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Heightened fire probability in Indonesia in non-drought conditions: the effect of increasing temperatures

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Abstract

In Indonesia, drought driven fires occur typically during the warm phase of the El Niño Southern Oscillation. This was the case of the events of 1997 and 2015 that resulted in months-long hazardous atmospheric pollution levels in Equatorial Asia and record greenhouse gas emissions.

Nonetheless, anomalously active fire seasons have also been observed in non-drought years. In this work, we investigated the impact of temperature on fires and found that when the July–October (JASO) period is anomalously dry, the sensitivity of fires to temperature is modest. In contrast, under normal-to-wet conditions, fire probability increases sharply when JASO is anomalously warm. This describes a regime in which an active fire season is not limited to drought years. Greater susceptibility to fires in response to a warmer environment finds support in the high evapotranspiration rates observed in normal-to-wet and warm conditions in Indonesia. We also find that fire probability in wet JASOs would be considerably less sensitive to temperature were not for the added effect of recent positive trends. Near-term regional climate projections reveal that, despite negligible changes in precipitation, a continuing warming trend will heighten fire probability over the next few decades especially in non-drought years. Mild fire seasons currently observed in association with wet conditions and cool temperatures will become rare events in Indonesia.

1. Introduction

Large areas of tropical humid forests are being altered by human activities such as clearing and logging (FAO 2015), making these landscapes more vulnerable to drought-driven fires (Brando *et al* 2014, Ceccato *et al* 2010, Chen *et al* 2011, Fernandes *et al* 2011, Murdiyarso and Adiningsih 2007, van der Werf *et al* 2008a, Van Der Werf *et al* 2008b) and to the interactions of human activities and land cover with the climate (Aiken 2004, Aldersley *et al* 2011, Aragão *et al* 2008, Field *et al* 2009, Gutiérrez-Vélez *et al* 2014, Schwartz *et al* 2015, Siegert *et al* 2001, Stolle *et al* 2003,

Uriarte *et al* 2012). In Indonesia fires are typically lit during the July to October (JASO) dry season to clear land for planting (Murdiyarso and Adiningsih 2007). While fire ignition is related to human activities, the interannual variability of fire spread and frequency responds to large-scale climate fluctuations (Ceccato *et al* 2010, Chen *et al* 2016, Murdiyarso and Adiningsih 2007, Siegert *et al* 2001, van der Werf *et al* 2008a). During the 1997 El Niño drought, disastrous fires in Indonesia resulted in months-long hazardous atmospheric pollution levels (Marlier *et al* 2013) and carbon emissions estimated at between 4% (Levine 1999) and 13% (Page *et al* 2002) of global annual carbon

emissions from fossil fuels (Boden *et al* 2016). Large fires were observed again during the 2015/2016 El Niño and fire-related greenhouse gases (GHG) emissions were second only to those of 1997 (Huijnen *et al* 2016). Despite the clear impact droughts have on fire occurrence in Indonesia, anomalously active fire seasons have recently been observed during non-drought years (Gaveau *et al* 2014), raising the question of whether climate and fire dynamics are any different in the absence of seasonal droughts. In non-tropical regions, temperature plays an important role in determining fire risk, often interacting with precipitation according to whether it is dry or wet (Aldersley *et al* 2011, Westerling and Bryant 2008). We investigate whether this is the case in Indonesia, as the current role of temperature in fire dynamics is not well understood and its future impact on fires, though not uniformly distributed globally (Moritz *et al* 2012), is projected to increase (Pechony and Shindell 2010). The atmosphere's water vapor demand increases with temperature and with it evapotranspiration rates (Breshears *et al* 2013). As a consequence, faster soil and vegetation water depletion (Williams *et al* 2013, Zhao and Running 2010) and greater susceptibility to fires (Abatzoglou and Williams 2016, Brando *et al* 2014) are observed. This has important implications for future fire activity assessments in Indonesia, as studies tend to focus on how projected changes in precipitation regimes will impact fire occurrence (Corlett 2016, Herawati and Santoso 2011, Lestari *et al* 2014) and less attention is given to potential compounding effects of temperature. Here, we investigate fires sensitivity to precipitation and temperature using a statistical model built from over two decades of remotely sensed fire observations and meteorological stations data. Then, we explore the role of evapotranspiration rates variability as a mechanism linking the empirically estimated fire probabilities to the climate predictors. Lastly, the fire probability model is driven by near-term precipitation and temperature projections with the goal of assessing future changes in fire activity in Indonesia.

2. Study area

Our domain of study is comprised of Sumatra and Kalimantan; the later is the Indonesian part of the island of Borneo. Fires in Kalimantan and Sumatra are typically lit during the dry season, defined here as the months from July to October (JASO), to clear land for planting (Murdiyarso and Adiningsih 2007).

3. Data and methods

We model burned area anomalies as a function of precipitation and temperature anomalies for the period 1995–2015. We propose a physical mechanism

to explain the modeled burned area anomalies response to the climate predictors by evaluating how evapotranspiration rates respond to contrasting climate conditions. Then, we used projections of regional temperature and precipitation to anticipate the likely response of fires to future climate in Indonesia.

