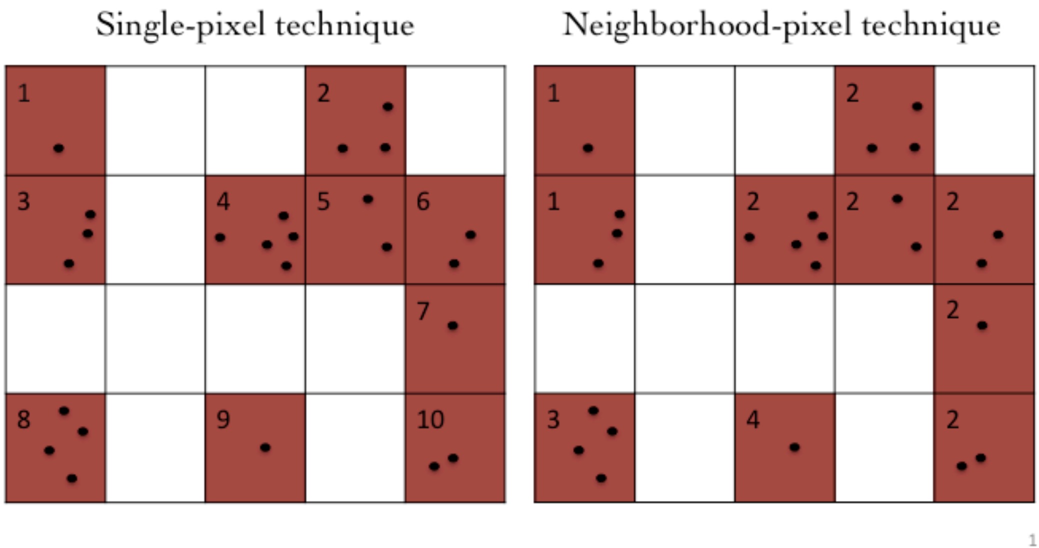


Figure 3. An example of the methodology for identifying individual fire events from fire detections using (a) the single-pixel technique and (b) the neighborhood-pixel technique. Using the single-pixel technique, fire detections within a given temporal threshold and within the same pixel are assigned to the same fire (designated by the same number). Using the neighborhood-pixel technique, fire detections within a given temporal threshold and within the same and adjacent pixels are assigned to the same fire. In this example, all fire detections are all within the temporal threshold.

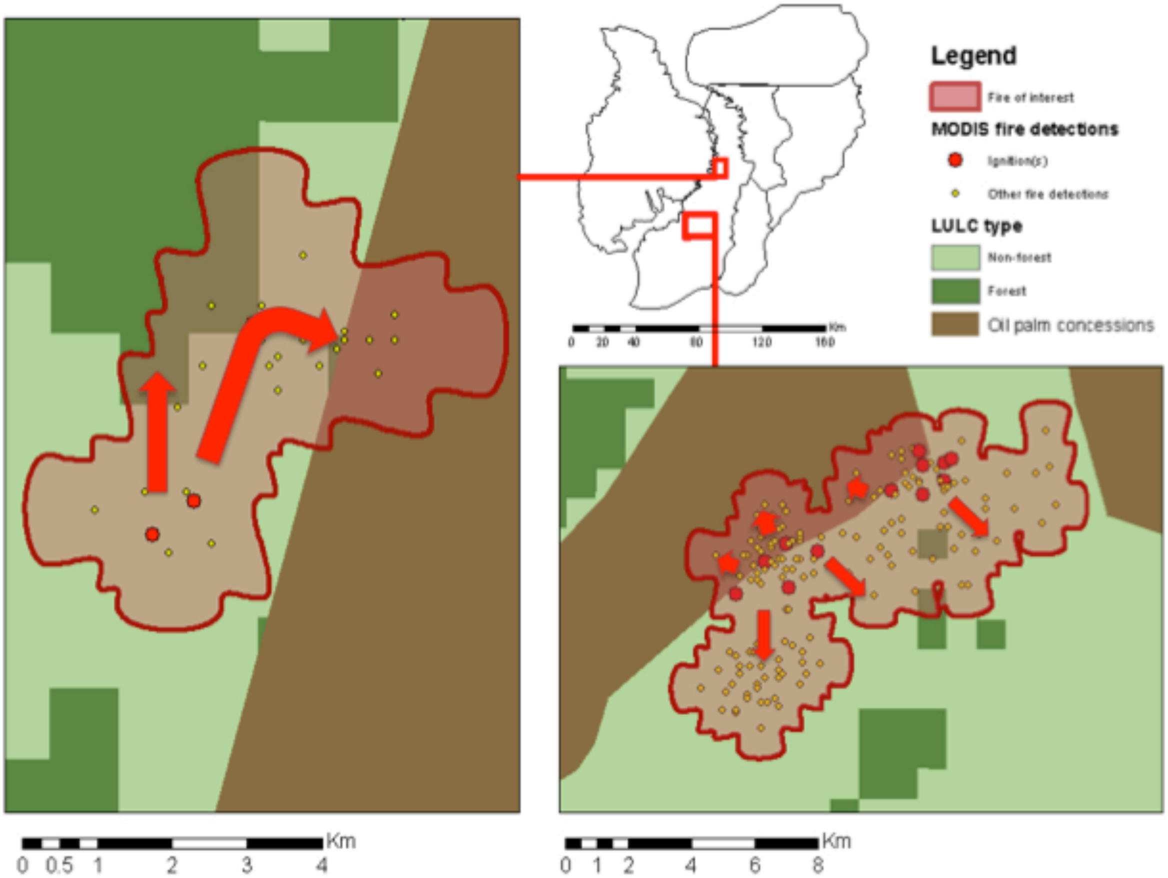


Figure 4. Two examples of individual fires in the study area identified by clustering MODIS fire detections together based on spatial and temporal rules. One fire (left) starts in non-forest and spreads into both forest and oil palm concession. Another (right) starts from several ignition points near the boundary of oil palm concession and non-forest and spreads further into each of these LULC classes.

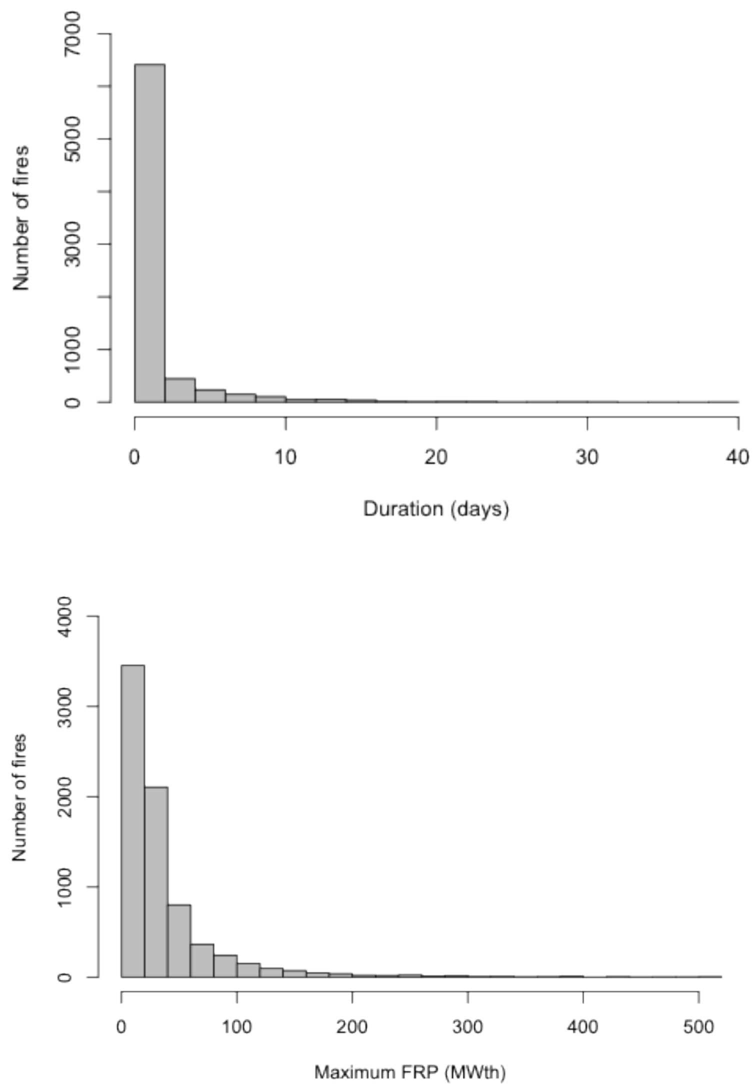


Figure 5. Distribution of fire duration and FRP for all fires in the study area identified using the neighborhood-pixel technique

Table 1. The percent of all fire ignitions that are located in each land use / land cover class for fires identified using the single-pixel technique (fires less than or equal to 1 km) and the neighborhood pixel technique (fires allowed to spread beyond 1 km) and the density of those fire ignitions. Numbers for high impact fires are in parentheses.

		Land use / land cover class								
	Fire ID method	Oil palm concession	Forest outside of concession	Non-forest outside of concession	Multiple	Within 5 km	Within 4 km	Within 3 km	Within 2 km	Within 1 km
Percent of ignitions	Single-pixel	18.5 (16.8)	13.1 (13.4*)	68.3 (69.5)	0.2 (0.3)	5.8 (3.1)	3.6 (1.9)	2.0 (0.8)	0.9 (0.4)	0.2 (0.1)
	Nhood-pixel	17.0 (17.7)	8.8 (9.3)	71.2 (68.3)	3.1 (4.6)	9.1 (6.0)	5.6 (3.4)	3.3 (1.8)	1.5 (0.9)	0.4 (0.3)
Density (ignitions km^{-2})	Nhood-pixel	0.055 (0.010)	0.006 (0.001)	0.060 (0.010)	NA	0.125 (0.015)	0.096 (0.011)	0.077 (0.008)	0.058 (0.006)	0.051 (0.008)

* Numbers in parentheses are for high-impact fires

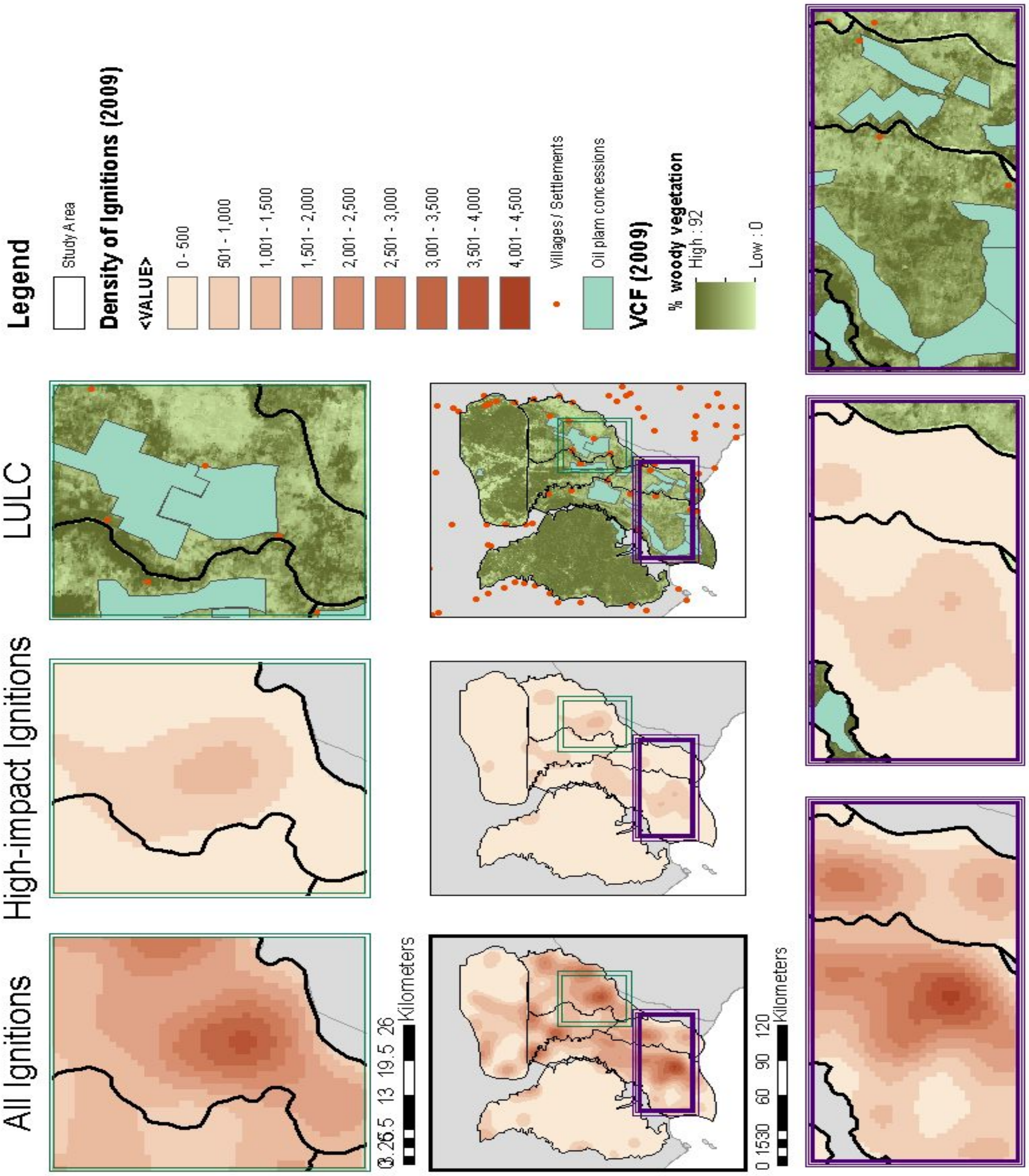


Figure 6. Spatial distribution of the density of ignitions for all fires and for high-impact fires shown with LULC class. Top row: details of an area of high ignition density that occurs on oil palm concession. Middle row: the entire study area. Bottom row: details of an area of high ignition density that occurs on non-forest near oil palm concession. For all rows, from left to right: the density of ignitions for all fires, the density of ignitions for high-impact fires, and LULC class.

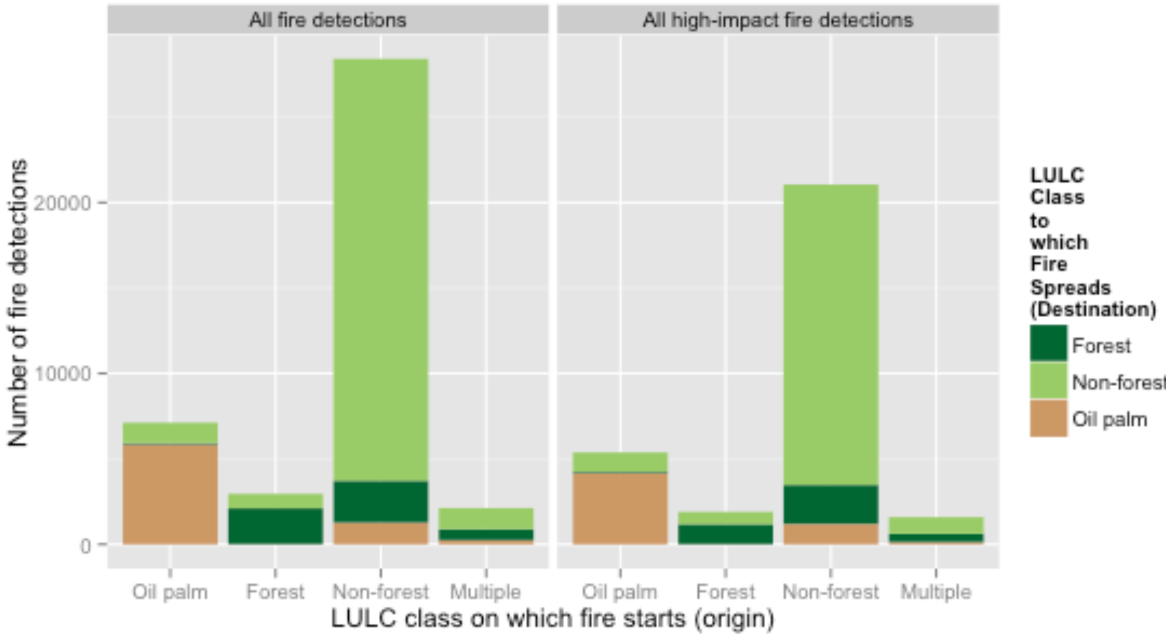


Figure 7. Fire origin and spread for all fires and high-impact fires: The number of fire detections associated with fires that start on each LULC class (origin), broken down by LULC class to which the fire spreads (destination).

Table 2. The percent of all fire detections in forest that are associated with all fires and with high-impact fires that originate in each land use / land cover class.

	LULC class on which fire starts (origin)				
Fire type	Oil palm	Forest	Non-forest	Multiple	Within 5 km of settlements
All fires	1.5	39.9	46.4	12.2	2.4
High-impact	2.0	29.4	56.7	11.9	1.3

Table 3. Percent of total fires and total fire detections in the study area that start on oil palm concessions or that start within 5 km of settlements rather than other LULC classes, broken down into those which escape from the source LULC class and those which do not escape. In parentheses are the percent of fires and fire detections that start on oil palm concessions or that start within 5 km of settlements, which escape from the source LULC class and do not escape.

Land use class class		Fire type	Percent of all fires that start on land use class	Percent of all fires (percent of fires that start on land use class) which escape from from land use class	Percent of all fires (percent of fires that start on land use class) which stay on land use class
Oil palm concession	Percent of ignitions	All fires	17.0	1.8 (10.5*)	15.2 (89.5)
		High-impact	17.7	6.8 (37.3)	11.1 (62.7)
	Percent of detections	All fires	17.5	3.1 (17.9)	14.4 (82.1)
		High-impact	17.9	4.1 (22.7)	13.8 (77.3)
Within 5 km of settlements	Percent of ignitions	All fires	10.2	1.2 (12.2)	8.9 (87.8)
		High-impact	6.8	3.0 (44.1)	3.8 (55.9)
	Percent of detections	All fires	5.0	2.2 (44.1)	2.8 (55.9)
		High-impact	3.4	2.4 (70.0)	1.0 (30.0)

* Numbers in parentheses are percent of fires that start on oil palm concessions rather than percent of all fires in the study area

Table 4. Mean duration in days and mean maximum FRP of fires that escape from oil palm concessions and from within 5 km of settlements, of fires that start on oil palm concessions and within 5 km of settlements but do not escape, and of all fires in the study area that do not start on oil palm concessions and from within 5 km of settlements.

	Mean duration (days)			Mean maximum FRP (MW_{th})		
Land use class	Escaped from land use class not started on	Other fires that start on land use class	All other fires not started on land use class	Escaped from land use class use class	Other fires that start on land land use class	All other fires
Oil palm concessions	6.7 (± 6.6)	1.6 (± 2.2)***	2.0 (± 3.2)***	102.7 (± 134.7)	34.2 (± 39.2)***	42.7 (± 77.9)***
Settlement	3.2 (± 3.9)	1.3 (± 1.6)***	2.1 (± 3.3)**	84.5 (± 144.4)	29.6 (± 58.9)***	43.3 (± 78.3)**

Significance codes for difference between denoted category and escaped fires: *<0.05, **<0.01, ***<0.001

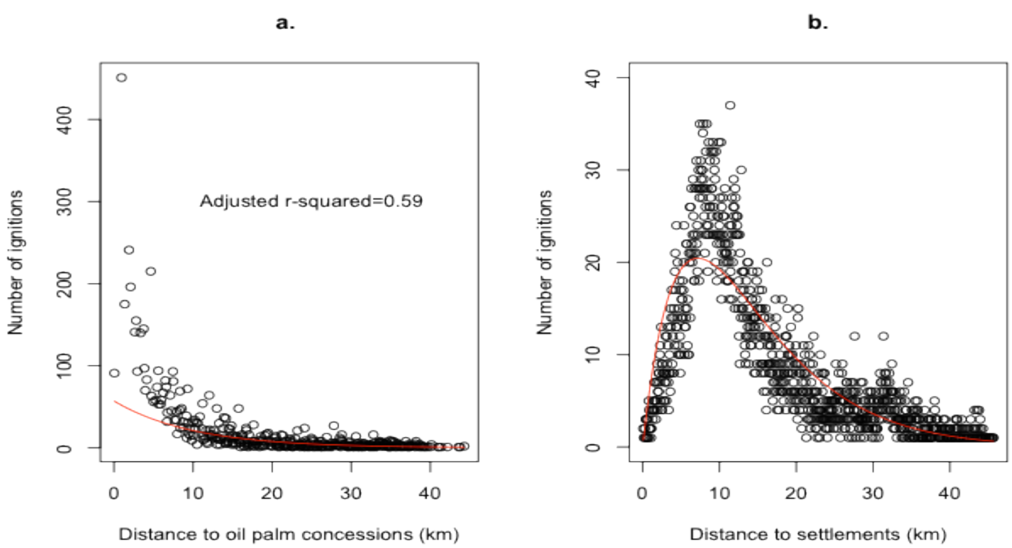
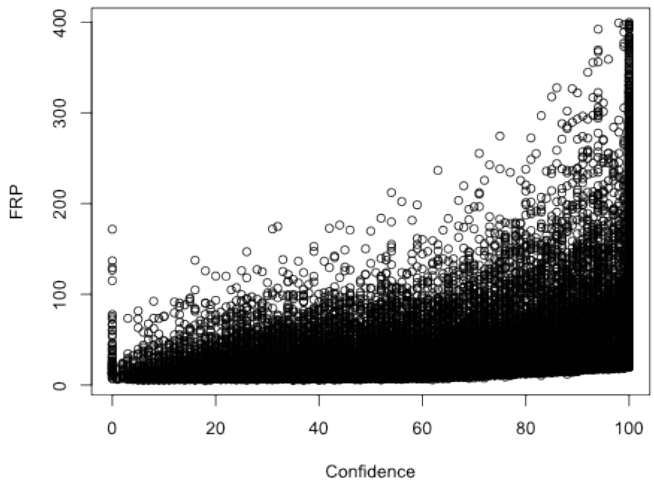
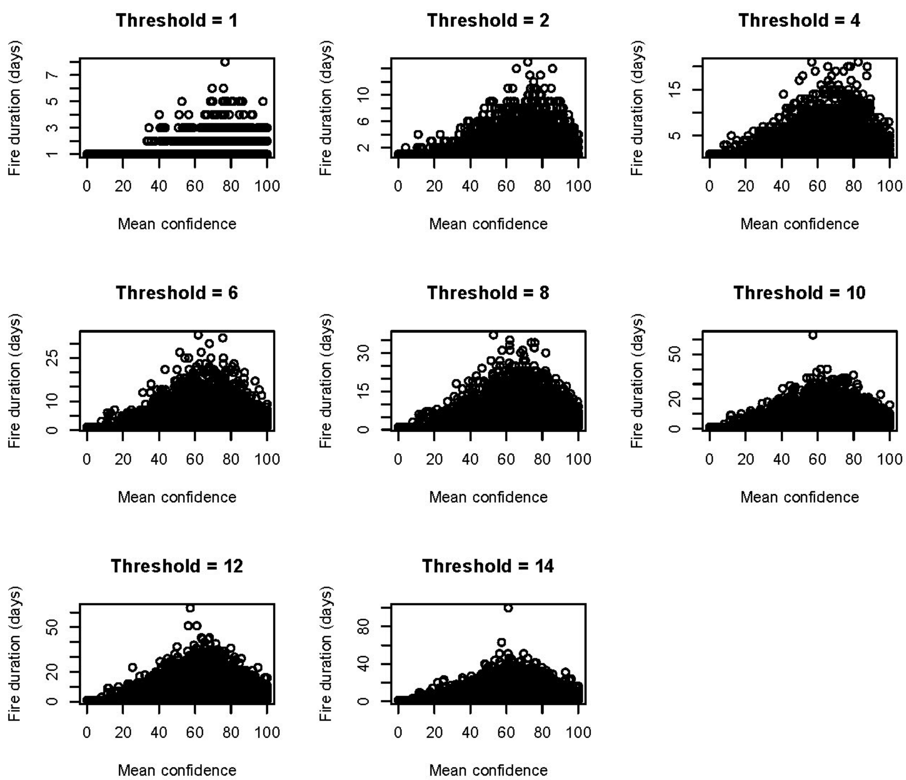


Figure 8. The number of fire ignitions for all fires identified using the neighborhood-pixel technique as a function of a. distance from oil palm concessions with regression lines fitted for exponential models (Adjusted R^2= 0.59, $p<0.001$) and b. distance from settlements with regression lines fitted with a Ricker model.

