Seasonal Forecasting of Fire over Kalimantan, Indonesia

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Abstract

Large-scale fires occur frequently across Indonesia, particularly in the southern region of Kalimantan and eastern Sumatra. They have considerable impacts on carbon emissions, haze production, biodiversity, health, and economic activities.

In this study, we demonstrate that severe fire and haze events in Indonesia can generally be predicted months in advance using predictions of seasonal rainfall from the ECMWF System 4 coupled ocean-atmosphere model. Based on analyses of up-to-date and long series observations on burnt area and rainfall, and tree cover, we demonstrate that fire activity is negatively correlated with rainfall, and is positively associated with deforestation in Indonesia. There is a contrast between the southern region of Kalimantan (high fire activity, high tree cover loss and strong non-linear correlation between observed rainfall and fire) and the central region of Kalimantan (low fire activity, low tree cover loss and weak non-linear correlation between observed rainfall and fire).

The ECMWF seasonal forecast provides skilled forecasts of burnt and fire affected area with several months lead time explaining at least 70% of the variance between rainfall and burnt and fire affected area. Results are strongly influenced by El Niño years which show a consistent positive bias. Overall, our findings point to a high potential for using a more physical-based method for predicting fires with several months lead time in the tropics, rather than one based on indexes only. We argue that seasonal precipitation forecasts should be central to Indonesia's evolving fire management policy.

1 Introduction

The rainforests of equatorial Southeast (SE) Asia comprise some of the largest, oldest, most biodiverse forests on the planet (Page *et al.,* 2011). Indonesian forests and peatlands are globally one of the largest reservoirs of terrestrial organic carbon, with an estimated 14 Gt of above-ground carbon in forests (Saatchi *et al.,* 2011) and around 60 Gt of carbon in the below-ground biomass of peatlands (Page *et al.,* 2011). While fires in Indonesia have occurred throughout paleo-history, their frequency before the 1960s was comparatively rare; coinciding with exceptional but relatively infrequent droughts mostly associated with strong El Niño events (Field *et al.,* 2009). The El Niño Southern Oscillation (ENSO) is the major driver of rainfall variability in the equatorial Pacific region, and occurs irregularly on a 2-7 year intervals lasting about one year but with varying strengths (Aldrian & Dwi Susanto, 2003; Dobles-Reyes *et al.,* 2013). During the warm ENSO phase (El Niño) sea surface temperatures in the western Pacific tend to be cooler than normal leading to below normal dry season rainfall and extended dry season length, which increases the risk of mainly degraded forest areas becoming dry enough to burn (Siegert *et al.,* 2001). Large-scale rainfall patterns in the region are also affected by other major weather systems such as the Indian Ocean Dipole (IOD) and the Madden Julian Oscillation (MJO), but their interaction with ENSO are highly complex (Field *et al.,* 2009; Reid *et al.,* 2012; Dobles-Reyes *et al.,* 2013). Furthermore, land rainfall in the maritime continent is also affected by a complex of biophysical effects including land–sea distribution, orography, land cover, and local SSTs (Aldrian & Dwi Susanto, 2003).

Since the early 1960s, however, large-scale fires and related widespread emissions episodes have occurred more frequently across Indonesia, particularly in the southern region of Kalimantan and eastern Sumatra (Field & Shen, 2008; Field et al., 2009; Schultz *et al.,* 2008). These episodes are nearly always associated with El Niño events, for example, emissions from biomass burning in Kalimantan were as much as 30 times greater during 2006, an El Niño year, than during 2000, a wet La Niña year (van der Werf *et al.,* 2008). Furthermore, the destructive fires in Indonesia during the exceptionally strong El Niño in late 1997 and early 1998 rank as some of the largest peak emissions events in recorded history. Past studies estimate about 1Gt of carbon was released to the atmosphere from the Indonesian fires in 1997, which were mostly concentrated in carbon-rich forested peatlands of the southern region of Kalimantan. This amount was equivalent to over 10% of the average global annual fossil fuel emissions released during the 1990s (Page *et al.,* 2002; Schultz *et al.,* 2008; van der Werf *et al.,* 2010).

Over the past couple of decades, Indonesia has experienced some of the world's highest rates of deforestation and forest degradation, principally due to fire (Langner *et al.,* 2007; Langner & Siegert 2009; Hoscilo *et al.,* 2011; Miettinen *et al.,* 2011; Page *et al.,* 2011; Hooijer *et al.,* 2012). The general consensus is that the relatively low fire frequency prior to the 1960s in Indonesia, and the relatively higher fire frequency post-1960s are not due to any significant step-up in drought frequency *per se*, but rather an increase in human-caused ignitions associated with expansion of agriculture, palm and pulp paper plantations, industrial deforestation and peat forest reclamation. Land use activities such as these all make extensive use of fire to clear forest, especially during droughts where the impact of fire is maximized. The activities generally started in Indonesia during the 1960s, and intensified greatly in the early 1990s as exemplified by the *Transmigrasi* projects, including the ill-fated Mega Rice project in the southern region of Kalimantan and subsequent peat reclamation projects in that region (Langner *et al.,* 2007; Langner & Siegert 2009; Hoscilo *et al.,* 2011; Miettinen *et al.,* 2011; Page *et al.,* 2011; Hooijer *et al.,* 2012).