3.1. Fire probability as a function of climate
3.1.1. Global fire emission database
We use the burned area (BA) product from the fourth generation of the Global Fire Emission Database (GFED4) (Giglio *et al* 2013) covering a period of 21 yr, including the two major fire events of 1997 and 2015 in Indonesia. GFED4 provides global monthly BA, in hectares, at 0.25° spatial resolution from 1995 to 2015. Interannual variability is evaluated by spatially averaging JASO BA over the entire study area then subtracting the 1995–2015 climatology and dividing by its standard deviation (StdBA). Anomalous BA is also calculated locally (at each grid cell) for the July–October season by removing the local 1995–2015 climatology. Because fire ignition in Indonesia is human-induced (Murdiyarso and Adiningsih 2007, Stolle *et al* 2003), pixels with BA equal to zero hectare were masked out, as we assume that an absence of fires over the entire JASO season is related to an absence of fire-related activities, not climate.

3.1.2. Precipitation and temperature data
The gridded Global Precipitation Climatology Centre (GPCC) rain-gauge only dataset is used at monthly time-steps from 1966 to 2015 (Schamm *et al* 2014, Schneider *et al* 2014). Precipitation is linearly re-gridded to 0.25° resolution to match the GFED4 burned area dataset. Domain averaged time series of standardized precipitation (StdPr) is calculated by spatially averaging the 1966–2015 JASO precipitation over the entire study area then subtracting the baseline climatology and dividing by its standard deviation. JASO StdPr is also calculated for every grid cell within the domain and the 1995–2015 period. The length of StdPr domain averaged time series is longer than the anomalies calculated at the grid cell level but the baseline climatology is the same (1995–2015). The individual grid cell StdPr was used to model fire (GFED4-BA) probability while the whole study area StdPr was used to model near future variability and change.

Near surface air temperature is provided by the National Oceanic and Atmospheric Administration (NOAA) Climate Prediction Center (CPC). This dataset results from two large meteorological station networks that are combined and interpolated globally to a 0.5° degree spatial resolution grid and monthly time-steps (Fan and Van den Dool 2008). Temperature anomalies (TempAn) for JASO 1966–2015 were calculated for the whole study area by spatially averaging JASO temperature and removing the

Table 1. Logistic regression coefficients (β), standardized errors (SE), and statistical significance (P) for regression predictors of above average burned area anomalies. Bayesian information criterion (BIC) and Akaike information criterion (AIC) for single variable models (TempAn and StdPr) and the multi-variable model with an interaction term (StdPr:TempAn). Lower BIC and AIC values indicate better fit. Variance Inflation Factor (VIF) for the variables included in the model. VIF > 5 are indicative of multicollinearity.

Predictor	β	SE	P	BIC	AIC	VIF
Intercept	−1.21	0.03	<0.01			
TempAn	2.1	0.1	<0.01	15 346	15 331	1.4
StdPr	−0.83	0.02	<0.01	14 074	14 059	1.24
StdPr:TempAn	1.14	0.08	<0.01	13 631	13 601	1.17

baseline period (1995–2015) climatology. This time series is used model near future variability and change. TempAn is also calculated locally by subtracting each grid cell's 1995–2015 JASO climatology and it is used to model fire (GFED4-BA) probability.

3.1.3. Statistical analysis of fire probability

Fire probability, measured as the probability of positive BA anomalies, is modeled as a function of temperature anomalies (TempAn) and precipitation standardized anomalies (StdPr). The JASO BA anomalies are calculated with respect to the 1995–2015 baseline period at each grid cell and categorized as 1 for positive (active fire season) and 0 for negative (mild fire season) values. Every grid cell that registered JASO BA different from zero (and corresponding TempAn and StdPr) is retained, totaling a sample of 13 848 in length.

Fire was modeled using logistic regression and expressed as:

$$\ln\left(\frac{P(BA=1)}{1-P(BA=1)}\right) = \alpha + \beta_1 X_1 + \ldots + \beta_n X_n \qquad (1)$$

where $P(BA = 1)$ is the probability of an active fire season (BA = 1) modeled as a linear combination of predictors X_n (StdPr and TempAn) with slopes β_n and an intercept α.

The logistic regression model was fit using Matlab's fitglm function (Mathworks 2015b) for a binomial distribution. We used the variance inflation factor (VIF) test for multicollinearity (Belsley 1991). The best model was selected by evaluating values of the Akaike and Bayesian Information Criteria (AIC, BIC) for each individual covariate and an interaction term between StdPr and TempAn (table 1). AIC and BIC are standard statistical measures for model selection and the lowest values indicate the best fit (Burnham and Anderson 1998, Raftery 1995). To test fires sensitivity to potential trends in the predictors, a model was fitted to de-trended TempAn and StdPr (table S1 available at stacks.iop.org/ERL/12/054002/mmedia).

3.2. MODIS evapotranspiration (MOD16)

Evapotranspiration (ET) rates, which is a function of temperature and moisture availability, accelerate in an anomalously warm environment resulting in fast soil and vegetation water depletion (Breshears *et al* 2013, Zhao and Running 2010) and greater susceptibility to

fires (Abatzoglou and Williams 2016, Brando *et al* 2014). With the goal of establishing a physical mechanism explaining fire behavior, we investigate how ET rates respond to interactions between temperature and precipitation and how it relates to fire probability as estimated by our statistical model. We use MODIS global evapotranspiration product (MOD16), obtained at a 0.5° spatial resolution and monthly time step available for the period January 2000 to December 2014 (Mu *et al* 2011, Zhao *et al* 2006). Seasonal JASO standardized ET (StdET) is calculated by subtracting the climatology in each grid cell and dividing it by its standard deviation. The final product is re-gridded linearly to 0.25° resolution to match the spatial resolution of the GFED4-BA product.