Supporting Information



a.



b.

Fig. S1. The relationship between a. fire radiative power (FRP) and confidence for all fire detections and b. fire duration (days) and mean confidence for each fire across the range of temporal thresholds used to identify fires. Detections with high FRP have high confidence values. The mean confidence values of the longest fires are approximately 60-80.

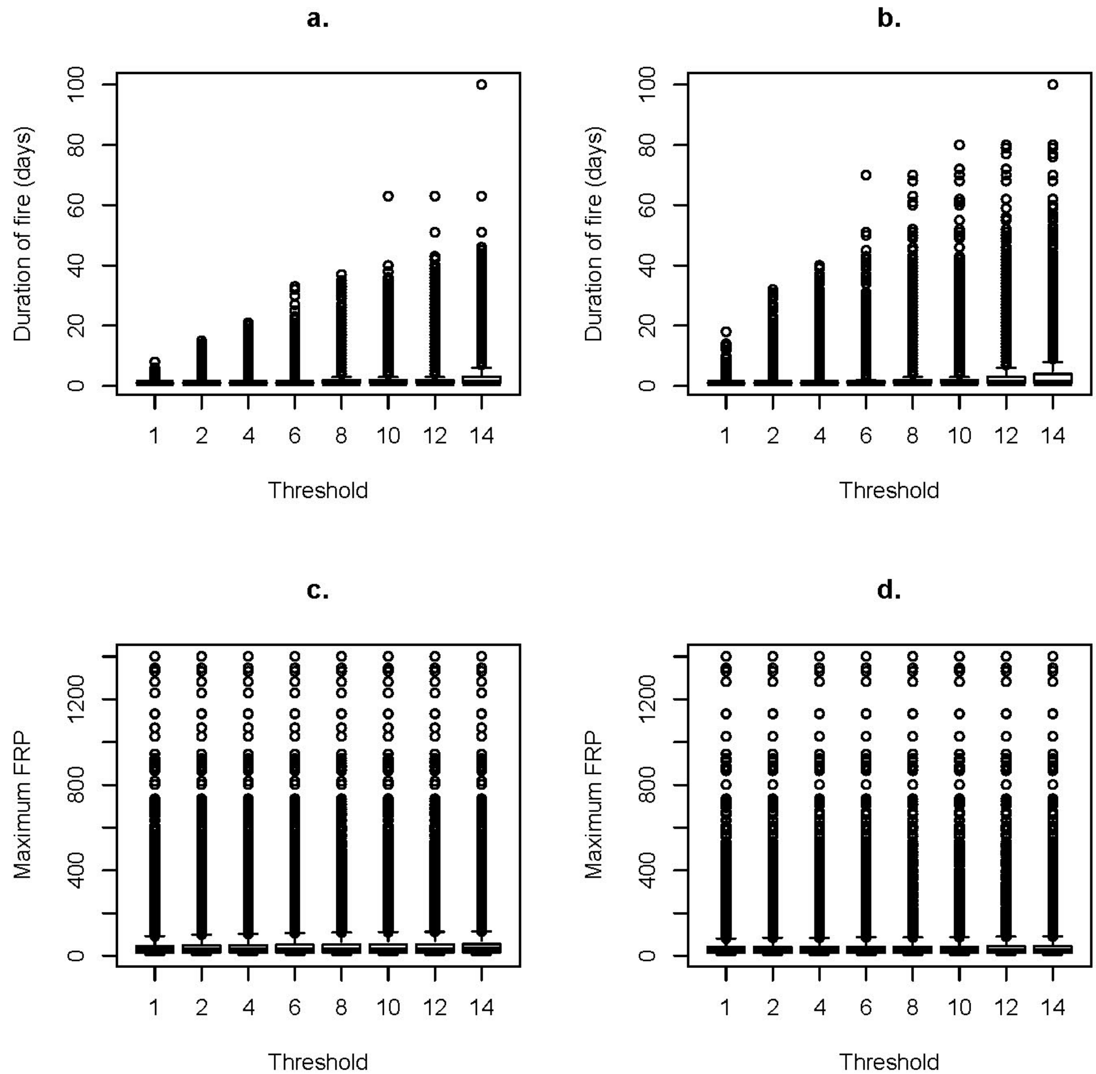


Fig. S2. The characteristics of the fires depending upon the temporal threshold chosen to identify unique fires a. duration of fires identified using the single-pixel technique, b. duration of fires identified using the neighborhood-pixel technique, c. maximum FRP of fires identified using the single-pixel technique, d. maximum FRP of fires identified using the neighborhood-pixel technique.

Table S1. The characteristics of fires depending upon the temporal threshold chosen to identify unique fires.

	Single-pixel technique				Neighborhood-pixel technique			
Temporal threshold	Mean duration (days)	Threshold long-duration fires (top 10%)	Mean maximum FRP	Threshold high-FRP fires (top 10%)	Mean duration (days)	Threshold long-duration fires (top 10%)	Mean maximum FRP	Threshold high-FRP fires (top 10%)
1	1.0	>1	42.0	86.1	1.1	>1	40.7	80.0
2	1.3	2	44.3	91.6	1.6	2	43.0	85.6
4	1.6	3	45.7	95.1	2.1	4	43.8	87.0
6	1.9	5	47.0	98.7	2.7	6	45.0	89.3
8	2.3	6	47.8	100.6	3.2	8	45.7	89.6
10	2.6	7	48.6	102.3	3.7	10	46.4	91.0
12	2.9	9	49.1	104.1	4.2	12	47.2	92.0
14	3.2	9	49.6	105.2	4.8	15	48.1	94.8

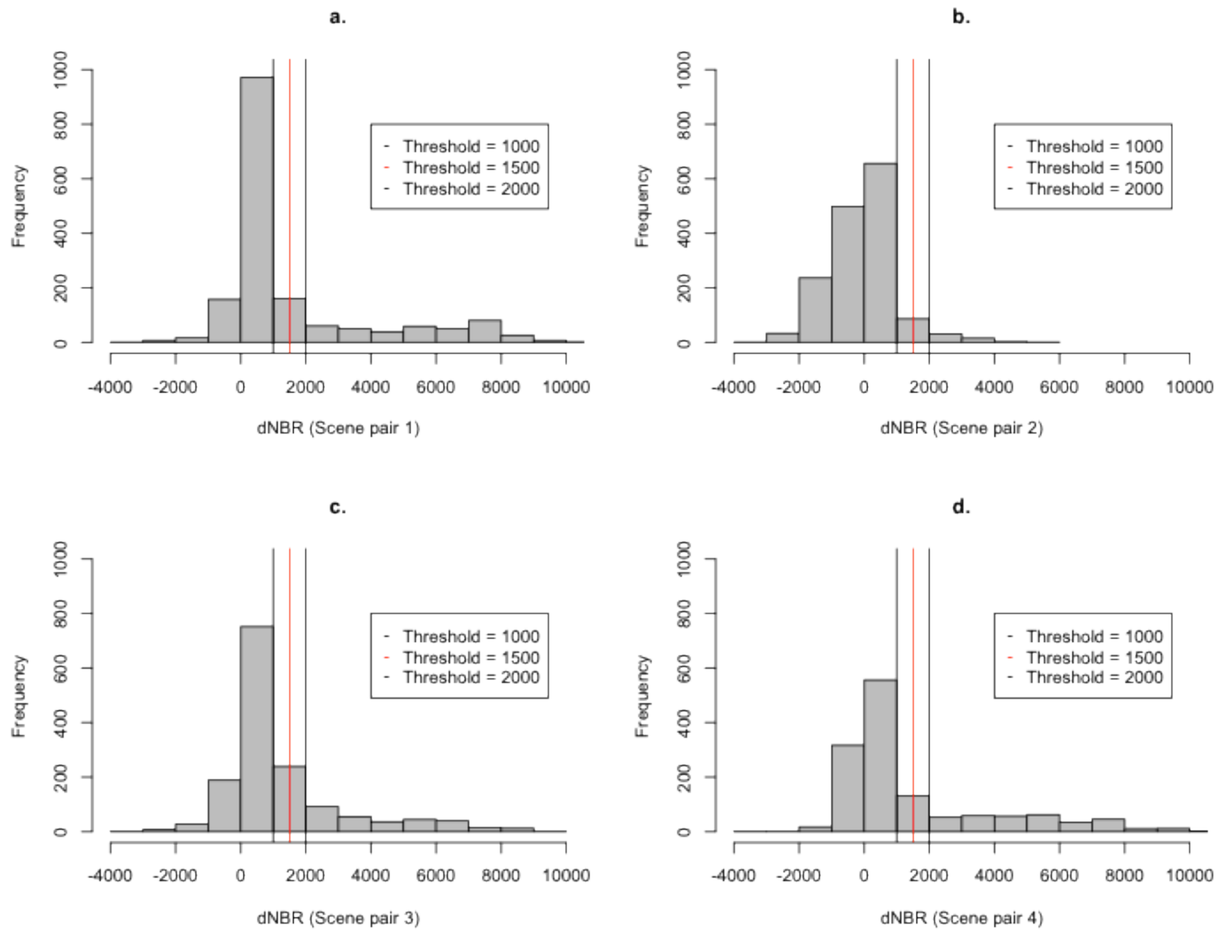


Fig. S3. Distribution of Landsat-derived dNBR values for each time period included in the accuracy assessment of fires identified by our algorithm. Every time period 2000-2010 is included for which Landsat 5 TM or Landsat 7 ETM+ scenes with less that 10% cloud cover are available that are fewer than 90 days apart, for a total of four scene-pairs and six scenes (WRS 2 Path 118 row 62, covering 83.5% of the study region). Each dNBR image is thesholded at 1500 (also 1000 and 2000) to create a binary burned - unburned layer.

Table S2. Error matrix for accuracy assessment of fires identified by our algorithm compared with Landsat-derived dNBR thresholded at 1500 (numbers in parentheses are for Landsat-derived dNBR thresholded at 1000 and 2000) from the same time period (WRS 2 Path 118 row 62, covering 83.5% of the study region), including overall accuracy as well as producer's and user's accuracy for burned and unburned land cover classes, based on a random sample of pixels stratified by burn status. Every time period 2000-2010 is included for which Landsat 5 TM or Landsat 7 ETM+ scenes with less that 10% cloud cover are available that are fewer than 90 days apart, for a total of four scene-pairs and six scenes.

Julian Day and year of scenes that bookend time periods	Landsat-derived dNBR			
152 2001 - 232 2001	MODIS algorithm	Burned	Unburned	User's Accuracy
	Burned	347 (322-391)	345 (301-370)	50 (47-57)%
	Unburned	93 (73-161)	908 (840-928)	91 (84-93)%
	Producer's Accuracy	79 (71-82)%	72 (71-74)%	Overall Accuracy = 74 (73-74)%
137 2004 - 169 2004	MODIS algorithm	Burned	Unburned	User's Accuracy
	Burned	315 (297-343)	380 (352-398)	45 (43-49)%
	Unburned	21 (11-50)	848 (819-858)	98 (94-99)%
	Producer's Accuracy	94 (87-96)%	69 (68-70)%	Overall Accuracy = 74 (74)%
169 2004 - 233 2004	MODIS algorithm	Burned	Unburned	User's Accuracy
	Burned	298 (267-381)	376 (293-407)	44 (40-57)%
	Unburned	104 (61-185)	737 (656-780)	88 (78-93)%
	Producer's Accuracy	74 (67-81)%	66 (66-69)%	Overall Accuracy = 68%
233 2004 - 265 2004	MODIS algorithm	Burned	Unburned	User's Accuracy
	Burned	273 (255-304)	197 (166-215)	58 (54-65)%
	Unburned	131 (104-179)	760 (712-787)	85 (80-88)%
	Producer's Accuracy	68 (63-71)%	79 (79-81)%	Overall Accuracy = 76 (75-77)%

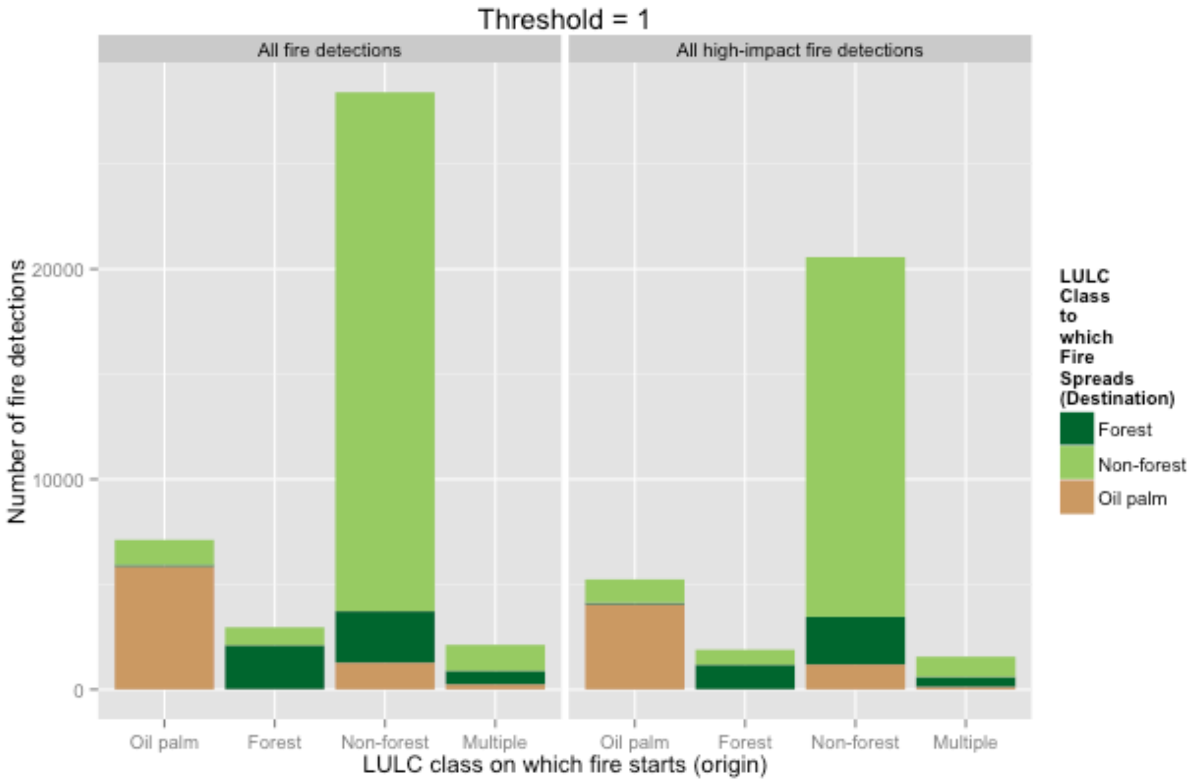
Table S3. Percent of total area of fires identified by our algorithm compared that is predicted as burned by the Landsat-derived dNBR thresholded at 1000, 1500, and 2000 from the same time period (WRS 2 Path 118 row 62, covering 83.5% of the study region). Every time period 2000-2010 is included for which Landsat 5 TM or Landsat 7 ETM+ scenes with less that 10% cloud cover are available that are fewer than 90 days apart, for a total of four scene-pairs.

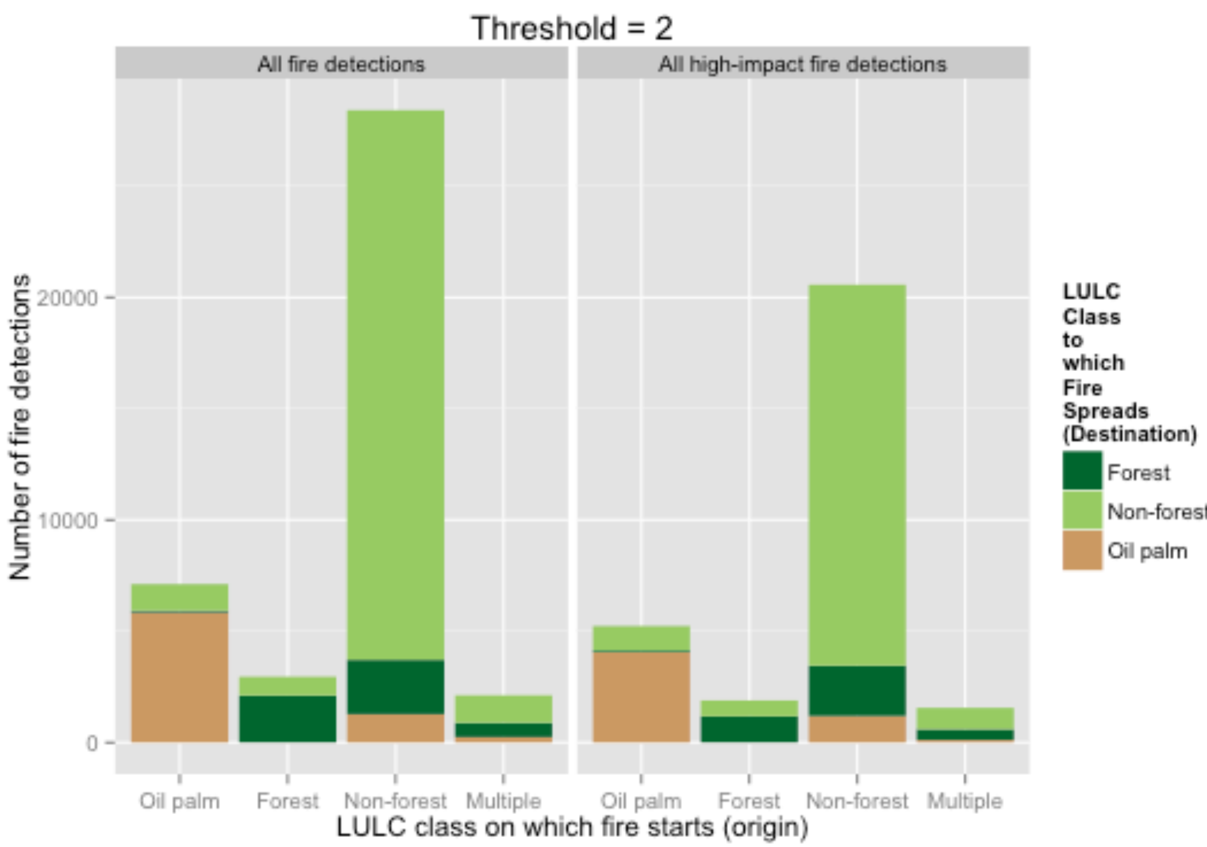
Julian Day and year of scenes that bookend time periods	dNBR Threshold = 1000	dNBR Threshold = 1500	dNBR Threshold = 2000
152 2001 - 232 2001	42.68	35.67	32.64
137 2004 -169 2004	39.73	34.68	32.11
169 2004 -233 2004	37.18	28.56	24.52
233 2004 -265 2004	41.83	37.67	35.09
Avergae	40.36 (± 2.45)	34.15 (± 3.93)	31.09 (± 4.57)

Table S4. The percent of all fire ignitions that are located in each land use / land cover class for fires identified using the single-pixel technique (fires less than or equal to 1km) and the neighborhood pixel technique (fires allowed to spread beyond 1km). Numbers for high impact fires are in parentheses.