A clear negative correlation between fire activity and antecedent rainfall in Indonesia, based on earth observation (EO) fire activity data (Field & Shen, 2008; van der Werf *et al.,* 2008) or proxies of fire activity such as aerosols (Sudiana *et al.,* 2003), haze (Field *et al.,* 2004; Wang *et al.,* 2004; Field *et al.,* 2009), and mid-tropospheric CO (Nasser *et al.,* 2009) has been established. Several studies have demonstrated a clear positive correlation between the fire activity and various indexes of El Nino strength (Fuller & Murphy, 2006; Reid *et al.,* 2012; Wooster *et al.,* 2012). Reid *et al.,* (2012) also discussed the various possible contributions of the ENSO, IOD and MJO to fire occurrence over Western Indonesia during 2000-2010; concluding that while ENSO is the largest factor influencing fire occurrence, the ENSO Modoki (modified ENSO) and the IOD are also important. Due to the strong influence of ENSO on rainfall patterns across Indonesia, Wooster *et al.* (2012) demonstrated that statistical forecasting of the extent and magnitude of fire activity a few months in advance based on ENSO indexes is possible. Chen *et al.* (2011) developed an empirical model to forecast regional fire season severity with lead times of 3 to 5 months in Amazonia based on a composite index derived from the Oceanic Niño Index and the Atlantic Multi-decadal Oscillation index.

Recent advances in seasonal climate forecasting based on the use of state-of-the-art dynamical models that couple atmosphere, ocean and land processes and assimilate a vast range of climate-related EO measurements (e.g. sea surface temperatures (SSTs)) (Doblas-Reyes *et al.,* 2013) opens up the possibility of forming a more physical-based method for predicting fires with several months lead time in the tropics, rather than one based on indexes only. The purpose of this study is to determine whether severe fire and haze events in Indonesia can be predicted in advance using one such system, the European Centre for Medium Weather Forecasting (ECMWF) Seasonal forecast system (System 4) (Molteni *et al.*, 2011).

Ensemble seasonal climate forecasts issued with several months lead-time is a well-established field, and these forecasts have been applied broadly including managing and assessing risks in agricultural production (Hansen *et al.,* 2011), malaria outbreaks (Jones & Morse, 2010), heatwaves (Lass *et al.,* 2013), flooding and droughts (Pappenberger *et al.,* 2011, 2013). Comparatively less work has been done on seasonal forecasting of fires, however. The USA has a long-standing seasonal fire danger prediction system (Roads et al 2005, 2010), which is based on the National Center for Environmental Prediction's Coupled Forecast System (NCEP-CFS) (Saha *et al.,* 2006, 2014). The latest version of the NCEP-CFS generates global and regional spectral model ensemble forecasts over a 3 to 7 month period, which in turn provides required input meteorological variables for calculating fire danger indices based on the National Fire Danger Rating System (Cohen & Deeming, 1985; Burgan, 1988). Roads *et al.* (2010) demonstrated the seasonal forecasts of fire danger indices driven by NCEP-CFS outputs had skill in predicting fire activity across western USA. The European Forest Fire Information System (EFFIS) (McInerney *et al.,* 2013) currently provides temperature and rainfall anomalies that are expected to exist over European and Mediterranean areas during the next two months based on the multi-member ECMWF System 4 seasonal forecast system. Areas that are drier and hotter than normal indicate higher forest fire danger (http://forest.jrc.ec.europa.eu/effis/applications/long-term-forecast/).

Since no equivalent seasonal fire forecasting system exists for Indonesia, we were motivated to develop and test one for the severely fire-affected region of southern Kalimantan as a case study, based on seven-month forecasts of monthly rainfall from the ECMWF System 4 for the period 1997-2010. The case study was identified from a comparison of observed burnt area and tree cover patterns across a broader region of southern-central Kalimantan, which generally exhibits a June-November dry season (Aldrian & Dwi Susanto, 2003). We evaluated the skill of the seasonal rainfall forecasts against observed rainfall, and in predicting observed burnt area and fire-affected area. We further assessed forecast skill by analysing observed burnt area and fire-affected area in relation to observed rainfall. Several previous studies have focused on the highly non-linear nature of precipitation and fire occurrence in the region; severe fire happens only below a threshold of seasonal precipitation (Field *et al.,* 2004; van der Werf *et al.,* 2008; Field & Shen,2008; Field *et al.,* 2009). It is only during years with a sufficiently strong precipitation deficit that disturbed peatlands can dry to their point of ignition and burn. In a practical sense, therefore, seasonal fire forecasting entails determining whether this threshold will be crossed during the upcoming dry season.