3.3. Near-term precipitation and temperature projections

Using the fire probability model (section 3.1.3) and selected near-term simulations of TempAn and StdPr, we assess future fire risk in Indonesia. The fire probability predictors, observed temperature and precipitation, are normally anti-correlated over equatorial land areas, but this feature is not consistently represented in General Circulation Models (GCMs). This is attributed to various soil moisture, cloud and precipitation parameterizations (Berg *et al* 2015, Koster *et al* 2009, Trenberth and Shea 2005, Wu *et al* 2013) in the models. Therefore, GCMs direct temperature and precipitation outputs are not adequate to assess these variables' co-variability in Indonesia. This dependence between precipitation and temperature requires they are modeled jointly and a multivariate modeling scheme is used here (Greene *et al* 2012). The method consists of creating synthetic climate sequences that retain the statistical properties of the original series. The simulations are based on annual time steps of JASO StdPr and TempAn for the study area and period 1966–2015. The time series are first de-trended by removing the variables' local response to anthropogenic climate forcings (Greene *et al* 2011). The 50 yr (1966–2015) de-trended JASO StdPr and TempAn (henceforth referred to as DetTempAn and DetStdPr) retain oscillations on the scale of years to decades. Multiyear and decadal oscillations can result from periodic predictable components explained by

Figure 1. JASO 1995–2015 climatological burned area (GFED4), in hectares per month.
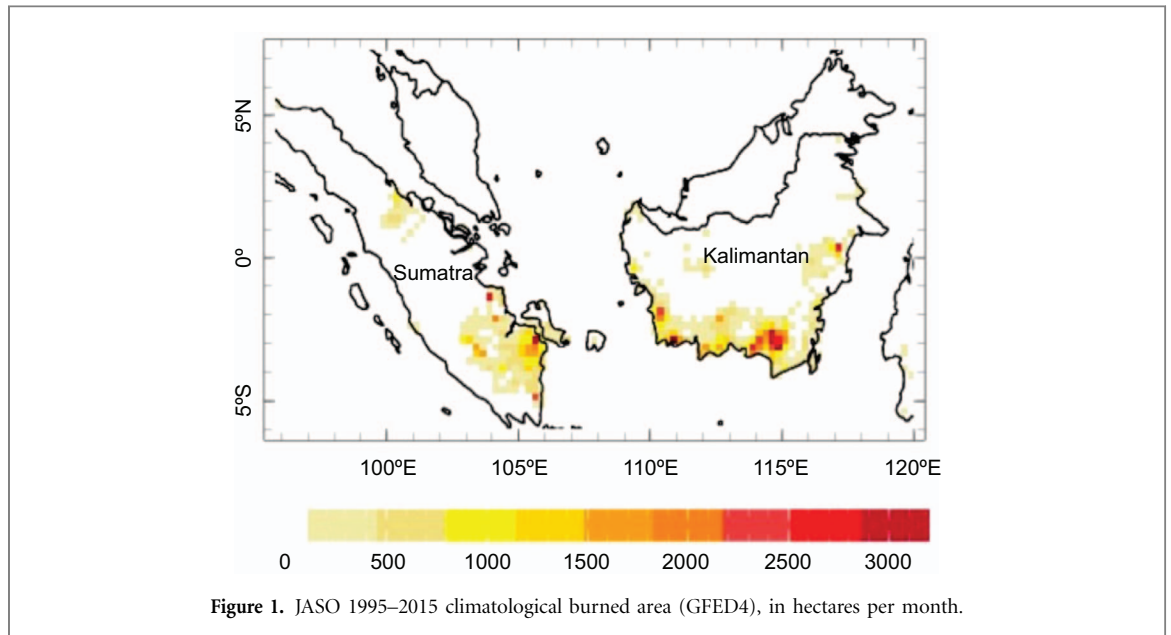
large-scale physical mechanisms and/or random components that exhibit temporal autocorrelation (memory). In Indonesia, there is no clear evidence of periodic multi-year or decadal oscillations in the climate (Malhi and Wright 2004) in contrast to the other large rainforest regions of the Amazon and Congo (Fernandes *et al* 2015, Labat *et al* 2005, Malhi and Wright 2004, Todd and Washington 2004). Nonetheless, we find statistically significant lag-1 JASO DetTempAn autocorrelation ($R = 0.36$, $P < 0.05$) as well as correlation between JASO DetTempAn and DetStdPr ($R = -0.39$, $P < 0.05$). This supports the use of a Vector Auto-Regressive (VAR) model (Greene *et al* 2012, Wilks 2011). VAR, which is a multivariate generalization of an Auto-Regressive (AR) model, is appropriate for simulating multiple co-varying variables that exhibit serial autocorrelation (Wilks 2011).