		Land use / land cover class								
Temporal Threshold	Fire id method	Oil palm concessions	Forest outside of concessions	Non-forest outside of concessions	Multiple	Within x km of settlements				
						5	4	3	2	1
1	Single-pixel	18.3 (15.3)	12.9 (13.3)	68.6 (71.0)	0.2 (0.4)	5.1 (3.0)	3.2 (1.6)	1.7 (0.6)	0.7 (0.4)	0.2 (0.2)
	Neighborhood-pixel	17.3 (16.3)	9.5 (11.1)	69.9 (67.3)	3.3 (5.4)	6.8 (4.0)	4.4 (2.5)	2.5 (1.4)	1.1 (0.7)	0.3 (0.2)
2	Single-pixel	18.3 (17.0)	13.1 (13.3)	68.5 (69.4)	0.2 (0.3)	5.5 (3.1)	3.4 (1.9)	1.9 (0.7)	0.8 (0.3)	0.2 (0.1)
	Neighborhood-	17.6 (17.8)	9.4 (9.4)	70.1 (69.2)	3.0 (3.6)	8.1 (5.6)	5.1 (3.5)	2.9 (1.8)	1.4 (0.9)	0.4 (0.2)

	pixel									
4	Single-pixel	18.5 (16.8)	13.1 (13.4)	68.3 (69.5)	0.2 (0.3)	5.8 (3.1)	3.6 (1.9)	2.0 (0.8)	0.9 (0.4)	0.2 (0.1)
	Neighborhood-pixel	17.0 (17.7)	8.8 (9.3)	71.2 (68.3)	3.1 (4.6)	9.1 (6.0)	5.6 (3.4)	3.3 (1.8)	1.5 (0.9)	0.4 (0.3)
6	Single-pixel	18.7 (16.8)	13.1 (13.5)	68.1 (69.4)	3 (0.3)	6.0 (3.1)	3.7 (1.8)	2.1 (0.8)	0.9 (0.4)	0.2 (0.1)
	Neighborhood-pixel	17.0 (17.9)	8.7 (9.1)	71.3 (67.6)	3.0 (5.4)	9.8 (6.2)	6.0 (3.3)	3.5 (2.0)	1.6 (1.1)	0.4 (0.4)
8	Single-pixel	18.7 (16.0)	13.1 (13.5)	68.0 (70.1)	0.2 (0.4)	6.1 (3.4)	3.8 (2.1)	2.1 (0.9)	0.9 (0.5)	0.2 (0.1)
	Neighborhood-pixel	17.0 (16.1)	8.7 (9.2)	71.4 (69.5)	2.9 (5.2)	10.3 (7.6)	6.3 (4.2)	3.7 (2.6)	1.8 (1.2)	0.5 (0.4)
10	Single-pixel	18.7 (16.6)	13.0 (13.5)	68.1 (69.6)	0.2 (0.4)	6.2 (3.4)	3.8 (2.2)	2.1 (0.9)	0.9 (0.4)	0.2 (0.1)
	Neighborhood-pixel	17.0 (15.9)	8.5 (9.3)	71.6 (69.1)	2.9 (5.7)	10.6 (7.9)	6.4 (4.5)	3.8 (2.8)	1.8 (1.5)	0.5 (0.4)
12	Single-pixel	18.7 (16.4)	13.0 (13.9)	68.1 (69.4)	0.2 (0.4)	6.2 (3.4)	3.9 (2.1)	2.1 (1.0)	0.9 (0.4)	0.3 (0.1)
	Neighborhood-pixel	16.9 (15.9)	8.5 (9.2)	71.7 (69.6)	2.9 (5.4)	10.8 (7.2)	6.6 (4.1)	3.9 (2.7)	1.9 (1.2)	0.5 (0.4)
14	Single-pixel	18.6 (16.6)	13.1 (13.7)	68.1 (69.3)	0.2 (0.4)	6.3 (3.5)	3.9 (2.2)	2.1 (1.0)	1.0 (0.4)	0.3 (0.1)
	Neighborhood-pixel	16.6 (16.4)	8.5 (8.4)	71.9 (69.3)	3.0 (5.9)	11.0 (7.2)	6.8 (4.0)	4.1 (2.4)	1.9 (1.2)	0.5 (0.3)


Threshold = 1
All fire detections
All high-impact fire detections
Number of fire detections
20000
10000
0
Oil palm
Forest
Non-forest
Multiple
LULC class on which fire starts (origin)
LULC Class to which Fire Spreads (Destination)
Forest
Non-forest
Oil palm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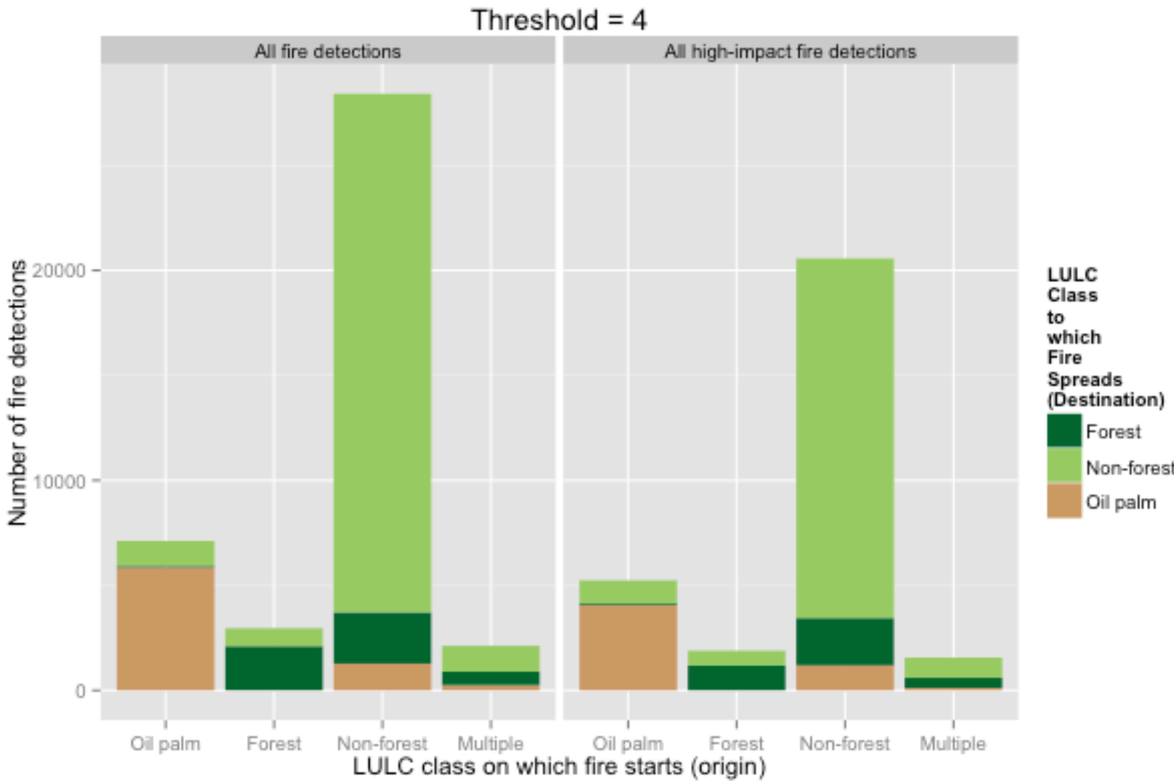
All fire detections
All high-impact fire detections
Number of fire detections
20000
10000
0
Oil palm
Forest
Non-forest
Multiple
LULC class on which fire starts (origin)
LULC Class to which Fire Spreads (Destination)
Forest
Non-forest
Oil palm


Threshold = 4
All fire detections
All high-impact fire detections
Number of fire detections
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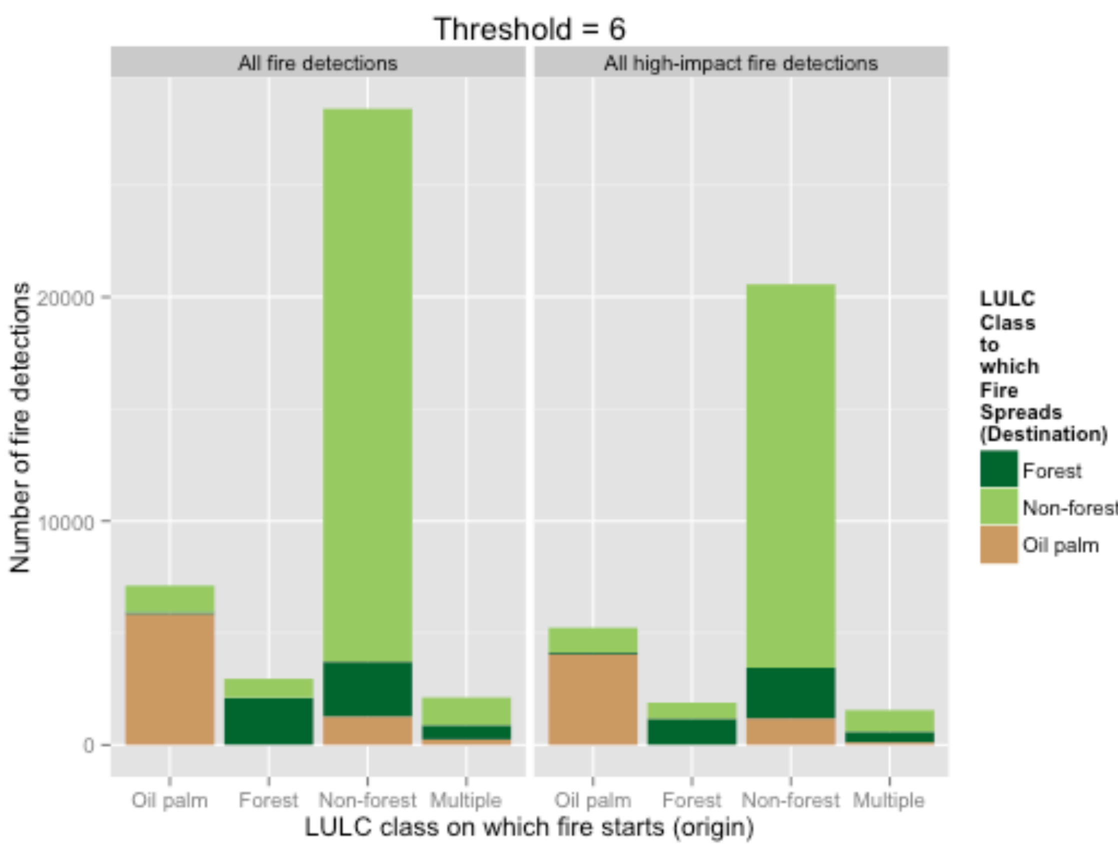
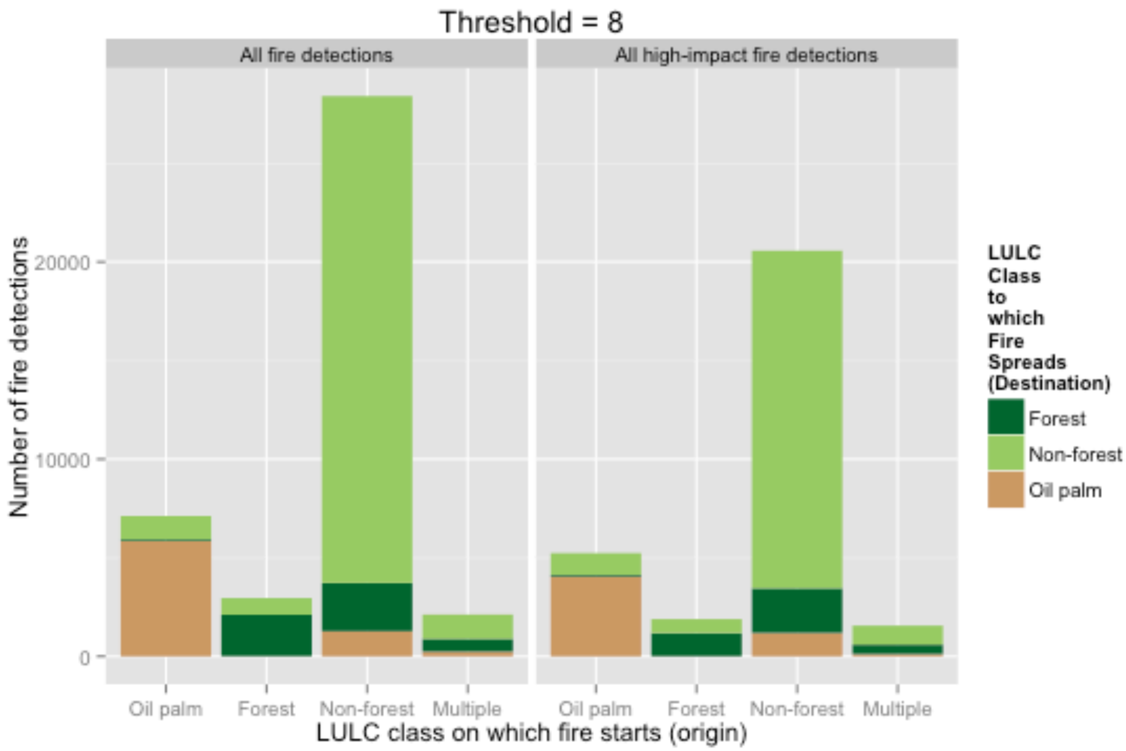
10000
0
Oil palm
Forest
Non-forest
Multiple
LULC class on which fire starts (origin)
LULC Class to which Fire Spreads (Destination)
Forest
Non-forest
Oil palm


Threshold = 6
All fire detections
All high-impact fire detections
Number of fire detections
20000
10000
0
Oil palm
Forest
Non-forest
Multiple
LULC class on which fire starts (origin)
LULC Class to which Fire Spreads (Destination)
Forest
Non-forest
Oil palm


Threshold = 8
All fire detections
All high-impact fire detections
Number of fire detections
20000
10000
0
Oil palm
Forest
Non-forest
Multiple
LULC class on which fire starts (origin)
LULC Class to which Fire Spreads (Destination)
Forest
Non-forest
Oil palm


Threshold = 10
All fire detections
All high-impact fire detections
Number of fire detections
20000
10000
0
Oil palm
Forest
Non-forest
Multiple
LULC class on which fire starts (origin)
LULC Class to which Fire Spreads (Destination)
Forest
Non-forest
Oil palm

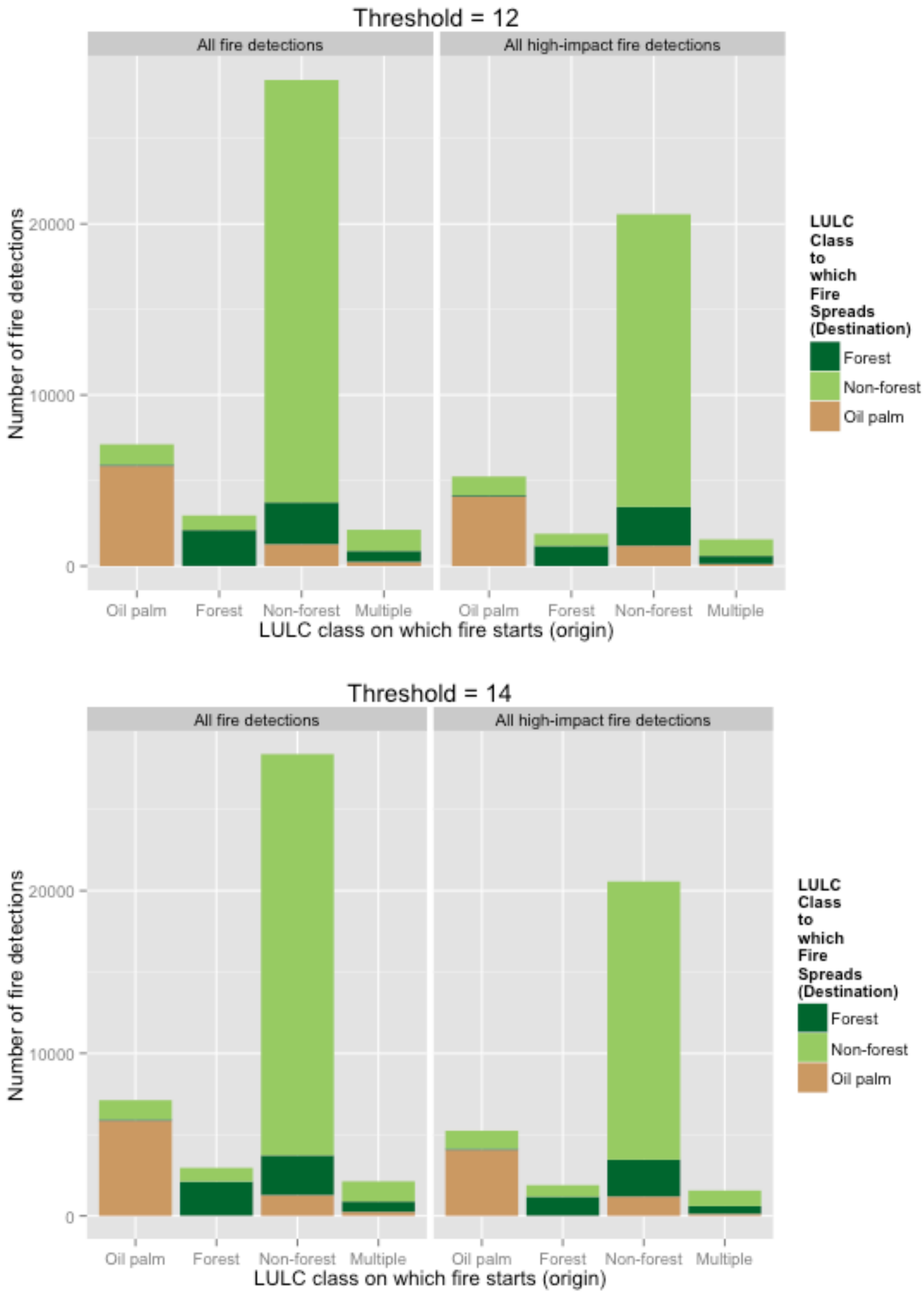


Fig. S4. Fire origin and spread for all fires and high-impact fires: The number of fires that spread to each LULC class (destination), broken down by the LULC class on which the fire starts (origin) across all temporal thresholds.

Table S5. The percent of all forest fires and high-impact forest fires that originate in each land use / land cover class across all temporal thresholds.

Temporal threshold		**LULC class on which fire starts (origin)**				
	Fire type	**Oil palm**	**Forest**	**Non-forest**	**Multiple**	**Within 5km of settlements**
1	All fires	0.9	55.4	33.8	10.0	3.0
	High-impact	1.4	37.5	53.0	8.2	1.7
2	All fires	1.4	48.3	40.3	10.0	2.5
	High-impact	1.8	38.4	50.6	9.2	1.5
4	All fires	1.5	39.9	46.4	12.2	2.4
	High-impact	2.0	29.4	56.7	11.9	1.3
6	All fires	3.8	38.0	45.6	12.6	3.1
	High-impact	5.0	26.6	55.2	13.3	2.3
8	All fires	3.9	38.2	46.7	11.2	2.3
	High-impact	5.1	26.9	56.2	11.8	1.2
10	All fires	5.9	36.7	46.0	11.4	2.5
	High-impact	7.6	26.7	53.8	12.0	1.5
12	All fires	3.9	35.4	49.6	11.2	3.6
	High-impact	4.8	26.2	57.6	11.4	3.1
14	All fires	4.3	34.3	50.2	11.2	3.6
	High-impact	5.4	24.4	58.6	11.6	3.1

Table S6. Percent of total fires and total fire detections in the study area that start on oil palm concessions rather than other LULC classes, broken down into those that escape and those that do not escape. In parentheses are the percent of fires and fire detections that start on oil palm concessions that escape and that do not escape.

				% of all fires in the study area	
	Temporal threshold	Fire type	All fires that start on land use class	Escape from land use class	Stay within land use class
Percent of ignitions	1	All fires	17.3	1.1 (6.4)	16.2 (93.6)
		High-impact	16.3	4.7 (28.7)	11.6 (71.3)
	2	All fires	17.6	1.6 (9.3)	15.9 (90.7)
		High-impact	17.8	5.7 (32.3)	12.0 (67.7)

	4	All fires	17.0	1.8 (10.5)	15.2 (89.5)
		High-impact	17.7	6.8 (37.3)	11.1 (62.7)
	6	All fires	17.0	1.9 (10.9)	15.2 (89.1)
		High-impact	17.9	7.5 (42.1)	10.4 (57.9)
	8	All fires	17.0	1.8 (10.5)	15.2 (89.5)
		High-impact	16.1	6.7 (41.4)	9.4 (58.6)
	10	All fires	17.0	1.9 (11.2)	15.1 (88.8)
		High-impact	15.9	6.5 (41.0)	9.4 (59.0)
	12	All fires	16.9	2.0 (12.0)	14.9 (88.0)
		High-impact	15.9	7.1 (44.4)	8.8 (55.6)
	14	All fires	16.6	2.0 (11.8)	14.7 (88.2)
		High-impact	16.4	7.1 (43.5)	9.2 (56.5)
Percent of detections	1	All fires	16.0	1.1 (7.1)	14.8 (92.9)
		High-impact	14.7	1.7 (11.4)	13.0 (88.6)
	2	All fires	18.0	2.9 (16.1)	15.1 (83.9)
		High-impact	18.3	3.9 (21.3)	14.4 (78.7)
	4	All fires	17.5	3.1 (17.9)	14.4 (82.1)
		High-impact	17.9	4.1 (22.7)	13.8 (77.3)
	6	All fires	20.5	6.1 (30.0)	14.4 (70.0)
		High-impact	22.0	8.1 (36.9)	13.9 (63.1)
	8	All fires	18.3	5.8 (31.9)	12.5 (68.1)
		High-impact	18.8	7.5 (39.8)	11.3 (60.2)
	10	All fires	19.1	7.0 (36.6)	12.1 (63.4)
		High-impact	19.7	8.9 (45.2)	10.8 (54.8)
	12	All fires	15.5	4.0 (25.5)	11.6 (74.5)
		High-impact	14.9	4.8 (32.2)	10.1 (67.8)
	14	All fires	14.2	3.5 (24.3)	10.8 (75.7)
		High-impact	13.2	4.1 (31.4)	9.0 (68.6)

Table S7. Percent of total fires and total fire detections in the study area that start within 5km of settlements rather than other LULC classes, broken down into those that escape and those that do not escape. In parentheses are the percent of fires and fire detections that start within 5km of settlements that escape and that do not escape.

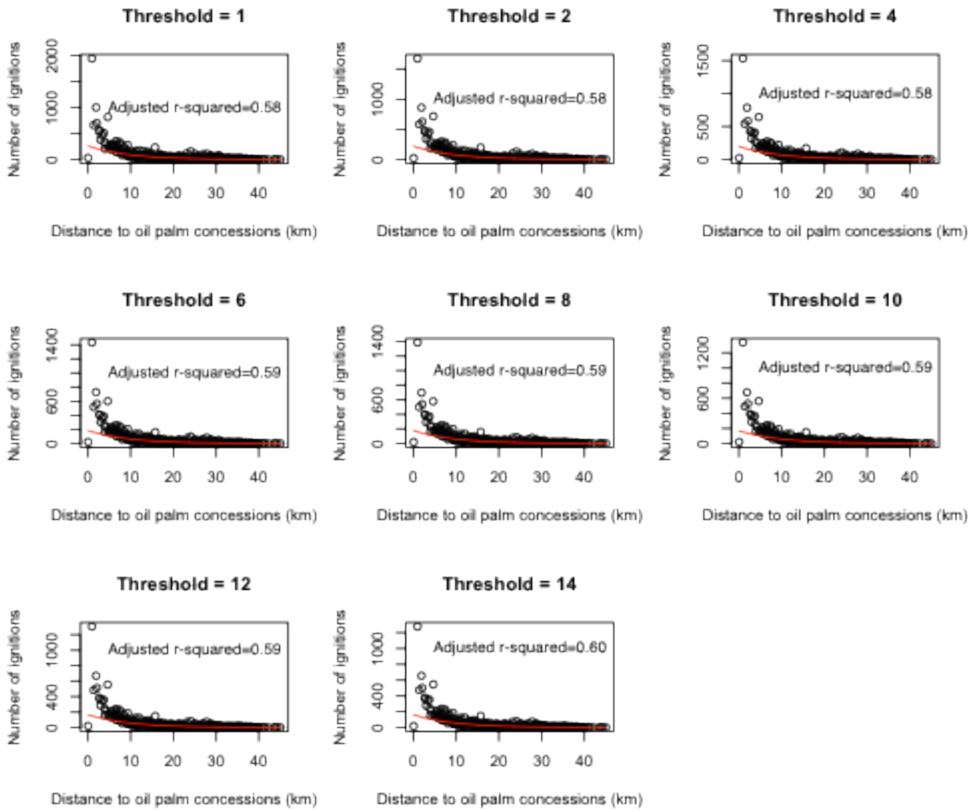
				% of all fires in the study area	
	Temporal threshold	Fire type	All fires that start on land use class	Escape from land use class	Stay within land use class
Percent of ignitions	1	All fires	8.1	0.9 (11.2)	7.2 (88.8)
		High-impact	5.4	2.1 (38.5)	3.3 (61.5)
	2	All fires	9.2	1.1 (11.4)	8.2 (88.6)
		High-impact	6.6	2.3 (34.1)	4.4 (65.9)

	4	All fires	10.2	1.2 (12.2)	8.9 (87.8)
		High-impact	6.8	3.0 (44.1)	3.8 (55.9)
	6	All fires	10.9	1.4 (12.7)	9.5 (87.3)
		High-impact	7.0	3.2 (46.2)	3.8 (53.8)
	8	All fires	11.4	1.4 (12.5)	9.9 (87.5)
		High-impact	7.9	4.0 (50.7)	3.9 (49.3)
	10	All fires	11.6	1.5 (12.9)	10.1 (87.1)
		High-impact	8.5	4.3 (50.7)	4.2 (49.3)
	12	All fires	12.0	1.6 (13.7)	10.3 (86.3)
		High-impact	8.5	4.5 (53.4)	4.0 (46.6)
	14	All fires	12.3	1.7 (13.5)	10.7 (86.5)
		High-impact	8.6	4.4 (51.5)	4.2 (48.5)
Percent of detections	1	All fires	5.0	1.7 (34.0)	3.3 (66.0)
		High-impact	2.9	1.9 (63.9)	1.0 (36.1)
	2	All fires	4.6	1.5 (32.8)	3.1 (67.2)
		High-impact	3.0	1.5 (50.9)	1.5 (49.1)
	4	All fires	5.0	2.2 (44.1)	2.8 (55.9)
		High-impact	3.4	2.4 (70.0)	1.0 (30.0)
	6	All fires	5.3	2.6 (49.4)	2.7 (50.6)
		High-impact	3.7	2.8 (75.7)	0.9 (24.5)
	8	All fires	4.8	2.1 (44.9)	2.6 (55.1)
		High-impact	3.2	2.2 (71.0)	0.9 (29.0)
	10	All fires	4.9	2.3 (47.4)	2.6 (52.6)
		High-impact	3.4	2.5 (73.6)	0.9 (26.4)
	12	All fires	5.8	3.3 (57.4)	2.5 (42.6)
		High-impact	4.6	3.8 (81.3)	0.9 (18.7)
	14	All fires	5.8	3.4 (57.9)	2.4 (42.1)
		High-impact	4.5	3.7 (82.0)	0.8 (18.0)

Table S8. Mean duration in days and mean maximum FRP of fires that escape from oil palm concessions and from within 5km of settlements, of fires that start on oil palm concessions and within 5km of settlements but do not escape, and of all fires in the study area that do not start on oil palm concessions and from within 5km of settlements across all temporal threshold. Escaped fires are statistically significantly longer and hotter-burning than other fires that were started on oil palm concessions or settlements that are not escaped fires and than all other fires in the study area, and this pattern holds across the temporal thresholds used to define individual fires.