2 Methods

In order to understand and assess seasonal forecast skill, our analyses proceeded in two stages. We first determined the strength of precipitation-fire relationships over the region of southern-central Kalimantan for our 1997-2010 analysis period, knowing *a priori* that these relationships have been identified in other and earlier versions of the data used. We then evaluated the forecast skill of System 4, focusing on the degree to which the model could separate the precipitation associated with normal and severe fire years.

2.1 Study Area and Study Periods

Borneo is divided among three countries: Indonesia, Malaysia and Brunei (Fig. 1). The broader region of southern-central Kalimantan (Indonesia) (Fig. 1) matches approximately the only region of Borneo identified by Aldrian & Dwi Susanto (2003) as having, on the average, a June to November dry season. Preliminary analyses of available data on burnt area data and fire-affected area (see below) revealed that over 95% of fires occurred during this period.

During our study period, 1997-2010, El Niño events were registered in 1997-1998, 2002, 2004, 2006, 2009 (http://www.cpc.noaa.gov/products/analysis_monitoring/ensostuff/ensoyears.shtml). However, drought and associated fires during 1998 phase of the 1997-1998 El Niño event were concentrated in East Kalimantan (Siegert *et al.,* 2001; Field *et al.,* 2004), which does not display as clearly defined wet and dry seasons (Aldrian & Dwi Susanto, 2003). Analyses of the Global Precipitation Climatology Project (GPCP) rainfall data (see below) confirmed 1998 as a non-drought year for the southern-central region of Kalimantan. For the purposes of this paper, therefore, we regard 1997, 2002, 2004, 2006, 2009 as El Niño years, but not 1998.

2.2 Fire Data

To increase the robustness of our analyses of burnt area and fire-affected area in relation to rainfall and forest cover change, we used two independent monthly datasets spanning 1997-2010, aggregated to 0.5^{o} gridcells. The first dataset is from the Global Fire and Emissions Database version 4 (GFED4) (Giglio *et al.,* 2013), and the second is from the Remote Sensing Solutions (RSS) GmbH (after Langner & Siegert, 2009, with unpublished updates from RSS GmbH).

The Global Fire and Emissions Database version 4 (GFED4) burnt area is available at a monthly time step at 0.25^{o} resolution, and is based on active fire detection from ERS (European Remote Sensing Satellite) ATSR (Along-Track Scanning Radiometer) World fire Atlas and TRMM (Tropical Rainfall Measuring Mission) VIRS (Visible and Infrared Scanner) as well as the MODIS (Moderate Resolution Imaging Spectroradiometer) burnt area product (MCD64A1) (Giglio *et al.,* 2013). For the MODIS era, the GFED4 monthly burnt area dataset was derived exclusively from the 500 m MCD64A1 burnt area product (Giglio *et al.,* 2013). For the pre-MODIS era, burnt area was derived from calibrating monthly active fire counts from the VIRS and ATSR sensors to monthly burnt area supplied by the MCD64A1 product which was modified according to Giglio *et al.* (2010).

RSS fire-affected area data are only available for Borneo, and are based on active fire detections derived from NOAA (National Oceanic and Atmospheric Administration) AVHRR (Advanced Very High Resolution Radiometer), ATSR, and MODIS imagery (Langner & Siegert, 2009). Fires before 2000 were derived from hotspots recorded by NOAA 14 and ATSR by adding their datasets. ATSR was used in addition to NOAA because especially in 1997 and 1998 several large fires were not recorded by NOAA due to operation errors at the receiving station. Fires from 2000 onwards were derived from MODIS hotspots (MOD14/MYD14). One single hotspot pixel (sensor element) represents the area of the corresponding sensor resolution of 1 km. This pixel can be affected by a single fire or more than one fire (Langner & Siegert, 2009). Following the convention of Langner & Siegert (2009), we define the RSS data as fire-affected area rather than burnt area because the actual size of the burnt area is unknown and strongly relates to the underlying land cover type. However, taking into account the possible combination of very hot sub-pixel fires and larger and/or reoccurring fires that result in overlapping hotspot areas, which are considered only once within each year; we assume that every hotspot pixel detected by the satellite is regarded as completely affected by fire.

2.3 Forest Cover Data

Our analyses are based on three tree cover products: the global AVHRR 1993 continuous percentage tree cover product available at 1 km (de Fries *et al.,* 2000), and two MODIS tree cover products available for SE Asia at 500m for the years 2000 and 2010 (Miettinen *et al.,* 2011).

2.4 Rainfall Data

Version 1.2 of the GPCP one-degree daily (1DD) rainfall data formed the basis for comparing burnt and fire affected area in relation to observed rainfall and evaluating seasonal rainfall forecasts from System 4. The dataset is a global product available at a 1^{o} resolution, and combines precipitation estimates from several sources, including infrared (IR) and passive microwave (PM) rain estimates, and rain gauge observations (Adler, 2003; Huffman *et al.,* 2009).