A lag-1 or first order VAR (1) model can be written as:

$$\mathbf{y}_t = A\mathbf{y}_{t-1} + \mathbf{u}_t \qquad (2)$$

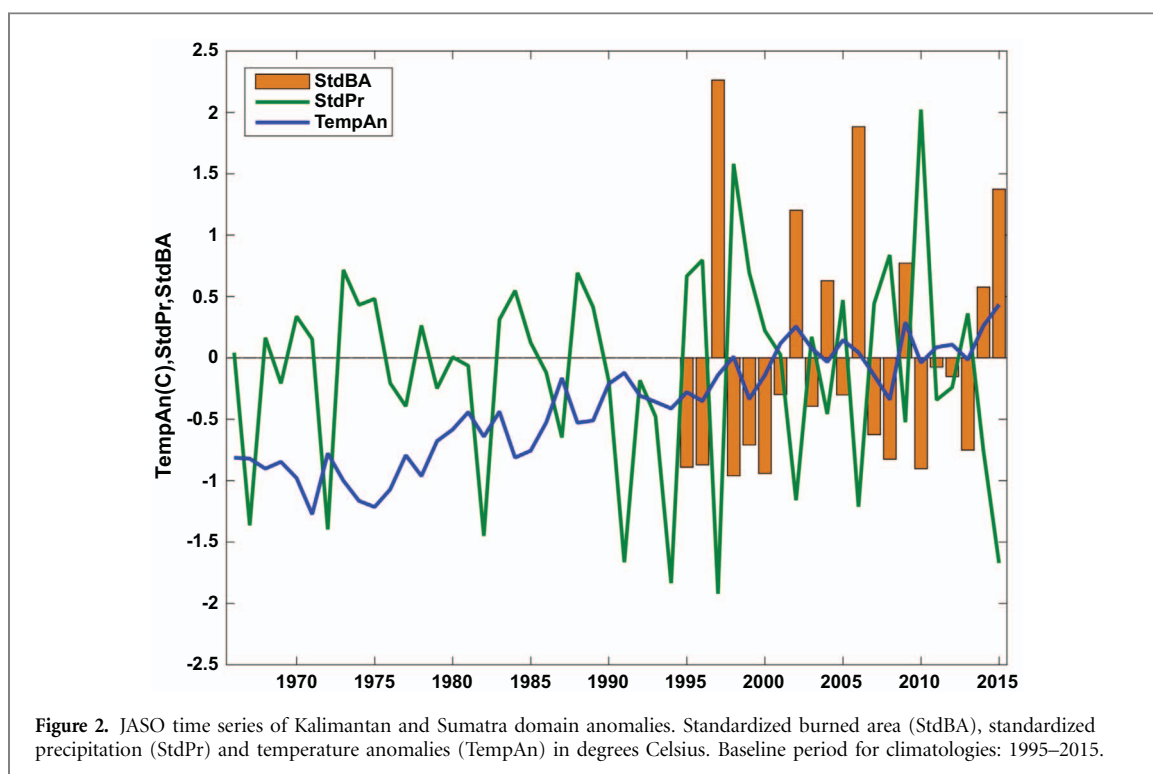where y is the climate vector (DetStdPr and DetTempAn) at time t and $t-1$. The time steps are years as the variables have one JASO entry per year. $\mathbf{A}$ is a matrix of coefficients and $\mathbf{u}_t$ is a stationary white noise (serially uncorrelated) vector. The VAR(1) was fitted to the 1966–2015 JASO regional series using Matlab's Econometric Toolbox VAR model functions (Mathworks 2015a).

The VAR (1) model is then used to generate a collection of 2016–2050 DetTempAn and DetStdPr (supplementary material). The trends corresponding to the regional variables' response to the estimated 2016–2050 anthropogenic atmospheric GHG forcing are added back to the series (Greene *et al* 2011, Greene *et al* 2012).

4. Results

4.1. Characterization of JASO burned area

Fires in Sumatra and Kalimantan, shown as burned area, are located mostly in the southern parts of the islands during the JASO season (figure 1). Over the study area domain, TempAn has shown a clear positive trend since 1966, while StdPr has remained unchanged (figure 2). The three most intense fire seasons since 1995 occurred in 1997, 2006 and 2015 (figure 2) and were related to negative StdPr typical of an El Niño year (NOAA 2016). We found a highly significant correlation between StdPr and StdBA ($R = -0.91$, $P < 0.05$), suggesting that the intensity of StdPr is a very good indicator of the intensity of burned area anomalies. This shows that over 80% of BA variance is explained by StdPr meaning that, for prediction purposes, the effect of any other variable on fires seems to be of secondary importance. Nonetheless, we test whether moisture availability, assessed as precipitation anomalies, impacts fire response to temperature by correlating StdBA and climate variables for two sub-samples: one comprised of dry JASOs (StdPr < 0) and one of wet JASOs (StdPr > 0) taken from the 1995–2015 record (figure 2). For the 9 dry JASOs, the correlation between StdBA and StdPr reproduces that of the entire sample and the correlation between StdBA and TempAn is not significant ($R = -0.19$, $P > 0.6$) showing in fact the opposite behavior expected of a warm environment leading to more fires. For the remaining 12 wet JASOs, the correlation between StdPr and StdBA is also statistically significant ($R = -0.59$, $P < 0.05$), but in contrast to dry JASOs, TempAn becomes a much more important variable with a significant positive correlation to StdBA ($R = 0.62$, $P < 0.05$). These results show that StdPr is the best indicator of StdBA anomalies under dry conditions, but that TempAn correlates more strongly

Figure 2. JASO time series of Kalimantan and Sumatra domain anomalies. Standardized burned area (StdBA), standardized precipitation (StdPr) and temperature anomalies (TempAn) in degrees Celsius. Baseline period for climatologies: 1995–2015.

with StdBA in a wetter dry season. This indicates that burned area response to temperature is controlled by the precipitation regime.