Land use class		Mean duration (days)			Mean FRP		
	Temporal threshold	Escaped	Other fires that start on land use class	All other fires	Escaped	Other fires that start on land use class	All other fires
Oil palm concessions	1	1.6	1.1***	1.1**	95.8	33.4***	40.4***
	2	3.9	1.3***	1.6***	102.2	33.9***	42.2***
	4	6.7	1.6***	2.0***	102.7	34.2***	42.7***
	6	9.6	1.8***	2.5***	110.1	34.7***	43.7***
	8	10.6	2.0***	3.1***	105.5	34.6***	44.6***
	10	12.4	2.2***	3.5***	104.5	34.6***	45.3***
	12	13.8	2.6***	4.0***	99.5	34.4***	46.1***
	14	14.9	2.9***	4.6***	93.0	35.4***	47.2***
Within 5km of settlements	1	1.2	1.0*	1.1	68.8	29.9***	40.5***
	2	2.0	1.2**	1.6	79.9	29.7***	42.7*
	4	3.2	1.3***	2.1**	84.5	29.6***	43.3**
	6	4.7	1.4***	2.6***	92.2	29.7***	44.3**
	8	5.9	1.6***	3.2***	86.3	29.5***	45.1*
	10	7.5	1.8***	3.6***	90.1	29.6***	45.8**
	12	9.0	2.0***	4.2***	92.7	29.7***	46.4**
	14	10.9	2.2***	4.7***	95.0	29.9***	47.3**

Significance codes for difference between denoted category and escaped fires from oil palm concessions: *<0.05, **<0.01, ***<0.001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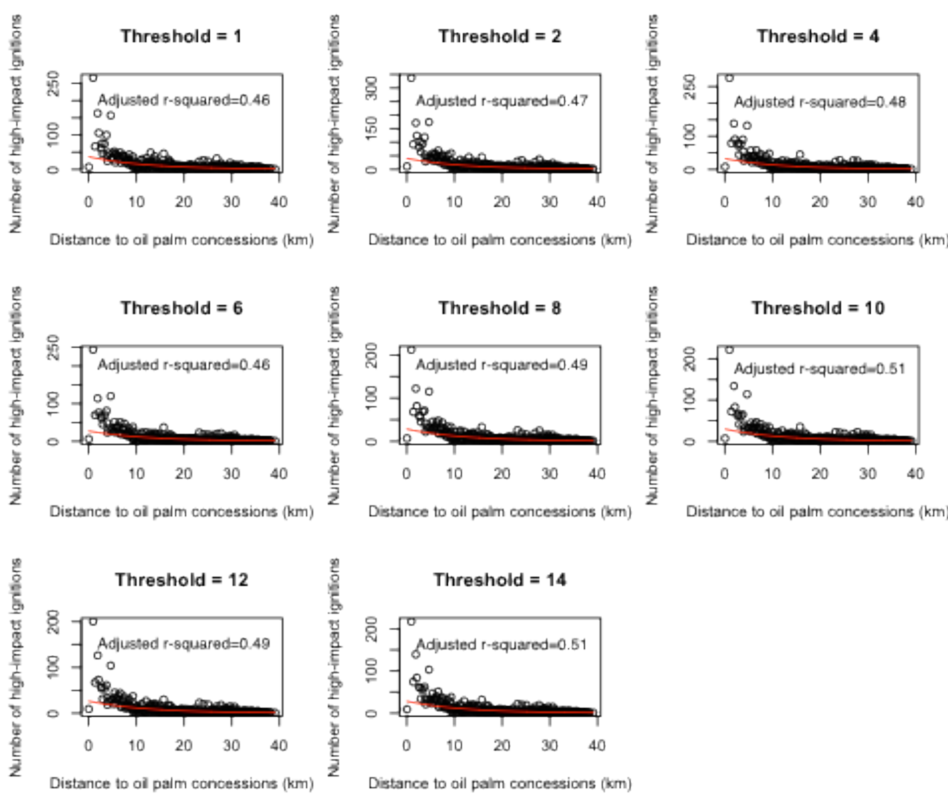
Threshold = 8
Adjusted r-squared=0.59
Threshold = 10
Adjusted r-squared=0.59
Threshold = 12
Adjusted r-squared=0.59
Threshold = 14
Adjusted r-squared=0.60
Number of ignitions
Distance to oil palm concessions (km)

a.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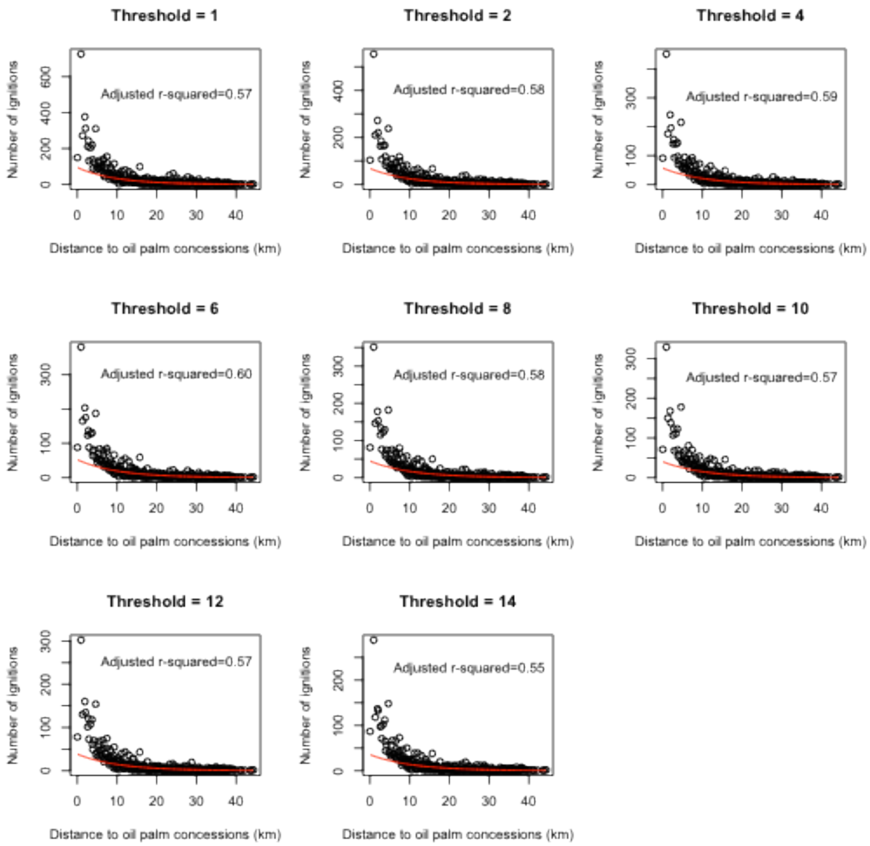
Threshold = 6
Adjusted r-squared=0.46
Threshold = 8
Adjusted r-squared=0.49
Threshold = 10
Adjusted r-squared=0.51
Threshold = 12
Adjusted r-squared=0.49
Threshold = 14
Adjusted r-squared=0.51
Number of high-impact ignitions
Distance to oil palm concessions (km)

b.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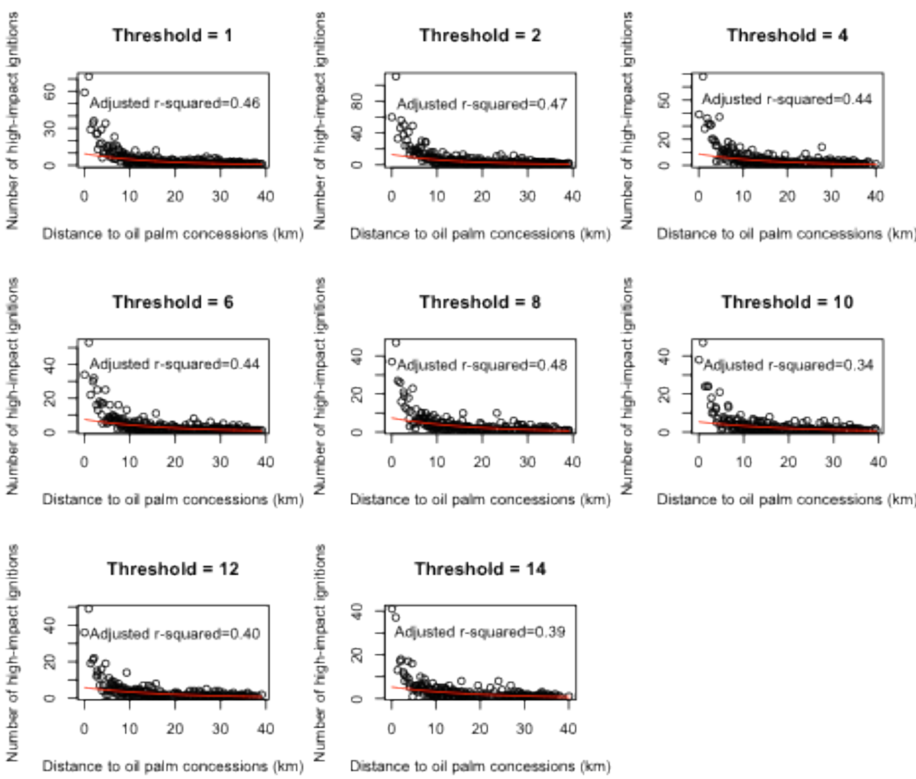
Threshold = 6
Adjusted r-squared=0.60
Threshold = 8
Adjusted r-squared=0.58
Threshold = 10
Adjusted r-squared=0.57
Threshold = 12
Adjusted r-squared=0.57
Threshold = 14
Adjusted r-squared=0.55
Number of ignitions
Distance to oil palm concessions (km)

c.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Threshold = 4
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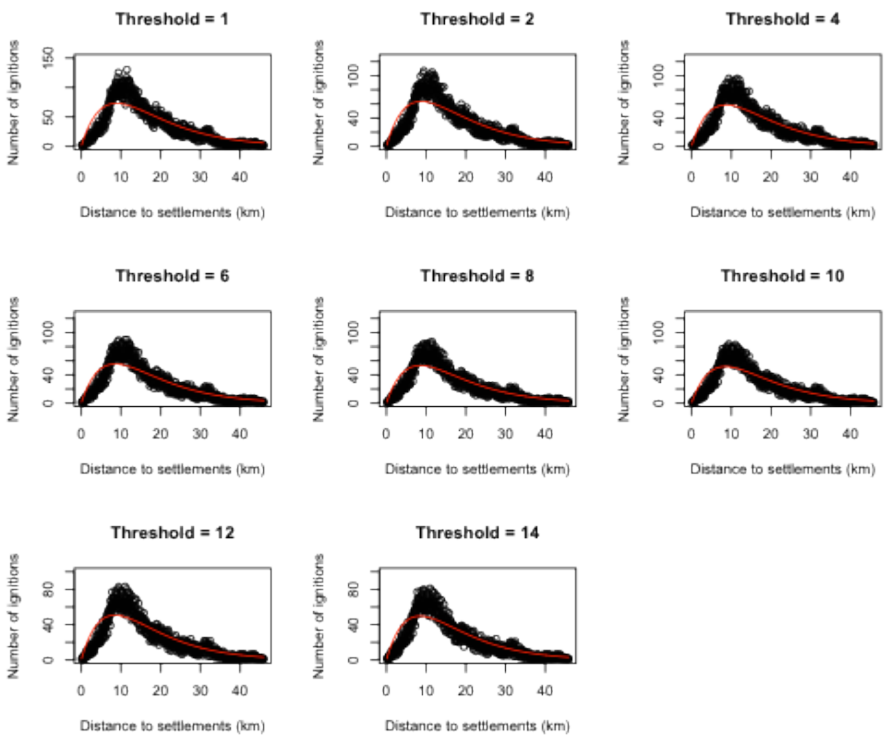
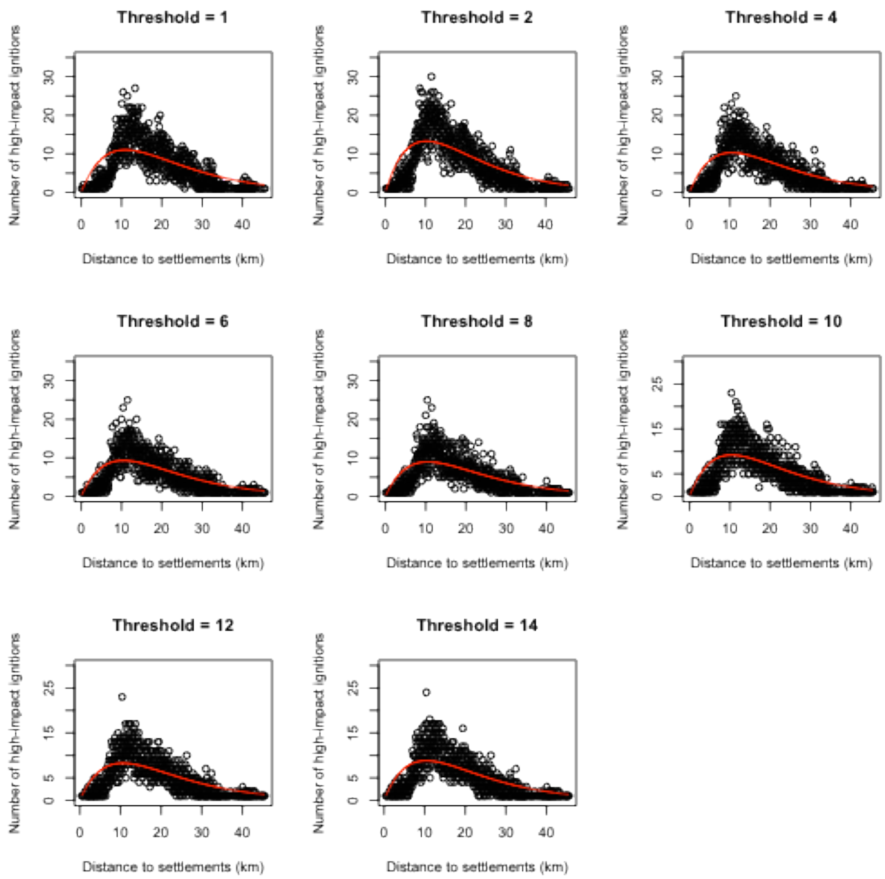
Threshold = 6
Adjusted r-squared=0.44
Threshold = 8
Adjusted r-squared=0.48
Threshold = 10
Adjusted r-squared=0.34
Threshold = 12
Adjusted r-squared=0.40
Threshold = 14
Adjusted r-squared=0.39
Number of high-impact ignitions
Distance to oil palm concessions (km)

d.

Fig. S5. The number of fires as a function of distance from oil palm concessions for a. all fires identified using the single-pixel technique, b. high-impact fires identified using the single-pixel technique, c. all fires identified using the neighborhood-pixel technique, and d. high-impact fires identified using the neighborhood-pixel technique with fitted with regression lines for exponential models across all temporal thresholds.



a.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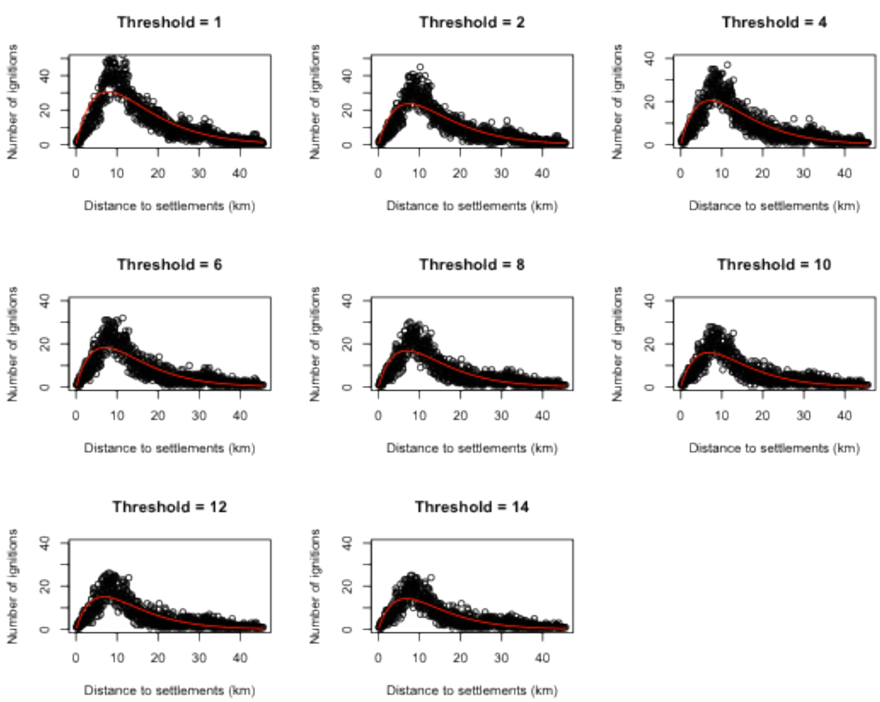
Threshold = 8
Threshold = 10
Threshold = 12
Threshold = 14
Number of high-impact ignitions
Distance to settlements (km)

b.


Threshold = 1
Threshold = 2
Threshold = 4
Threshold = 6
Threshold = 8
Threshold = 10
Threshold = 12
Threshold = 14
Number of ignitions
Distance to settlements (km)

c.

d.

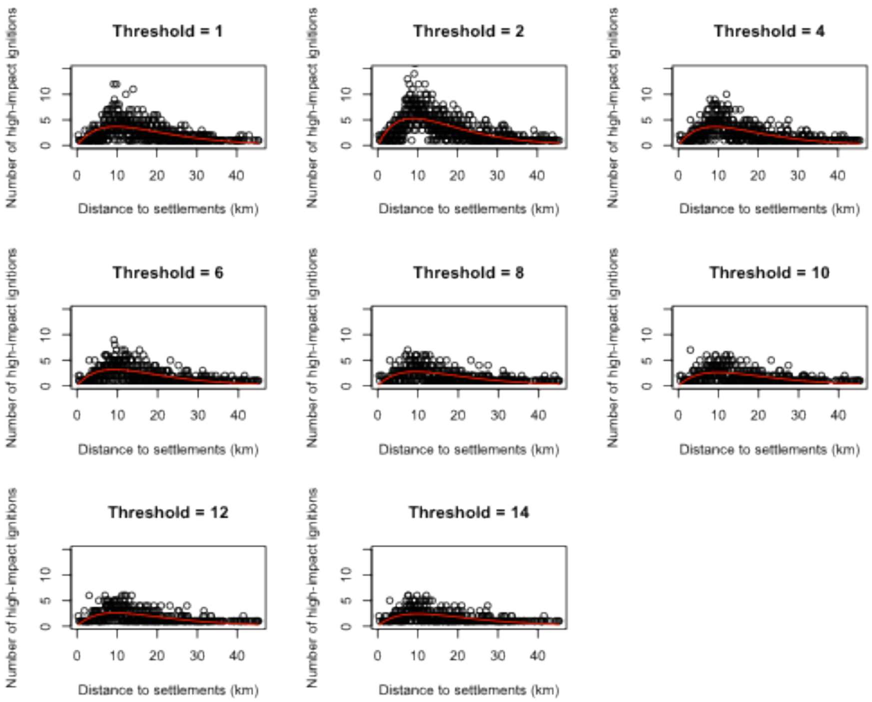


Figure S6. The number of fires as a function of distance from settlements across all temporal thresholds for a. all fires identified using the single-pixel technique, b. high-impact fires identified using the single-pixel technique, c. all fires identified using the neighborhood-pixel technique, and d. high-impact fires identified using the neighborhood-pixel technique with fitted with regression lines.

CHAPTER THREE: Effectiveness of Roundtable on Sustainable Palm Oil (RSPO) for reducing fires on oil palm concessions in Indonesia from 2012 to 2015

Megan E. Cattau, Miriam E. Marlier, and Ruth DeFries

ABSTRACT

Fire is a common tool for land conversion and management associated with oil palm production. Fires can cause biodiversity and carbon losses, emit pollutants that deteriorate air quality and harm human health, and damage property. The Roundtable on Sustainable Palm Oil (RSPO) prohibits the use of fire on certified concessions. However, efforts to suppress fires are more difficult during El Niño conditions and on peatlands. In this paper, we address the following questions for oil palm concessions developed prior to 2012 in Sumatra and Kalimantan, the leading producers of oil palm both within Indonesia and globally: 1) For the period 2012-2015, did RSPO-certified concessions have a lower density of fire detections, fire ignitions, or 'escaped' fires compared with those concessions that are not certified? and 2) Did this pattern change with increasing likelihood of fires in concessions located on peatland and in dry years? These questions are particularly critical in fuel-rich peatlands, of which approximately 46% of the area was designated as oil palm concession as of 2010. We conducted propensity scoring to balance covariate distributions between certified and non-certified concessions, and we compare the density of fires in certified and non-certified concessions using Kolmogorov-Smirnov tests based on Moderate Resolution Imaging Spectroradiometer (MODIS) Active Fire Detections from 2012-2015 clustered into unique fire events. We find that fire activity is significantly lower on RSPO certified concessions than non-RSPO certified concessions when the likelihood of fire is low (i.e., on non-peatlands in wetter years), but not when the likelihood of fire is high (i.e., on non-peatlands in dry years or on peatlands). Our results provide evidence that RSPO has the potential to reduce fires, though it is currently only effective when fire likelihood is relatively low. These results imply that, in order for this mechanism to reduce fire, additional strategies will be needed to control fires in oil palm plantations in dry years and on peatlands.

INTRODUCTION

Agricultural expansion and intensification has occurred over the last few decades and is expected to continue, especially in the tropics, in order to meet the demands of a growing global population. Oil palm (*Elaeis guineensis*), a major global commodity that dominates the vegetable oils market and is used for biofuel, is one of the world's most rapidly expanding crops. It is grown exclusively in the humid tropics. Production of oil palm and planted area have increased over the past few decades, especially in Indonesia, which is currently the largest oil palm producer (FAO 2015). The area under oil palm cultivation in Indonesia expanded 600% to 7.8 Mha from 1990-2000 (Agriculture 2010).