2.5 ECMWF Seasonal forecast System (System 4)

Seasonal predictions of rainfall were derived from the ECMWF Seasonal forecast System (System 4), which provides operational seasonal predictions (Molteni *et al.,* 2011). System 4 is the most recent ECMWF seasonal forecast system and includes 51 member ensembles and consists of 7 month forecasts initialized on the 1st day of every month. The seasonal forecast has a resolution of ~79km (T255L91). It is coupled with an ocean model which has a horizontal resolution of 1^{o}. Singular vectors and an ensemble of ocean analysis, including SSTs provide the initial perturbations. Atmospheric model uncertainties are included through a 3-time-level stochastically perturbed parameterized tendency scheme and the stochastic back-scatter scheme, which is similar to the ECMWF medium range forecasting system. The operational seasonal forecast are accompanied by a hindcast system which covers a 30 year period (from 1981 to today) where the land surface is initialized using an offline simulation driven by ERAInterim data (Dee *et al.,* 2011). The hind cast has usually 15 ensemble members. Molteni *et al.* (2011) presented an overview of S4 model biases and forecast performance.

We restricted our use of the ECMWF System 4 rainfall forecasts to 1 May initializations, that is, seasonal forecasts spanning 1 May to 30 November, each year 1997-2010. Mean daily rainfall for each month and each ensemble member was calculated.

2.6 Data preparation and statistical analyses

We aggregated the burnt area data (GFED4), the fire-affected area data (RSS) and the tree cover data (1993, 2002 and 2010) to 0.5° grid cells, and down-scaled the GPCP data to 0.5° grid cells by linear interpolation.

Total area burnt (GFED4) and total fire-affected area (RSS) were calculated for each 0.5° grid cell in the southern-central region of Kalimantan by summing the respective monthly burnt areas between June and November, 1997-2010. Since a 1997 tree cover product does not exist for the study area, we derived a 1997 tree cover dataset based on simple linear interpolation between 1993 and 2000 tree covers. Spatial plots of total fire-affected area (RSS), total area burnt (GFED4) were then visually compared to spatial plots of tree cover (1993), tree cover (1997) and tree cover (2010) at 0.5o resolution.

For the central and southern regions of Kalimantan and each year, seasonal mean GFED4 burnt area per grid cell and seasonal mean RSS fire-affected area per grid cell were calculated by firstly summing the respective monthly burnt areas or fire-affected areas between June and November for each 0.5° grid cell, then summing these values over all grid cells, and finally dividing by the number of grid cells. The range of each seasonal mean burnt area per grid cell or fire-affected area per grid cell was calculated as $\pm 1.96 \times SE_{mean}$. This is similar to previous studies using seasonal (van der Werf *et al.,* 2008; Wooster *et al.,* 2012) or monthly mean (Wang *et al.,* 2004; Field & Shen, 2008; Field *et al.,* 2009) estimates of fire activity or haze at an island-scale.

For the central and southern regions of Kalimantan and each year, seasonal mean GPCP rainfall per grid cell was calculated by firstly taking the average of the daily mean rainfall per month values between June and November for each 0.5° grid cell, then summing these values over all grid cells, and finally dividing by the number of grid cells. The range of each seasonal mean GPCP rainfall per grid cell was calculated as $\pm 1.96 \times SE_{mean}$.

For the southern region of Kalimantan only and each year, seasonal mean System 4 rainfall per grid cell was calculated by firstly restricting the System 4 outputs to the middle-ranked 17 members of the 51 member ensemble (middle tercile), then averaging over the mean daily rainfall per month values between June and November for each System 4 grid cell, then summing these values over all grid cells, and finally dividing by the number of grid cells. The mean of the highest-ranked 17 members of the 51 member System 4 ensemble (upper tercile) and the mean of the lowest-ranked 17 members of the 51 member System 4 ensemble (lower tercile) were calculated similarly. The upper range for each year was defined as $mean_{upper\ tercile} - mean_{middle\ tercile}$, and the lower range for each year was defined as $mean_{middle\ tercile} - mean_{lower\ tercile}$.

The following statistical analyses were undertaken:

- correlation between seasonal mean GFED4 burnt area per grid cell and seasonal mean RSS fire-affected area per grid cell;
- regression of seasonal mean GFED4 burnt area per grid cell on seasonal mean GPCP rainfall per grid cell, central and southern regions of Kalimantan;
- regression of seasonal mean RSS fire-affected area per grid cell on seasonal mean GPCP rainfall per grid cell, central and southern regions of Kalimantan;
- regression of seasonal mean GFED4 burnt area per grid cell on seasonal mean System 4 rainfall per grid cell, southern region of Kalimantan;
- regression of seasonal mean RSS fire-affected area per grid cell on seasonal mean System 4 rainfall per grid cell, southern region of Kalimantan; and
- correlation between seasonal mean GPCP rainfall per grid cell and seasonal mean System 4 rainfall per grid cell, southern region of Kalimantan.

Each regression analysis comprised two parts: linear regression of the form $Y = a + b \times X$, and non-linear regression of the form $Y = a + b \times \ln(X)$; where Y is seasonal mean burnt area per grid cell (GFED4) or seasonal mean fire-affected area per grid cell (RSS), X is seasonal mean daily rainfall per grid cell (GPCP or System 4) and ln is the natural log transformation.