4.2. Fire probability model

The logistic regression model with the best fit (lower AIC and BIC values) includes an interaction term between StdPr and TempAn (table 1) and can be rewritten from equation (1) and table 1 as:
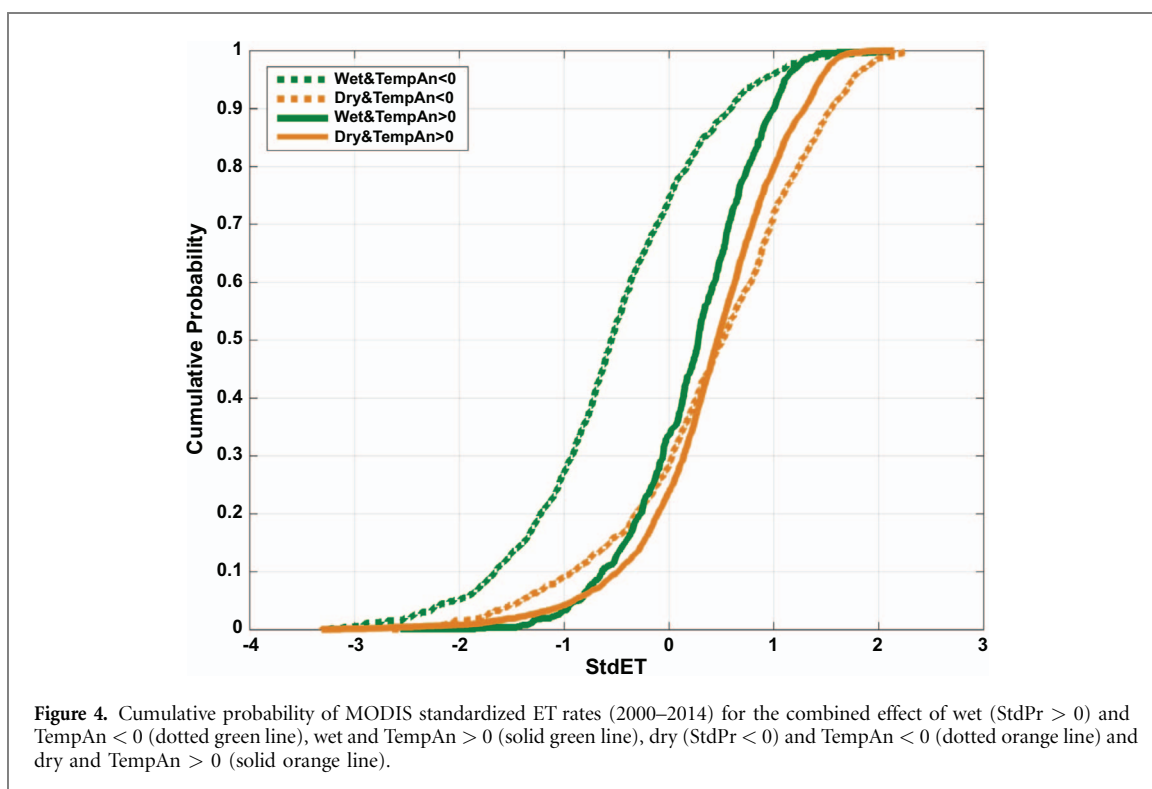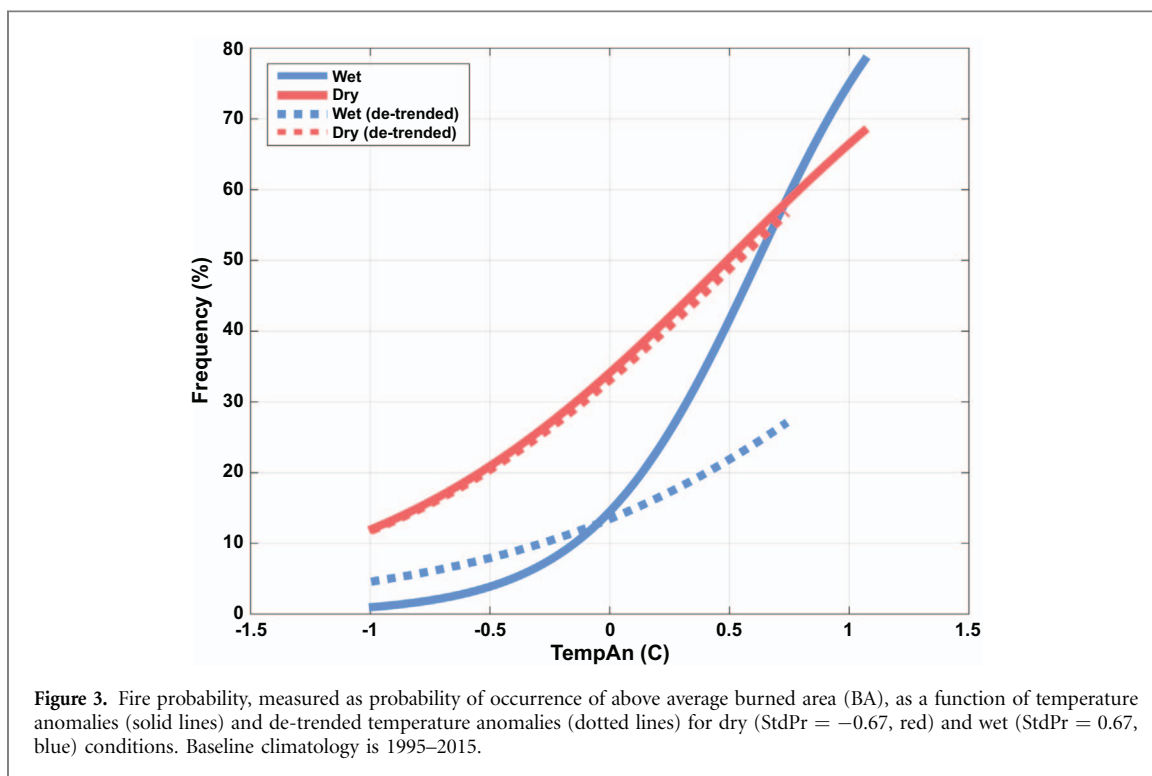
$$P(\mathrm{BA} = 1)$$
$$= \frac{e^{-1.21 + 2.1\mathrm{TempAn} - 0.83\,\mathrm{StdPr} + 1.14\,\mathrm{StdPr} * \mathrm{TempAn}}}{1 + e^{-1.21 + 2.1\mathrm{TempAn} - 0.83\,\mathrm{StdPr} + 1.14S\,\mathrm{tdPr} * \mathrm{TempAn}}}$$