With land use conversion for the expansion of oil palm in Southeast Asia have come myriad environmental and social concerns, including deforestation (e.g, Carlson, Curran et al. 2012) and land tenure and other social conflicts (e.g., displacement of local people, Colchester and Jiwan 2006). The loss of forest through oil palm expansion is a threat to biodiversity (Wilcove and Koh 2010, Koh, Miettinen et al. 2011), with plantations hosting species-poor communities dominated by generalists with few forest species (Danielsen, Beukema et al. 2009). The development of oil palm plantations can also result in greenhouse emissions from the conversion process. The carbon losses from the development on peatlands are particularly high (Hooijer, Silvius et al. 2006, Koh, Miettinen et al. 2011). Even when oil palm is used as a biofuel, the carbon savings from avoided fossil fuel combustion do not offset the losses in ecosystem carbon from land clearing until decades to centuries, particularly on peatlands (Gibbs, Johnston et al. 2008, Danielsen, Beukema et al. 2009), although the payback time is much shorter for previously degraded lands. However, proponents of oil palm argue that it has a much higher yield than the alternatives (e.g., soybean, sunflower, rapeseed), and with increased production efficiency, less land in cultivation is required to produce the same amount on a per hectare basis (Teoh 2010). There is also evidence that oil palm development can reduce poverty, contribute to national economies, and act as a carbon sink (relative to degraded lands) (Koh, Ghazoul et al. 2010, Teoh 2010).

Oil palm concession development can lead to increased fire incidence, as fire is often used to clear land prior to the initial crop planting, prior to replanting after a complete crop cycle, or to clear brush or eliminate pests mid-cycle (Simorangkir, Moore et al. 2002). Fires that are started on oil palm concessions may escape the boundaries of the concession and burn other land cover types, including primary forest (e.g., Carlson, Curran et al. 2012, Cattau, Harrison et al. 2016). Fires occurring within or outside of concession boundaries, particularly on peatlands, are a major cause of smog and particulate air pollution (Hayasaka, Noguchi et al. 2014, Reddington, Yoshioka et al. 2014), habitat loss and degradation (Yule 2010, Posa, Wijedasa et al. 2011, Jaafar and Loh 2014), and economic costs associated with fire suppression efforts, lost timber and crop resources, and missed workdays (Ruitenbeek 1999, Barber and Schweithelm 2000, Tacconi 2003). Oil palm and timber concessions, particularly on peatlands and non-forest lowlands, contribute to emissions and hazardous regional air pollution; oil palm concessions are the largest source of concession-related emissions in Kalimantan (Marlier, DeFries et al. 2015). However, the majority of emissions can be attributed to fires outside of concessions in both Sumatra and Kalimantan (Marlier, DeFries et al. 2015).

Land use conversion can interact with climate and other biophysical factors by further increasing fire risk in conditions under which fire risk is already elevated. For example, during El Niño conditions of the El Niño Southern Oscillation (ENSO), there is increased likelihood of drought in Southeast Asia and, thus, fires are tied to ENSO cycles throughout insular Southeast Asia, including Indonesia (e.g., Deeming 1995, Kita, Fujiwara et al. 2000, Siegert, Ruecker et al. 2001, Page, Siegert et al. 2002, Wang, Field et al. 2004, Fuller and Murphy 2006, Wooster, Perry et al. 2012, Spessa, Field et al. 2015). In peatlands, canals drain the peat and lower the water table, improving oil palm planting conditions, but also making the peat even more susceptible to fire in the dry season, particularly during El Niño phases (Hooijer 2006, Turetsky, Benscoter et al. 2015).

The land area in oil palm concession in Indonesia is projected to grow as Indonesia has pledged to double its oil palm production from 2010 to 2020 (Maulia 2010). In order to meet emissions reductions targets and improve air quality in the region, it will be critical that agricultural practices minimize fire occurrence on this land use type, either through regulatory, incentive-based, or technological mechanisms. Wilcove and Koh (2010) discuss how financial incentives can promote desirable behavior in the oil palm industry that would reduce the threats to biodiversity from land use conversion; these incentives can reduce practices that promote negative outcomes on oil palm concessions more generally, including fire. The Roundtable on Sustainable Palm Oil (RSPO) certification program, established in 2004, is one such incentive. RSPO is non-profit industry-led trade organization designed, in part, to address the growing concerns about the negative environmental impacts of palm oil. RSPO is currently the largest multi-stakeholder organization focused on sustainability within the palm oil sector and the only global sustainability standard in the edible oil sector. Thus, RSPO has a large potential to reduce the negative impacts of oil palm concession development globally. According to the RSPO Principles and Criteria, RSPO does not permit the use of fire for preparing land for new plantings or for replanting on certified plantations except "where an assessment has demonstrated that it is the most effective and least environmentally damaging option for minimizing the risk of severe pest and disease outbreaks, and exceptional levels of caution should be required for use of fire on peat" (RSPO 2013). Therefore, the RSPO certification mechanism has the potential to reduce fire on oil palm plantations, presuming that companies follow the RSPO Principles and Criteria. This issue is particularly critical in peatland areas, because fires in these fuel-rich systems result in high emissions from aboveground and belowground biomass burning. Approximately 46% of peatland area was designated as oil palm concession as of 2010 (WRI 2014). In late 2015 after the most severe fire season since 1997/98, the Indonesian president Joko Widodo, through presidential instructions, did ban clearance and conversion on peatlands, including on existing concessions (Indonesia 2015). However, this is not yet a legally binding law, though one is forthcoming. Furthermore, by targeting economic incentives, RSPO certification might result in monitoring and enforcement beyond what would exist as a result of regulatory policy alone.

Although there have been concerns that the RSPO Principles and Criteria are not sufficiently stringent, currently there is minimal evidence regarding how RSPO certification affects fire occurrence. In this research, we assess if fire activity was reduced on RSPO certified oil palm concessions in Indonesia from 2012 to 2015. We ask: 1) Did certified concessions have a lower density of fire detections, fire ignitions, or 'escaped' fires compared with those concessions that are not certified? and 2) Did this pattern change with increasing likelihood of fires in concessions located on peatland and in dry years?

METHODS

We assess whether fire activity is reduced on RSPO certified oil palm concessions. We first identify concessions that are RSPO-certified and concessions that are not certified, and select only concessions that are already converted. We then derive three metrics of fire activity: the density fire detections, fire ignitions, and 'escaped' fires. We use nonparametric matching methods to control for bias and then determine if RSPO certified concessions have reduced fire activity, relative to the control group of non-certified concessions, in low fire-risk conditions (i.e., in wet years and on non-peatlands), in intermediate fire-risk conditions (i.e., in wet years and on non-peatlands), and in high fire-risk conditions (i.e., in dry years and on peatlands). In the subsections that follow, we describe the study area, concession and other datasets, remotely sensed fire observations, and our methodology to compare fire activity within RSPO-certified and non-certified concessions.

Study Area

The study area consists of the island of Sumatra and of Kalimantan, the Indonesian portion of the island of Borneo (Fig. 1), Indonesia's largest islands, with a total area of 473,481 km^2 and 544,150 km^2, respectively. Both islands straddle the equator and have a hot and humid tropical climate marked by distinct wet and dry seasons. The western interior of Sumatra is mountainous and the eastern interior is lowlands and swamp. The interior of Borneo (i.e., the northern border of Kalimantan) consists of upland areas with the outer areas primarily lowlands and swamp. Both islands were once dominated by tropical rainforest, but development, illegal logging, and fire have greatly reduced the extent of that forest (e.g., 28.3% and 51.9% mature forest remained in 2012 on Sumatra and Kalimantan, respectively (Margono, Potapov et al. 2014)).

We focus on Sumatra and Kalimantan because over 90% of oil palm development in Indonesia occurred there over the past few decades (Indonesia 2010). As of 2010, 95.8% of all the oil palm concessions in Indonesia were located in Sumatra and Kalimantan, covering 13.8% of the total land area (WRI 2014). Industrial oil palm plantations that have already been developed cover 18.2% and 12.6% of peatlands in Sumatra and Kalimantan, respectively (Miettinen, Shi et al. 2016).

Data and processing

We obtain oil palm concession locations in Indonesia from the Global Forest Watch portal (GFW) (WRI 2014). Produced by the Indonesian Ministry of Forestry, these are the boundaries of the area allocated by the Indonesian government for industrial-scale oil palm plantations developed or planned by 2010. These data are known to be incomplete but are currently the best available; they do not include oil palm plantations that exist outside of the official concession boundaries. These data include the company to which each concession belongs, but not information about whether an individual concession is RSPO certified. Because spatially explicit data on the location of RSPO certified plantations is currently not publically available, we are not able to directly evaluate fire activity on all concessions that are certified versus those that are not.

Instead, data on the total number of hectares of oil palm concession that each company owns and the number of hectares associated with concessions that are RSPO certified that each company owns as of 2012 is obtained from Greenpeace (Rosoman and Rahmawa 2015), and we evaluate fire activity on concessions belonging to companies that have 0% of their concession area certified (hereafter, referred to as non-RSPO certified concessions) versus concessions belonging to companies that have ≥85% of their concession area certified (hereafter, referred to as RSPO certified concessions). There is a general lack of agreement between the oil palm concession boundary data from GFW and tabular data on certification from Greenpeace. Of the 167 concessions reported by Greenpeace to belong to companies that have ≥85% of their concession area certified, only 58 are present in the GFW data. Of the 239 concessions reported by Greenpeace to belong to companies that have 0% of their concession area certified, only 34 are in the GFW data. Therefore, our analyses do not include all of the concessions that are RSPO certified or non-certified, but rather only the subset that are owned by companies for which data is present in both datasets.

Because fire is often used differently at different stages of plantation development, we separate concessions that were developed prior to the study period (2012-2015), during the study period, or are not yet developed. To derive the year of development for each RSPO certified and non-certified concession, we visually inspect Google Earth imagery for signs of clearing or planting (e.g., irrigation canals, new vegetation that is spatially ordered). We did not definitively identify any concessions that either remained undeveloped during the entire study period 2012-2015 or that were developed sometime during the study period. Thus we restrict the analysis to concessions that we determined to be already developed by 2012, including 28 RSPO certified concessions totaling 180,333 ha (4 on peatlands and 24 on non-peatlands) and 25 non-RSPO certified concessions totaling 326,205 ha (11 on peatlands and 14 on non-peatlands) (detailed in Fig. 1). The subset of concessions used for our analyses do not show a spatial bias, as they have a representative distribution across the study area (i.e., the majority of concessions are found on Kalimantan), but may be biased in terms of size and accessibility (Table A.1 in *Appendix*).

We retrieve all fire detections occurring in Kalimantan and Sumatra during 2012-2015 at the nominal 1 km^2 resolution from the Moderate Resolution Imaging Spectroradiometer (MODIS) Active Fire Detections, extracted from MCD14ML Collection 5 and distributed by NASA FIRMS. This product is considered the most accurate and complete among alternative methods for detecting fires (Langner and Siegert 2009), and correlations between the number of fire detections and the area burned on the ground is high in peatlands (R2 = 0.75 in Tansey, Beston et al. 2008). We use this product to derive the metrics of fire activity on concessions: the density fire detections, fire ignitions, and 'escaped' fires. Fire detections on concessions could be associated with fires that originate outside of the concession and escape into the concession, and are thus not directly the result of activities on the concession itself. To account for this possibility, we identify fire ignitions on and escaped fires from concessions, in addition to just fire detections occurring on concessions. The MODIS fire detections indicate the center point of a 1 km^2 area in which a fire was detected, but not the location or size of the fire (Langner, Miettinen et al. 2007, Miettinen, Andreas et al. 2007, Langner and Siegert 2009). Thus, depending on the location and size of the associated fires, MODIS fire detections that are temporally proximate and that represent adjacent pixels may be associated with a spatially contiguous fire event or they may represent isolated fire events. In order to identify fire ignitions, we group all fire detections into fire events (i.e., a fire with a common ignition source, which may consist of multiple fire detections) using a spatial rule that allows fire events to spread beyond their pixel of origin (i.e., neighborhood-pixel technique explained in detail in Cattau, Harrison et al. 2016). The overall accuracy of fires identified by our algorithm is 73 (±3)% when compared with finer-resolution ($30m^2$) Landsat data (Cattau, Harrison et al. 2016). For each fire event, we identify the location of the ignition(s) as the earliest detection(s) associated with that fire event.

Fire activity on RSPO certified and non-RSPO certified oil palm concessions

For each oil palm concession that is identified as RSPO certified or non-certified, we identify fire detections and fire ignitions located within that concession. We also identify fires that 'escape' from each oil palm concessions into the surrounding landscape by isolating fire events whose ignition detection(s) are within that concessions and that have at least one associated detection outside the concession boundaries. For each concession, we calculate the annual density of fire detections, of fire ignitions, and of fires that 'escape' from the concession into the surrounding landscape by dividing the number of detections, ignitions, and escaped fires respectively occurring on each concession each year by the area of that concession.

We determine if the density of fire detections, ignitions, or escaped fires on RSPO certified concessions are different from that on non-RSPO certified concessions between 2012-2015 using the Kolmogorov-Smirnov (KS) test, a non-parametric test to evaluate if the distribution differs between two groups. We conduct these analyses on data stratified by whether a concession was located in peatland or non-peatland rather than grouping them all together, because the likelihood of fire is different in those classes. We obtain the location of peatlands from the Global Forest Watch portal (WRI 2014), which is a layer of peat depth at the sub-meter resolution from the atlas of peat land distribution Kalimantan originally derived from remotely sensed data validated with field data (Wahyunto and Suryadiputra 2008). We further separate the data by wet years (2012 and 2013) and dry years (2014 and 2015). In the wet years, the 3-month running mean of SST anomalies in the Niño 4 region never surpassed a threshold of +0.5 °C. In the dry years, it surpassed the threshold in 6 months in 2014 and 12 months in 2015 (Fig. A.1 in *Appendix*).

Because our data are observational, we improve causal inferences by controlling for bias (i.e., factors that may have an influence on whether a concession is RSPO certified and thereby affecting comparability with non-certified concessions). We conduct propensity score matching using the 'MatchIt' package in R (Ho, Imai et al. 2011), which uses nonparametric matching methods to match samples of the treated (i.e., RSPO certified) and control (i.e., non-RSPO certified) groups with similar covariate distributions in order to improve statistical models. For each concession, we calculate the following covariates: concession area in hectares and mean road density (i.e., access to infrastructure) (See Fig. A.2 in *Appendix* for covariate distributions). Road density is derived from a layer of road locations, including both paved and unpaved roads, obtained from WRI (Minnemeyer, Boisrobert et al. 2009). We estimate propensity scores (i.e., the probability that a concession is RSPO certified) using a generalized linear model with a logit link, and match samples on propensity scores using nearest neighbor matching. We then determine if the distributions of the density of fire detections, ignitions, or escaped fires on RSPO certified concessions are different from that on non-RSPO certified concessions using KS tests on matched samples.

RESULTS

In the study area, the intra-annual pattern of fire activity from 2012 to 2015 peaks during the dry season months (August-October) both within all concessions in the study area (i.e., all concessions in the GFW dataset) and outside of concessions (Fig. 2(a) and (b), respectively). The inter-annual pattern of fire activity within all concessions in the study area is also similar to that outside of concessions across the years 2012-2015 (Fig. 2(c) and (d), respectively). Although most fire activity in the study area occurs outside of oil palm concessions, a substantial percentage (16.6%) of all the fire detections during the study period are located within oil palm concessions (Fig. 3), distributed among 70.5% of the total concessions. During the study period, a disproportionate percentage of the total fire detections (52.3%) occur on peatlands (Fig. 3), considering peatlands cover approximately 13.7% of the land area in Sumatra and Kalimantan.

Propensity scoring

On peatlands, concession area does not differ between RSPO certified and non-certified concessions, but road density does (Fig. A.2 and Table A.2 in Appendix). We thus conduct propensity scoring using just road density to improve inference on peatlands. Propensity scoring resulted in one-to-one matching of 4 RSPO certified concessions with 4 non-certified concessions and a 79.7% balance improvement on mean road density, meaning that the mean of that measured covariate is more similar between the RSPO certified and non-certified concessions after matching than prior to matching (Table A.2 in Appendix). On non-peatlands, concession area and road density differ between RSPO certified and non-certified concessions (Table A.2 in Appendix); we thus conduct propensity scoring using both covariates to improve inference on non-peatlands. Propensity scoring resulted in matching with replacement of 24 RSPO certified concessions with 8 non-certified concessions and a 25.5% balance improvement on mean road density and a 96.4% balance improvement on concession area (Table A.2 in Appendix).

Fire activity on RSPO certified and non-RSPO certified oil palm concessions

During the study period, fire activity - including the density of fire detections and fire ignitions - is not significantly different between RSPO certified and non-certified concessions on peatlands for matched or unmatched samples (Fig. 4 and Table A.3 in Appendix). This result is consistent in wet years (2012-2013) and dry years (2014-2015). Fire activity is also not significantly different between RSPO certified and non-certified concessions on non-peatlands in dry years. However, fire activity is significantly lower on RSPO certified concessions compared with non-certified concessions on non-peatlands in wet years. During the study period, only eight fires escaped from inside the boundaries of a developed concession included in our analysis into other land use classes; five from certified concessions and three from non-certified concessions. Thus, we do not consider escaped fires further in our analysis.

DISCUSSION AND CONCLUSION

We find that, from 2012-2015, fire activity (i.e., the density of fire detections and fire ignitions) is significantly lower on RSPO certified concessions than non-RSPO certified concessions when the likelihood of fire is low (i.e., on non-peatlands in wet years), but not statistically different when the likelihood of fire is high (i.e., on peatlands in all years or on non-peatlands in dry years). Our results provide evidence that RSPO has the potential to reduce fires, but is currently only effective when fire likelihood is relatively low and thus fewer fires occur and are presumably more easily controllable; during the study period, only 16.3% of fire detections on RSPO certified and non-certified concessions occurred on non-peatlands in wet years. This result implies that, in order for this mechanism to reduce fire, greater efforts may be needed to control fires in dry years and on peatlands.

The potential for RSPO certification to further reduce environmental impacts, including fire, may depend in part upon further clarification of what is required under the RSPO Principles and Criteria. A few relatively new initiatives may strengthen the RSPO; The Palm Oil Innovation Group (POIG) and The Sustainable Palm Oil Manifesto (SPOM) have been developed to provide additional clarification and criteria above and beyond what is required by the RSPO, and the Indonesian Sustainable Palm Oil (ISPO) standard introduces accountability for domestic growers.

Fire activity on RSPO certified concessions may also be reduced with improved monitoring and enforcement. A single, undisputed set of map data containing the location of Indonesian oil palm concessions, including RSPO certified plantations, is not currently publically available. Because of these data constraints, our sample size was reduced to the concessions that belong to companies for which the percent of their holdings that are RSPO certified are known to be either 0% (for non-certified concessions) or over 85% (for certified concessions). This issue is the major limitation of this study. RSPO members were required by General Assembly Resolution in November 2013 to submit their concession maps to RSPO. However, Indonesia and Malaysia questioned the legality of this (e.g., Directorate General of Plantation 2015), resulting in a freeze of the implementation of this resolution and of the release of these data since 2013. However, this issue limits the ability not only of independent researchers to evaluate the effects of RSPO certification, but also of RSPO to monitor its members. The RSPO monitors fire hotspots through the GFW platform (WRI 2014); if a fire detection is located within a RSPO certified concession, the RSPO member must provide evidence of what the situation is on the ground and report back to RSPO with the results of the actions they have taken to remediate the situation (RSPO 2015). These concession maps are often different than the boundary maps that the oil palm companies hold. Without an undisputed map of certified concessions, RSPO cannot hold its members accountable. Although RSPO indicates it will publish its members' oil palm concession maps during the second quarter of 2016 (RSPO 2015), this will be map data disclosed primarily by the RSPO member companies that hold the concessions themselves. In order to comprehensively evaluate if fire activity is reduced on RSPO certified concessions, as well as to accurately assign responsibility for fires in order to hold RSPO members and other concession owners accountable, spatially explicit data that are publically accessible, accurate, current, exhaustive, and recognized by all parties is essential.

We recognize some important limitations in assessing fire activity using MODIS-derived active fire detections, including the relatively large and variable MODIS pixel size and the spatial uncertainty of the fire size and fire location within the MODIS pixel. However, the average concession that we used for our analyses is 96 km^2; thus, the percent of all fires along the concession boundaries that are misattributed to either the area inside a concession or outside a concession is likely to be only a small percent of all fires and not biased in one direction. Although using moderate resolution data to map burned area might allow us to more accurately identify the spatial location and size of fires, there is a paucity of available moderate resolution data that is relatively cloud-free during the study period (e.g., only 4 images with 10% or less cloud cover are available for Path 118 Row 62 from Landsat 7 during the entire study period). Furthermore, the temporal resolution is too coarse to identify ignitions, escaped fires, or repeat fires at a return interval more frequent than concurrent cloud-free images.

We acknowledge several limitations in our study that may result in under- or overestimating fire activity and / or the effect of RSPO on fire activity. Our estimate that 16.6% of fire detections are located within oil palm concessions includes fires that occurred during the study period on all concessions. However, our estimates for fire activity on RSPO certified and non-certified concessions were limited to concessions that were already developed by the beginning of the study period in 2012 because there were insufficient data to include concessions developed during the study period. Thus, we do not capture fire related to the clearing stage, and our estimates of fire activity are therefore conservative. When more data become available, the effect that RSPO certification has on reducing fire activity will be substantially improved by evaluating conversion fires. The subset of concessions used for our analyses may be biased, as they are larger and more accessible than the average concession in Sumatra and Kalimantan. However, this bias is unlikely to affect the results, as the concessions are still representative of the larger landscape (i.e., well within a standard deviation for size and accessibility of all concessions) and there is no clear relationship between either the size of a concession and fire activity on that concession or between road density around a concession and fire activity on that concession (Fig. A.3 in *Appendix*). We control for concession size and accessibility when matching certified and non-certified concessions, but more research is needed to identify if additional factors affect the relationship between certification status and fire activity. These covariates may include biophysical factors (e.g., slope), anthropogenic factors (e.g., land use history), as well as complex interactions between these factors (e.g., the climatological conditions in the year of initial clearing). Additionally, the omission rate for MODIS active fire detections in Kalimantan and Sumatra is estimated at 34-60% (Liew, C. et al. 2003, Miettinen, Andreas et al. 2007, Tansey, Beston et al. 2008). Fire detection density therefore likely underestimates fire activity, especially in areas with high tree cover including mature plantations, though we do allow for missed detections when we cluster fire detections into fire events to derive ignition density (see Cattau, Harrison et al. 2016 for further explanation). Finally, we include only legal, agro-industrial oil palm concessions, though smallholders are eligible for RSPO certification. The effect of RSPO on fire activity or the trends of fire activity more generally may be different on smallholder plantations than on agro-industrial concessions, but data are not currently available to evaluate this issue.