3. Results

3.1 Fire activity versus tree cover change

Fire activity and tree cover loss were clearly both much higher across a distinct southern region of Kalimantan (N = 53 grid cells at 0.5^{o} resolution) compared with a central region of Kalimantan immediately above it (N = 40 grid cells at 0.5^{o} resolution) (Fig 1). Seasonal mean GFED4 area burnt in the south was, on the average, 27.1 times higher than in the central region (Table 1); and seasonal mean RSS fire-affected area in southern region was, on the average, 4.2 times higher than in the central region (Table 1). In the southern region, the mean tree cover in 2010 was 17.9% lower than that for 1993, and 10.2% lower than that for 1997 (Table 1). In the central region, the mean tree cover in 2010 was 8.2% lower than that for 1993, and 4.4% lower than that for 1997 (Table 1).

3.2 RSS fire-affected area versus GFED4 burnt area

Seasonal mean RSS fire-affected area and seasonal mean GFED4 burnt area was highly correlated in the southern region (R^2 = 0.96) and the central region (R^2 = 0.88). Across the years in which El Nino affected the central-southern region (1997, 2002, 2003, 2004, 2006 and 2009), seasonal mean RSS fire-affected area was consistently much higher than seasonal mean GFED4 burnt area. In 1997 (pre-MODIS), seasonal mean RSS fire-affected area was 1.9 times higher than seasonal mean GFED4 burnt area in the south, and 10.2 times higher than the equivalent for GFED4 in the central region (Table 1). Averaged across the other El-Nino affected years (all post-MODIS), RSS fire-affected area was 1.4 times higher than seasonal mean GFED4 burnt area in the south, and 9.6 times higher than the equivalent for GFED4 in the central region (Table 1).

3.3 Burnt and fire-affected area versus observed rainfall

Seasonal mean burnt and fire-affected area was non-linearly and highly correlated with seasonal mean GPCP rainfall for the GFED4 dataset (southern region: R^2 = 0.86; central region: R^2 = 0.80; Figs 2a, b) and for the RSS dataset (southern region: R^2 = 0.90; central region: R^2 = 0.70; Figs 3a, b). For the GFED4 dataset, the magnitude of the slopes and the intercepts determining the non-linear relationships were respectively 29.8 and 27.2 times greater for the southern region than the central region (Figs 2a, b). For the RSS dataset, the magnitude of the slopes and the intercepts determining the non-linear relationships were respectively 5.2 and 4.6 times greater for the southern than in the central region (Figs 3a, b). For the southern region, we diagnosed a clear rainfall threshold approximately equal to 6mm, above which fire activity was almost negligible, and below which it increased exponentially (Figs 2b, 3b).

3.4 Burnt and fire-affected area versus System 4 rainfall

Focusing on the southern region, seasonal mean burnt and fire-affected area was non-linearly and significantly correlated with seasonal mean daily System 4 rainfall for the RSS dataset (R^2 = 0.70) (Fig 4a) and the GFED4 dataset (R^2 = 0.76) (Fig 4b). For each System 4-based relationship, the year 2006 was an obvious outlier. Both System 4-based analyses revealed a similar rainfall threshold approximately equal to 7 mm, but this is less clear-cut compared to the GPCP-based analyses (Figs 4a, b).

3.5 System 4 rainfall versus observed rainfall

Seasonal mean System 4 rainfall and seasonal mean GPCP rainfall were highly correlated (R^2 = 0.91), and for each year, their respective values overlapped (Fig. 5). Seasonal mean System 4 rainfall was higher than seasonal mean GPCP rainfall during each El Nino-affected year: 1997 (+ 0.19 mm), 2002 (+1.46 mm), 2004 (+0.52 mm), 2006 (+2.2 mm) and 2009 (+ 0.88 mm) (Fig. 5).

3.6 System 4 predicted versus observed SSTs

Further analyses of the 15 member ensemble System4 hindcasts from 1997 to 2010 demonstrated that while most members correctly predicted observed SSTs, 2006 was particularly anomalous (Fig. 6). Only 2 out of 15 members predicted the SST cooling in this year. By contrast, in 1997, when the strongest cooling was observed, 13 out of 15 members predicted a strong cooling (Fig. 6).