(3)

The presence of an interaction term in the model demonstrates that the nature of positive BA anomalies response to temperature varies according to the level of the precipitation anomaly, consistent with the correlation analysis presented in the previous section. The interaction effect between the predictors is further illustrated by plotting fire probability as a function of TempAn and contrasting wet and dry conditions (figure 3). We set in the model the values for dry (StdPr = −0.67) and wet (StdPr = 0.67) to represent the 25% drier and wetter tails of each grid cell precipitation distribution. In dry conditions (solid red line in figure 3) there is a nearly constant increase in fire probability per unit increase in temperature anomalies (9% to 14% per 0.5°C). In wetter than normal JASOs (solid blue line), negative TempAn is related to low fire probability, but the chances of observing an active fire season increases sharply from approximately 15% under normal temperature to

above 40% at anomalies of 0.5 °C. This behavior is consistent for a range of positive StdPr (online supplementary figure S2). The probability of an anomalously active fire season is mainly determined by whether it is dry or wet if TempAn is near or below normal (solid lines in figure 3), but as TempAn becomes positive, it turns into a much stronger driver especially in wet conditions. In the case of the model fitted to the de-trended variables, we find that fire probability is always higher in dry than in wet environments (dotted lines in figure 3), regardless of TempAn. This is characteristic of a response in which the interaction between the variables is negligible (online supplementary table S1). But more importantly, when it is wet, the response of fire probability to TempAn is much weaker than in the model fitted to the original variables (blue lines in figure 3). This suggests that fires in non-drought conditions would be less influenced by temperature anomalies in any given year were not for the compounding effect of increasing trends. In contrast, fire probability responds very similarly to TempAn in both models (red lines in figure 3) showing that temperature trends have no particular enhancing effect on fires under dry conditions.
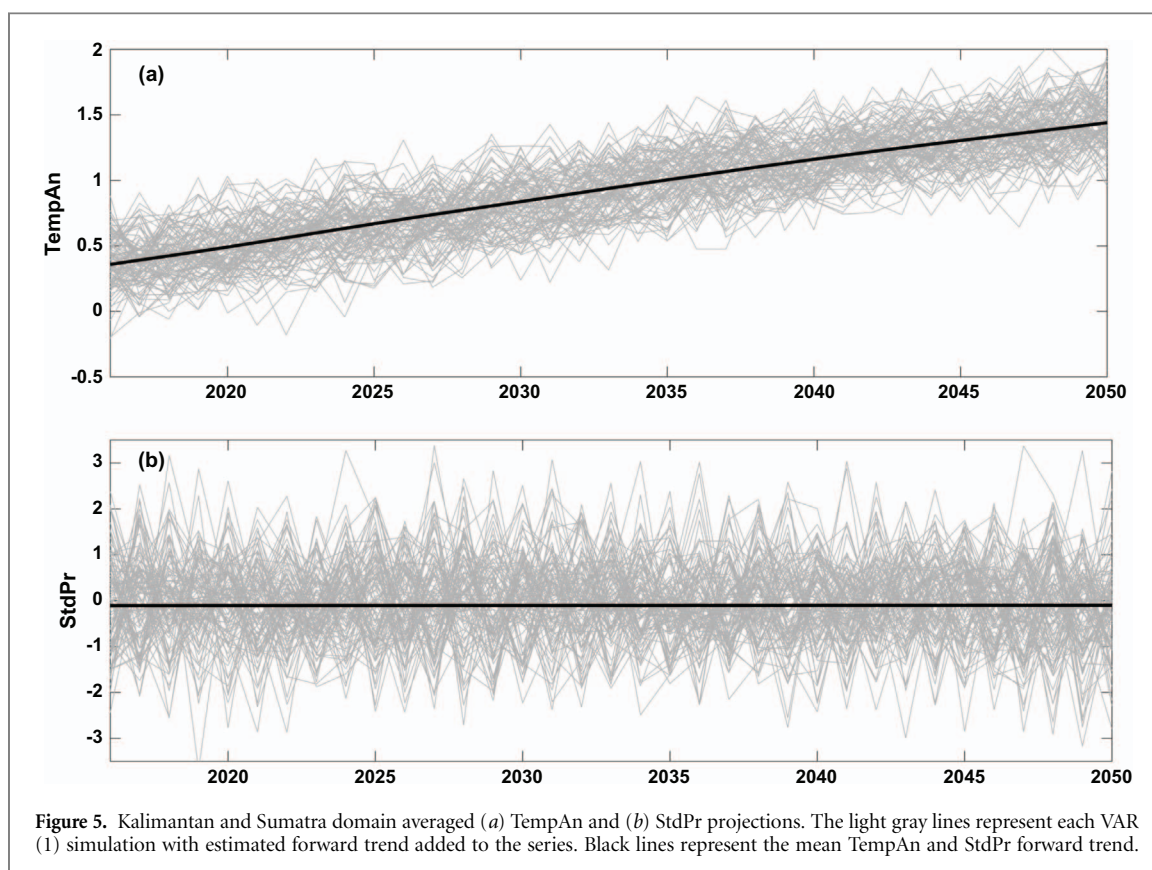
4.3. The role of evapotranspiration rates (ET)