Financial mechanisms (e.g., RSPO certification) used in tandem with regulatory approaches (Wilcove and Koh 2010) may be effective for reducing fire. There have been previous attempts to reduce fire in Indonesia through national and international regulatory mechanisms (e.g., ASEAN Agreement on Transboundary Haze Pollution, Singapore's Transboundary Haze Pollution Act, and Indonesia's national law (Act No 41/1999) banning corporations from using fire to clear land for palm-oil plantations), but with limited success. The presidential instructions banning clearance and conversion on peatlands, including on existing concessions (Indonesia 2015) may prove effective if it becomes legally binding law. Furthermore, the effectiveness of regulatory approaches to reducing fire on oil palm will depend, in part, upon the capacity for enforcement. In a clear demonstration of regulatory enforcement, the Indonesian government is currently taking legal recourse on companies responsible for fires associated with the 2015 haze crisis, most of which are in pulp and paper, by revoking or suspending their licenses (Butler 2015).

Protecting high carbon value areas, particularly peatlands, from fire activity will be essential in reducing concessions-related emissions. During the study period, a disproportionate percentage of the total fire detections (52.3%) occur on peatlands, which cover approximately 13.7% of the land area in Sumatra and Kalimantan. Furthermore, fires in peatlands have higher emissions potential because of the high fuel loads in belowground biomass. Nearly half of all peatland area is designated as oil palm concession, and so the management of those concessions will have a large influence on fire activity on peatlands and the integrity of peatland ecosystems at the national scale. The relevant management includes not only direct burning, but also whether canals are dug, which can alter the hydrology of these systems and make them more susceptible to ignition and burning (e.g., critical threshold of groundwater depths below which fire is very likely Usup, Hashimoto et al. 2004, Wosten, van den Berg et al. 2006)).

We find that RSPO does have a limited potential to reduce fires on agro-industrial concessions in Indonesia. More research is needed to understand if and in what capacity fire activity is reduced on RSPO certified smallholder plots in Indonesia and on smallholder and agro-industrial plantations in other countries. Given the global reach of the association, the capacity for this mechanism to result in oil palm production that is more sustainable is considerable.

TABLES AND FIGURES

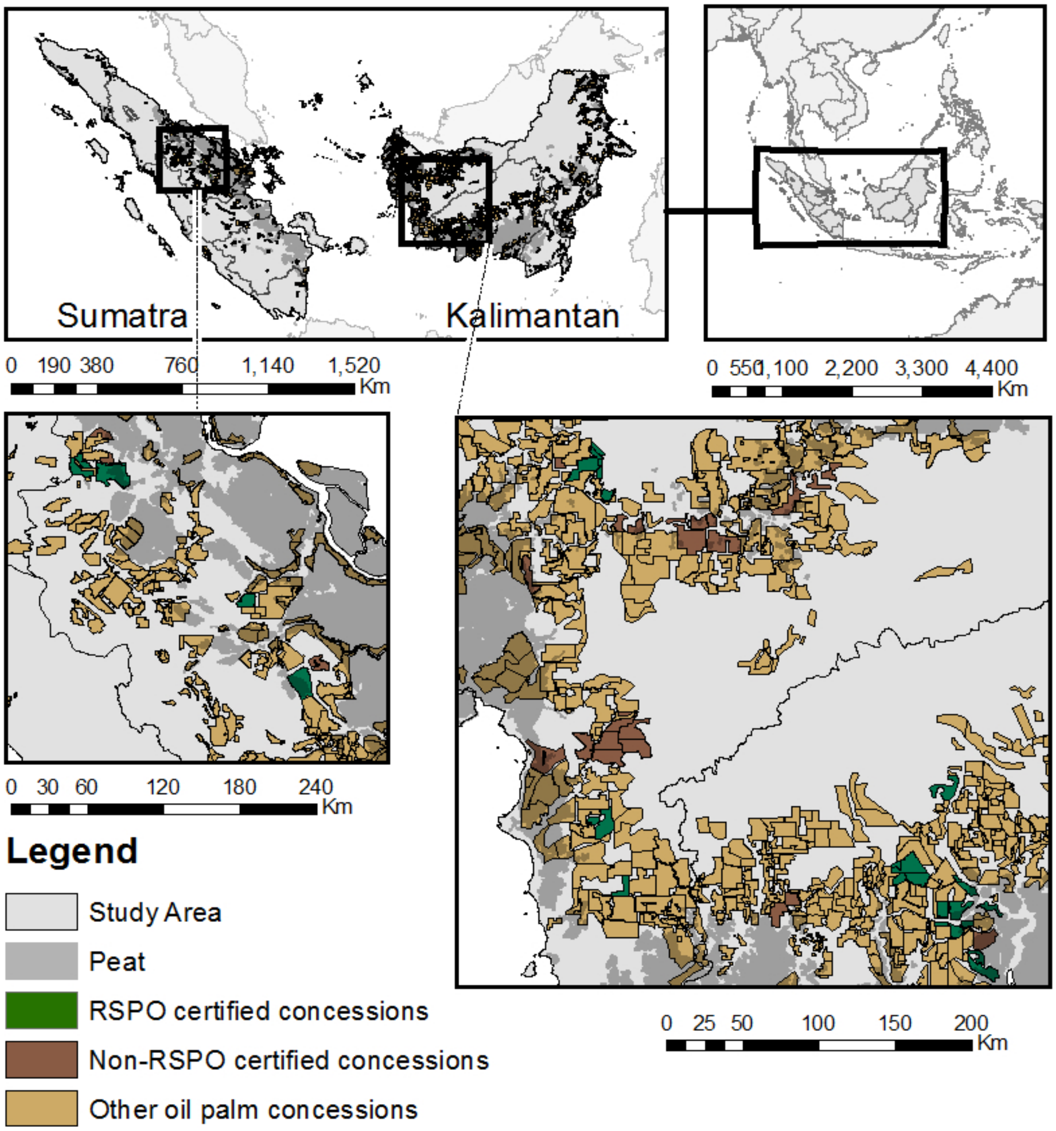


Figure 1. The study area: oil palm concessions on Sumatra and Kalimantan, Indonesia. Inset: details of two portions of the study area displaying non-exhaustive locations of oil palm concessions, including those that are RSPO certified, those that are non-RSPO certified, and those for whom certification status is unknown, as well as the distribution of peatland. See *Data and Processing* for a description of categorization of oil palm concessions into those that are RSPO certified and those that are non-RSPO certified.

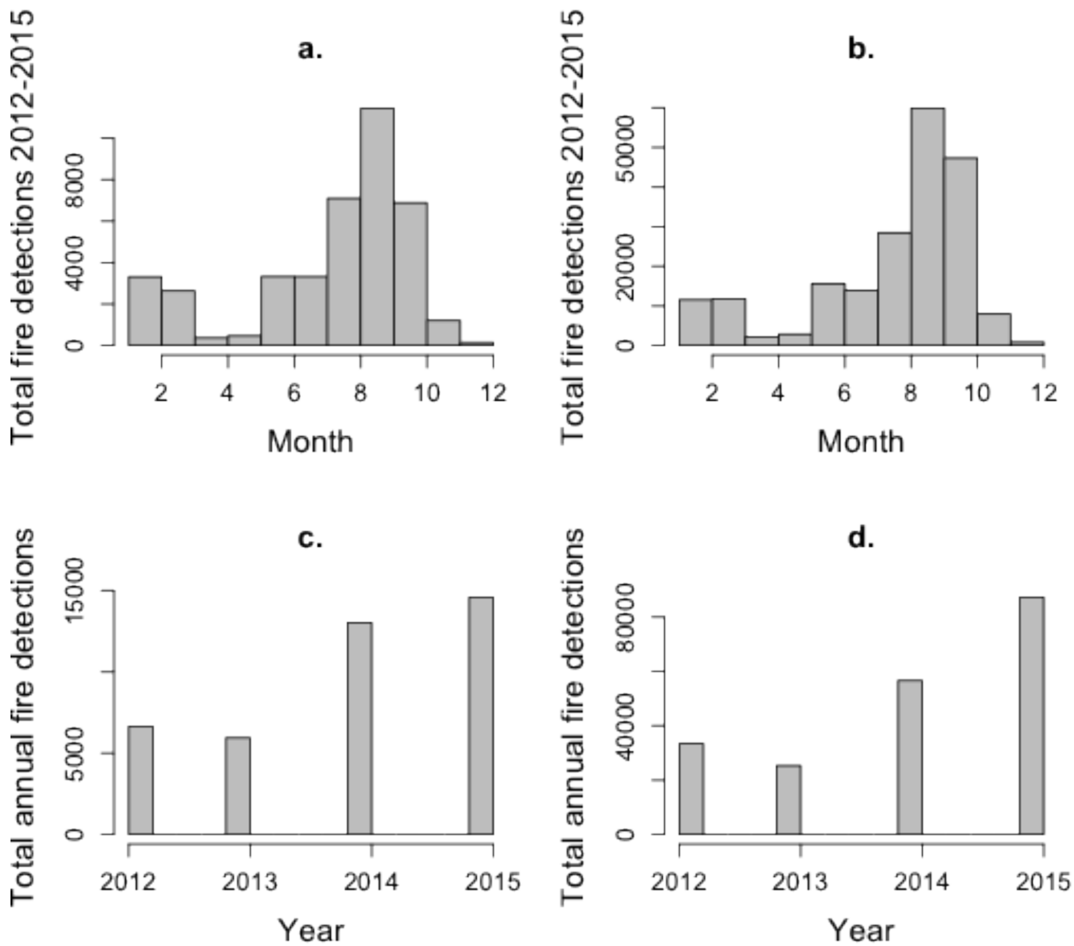


Figure 2. Temporal pattern of fire in the study area 2012-2015: the number of MODIS fire detections within the study area (total N fire detections = 242,957: 110,884 on Kalimantan and 132,073 on Sumatra) that occur per month (a) on all oil palm concessions in the study area (N concessions = 1,764) and (b) outside of oil palm concessions, and that occur per year (c) on all oil palm concessions in the study area and (d) outside of oil palm concessions. Fire activity peaks during the dry season months (August-October) both within and outside of concessions. Fire activity was higher in dry years 2014 (Mean 3-month average Niño 4 Index: 0.50 ± SD 0.27) (28.7% of fire detections) and 2015 (1.21 ± SD 0.28) (41.9% of fire detections) than wet years 2012 (-0.01 ± SD 0.47) (16.5% of fire detections) and 2013 (0.08 ± SD 0.10) (12.9% of fire detections), both within and outside of concessions. Note differences in scale.

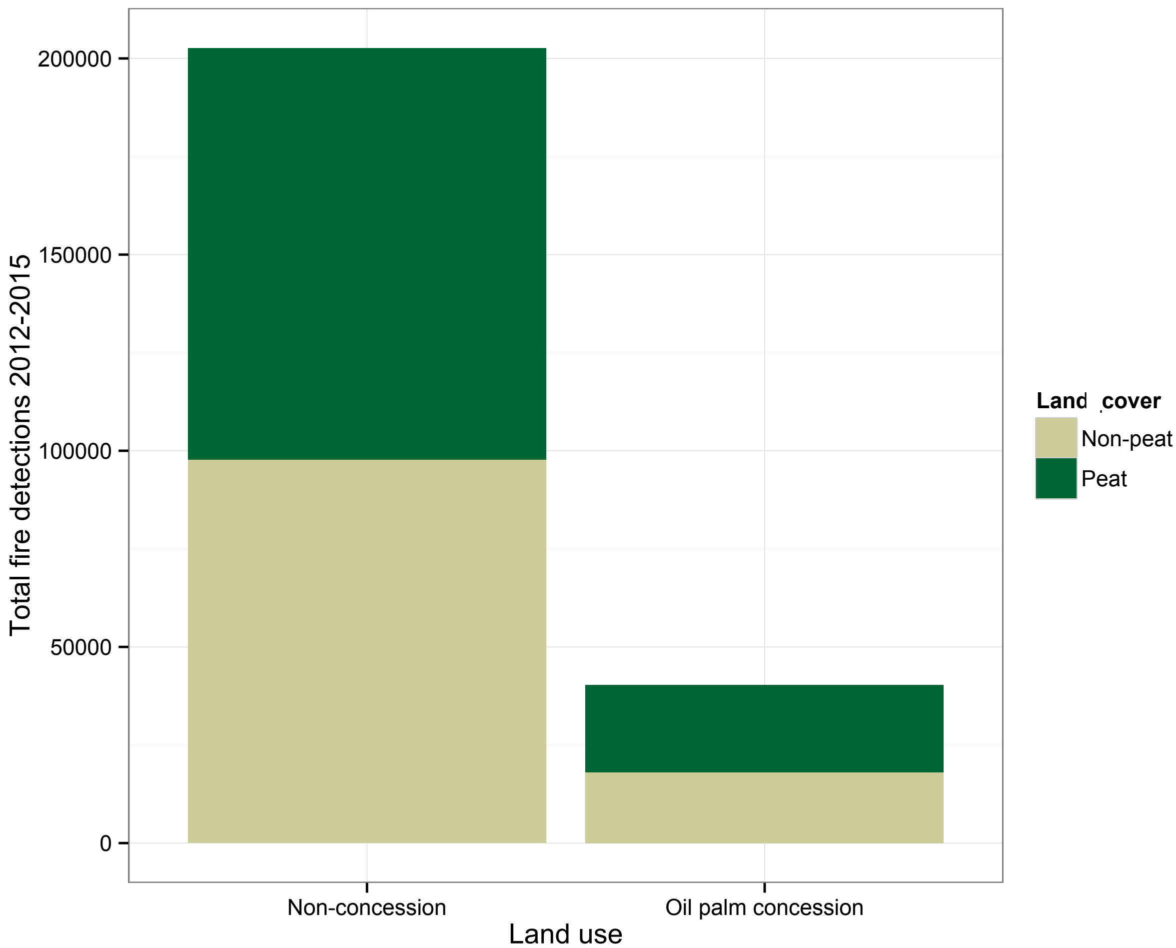


Figure 3. The number of fire detections (N = 205,749) within all oil palm concessions in the study area (N= 1,764) and outside of concessions on Kalimantan and Sumatra 2012-2015, divided into peatlands (13.7% of the land area) and non-peatlands (86.3% of the land area). 16.6% of all the fire detections during the study period are located within oil palm concessions.

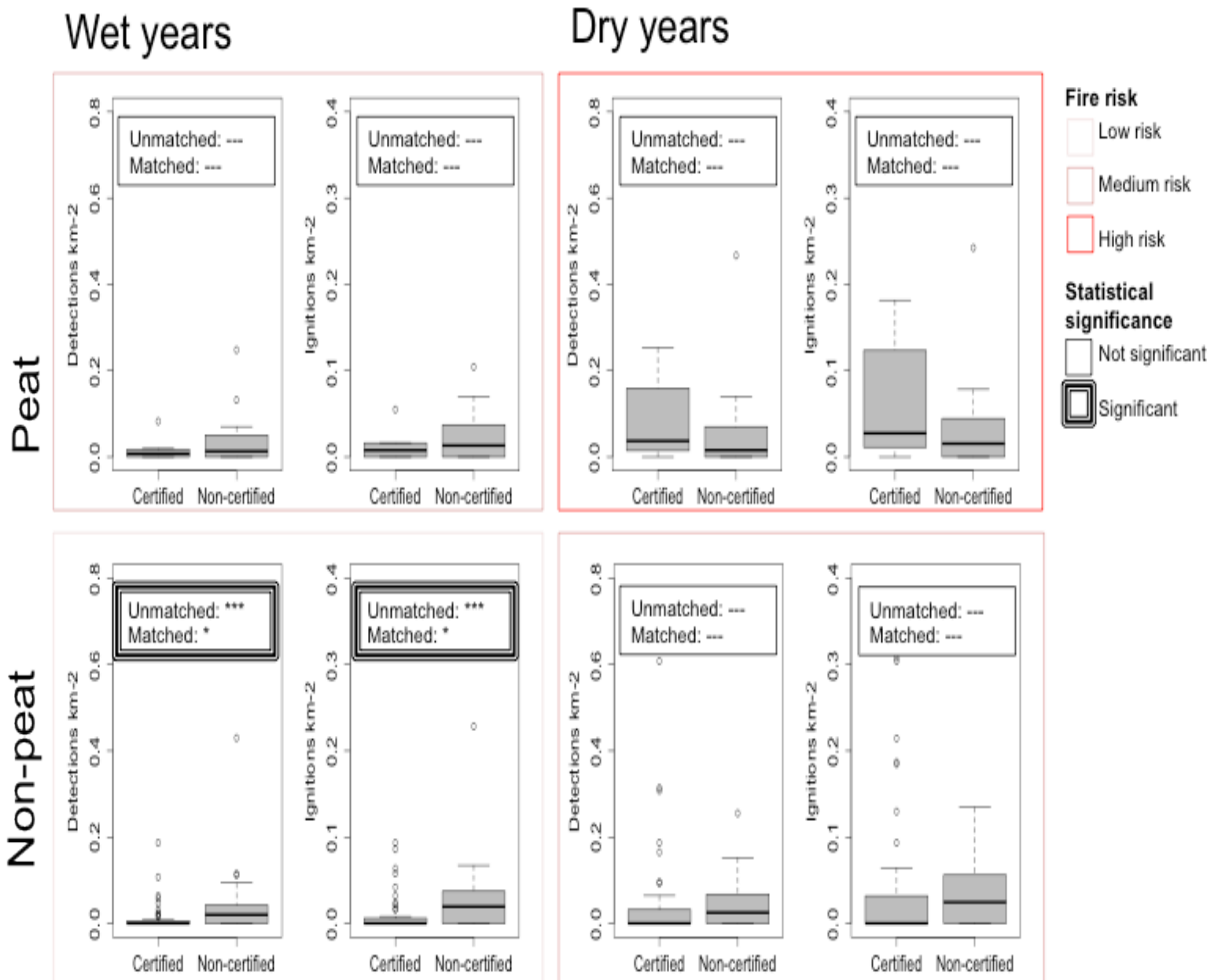


Figure 4. Density of fire activity, including the density of fire detections and density of fire ignitions for RSPO certified concessions (N=48) and non-certified concessions (N=28) on non-peatlands for wet years (2012-2013), RSPO certified concessions (N=48) and non-certified concessions (N=28) on non-peatlands for dry years (2014-2015), RSPO certified concessions (N=8) and non-certified concessions (N=22) on peatlands for wet years (2012-2013), and RSPO certified concessions (N=8) and non-certified concessions (N=22) on peatlands for dry years (2014-2015). Differences in fire activity between RSPO certified and non-certified concessions

before and after matching tested using KS-tests are shown with the following significance codes: --- > 0.10, * < 0.10, ** < 0.05, *** < 0.01. See Table S2 in *Supporting Information* for data on fire activity on RSPO certified concessions compared with non-certified concessions both on peatlands and on non-peatlands divided into wet and dry years.

Supporting Information

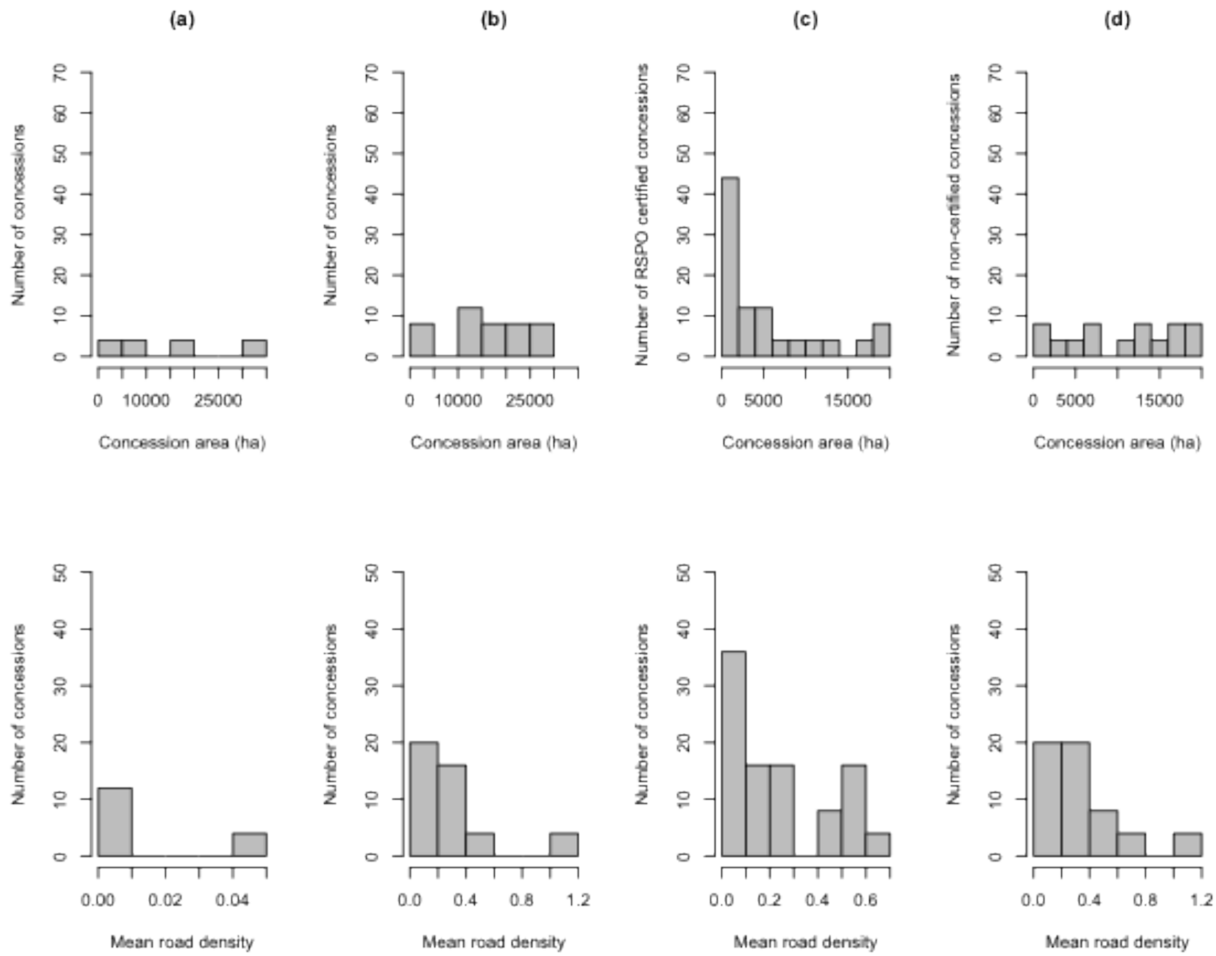


Fig. S1. Covariate distribution for propensity scoring. Frequency distribution of concessions for concession area (ha) and mean road density for (a) RSPO certified concessions and (b) non-certified concessions in peatlands and for (c) RSPO certified concessions and (d) non-certified concessions in non-peatlands.

Table S1. Characteristics of covariates for propensity scoring: mean and standard deviation of concession area (ha) and mean road density for RSPO certified concessions and non-certified concessions in peatlands and in non-peatlands. Differences covariates between RSPO certified and non-certified concessions tested using KS-tests are shown with the following significance codes: --- > 0.10, * < 0.10, ** < 0.05, *** < 0.01.