4 Discussion

4.1 Observed fire, rainfall, tree cover patterns

Based on analyses of a comparatively up-to-date and long series observations on burnt and fire-affected area and rainfall (14 years from 1997 to 2010), and tree cover (1993, 1997, 2000 and 2010), our work supports a large body of work that demonstrates for different tropical regions, fire activity is negatively correlated with rainfall, and positively associated with deforestation in Indonesia (Langner *et al.,* 2007; van der Werf *et al.,* 2008; Langner & Siegert, 2009; Field *et al.,* 2009), Amazonia (Aragao *et al.,* 2008) and Columbia (Armenteras-Pascual *et al.,* 2011). Our results highlight the stark contrast between the southern region of Kalimantan (high fire activity, high tree cover loss and strong non-linear correlation between rainfall and fire) and the central region of Kalimantan (low fire activity, low tree cover loss and weak non-linear correlation between rainfall and fire). The amount of forest cover loss between 1997 and 2010 we estimated is likely to be conservative. Forest cover immediately prior to the major El Nino-induced fires of 1997 probably matches more closely forest cover in 1993, than that based on a simple linear interpolation between forest cover in 1993 and 2002. Although fire data covering the 1993 to 1997 period are not available, no major El Nino events occurred during this period, except for a relatively minor event in 1994-1995 (http://www.cpc.noaa.gov/products/analysis_monitoring/ensostuff/ensoyears.shtml). Our finding of strong non-linear relationships between fire and rainfall for southern Kalimantan confirms similar relationships reported for the region (van der Werf *et al.,* 2008; Field *et al.,* 2009). The exponential increase in fire activity in southern Kalimantan below a moisture threshold of around 6mm per day supports the finding of a similar fire moisture threshold for the region (Field *et al.,* 2009).

Our results support the general consensus that while fire activity is strongly linked to drought in Kalimantan, the strength of this relationship is mediated by land use and land cover change and the presence of disturbed peatlands. Numerous studies have reported the widespread deliberate use of fire in the southern region of Kalimantan to clear forests to establish plantations (mainly rice, oil palm and acacia), as well as the widespread incidence of escaped fires associated with these activities and logging (Langner *et al.,* 2007; van der Werf *et al.,* 2008; Langner & Siegert, 2009). Furthermore, extensive areas of peatland have been drained for plantation establishment, which has led to an increase in fire activity in these areas because drained peats lower the water table, exposing a greater depth of dry peat to burning (Page *et al.,* 2011; Hooijer *et al.,* 2012). By contrast, the central region of Kalimantan has undergone comparatively little development to date (Langner *et al.,* 2007, Langner & Siegert, 2009; Margono *et al.,* 2014). The central region has steep slope sections which reduce the ease of forest exploitation and clearing compared to the relatively more flat terrain of the southern region (Langner & Siegert, 2009). Due to its highly uneven topography, the central region also contains relatively less peat (Page *et al.,* 2011; Hooijer *et al.,* 2012).

4.2 Seasonal forecasting of fire

Based on two independent burnt and fire-affected area datasets, we demonstrated that seasonal forecasts of rainfall from the ECMWF System 4 can predict fire activity during the June-November dry season in the southern region of Kalimantan. The empirical fits between System 4 rainfall and fire activity were highly non-linear, similar to those based on observed rainfall. The correlations between System 4 rainfall and fire activity while not as good as those between observed rainfall and fire activity were nonetheless significant (RSS fire-affected area dataset: $R^2 = 0.70$; GFED4 burnt area dataset: $R^2 = 0.76$). These significant relationships between System 4 rainfall and burnt area and between System 4 rainfall and fire-affected area demonstrate a prospective use of System 4 rainfall to predict seasonal fire activity as part of a region-wide fire management programme for the southern region of Kalimantan. Further development of any such programme would need to consider however three important factors potentially affecting the robustness of predicting burnt area as a simple function of modelled rainfall. These factors are: i) a positive rainfall bias in the System 4 model, ii) biases in the burnt area and fire-affected area datasets used to construct these relationships, and iii) the influence of land use and land cover change, as well as peat drainage, on rainfall versus fire relationships for the southern region of Kalimantan.

4.3 Rainfall bias in seasonal forecast

Although ECMWF and observed rainfall were well-correlated ($R^2 = 0.91$), ECMWF rainfall was consistently higher during the El Nino-affected years of 1997, 2002, 2004, 2006 and 2009, that is, years with high fire activity. Furthermore, this bias was not consistent across these drought years. The smallest positive bias occurred during the strong 1997 El Nino year of 1997 (+0.19 mm), and the greatest positive bias occurred during the moderate El Nino year of 2006 (+2.2 mm). The later was clearly an outlier that reduced the goodness-of-fit of the empirical relationships between ECMWF rainfall and fire activity. Although the estimated moisture threshold diagnosed from the ECMWF rainfall versus fire relationships (7 mm) was similar to that estimated from the GPCP rainfall versus fire relationships (6 mm), it not as clear-cut because of the 2006 outlier.

Seasonal predictability in the maritime continent is to a large extent due to the ENSO; and the changes in SSTs associated with these oscillations (Oldenborgh *et al.,* 2005; Lavers *et al.,* 2009;

Dobles-Reyes *et al.,* 2013). In general, cooler SSTs indicate below-average rainfall, and warmer SSTs indicate above-average rainfall. Our analyses of SSTs from multi-member System 4 hindcasts covering our study region clearly showed that while most members correctly predicted observed SSTs, the worst result was in 2006, where only 13% of members predicted the SST cooling in that year. The best was in 1997 where close to 90% predicted the SST cooling, corresponding with our observation that the smallest difference in System4 and GPCP rainfall during any drought year was in 1997. Whether the relatively poor prediction in 2006 is a consequence of model error, or is simply due to the event having low predictability, is not known. Some variations in SST and rainfall will always be unpredictable, but we do know that model error has the potential to play a role.