The role of temperature and moisture availability, measured as precipitation anomalies, on ET rates is evaluated by analyzing a sample comprised of JASO MODIS StdET from every grid cell within our study area and period 2000–2014 The StdET sample is binned into four sub-samples, describing Wet & TempAn > 0, Wet & TempAn < 0, Dry & TempAn > 0 and Dry & TempAn < 0 (figure 4). The StdET

Figure 3. Fire probability, measured as probability of occurrence of above average burned area (BA), as a function of temperature anomalies (solid lines) and de-trended temperature anomalies (dotted lines) for dry (StdPr $= -0.67$, red) and wet (StdPr $= 0.67$, blue) conditions. Baseline climatology is 1995–2015.

Figure 4. Cumulative probability of MODIS standardized ET rates (2000–2014) for the combined effect of wet (StdPr > 0) and TempAn < 0 (dotted green line), wet and TempAn > 0 (solid green line), dry (StdPr < 0) and TempAn < 0 (dotted orange line) and dry and TempAn > 0 (solid orange line).

cumulative probability in wet conditions (StdPr > 0) reveals that for most part anomalously low StdET rates are related to TempAn < 0 (dashed green line in figure 4), whereas in cases of wet and TempAn > 0 nearly 65% of the sampled StdET rate is anomalously high (solid green line in figure 4). Thus, provided that moisture is available, anomalously positive StdET rates are consistently higher in warm than in cool conditions. In dry (StdPr < 0) conditions the

distribution of StdET for both TempAn < 0 and Temp > 0 (orange lines in figure 4) is not as contrasting, indicating that the evaporative regime in this case is less dependent of temperature and constrained instead by moisture availability. The higher StdET rates associated to positive TempAn in normal-to-wet conditions provides evidence consistent with the heightened modeled fire probability found for a warm and wet environment.