Land cover type	Covariate	RSPO certified concessions (unmatched)	Non-certified concessions (unmatched)	Non-certified concessions (matched)	KS-tests	% balance improvement
Peatland	Concession area (ha)	14,525.8 (±SD 11,230.0)	16,242.0 (±SD 9,390.7)	NA	---	NA
	Mean road density	0.013 (±SD 0.021)	0.286 (±SD 0.275)	0.068 (±SD 0.051)	***	79.7
Non-peatland	Concession area (ha)	5,092.9 (±SD 6,078.8)	10,538.8 (±SD 6,229.2)	5,287.2 (±SD 6,111.9)	***	96.4
	Mean road density	0.238 (±SD 0.209)	0.330 (±SD 0.269)	0.170 (±SD 0.247)	***	25.5

Table S2. Density of fire activity, including the density of fire detections km^{-2}, fire ignitions km^{-2}, and escaped fires km^{-2} for RSPO certified (n=16) and non-certified (n=44 for unmatched samples and n=16 for matched samples) concessions on peatlands divided into wet years (2012-2013) and dry years (2014-2015) and for RSPO certified (n=96) and non-certified (n=56 for unmatched samples and n=32 for matched samples) concessions on non-peatlands divided into wet and dry years. Differences in fire activity between RSPO certified and non-certified concessions before and after matching tested using KS-tests are shown with the following significance codes: --- > 0.10, * < 0.10, ** < 0.05, *** < 0.01.

Land cover type	Years	Fire activity	RSPO certified concessions	Non-certified concessions (unmatched samples)	Non-certified concessions (matched samples)	KS-tests (unmatched)	KS-tests (matched)
Peatland	Wet years (2012-2013)	Fire detections km^{-2}	0.017 (±SD 0.028)	0.036 (±SD 0.057)	0.030 (±SD 0.025)	---	---
		Fire ignitions km^{-2}	0.013 (±SD 0.018)	0.023 (±SD 0.028)	0.023 (±SD 0.018)	---	---
		Escaped fires km^{-2}	0.000 (±SD 0.000)	0.000 (±SD 0.000)	0.000 (±SD 0.000)	NA	NA
	Dry years (2014-2015)	Fire detections km^{-2}	0.180 (±SD 0.348)	0.054 (±SD 0.102)	0.012 (±SD 0.015)	---	---
		Fire ignitions km^{-2}	0.087 (±SD 0.128)	0.032 (±SD 0.053)	0.011 (±SD 0.013)	---	---
		Escaped fires km^{-2}	0.001 (±SD 0.002)	0.000 (±SD 0.001)	0.000 (±SD 0.001)	NA	NA
Non-peatland	Wet years (2012-2013)	Fire detections km^{-2}	0.012 (±SD 0.033)	0.043 (±SD 0.083)	0.027 (±SD 0.037)	***	*
		Fire ignitions km^{-2}	0.010 (±SD 0.022)	0.029 (±SD 0.045)	0.019 (±SD 0.022)	***	*
		Escaped fires km^{-2}	0.000 (±SD 0.000)	0.000 (±SD 0.003)	0.000 (±SD 0.000)	NA	NA
	Dry years (2014-2015)	Fire detections km^{-2}	0.059 (±SD 0.142)	0.045 (±SD 0.059)	0.034 (±SD 0.042)	---	---
		Fire ignitions km^{-2}	0.038 (±SD 0.077)	0.032 (±SD 0.035)	0.025 (±SD 0.026)	---	---
		Escaped fires km^{-2}	0.001 (±SD 0.008)	0.000 (±SD 0.000)	0.000 (±SD 0.000)	NA	NA

SYNTHESIS

The preceding chapters present new information on the novel fire disturbance regime in the globally important peat-swamp forest of Indonesia. The studies in these chapters reveal trends in fire dynamics from the framework of coupled human and natural systems, where anthropogenic and biophysical data are integrated in a coherent modeling framework. These chapters advance our understanding of how anthropogenic factors influence the controls of fire, both directly (i.e., human-caused ignitions) and indirectly (i.e., changing the susceptibility of the landscape to ignitions and to burning). This synthesis serves to present the main findings included in this dissertation and to evaluate their influence on future research and on the management and conservation of this landscape.

Chapter One estimates the relative influence of anthropogenic and biophysical factors - climate, vegetation, human access, hydrology, and fire history - on the probability of fire occurrence in a peat-swamp forest area in Central Kalimantan, Indonesia from 2000 to 2010. The results of this chapter reveal that climate is the most important factor driving fire occurrence (standardized regression coefficient: 1.29 (95% credible interval: 1.21-1.37)), which is consistent with findings in many other parts of the tropics. The influence of canals (-0.78 (-0.64- -0.92)), which were put in place as part of a failed agricultural project and have lowered the water table, and the influence of vegetation (-0.92 (-1.01- -0.83)), which has decreased over time, are almost as strong as the influence of climate. Our results that vegetation and hydrology contribute almost as much as climate to fire probability demonstrates that the impact of canals and deforestation continues to contribute to fire risk for the area, even two decades after its abandonment.

However, results also suggest a great potential for hydrological rehabilitation coupled with planting to reduce fire and thus offset effects of climate on fires.

Chapter Two challenges the assumption that most fire ignitions are located on oil palm concessions or on smallholder farms near settlements. Most fires (68-71%) originate in non-forest, compared to oil palm concessions (17%-19%), and relatively few (6-9%) are within 5 km of settlements. Additionally, very few fires that burn forest originate in oil palm concessions (2%) or within close proximity to settlements (2%). Moreover, most fires started within oil palm concessions and in close proximity to settlements stay within those boundaries (90% and 88%, respectively), and fires that do escape constitute only a small proportion of all fires on the landscape (2% and 1%, respectively). However, fire ignition density in oil palm (0.055 ignitions km-2) is comparable to that in non-forest (0.060 km-2 ignitions km-2), which is approximately ten times that in forest (0.006 ignitions km-2). Ignition density within 5 km of settlements is the highest at 0.125 ignitions km-2. Furthermore, increased anthropogenic activity in close proximity to oil palm concessions and settlements produces a detectable pattern of fire activity. The number of ignitions decreases exponentially with distance from concessions; the number of ignitions initially increases with distance from settlements, and, around 7.2 km, decreases with distance from settlements. These results refute the claim that most fires originate in oil palm concessions, and that fires escaping from oil palm concessions and settlements constitute a major proportion of fires in this study region. However, as the density of ignitions in oil palm and settlements high, and there is a detectable pattern of fire activity outside the immediate boundaries, there is a potential for these land use types to contribute substantially to the fire landscape if their area expands.

Chapter Three determines if fire activity is reduced on Roundtable on Sustainable Palm Oil (RSPO) certified concessions relative to non-certified concessions in Kalimantan and Sumatra, Indonesia. Fire activity is significantly lower on RSPO certified concessions than non-RSPO certified concessions when the likelihood of fire is low (i.e., on non-peatlands in wetter years), but not when the likelihood of fire is high (i.e., on non-peatlands in dry years or on peatlands). Our results provide evidence that RSPO has the potential to reduce fires, though it is currently only effective when fire likelihood is relatively low. This result implies that, in order for this mechanism to reduce fire, additional strategies will be needed to control fires in dry years and on peatlands.

As international attention is being directed toward Indonesia after the recent haze crisis in 2015, blame is being place on large agro-industrial companies, especially oil palm, and to a lesser extent on smallholders (e.g., Allen 2015, Meijaard 2015, Mollman 2015, Soares 2015). The prevailing opinion now is that the main driver of fire in tropical peat swamp, apart from climate, is escaped fire from land management on those land use classes, meaning fires that accidentally burn out of the intended boundaries. The findings presented in this dissertation indicate that oil palm concessions are associated with high fire probability (Chapter One) and a substantial amount of ignitions and relatively high ignition density (Chapter Two). One of the more pointed ways to target fire on oil palm concessions is through RSPO certification; however, we find that certification is only effective when fire likelihood is already low, suggesting that, in order for this mechanism to reduce fire, more assistance may be needed to control fires in dry years and on peatlands (Chapter Three). The recent ban on clearing and converting peatlands, even on existing concessions (Indonesia 2015), is a promising step toward reducing peat fire, but it is insufficient by itself, because placing all the blame on agro-industrial companies is an oversimplification of the issue. The work in this dissertation determined that fires that escape the boundaries of oil palm concessions are actually quite low (Chapter Two). Furthermore, non-forested, degraded areas contribute much more to fire activity on this landscape; these areas experience the greatest number of ignitions, have highest ignition density, and are the primary source of forest fires (Chapter Two). The declines in vegetation and the hydrological alteration in these degraded areas contribute substantially to fire occurrence (Chapter One). Effective fire management in this area, including fire prevention and suppression efforts, should therefore target not just oil palm concessions and smallholdings around settlements, but should also focus strongly on non-forested, degraded areas –and in particular those near oil palm concession boundaries and outside the immediate vicinity of settlements – where fire probability is high and where ignitions and fires escaping into forest are most likely to occur. Rehabilitation of the degraded landscape through restoring hydrology and replanting, together with awareness-raising, fire fighting and law enforcement, will be key to fire reduction.

In addition to assessing how human-driven and biophysical landscape changes alter fire disturbance in Indonesia, the methodological approaches in the preceding chapters demonstrate ways in which remote sensing and analytical technologies can be used to answer complex questions about coupled human and natural systems that fuse social and environmental data, for both theoretical and management applications. Chapter One uses biophysical information from remotely sensed products and fieldwork with information about human access on the landscape and integrates them together with Moderate Resolution Imaging Spectroradiometer (MODIS)

Active Fire detections under a Bayesian framework. Variables related to climate, hydrology, vegetation, human access, and fire history are standardized so that comparisons can be made between seemingly disparate types of data. Chapters Two and Three use a novel technique to cluster remotely sensed data on fire occurrence (MODIS Active Fire detections) into fire events (i.e., a fire with a common ignition source, which may consist of multiple fire detections). Because many studies using satellite data to analyze fire consider individual fire detections at the 1 km^2 resolution (e.g., Langner and Siegert 2009) and not individual fire events (i.e., a fire with a common ignition source, which may consist of multiple fire detections), it is often difficult to pinpoint the LULC classes on which ignitions occur rather than the LULC classes associated with fire or that are predisposed to burning. This issue complicates efforts to determine where to target fire reduction efforts aimed at reducing ignitions, particularly if fires quickly escape a LULC boundary and burn into another LULC class. The novel approach to analyzing MODIS data so that ignitions can be isolated presented in this dissertation allows us to answer questions related to fire origin, spread, and impact that cannot be investigated by evaluating fire detections alone.

This dissertation addresses a gap in knowledge regarding the anthropogenic contributions to increased fire probability and to ignitions in peat swamp, and the approaches could be applied to other degraded peatland areas in Indonesia that are candidate sites for restoration (e.g., under the newly established Peatland Restoration Agency), especially in Sumatra, Papua, and other parts of Kalimantan, and to degraded peatlands that experience a novel fire regime in other parts of the tropics, including lowland peatlands in Africa. Furthermore, this dissertation evaluates the capacity for RSPO certification to reduce fire activity on oil palm concessions across Sumatra and Kalimantan, Indonesia, and the analyses conducted could be applied to landscapes in other parts of the tropics experiencing oil palm development.

In conclusion, the research findings presented in this dissertation are a product of combining social and environmental data and evaluating this data with a suite of classic and novel modeling approaches. Given the variety and severity of the consequences of tropical peatland fires in Indonesia, and the policy efforts to control these fires, it is of global interest to understand this changing disturbance regime and reduce fire occurrence. This dissertation is presented in the hope that it contributes to our understanding of fire dynamics in Indonesia and that the outcomes of this research provide empirical information for conservation and management on this landscape.

REFERENCES

(ADB), A. D. B. (1999). Causes, Extent and Costs of the 1997/1998 Fires in Indonesia - Summary of Phase I. Planning for fire prevention and drought

management project, July 1998 - March 1999. Jakarta, Indonesia, Asian Development Bank.

Agriculture, M. o. (2010). Area and Production by Category of Producers: Oil Palm, 1967-2010. Jakarta, Indonesia, Indonesian Ministry of Agriculture.

Aldhous, P. (2004). "Land remediation: Borneo is burning." Nature **432**: 144-146.

Allen, L. (2015). Is Indonesia's fire crisis connected to the palm oil in our snack food? The Guardian.

Applegate, G. B. A., U. Chokkalingam and S. Suyanto (2001). The underlying causes and impacts of fires in Southeast Asia final report. Bogor, Indonesia, Center for International Forestry Research (CIFOR), International Centre for Research in Agroforestry, SEA Regional Research Programme, USAID, USDA Forest Service.

Atmadja, S. S., Y. Indriatmoko, N. A. Utomo, M. Komalasari and A. D. Ekaputri (2014). Kalimantan Forests and Climate Partnership, Central Kalimantan, Indonesia. REDD+ on the ground, A case book of subnational initiatives across the globe. E. O. Sills, S. S. Atmadja, C. d. Sassi et al., CIFOR.

Baker, P. J. and S. Bunyavejchewin (2009). Fire behavior and fire effects across the forest landscape of continental Southeast Asia. Tropical Fire Ecology: Climate Change, Land Use and Ecosystem Dynamics. M. A. Cochrane, Springer**:** 682.

Ballhorn, U., F. Siegert, M. Mason and S. Limin (2009). "Derivation of burn scar depths and estimation of carbon emssions with LIDAR in Indonesian peatlands." PNAS **106**(50): 21213-21218.

Bank, W. (2015). Indonesia Economic Quarterly, Reforming amid uncertainty, December 2015. Indonesia Economic Quarterly. Jakarta.

Barber, C. V. and J. Schweithelm (2000). Trial by Fire: Forest Fire and Forestry Policy in Indonesia's Era of Crisis and Reform. Washington, D. C., World Resources Institute.

Boehm, H. D. V. and F. Siegert (2001). Ecological Impact of the One Million Hectare Rice Project in Central Kalimantan, Indonesia, Using Remote Sensing and GIS. 22nd Asian Conference on Remote Sensing. Singapore.

Bompard, J. M. and P. Guizol (1999). Land management in the province of South Sumatra, Indonesia. Fanning the flames: the institutional causes of vegetation fires. European Union Forest Fire Prevention and Control Project. Palembang, European Union Ministry of Forestry and Estate Crops.

Bowen, M. R., J. M. Bompard, I. P. Anderson, P. Guizol and A. Gouyon (2000). Anthropogenic fires in Indonesia: A view from Sumatra. Forest Fires and Regional Haze in Southeast Asia. P. Eaton and M. Radojevic. New York, Nova Science**:** 41–66.

Bowman, D. M. J. S., J. Balch, P. Artaxo, W. J. Bond, M. A. Cochrane, C. M. D'Antonio, R. DeFries, F. H. Johnston, J. E. Keeley, M. A. Krawchuk, C. A. Kull, M. Mack, M. A. Moritz, S. Pyne, C. I. Roos, A. C. Scott, N. S. Sodhi, T. W. Swetnam and R. Whittaker (2011). "The human dimension of fire regimes on Earth." Journal of Biogeography **38**(12): 2223-2236.

Bowman, D. M. J. S., J. K. Balch, P. Artaxo, W. J. Bond, J. M. Carlson, M. A. Cochrane, C. M. D‚ÄôAntonio, R. S. DeFries, J. C. Doyle, S. P. Harrison, F. H. Johnston, J. E. Keeley, M. A. Krawchuk, C. A. Kull, J. B. Marston, M. A. Moritz, I. C. Prentice, C. I. Roos, A. C. Scott, T. W. Swetnam, G. R. van der Werf and S. J. Pyne (2009). "Fire in the Earth System." Science **324**(5926): 481-484.

Brauer, M. and J. Hisham-Hashim (1998). "Fires in Indonesia: Crisis and Reaction." Environmental Science & Technology **32**(17): 404A-407A.

Brown, N. (1998). "Out of control: fires and forestry in Indonesia." Trends in Ecology & Evolution **13**(1): 41.

Butler, R. A. (2015). 50+ companies being investigated or punished for Indonesia’s haze crisis. Mongabay.

Carlson, K. M., L. M. Curran, D. Ratnasari, A. M. Pittman, B. S. Soares-Filho, G. P. Asner, S. N. Trigg, D. A. Gaveau, D. Lawrence and H. O. Rodrigues (2012). "Committed carbon emissions, deforestation, and community land conversion from oil palm plantation expansion in West Kalimantan, Indonesia." Proceedings of the National Academy of Sciences **109**(19): 7559-7564.

Cattau, M. E., M. E. Harrison, I. Shinyo, S. Tungau, M. a. Uriarte and R. DeFries (2016). "Sources of anthropogenic fire ignitions on the peat-swamp landscape in Kalimantan, Indonesia." Global Environmental Change **39**: 205-219.

Cattau, M. E., S. Husson and S. M. Cheyne (2014). "Population status of the Bornean orang-utan Pongo pygmaeus in a vanishing forest in Indonesia: the former Mega Rice Project." Oryx **FirstView**: 1-8.

Cheyne, S. M., C. J. H. Thompson, A. C. Phillips, R. M. C. Hill and S. H. Limin (2008). "Density and population estimate of gibbons (Hylobates albibarbis) in the Sabangau catchment, Central Kalimantan, Indonesia." Primates **49**(1): 50-56.

Cochrane, M. A. (2003). "Fire science for rainforests." Nature **421**: 913-919.

Cochrane, M. A. (2009). Fire in the Tropics. Tropical Fire Ecology: Climate Change, Land Use, and Ecosystem Dynamics. M. A. Cochrane. Germany / Chicheser, U.K., Springer / Praxis.

Cochrane, M. A. and W. F. Laurance (2008). "Synergisms among Fire, Land Use, and Climate Change in the Amazon." AMBIO: A Journal of the Human Environment **37**(7): 522-527.

Cochrane, M. A. and K. C. Ryan (2009). Fire and fire ecology: Concepts and principles. Tropical Fire Ecology: Climate Change, Land Use, and Ecosystem Dynamics. M. A. Cochrane. Germany / Chicheser, U.K., Springer / Praxis.

Cochrane, M. A. and M. D. Schulze (1999). "Fire as a Recurrent Event in Tropical Forests of the Eastern Amazon: Effects on Forest Structure, Biomass, and Species Composition." Biotropica **31**(1): 2-16.

Colchester, M. and N. Jiwan (2006). Ghosts on our own land: Indonesian oil palm smallholders and the Roundtable on Sustainable Palm Oil. Bogor, Indonesia, Forest Peoples Programme, Moreton-in-Marsh, UK, and Perkumpulan Sawit Watch.

Countryman, C. M. (1972). The Fire Environment Concept. U. S. D. o. A. F. S. P. S. F. a. R. E. Station. Berkeley, CA.

Crutzen, P. J. and A. O. Andreae (1990). "Biomass Burning in the Tropics: Impact on Atmospheric Chemistry and Biogeochemical Cycles." Science **250**(4988): 1669-1678.

Danielsen, F., H. Beukema, N. D. Burgess, F. Parish, C. A. BrÜHl, P. F. Donald, D. Murdiyarso, B. E. N. Phalan, L. Reijnders, M. Struebig and E. B. Fitzherbert (2009). "Biofuel Plantations on Forested Lands: Double Jeopardy for Biodiversity and Climate

Plantaciones de Biocombustible en Terrenos Boscosos: Doble Peligro para la Biodiversidad y el Clima." Conservation Biology **23**(2): 348-358.

Davies, S. J. and L. Unam (1999). "Smoke-haze from the 1997 Indonesian forest fires: effects on pollution levels, local climate, atmospheric CO2 concentrations, and tree photosynthesis." Forest Ecology and Management **124**: 137-144.

Deeming, J. E. (1995). Development of a fire danger rating system for East-Kalimantan, IFFM short term report, . Eschborn, GTZ. **Document No. 08**.

Dennis, R., J. Mayer, G. Applegate, U. Chokkalingam, C. P. Colfer, I. Kurniawan, H. Lachowski, P. Maus, R. Permana, Y. Ruchiat, F. Stolle, Suyanto and T. Tomich (2005). "Fire, People and Pixels: Linking Social Science and Remote Sensing to Understand Underlying Causes and Impacts of Fires in Indonesia." Human Ecology **33**(4): 465-504.

DiMiceli, C. M., M. L. Carroll, R. A. Sohlberg, C. Huang, M. C. Hansen and J. R. G. Townshend (2011). Vegetation Continuous Fields MOD44B, 20011 Percent Tree Cover, University of Maryland. **Collection 5**.

Directorate General of Plantation, M. o. A. (2015). Letter No. 120/HM.230/02/2015 to the Indonesian Growers Caucus of the RSPO on provision of Indonesian plantation maps to the RSPO and NGOs.

Dove, M. R. (1985). Swidden Agriculture in Indonesia: The Subsistence Strategies of the Kalimantan Kantu. Berlin: Mouton.

ESRI (2011). ArcGIS Desktop: Release 10. Redlands, CA, Environmental Systems Research Institute.

Eva, H. and E. Lambin (2000). "Fires and land-cover changes in the tropics: A remote sensing analysis at the landscape scale." Journal of Biogeography **27**: 765–776.

FAO, F. a. A. O. o. t. U. N. (2015). FAOSTAT: FAO Statistical Databases.

Ferry Slik, J. W., R. Verburg and P. A. Ke√üler (2002). "Effects of fire and selective logging on the tree species composition of lowland dipterocarp forest in East Kalimantan, Indonesia." Biodiversity & Conservation **11**(1): 85-98.

Field, R. D., G. R. van der Werf, T. Fanin, E. J. Fetzer, R. Fuller, H. Jethva, R. Levy, N. J. Livesey, M. Luo, O. Torres and H. M. Worden (2016). "Indonesian fire activity and smoke pollution in 2015 show persistent nonlinear sensitivity to El Niño-induced drought." Proceedings of the National Academy of Sciences **113**(33): 9204-9209.

Field, R. D., G. R. van der Werf and S. S. P. Shen (2009). "Human amplification of drought-induced biomass burning in Indonesia since 1960." Nature Geosci **2**(3): 185-188.

FRIM-UNDP/GEF (2006). Malaysia's peat swamp forests. Conservation and sustainable use. Malaysia, United Nations Development Programme.

Fuller, D. O. and K. Murphy (2006). "The ENSO-fire dynamic in insular Southeast Asia." Climatic Change **74**: 435-455.

G√∂nner, C. (1998). Conflicts and fire causes in a district of Kutai Regency, East Kalimantan, Indonesia, World Wildlife Fund for Nature (WWF).

Gaveau, D. L. A., M. A. Salim, K. Hergoualc'h, B. Locatelli, S. Sloan, M. Wooster, M. E. Marlier, E. Molidena, H. Yaen, R. DeFries, L. Verchot, D. Murdiyarso, R. Nasi, P. Holmgren and D. Sheil (2014). "Major atmospheric emissions from peat fires in Southeast Asia during non-drought years: evidence from the 2013 Sumatran fires." Sci. Rep. **4**.

Gerwing, J. J. (2002). "Degradation of forests through logging and fire in the eastern Brazilian Amazon." Forest Ecology and Management **157**(1,Äì3): 131-141.

GFED. (2015). "Indonesian fire season progression." from http://www.globalfiredata.org/updates.html.

Gibbs, H. K., M. Johnston, J. Foley, T. Holloway, C. Monfreda, N. Ra-mankutty and D. Zaks (2008). "Carbon payback times for crop-based biofuel expansion in the tropics: the effects of changing yield and technology." Environmental Research Letters **3**.

Giglio, L., J. Descloitres, C. O. Justice and Y. Kaufman (2003). "An enhanced contextual fire detection algorithm for MODIS." Remote Sensing of Environment, **87**: 273-282.

Goldammer, J. (2007). "History of equatorial vegetation fires and fire research in Southeast Asia before the 1997–1998 episode: a reconstruction

of creeping environmental changes." Mitigation and Adaptation Strategies for Global Change **12**: 13–32.