Molteni *et al.* (2011) reported a positive rainfall bias in Indonesia for System 4. They suggested this was consistent with too strong easterly trade winds simulated by the System 4 atmospheric model in the central and western Pacific, which act to reduce the movement of the western warm pool towards the east Pacific during El Nino onset, hence maintaining warmer than expected SSTs in the model for Indonesia. The impact of this bias on the specific 2006 forecast is not known, but it suggests that more work is needed to improve the feedback between SSTs and climate in System 4, with direct benefits for seasonal forecasting of fires in the region.

4.4 Biases in the burnt area and fire-affected area products

Although the RSS fire-affected area and GFED4 burnt area data yielded similar patterns (southern region of Kalimantan burning much more than the central region, and non-linear relationships between observed rainfall and fire activity, and between System 4 rainfall and fire activity), RSS fire-affected area was consistently higher than GFED4 burnt area. During the MODIS era (2000 onwards), GFED4 is based on 500m MODIS burnt area product (MDC64A1) (Giglio *et al.,* 2013), and RSS is based on 1 km^2 MODIS active fire product (MOD14/MYD14) (Langner & Siegert, 2009). Previous work has shown that the MODIS burnt area product tends to underestimate fire activity in the tropics because a 16-day cloud free mosaic is necessary to map the burnt areas (Roy *et al.,* 2008). By contrast, the RSS data, which is based on active fire detections (hotspots), can lead to an overestimation of the actual burnt area, as a single sensor element can even be saturated by a small-scale (sub-pixel) fire of high temperature. On the other hand, areas of overlapping hotspots are only counted once per year, leading to an underestimate of the burnt area. In general, the actual burnt area is difficult to predict and much depends on year, season and vegetation type (Miettinen *et al*., 2007). Due to these reasons Langner & Siegert (2009) refer to 'fire-affected' instead of 'burnt area' and a comparison with other burnt area products requires caution. Pre-MODIS RSS burnt area data are based on AVHRR 14 and ATSR hotspot data (Langner & Siegert, 2009) and pre-MODIS GFED4 data are based on ATSR and VIRS hotspots followed by a further correction (Giglio *et al.*, 2010, 2013). For several reasons, AVHRR generally detects a much higher number of active fire events than ATSR (Langner & Siegert, 2009), which most likely explains the higher burnt area recorded by the RSS dataset compared with the GFED4 dataset in 1997. The AVHRR sensor records data in Borneo twice a day, but is saturated at low temperatures and sun glint, leading frequently to false alarms. While the spatial accuracy of the ATSR sensor is high and there are few false alarms due to night-time acquisition, it displays a high rate of omission because fire activity often peaks in the afternoon and the revisit cycle is only every 3 days.

4.5 Influence of land use and land cover change, and peat drainage

The southern region of Kalimantan has undergone extensive drainage of peatlands and widespread fire-induced loss of pristine forests due to logging activities and plantation establishment, as discussed above. This has created large tracts of forest that are highly degraded and fragmented (Siegert *et al.,* 2001; Langer *et al.,* 2007; Langner & Siegert*,* 2009; Hoscilo *et al.,* 2011). Future increases in the extent of degraded forests and drained peats will likely modify seasonal rainfall-burnt area relationships. Degraded forests respond more rapidly to rainfall deficits than undisturbed forests due to increased solar radiation reaching the surface and hence, higher evaporation rates; and provide a relatively greater source of flammable fuels for burning, such as invasive grasses and ferns, as well as debris from logging and land clearing operations (Siegert *et al.,* 2001; Langer *et al.,* 2007; Langner & Siegert*,* 2009; Hoscilo *et al.,* 2011). The moisture content of peats is controlled by the water table, and as previously discussed; the lower water table of drained peats means more dry peat available for burning than undisturbed peats (Field & Shen, 2008; Page *et al.,* 2011; Hooijer *et al.,* 2012). An increase in the availability of drier fuels from degraded forests and drained peats would therefore potentially increase the amount of burning beyond that forecasted by seasonal rainfall alone. This could be manifested as an increase in the rate of change in burnt area with respect to a unit decrease in rainfall and/or a higher rainfall threshold controlling fire activity.

5 Conclusion

While operational seasonal fire prediction over Indonesia will have to incorporate the above factors, we have demonstrated, for the first time, that severe fire events (and potentially associated haze) are fundamentally predictable months in advance using state-of-the art seasonal rainfall forecasts. Predictions are not perfect, and occasionally a year may turn out differently to what was expected, fundamentally because ENSO and other factors are not perfectly predictable, but also because of remaining model imperfections. Any operational forecasting system needs to take account of such uncertainties, for example by use of ensemble methods. Nonetheless, seasonal forecasts are expected to continue to improve in the future and additional post-processing may increase the skill of the fire forecast (Peng et al., 2014). Given the considerable effort required in mobilising prevention and preparedness measures in Indonesia, we therefore argue that seasonal precipitation forecasts should be central to Indonesia's evolving fire management policies. Other potential applications of seasonal fire forecasting include improved risk assessments of biodiversity and carbon losses through fire; both important considerations for tropical forest protection programmes (e.g. REDD+; Barlow *et al.*, 2012), and forest (re)insurance enterprises (Cottle, 2007).