Goldammer, J. G. (1990). Tropical wild land fires and global changes: Prehistoric evidence, present fire regimes, and future trends. Global Biomass Burning: Atmospheric, Climatic, and Biospheric Implications. J. S. Levine. Cambridge, MA, MIT Press.

Goldammer, J. G. (1991). Tropical wild-land fires and global changes: Prehistoric evidence, present fire regimes, and future trends. Global Biomass Burning: Atmospheric, Climatic, and Biospheric Implications. J. S. Levine. Cambridge, MIT Press**:** 83-91.

Guhardja, E., M. Fatawi, M. Sutisna, T. Mori and S. Ohta (2000). Rainforest Ecosystems of East Kalimantan, El Nino, Drought, Fire and Human Impacts. New York, Springer.

Gutierrez-Velez, V. H., M. Uriarte, R. DeFries, M. Pinedo-Vasquez, K. Fernandes, P. Ceccato, W. Baethgen and C. Padoch (2014). "Land cover change interacts with drought severity to change fire regimes in Western Amazonia." Ecological Applications **24**(6): 1323-1340.

Handadhari, T. (2015). "Bom Wakti Perusakan Hutan." Jakarta Globe.

Hao, W. M., M.-H. Liu and P. J. Crutzen (1990). Estimates of Annual and Regional Releases of CO2 and Other Trace Gases to the Atmosphere from Fires in the Tropics, Based on the FAO Statistics for the Period 1975–1980. Fire in Tropical Biota: Ecosystem Processes and Global Challenges. D. J. G. Goldammer. Berlin, Springer-Verlag**:** 440-462.

Hao, W. M. and D. E. Ward (1993). "Methane production from global biomass burning." J. Geophys. Res.: 20657-20661.

Harris, N., S. Minnemeyer, N. Sizer, S. A. Mann and O. A. Payne (2015). "With Latest Fires Crisis, Indonesia Surpasses Russia as World's Fourth-Largest Emitter."

Harrison, M. E., S. E. Page and S. H. Limin (2009). "The global impact of Indonesian forest fires." Biologist **56**(3): 156-183.

Hayasaka, H., I. Noguchi, E. I. Putra, N. Yulianti and K. Vadrevu (2014). "Peat-fire-related air pollution in Central Kalimantan, Indonesia." Environmental Pollution **195**(0): 257-266.

Ho, D. E., K. Imai, G. King and E. A. Stuart (2011). "MatchIt: Nonparametric Preprocessing for Parametric Causal Inference." Journal of Statistical Software **42**(8): 1-28.

Hoffmann, A. A., A. Hinrichs and F. Siegert (1999). Fire damage in East Kalimantan in 1997/98 related to land use and vegetation classes: Satellite radar inventory results and proposal for further actions. G. a. K. MOFEC. Samarinda, East Kalimantan.

Hooijer, A. (2006). Tropical peatlands in southeast Asia. Oxford, Oxford University Press.

Hooijer, A., M. Silvius, H. Wösten and S. Page (2006). PEAT-CO2, Assessment of CO2 emissions from drained peatlands in SE Asia, Delft Hydraulics.

Hoscilo, A., S. E. Page, K. J. Tansey and J. O. Rieley (2011). "Effect of repeated fires on land-cover change on peatland in southern Central Kalimantan, Indonesia, from 1973 to 2005." International Journal of Wildland Fire **20**(4): 578-588.

Indonesia, G. o. (2015). Instruksi Presiden Republik Indonesia nomor 11 tahun 2015 tentang peningkatan pengendalian kebakaran hutan dan lahan.

Indonesia, G. o. (2016). Instruksi Presiden Republik Indonesia nomor 1 tahun 2016 tentang Badan Restorasi Gambut. **1**.

Indonesia, P. C. (2010). Palm Oil Plantation: Industry Landscape, Regulatory and Financial Overview. Jakarta, Indonesia, PricewaterhouseCoopers Indonesia**:** 1–16.

Isbell, F., V. Calcagno, A. Hector, J. Connolly, W. S. Harpole, P. B. Reich, M. Scherer-Lorenzen, B. Schmid, D. Tilman, J. van Ruijven, A. Weigelt, B. J. Wilsey, E. S. Zavaleta and M. Loreau (2011). "High plant diversity is needed to maintain ecosystem services." Nature **477**(7363): 199-202.

Ishii, Y., K. Koizumi, H. Fukami, K. Yamamoto, H. Takahashi, S. H. Limin, K. Kusin, A. Usup and G. E. Susilo (2016). Groundwater in Peatland. Tropical Peatland Ecosystems. M. Osaki and N. Tsuji, Springer.

Jaafar, Z. and T.-L. Loh (2014). "Linking land, air and sea: potential impacts of biomass burning and the resultant haze on marine ecosystems of Southeast Asia." Global Change Biology **20**(9): 2701-2707.

Kita, K., M. Fujiwara and S. Kawakami (2000). "Total ozone increase associated with forest fires over the Indonesian region and its relation to the El Niño-Southern oscillation." Atmospheric Environment **34**(17): 2681-2690.

Koh, L., J. Miettinen, S. Liew and J. Ghazoul (2011). " Remotely sensed evidence of tropical peatland conversion to oil palm." Proc Natl Acad Sci **108**: 5127–5132.

Koh, L. P., J. Ghazoul, R. A. Butler, W. F. Laurance, N. S. Sodhi, J. Mateo-Vega and C. J. A. Bradshaw (2010). "Wash and Spin Cycle Threats to Tropical Biodiversity." Biotropica **42**(1): 67-71.

Koplitz, S. N., L. J. Mickley, M. E. Marlier, J. J. Buonocore, P. S. Kim, T. Liu, M. P. Sulprizio, R. S. DeFries, D. J. Jacob, J. Schwartz and S. S. Myers (2016). "Public health impacts of the severe haze in Equatorial Asia in September-October 2015: A new tool for fire management to reduce downwind smoke exposure in the future." Environmental Research Letters **in press**.

Kunii, O. (1999). Basic facts - Determining downwind exposures and their associated health effects, assessment of heath effects in practice: a case study in the 1997 forest fires in Indonesia. Health Guidelines for Vegetation Fire Events: Background Papers K.-T. Goh, D. Schwela, J. G. Goldammer and O. Simpson. Lima, Peru, World Health Organization**:** 295-312.

Kunii, O., S. Kanagawa, I. Yajima, Y. Himatsu, S. Yamamura, T. Amagi and I. Ismail (2002). "The 1997 haze disaster in Indonesia: its air quality and health effects." Arch Environ Health **57**: 16–22.

Langmann, B. and H. F. Graf (2002). Indonesian smoke aerosols from peat fires and the contribution from volcanic sulfur emissions. Hamburg, Max Planck Institute for Meteorology.

Langner, A., J. Miettinen and F. Siegert (2007). "Land cover change 2002–2005 in Borneo and the role of fire derived from MODIS imagery." Global Change Biology **13**(11): 2329-2340.

Langner, A. and F. Siegert (2009). "Spatiotemporal fire occurrence in Borneo over a period of 10 years." Global Change Biology **15**(1): 48-62.

Liew, S. C., S. C., L. J., L. A. and K. L.K. (2003). Validation of MODIS fire product over Sumatra and Borneo using highresolution SPOT imagery. Proceedings of 24th Asian Conferenceon Remote Sensing and 2003 International Symposium on RemoteSensing.

Margono, B. A., P. V. Potapov, S. Turubanova, F. Stolle and M. C. Hansen (2014). "Primary forest cover loss in Indonesia over 2000–2012." Nature Clim. Change.

Marlier, M. E., R. DeFries, D. Pennington, E. Nelson, E. M. Ordway, J. Lewis, S. N. Koplitz and L. J. Mickley (2015). "Future fire emissions associated with projected land use change in Sumatra." Global Change Biology **21**(1): 345-362.

Marlier, M. E., R. S. DeFries, P. S. Kim, S. N. Koplitz, D. J. Jacob, L. J. Mickley and S. S. Myers (2015). "Fire emissions and regional air quality impacts from fires in oil palm, timber, and logging concessions in Indonesia." Environmental Research Letters **10**(8).

Marlier, M. E., R. S. DeFries, A. Voulgarakis, P. L. Kinney, J. T. Randerson, D. T. Shindell, Y. Chen and G. Faluvegi (2012). "El Ni‚Äö√Ñ√∂‚àö√´‚àö‚àÇ‚Äö√ñ√†√∂‚Äö√Ñ√∂‚Ä†‚Äö√ñ√†√∂‚àö√°¬¨¨®¬¨¨Æ¬¨¨®¬¨¬±o and health risks from landscape fire emissions in southeast Asia." Nature Climate Change **in press**.

Marlier, M. E., R. S. DeFries, A. Voulgarakis, P. L. Kinney, J. T. Randerson, D. T. Shindell, Y. Chen and G. Faluvegi (2012). "El Ni√±o and health risks from landscape fire emissions in southeast Asia." Nature Climate Change **in press**.

Maulia, E. (2010). Indonesia pledges to ‘feed the world'. Jakarta Post. Jakarta.

Meijaard, E. (2015). Get Your Facts Right on Indonesia's Haze Problem. Jakarta Globe. Jakarta.

Meijaard, E. and R. Dennis (1997). Forest fires in Indonesia: bibliography and background information. Amsterdam, The Netherlands, World Wide Fund for Nature.

Miettinen, J., L. Andreas and F. Siegert (2007). "Burnt area estimation for the year 2005 in Borneo using multi-resolution satellite imagery." International Journal of Wildland Fire **16**(1): 45-53.

Miettinen, J., C. Shi and S. C. Liew (2016). "Land cover distribution in the peatlands of Peninsular Malaysia, Sumatra and Borneo in 2015 with changes since 1990." Global Ecology and Conservation **6**: 67–78.

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

Mollman, S. (2015). Indonesia’s palm oil production is smoking out its neighbors. Quartz.

Murdiyarso, D., M. Widodo and D. Suyamto (2002). "Fire risks in forest carbon projects in Indonesia." Science in China **45**: 66-74.

Nicolas, M. V. J. (1998). Fighting the forest fires: the South Sumatra experience, Internal report. Palembang, Indonesia, EU-Forest Fire Prevention and Control Project**:** 22.

Page, S., A. Hoscillo, H. Wösten, J. Jauhiainen, M. Silvius, J. Rieley, H. Ritzema, K. Tansey, L. Graham, H. Vasander and S. Limin (2009). "Restoration Ecology of Lowland Tropical Peatlands in Southeast Asia: Current Knowledge and Future Research Directions." Ecosystems **12**(6): 888-905.

Page, S., A. Hoscilo, A. Langner, K. Tansey, F. Siegert, S. Limin and J. Rieley (2009). Tropical peatland fires in Southeast Asia. Tropical Fire Ecology: Climate Change, Land Use, and Ecosystem Dynamics. M. A. Cochrane. Germany / Chicheser, U.K., Springer/Praxis**:** 263-287.

Page, S. E., J. O. Rieley and C. J. Banks (2011). "Global and regional importance of the tropical peatland carbon pool." Global Change Biology **17**(2): 798-818.

Page, S. E., J. O. Rieley, W. Shotyk and D. Weiss (1999). "Interdependence of peat and vegetation in a tropical peat swamp forest." Philosophical Transactions of the Royal Society B: Biological Sciences **354**(1391): 1885-1897.

Page, S. E., J. O. Rieley and R. W√°st (2006). Lowland tropical peatlands of Southeast Asia. Peatlands: basin evolution and depository of records on global environmental and climatic changes. P. Martini, A. Martinez-Cortizas and W. Chesworth. Amsterdam, Elsevier**:** 145-172.

Page, S. E., F. Siegert, J. O. Rieley, H.-D. V. Boehm, A. Jaya and S. Limin (2002). "The amount of carbon released from peat and forest fires in Indonesia during 1997." Nature **420**(6911): 61-65.

Posa, M. R. C., L. S. Wijedasa and R. T. Corlett (2011). "Biodiversity and Conservation of Tropical Peat Swamp Forests." BioScience **61**(1): 49-57.

Potter, L. and J. Lee (1998). Oil palm in Indonesia: its role in forest conversion and the fires of 1997/98. W. I. Programme. Jakarta, Indonesia.

Pyne, S. J., P. A. Andrews and R. D. Laven (1996). Introduction to Wildland Fire. New York, Wiley.

Reddington, C. L., M. Yoshioka, R. Balasubramanian, D. Ridley and Y. Y. Toh (2014). "Contribution of vegetation and peat fires to particulate air pollution in Southeast Asia." Environmental Research Letters **9**(9): 094006.

Rein, G. (2013). Fire Phenomena in the Earth System: An Interdisciplinary Approach to Fire Science, Wiley.

Rieley, J. O., A.-A. Ahmad-Shah and M. A. Brandy (1996). The extent and nature of tropical peat swamps. Tropical Lowlands of Southeast Asia. E. Maltby, C. P. Immirzi and R. J. Safford. Gland, Switzerland, IUCN**:** 17-53.

Rollins, M. S., A. D. Cohen and J. R. Durig (1993). "Effects of fires on the chemical and petrographic composition of peat in the Snuggedy Swamp, North Carolina." Int. J. Coal. Geol **22**: 101–117.

Rosoman, G. and A. Rahmawa (2015). Oil palm growers.

RSPO, R. o. S. P. O. (2013). Principles and Criteria for the Production of Sustainable Palm Oil **5.5 and 7.7**.

RSPO, R. o. S. P. O. (2015) "Palm oil concession maps of RSPO members to become publically available."

RSPO, R. o. S. P. O. (2015) "RSPO Statement on the Indonesian Forest Fires."

Ruitenbeek, J. (1999). Indonesia. Indonesia's Fire and Haze: The Cost of Cataptrophe. D. Glover and T. Jessup. Ottawa, Institute of Southeast Asian Studies (ISEAS) / International Development Research Centre (IDRC).

Seavoy, R. E. (1973). "The shading cycle in shifting cultivation." Annals of the Association of American Geographers **63**: 218-225.

Seidl, R., W. Rammer and T. A. Spies (2014). "Disturbance legacies increasethe resilience of forest ecosystem structure, composition, and functioning." Ecological Applications **24**: 2063–2077.

Shilisky, A., A. Alencar, M. Manta and L. M. Curran (2009). Overview: Global fire regime conditions, threats, and opportunities for fire management in the tropics. Tropical Fire Ecology: Climate Change, Land Use, and Ecosystem Dynamics. M. A. Cochrane. Germany / Chicheser, U.K., Springer / Praxis.

Shlisky, A., J. Waugh, P. Gonzalez, M. Gonzalez, M. Manta, H. Santoso, E. Alvarado, A. A. Nuruddin, D. A. Rodríguez-Trejo, R. Swaty, D. Schmidt, M. Kaufmann, R. Myers, A. Alencar, F. Kearns, D. Johnson, J. Smith, D. Zollner and W. Fulks (2007). Fire, Ecosystems and People: Threats and Strategies for Global Biodiversity Conservation. GFI Technical Report. Arlington, VA, The Nature Conservancy. **2007-2**.

Siegert, F., G. Ruecker, A. Hinrichs and A. A. Hoffmann (2001). "Increased damage from fires in logged forests during droughts caused by El Nino." Nature **414**: 437–440.

Simorangkir, D., P. Moore, N. Haase and G. Ng (2002). Land Clearing on Degraded Lands for Plantation Development. A Workshop on Economics of Fire Use in Agriculture and Forest Plantations. P. F. S. E. Asia. Kuching.

Soares, S. (2015). Oil Palm Companies Suspected to Cause Forest Fires. Tempo. Jakarta, Indonesia.

Someshwar, S., R. Boer and E. Conrad (2010). Managing Peatland Fire Risk in Central Kalimantan, Indonesia. World Resources Report Case Studies. Washington DC, World Resources Institute.

Spessa, A. C., R. D. Field, F. Pappenberger, A. Langner, S. Englhart, U. Weber, T. Stockdale, F. Siegert, J. W. Kaiser and J. Moore (2015). "Seasonal forecasting of fire over Kalimantan, Indonesia." Nat. Hazards Earth Syst. Sci. **15**(3): 429-442.

Stolle, F., K. M. Chomitz, E. F. Lambin and T. P. Tomich (2003). "Land use and vegetation fires in Jambi Province, Sumatra, Indonesia." Forest Ecology and Management **179**(1-3): 277-292.

Stott, P. (2000). "Combustion in tropical biomass fires: a critical review." Progress in Physical Geography **24**(3): 355-377.

Stuart, H. (2012). "Indonesia Fires, Singapore Smog Likely Caused By Palm Oil Companies." Retrieved August 1, 2015.

Suyanto, S. (2000). Fire, deforestation and land tenure in the north-eastern fringes of Bukit Barisan Selatan National Park, Lampung. Bogor, Indonesia, Center for International Forestry Research (CIFOR).

Tacconi, L. (2003). Fires in Indonesia: Causes, Costs, and Policy Implications. Jakarta, Indonesia, Center for International Forestry Research.

Tansey, K., J. Beston, A. Hoscilo, S. E. Page and C. U. Paredes Hern·ndez (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**(D23): D23112.

Taylor, D., P. Saksena, P. G. Sanderson and K. Kucera (1999). "Environmental change and rain forests on the Sunda shelf of Southeast Asia: drought, fire and the biological cooling of biodiversity hotspots." Biodiversity and Conservation **8**: 1159-1177.

Team, R. C. (2012). R: A Language and Environment for Statistical Computing. Vienna, Austria, R Foundation for Statistical Computing.

Teoh, C. H. (2010). Key Sustainability Issues in the Palm Oil Sector. T. W. B. Group. Washington, DC.

Tomich, T. P., A. M. Fagi, H. De Foresta, G. Michon, D. Murdiyarso, F. Stolle and M. Van Noordwijk. (1998). "Indonesia's fires: smoke as a problem, smoke as a symptom." Agroforestry Today **10**: 4–7.

Townshend, J. R. G., M. Carroll, C. Dimiceli, R. Sohlberg, M. Hansen and R. DeFries. (2011). "Vegetation Continuous Fields MOD44B, 2000-2010 Percent Tree Cover, Collection 5." Retrieved 01/15/2015.

Turetsky, M. R., B. Benscoter, S. Page, G. Rein, G. R. van der Werf and A. Watts (2015). "Global vulnerability of peatlands to fire and carbon loss." Nature Geosci **8**(1): 11-14.

Uriarte, M., M. Pinedo-Vasquez, R. S. DeFries, K. Fernandes, V. Gutierrez-Velez, W. E. Baethgen and C. Padoch (2012). "Depopulation of rural landscapes exacerbates fire activity in the western Amazon." Proceedings of the National Academy of Sciences **109**(52): 21546–21550.

Usup, A., Y. Hashimoto, H. Takahashi and H. Hayasaka (2004). "Combustion and thermal characteristics of peat fire in tropical peatland in Central Kalimantan, Indonesia." Tropics **14**: 1-19.

van der Werf, G. R., J. Dempewolf, S. N. Trigg, J. T. Randerson, P. S. Kasibhatla, L. Giglio, D. Murdiyarso, W. Peters, D. C. Morton, G. J. Collatz, A. J. Dolman and R. S. DeFries (2008). "Climate regulation of fire emissions and deforestation in equatorial Asia." Proceedings of the National Academy of Sciences **105**(51): 20350-20355.

van der Werf, G. R., J. T. Randerson, L. Giglio, N. Gobron and A. J. Dolman (2008). "Climate controls on the variability of fires in the tropics and subtropics." Global Biogeochem. Cycles **22**(3).

Van Nieuwstadt, M. G. L., D. Sheil and K. Kartawinata (2001). "The ecological consequences of logging in the burned forests of East Kalimantan, Indonesia." Conserv. Biol. **15**: 1183-1186.

Varma, A. (2003). "The economics of slash and burn: A case study of the 1997/1998 Indonesian forest fires." Ecological Economics **46**: 159-171.

Vayda, A. P. (2006). "Causal Explanation of Indonesian Forest Fires: Concepts, Applications, and Research Priorities." Human Ecology **34**: 615-635.

Venables, W. N. and B. D. Ripley (2002). Modern Applied Statistics with S. New York, Springer.

Wahyunto and I. N. N. Suryadiputra (2008). Peatland Distribution in Sumatra and Kalimantan-explanation of its data sets including source of information, accuracy, data constraints and gaps Bogor, Indonesia, Wetlands International.

Wan Ahmad, W. M. S. (2001). Fire Situation in Malaysia. Global Forest Fire Assessment 1990-2000. J. G. Goldammer. Rome, Forestry Department, Food and Agriculture Organization of the United Nations (FAO).

Wang, Y. H., R. D. Field and O. Roswintiarti (2004). "Trends in atmospheric haze induced by peat fires in Sumatra Island, Indonesia and El Nino phenomenon from 1973–2003." Geophys. Res. Lett. **31**.

Westerling, A. L., H. G. Hidalgo, D. R. Cayan and T. W. Swetnam (2006). "Warming and earlier spring increase western U.S. forest wildfire activity." Science **313**: 940–943.

Wibowo, A., M., A. P. S. Suharti, H. H. Sagala and M. V. Noordwijk (1997). "Fire management on Imperata grasslands as part of agroforestry development in Indonesia." Agroforestry Systems **36**: 203-217.

Wich, S. A., E. Meijaard, A. J. Marshall, S. Husson, M. Ancrenaz, R. C. Lacy, C. P. van Schaik, J. Sugardjito, T. Simorangkir, K. Traylor-Holzer, M. Doughty, J. Supriatna, R. Dennis, M. Gumal, C. D. Knott and I. Singleton (2008). "Distribution and conservation status of the orang-utan (Pongo spp.) on Borneo and Sumatra: how many remain?" Oryx **42**(03): 329-339.

Wickham, H. and R. Francois (2014). dplyr: a grammar of data manipulation. R package version 0.2.

Wilcove, D. S. and L. P. Koh (2010). "Addressing the threats to biodiversity from oil-palm agriculture." Biodiversity and Conservation **19**(4): 999-1007.

Wong, J., Q. Marshall, A. Jay and R. Boer (2010). The Use of a Seasonal Fire Early Warning Tool for Managing Peat Fires in Indonesia. Bogor, Indonesia, INTERNATIONAL RESEARCH INSTITUTE FOR CLIMATE AND SOCIETY,

BOGOR AGRICULTURAL UNIVERSITY.

Wooster, M. J., G. L. W. Perry and A. Zoumas (2012). "Fire, drought and El Nino relationships on Borneo (Southeast Asia) in the pre-MODIS era (1980-2000)." Biosciences **9**: 317-340.

Wösten, J. H. M., E. Clymans, S. E. Page, J. O. Rieley and S. H. Limin (2008). "Peat–water interrelationships in a tropical peatland ecosystem in Southeast Asia." Catena **73**: 212–224.

Wosten, J. H. M., J. van den Berg, P. van Eijk, G. J. M. Gevers, W. B. J. T. Giesen, A. Hooijer, A. Idris, P. H. Leenman, D. S. Rais and C. Siderius (2006). "Interrelationships between hydrology and ecology in the fire degraded tropical peat swamp forests." Water Resources Development **22**: 157-174.

WRI, W. R. I. (2014). Global Forest Watch.

Yule, C. (2010). "Loss of biodiversity and ecosystem functioning in Indo-Malayan peat swamp forests." Biodiversity and Conservation **19**(2): 393-409.