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Table 1 Summary statistics for burnt and fire-affected area and tree cover in the southern and central regions of Kalimantan. Values shown are mean ± 1.96 × SE_{mean}. Number of grid cells in the southern region = 53. Number of grid cells in the central region = 40. Grid cell resolution = 0.5^{o}.

	southern region of Kalimantan	central region of Kalimantan
Seasonal mean GFED4 burnt area per grid cell (averaged over 1997-2010) (km^2)	81.3 ± 15.0	3 ± 1.3
Seasonal mean RSS fire-affected area per grid cell (averaged over 1997-2010) (km^2)	146.9 ± 15.0	35.1 ± 5.7
Mean tree cover per grid cell 1993 (%)	76.0 ± 1.5	92.4 ± 0.9
Mean tree cover per grid cell 1997 (%)	68.3 ± 2.0	87.6 ± 1.4
Mean tree cover per grid cell 2010 (%)	58.1 ± 2.5	84.2 ± 1.8
Seasonal mean GFED4 burnt area per grid cell (1997) (km^2)	363.1 ± 54.5	9.5 ± 4.4
Seasonal mean RSS fire-affected area per grid cell (1997) (km^2)	514.5 ± 52.8	96.5 ± 13.9
Seasonal mean GFED4 burnt area per grid cell (averaged over El Nino years 2002, 2004, 2006, 2009) (km^2)	155.6 ± 34.7	5.7 ± 2.8
Seasonal mean RSS fire-affected area per grid cell (averaged over El Nino years 2002, 2004, 2006, 2009) (km^2)	291.5 ± 31.7	54.5 ± 9.2

Figure Captions

Figure 1 The Island of Borneo showing burnt and fire-affected area (top) and tree cover patterns (bottom) across the southern-central region of Kalimantan. (a, top left) total GFED4 burnt area, (b, top right) total RSS fire-affected area, (c, bottom left) mean 1993 tree cover, (d bottom middle) mean 1997 tree cover, (e, bottom right) mean 2010 tree cover. Data are plotted at 0.5^{o} grid cell resolution. Number of 0.5^{o} grid cells in southern Kalimantan = 53. Number of 0.5^{o} grid cells in southern Kalimantan = 40.

Figure 2 a) Southern region of Kalimantan: Seasonal mean GFED4 burnt area per grid cell as a function of seasonal mean GPCP rainfall per grid cell; and b) central region of Kalimantan: Seasonal mean monthly GFED4 burnt area per grid cell as a function of seasonal mean GPCP rainfall per grid cell. The edges of the whiskers refer to the 5^{th} and 95^{th} percentiles, respectively ($\pm 1.96 \times SE_{mean}$).

Figure 3 a) Southern Kalimantan: Seasonal mean RSS fire-affected area (FAA) per grid cell as a function of seasonal mean GPCP rainfall per grid cell; and b) Central Kalimantan: Seasonal mean RSS fire-affected area (FAA) per grid cell as a function of seasonal mean GPCP rainfall per grid cell. The edges of the whiskers refer to the 5^{th} and 95^{th} percentiles, respectively ($\pm 1.96 \times SE_{mean}$).

Figure 4 Southern Kalimantan: a) Seasonal mean GFED4 burnt area per grid cell as a function of seasonal mean System 4 rainfall per grid cell; and b) Seasonal mean RSS fire-affected area (FAA) per grid cell as a function of seasonal mean System 4 mean rainfall per grid cell. Number of System 4 grid cells in southern Kalimantan = 23. The edges of the burnt and fire-affected area whiskers refer to the 5^{th} and 95^{th} percentiles, respectively ($\pm 1.96 \times SE_{mean}$). The upper edge of the System 4 whiskers = $mean_{upper\ tercile} - mean_{middle\ tercile}$, and the lower edge of the System 4 whiskers = $mean_{middle\ tercile} - mean_{lower\ tercile}$ (refer data preparation in Methods).

Figure 5 Southern Kalimantan: Seasonal mean GPCP rainfall per grid cell versus seasonal mean System 4 rainfall per grid cell. The edges of the GPCP whiskers refer to the 5^{th} and 95^{th} percentiles, respectively ($\pm 1.96 \times SE_{mean}$). The upper edge of the System 4 data point whiskers = $mean_{upper\ tercile} - mean_{middle\ tercile}$, and the lower edge of the System 4 whiskers = $mean_{middle\ tercile} - mean_{lower\ tercile}$ (refer data preparation in Methods).

Figure 6 System 4 SST anomalies versus observed SST anomalies over the Indian ocean (0^{o}-10^{o}S, 90^{o}-110^{o}E), 1997-2010. In this figure the variance has been corrected to match the variance of the observations. The observed anomalies are derived from ERA Interim and the forecasts shown are based on the S4 hindcast system with 15 ensemble members.