Figure 5. Kalimantan and Sumatra domain averaged (*a*) TempAn and (*b*) StdPr projections. The light gray lines represent each VAR (1) simulation with estimated forward trend added to the series. Black lines represent the mean TempAn and StdPr forward trend.
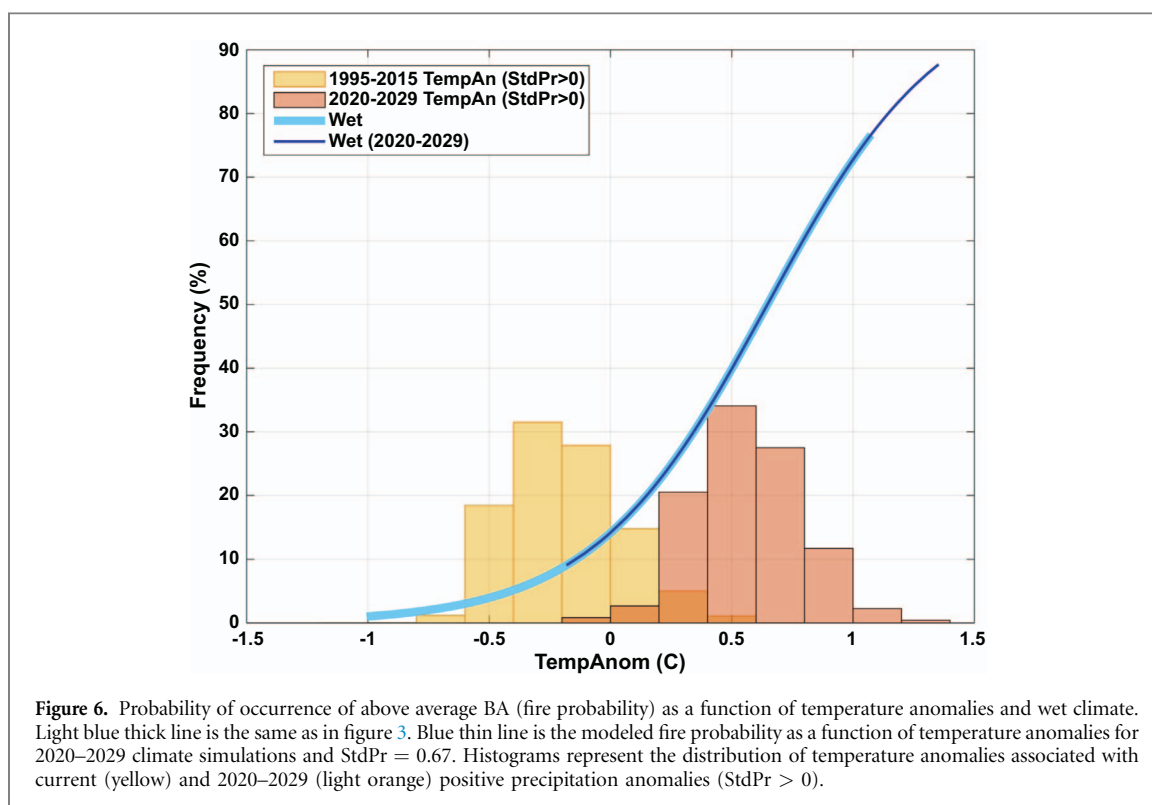
4.4. Future fire probability

Figure 5 shows the 100 realizations of modeled TempAn and StdPr paired simulations for the period 2016–2050 (see details in the online supplementary data). The forward estimates of TempAn and StdPr result in a continuing positive trend in TempAn and no significant change in StdPr through 2050. Around the end of the period, StdPr shows a range of values similar to currently observed, whereas TempAn values fluctuate around 1.5 °C anomalies (with respect to baseline 1995–2015) in contrast to much lower values observed currently (figure 2). We evaluate how continuing warming may impact future fire regimes in Indonesia by inputting the projected TempAn into the fire probability model derived from the current climate. The JASO TempAn and StdPr used to fit the logistic model represent the local grid cell value corresponding to the JASO BA anomalies, while the 2016–2050 projected time series are based on the study area domain averaged TempAn and StdPr anomalies. Nonetheless, we find that the 1995–2015 gridded and domain averaged samples of StdPr (and TempAn) come from the same distribution (tested using a two-sample Kolmogorov-Smirnov at alpha = 0.05 significance level) and the logistic regression can adequately model fire probability based on domain-averaged StdPr and TempAn. We chose to test fire sensitivity using the projected 2020–2029 TempAn simulations, as most values in that decade (figure 5(*a*)) remains below the upper limit (1.1 °C) of the observed TempAn sample used to fit the fire probability model (figure 3). Fire

probability modeled for wet (StdPr = 0.67) conditions and the 100 realizations of 2020–2029 JASO TempAn point to higher fire probability in general, but more importantly, low fire probability related to the combined effect of negative TempAn and wet conditions is much less likely in the 2020–2029 simulations (thin blue line in figure 6) than currently observed (thick blue line in figure 6). Also, the distribution of simulated TempAn in association with the 2020–2029 normal-to-wet conditions (StdPr > 0) shifts to mostly positive values in contrast to the distribution used to fit the fire probability model (histograms of figure 6). In other words, the chances of observing wet and warm conditions in the next few decades are much greater than in the current climate. At the same time, wet accompanied by cool temperatures (TempAn < 0) will become nearly inexistent in the near future, turning mild fire seasons into a rare event in Indonesia. Fires are less sensitive to TempAn in dry conditions and the 2020–2029 simulated fire probabilities mostly overlap the function representing current characteristics (not shown).

5. Discussion and conclusions

Drought related fire is a fairly well understood phenomenon in Indonesia but the impacts of an increasingly warm environment on fire dynamics has been less explored. The lesser interest in temperature and fire dynamics finds support in fire intensity responding mostly to the severity of precipitation

Figure 6. Probability of occurrence of above average BA (fire probability) as a function of temperature anomalies and wet climate. Light blue thick line is the same as in figure 3. Blue thin line is the modeled fire probability as a function of temperature anomalies for 2020–2029 climate simulations and StdPr = 0.67. Histograms represent the distribution of temperature anomalies associated with current (yellow) and 2020–2029 (light orange) positive precipitation anomalies (StdPr > 0).

anomalies during the July–October dry season. Indeed, in a dry environment the effect of temperature is modest and our model estimates a nearly constant increase in fire probability per unit increase in temperature anomalies (9% to 14% per 0.5 °C). However, this characteristic is not linear across contrasting precipitation patterns and in wet conditions temperature is a far more important variable determining fire probability. A sharp increase in modeled fire probability (15% to 40%) is found when temperatures go from near normal to 0.5 °C anomalies. This is in part due to an observed regional warming trend. In a wet environment, fires are highly sensitive to anomalously positive temperatures only if trends are retained in the data used to model fire probability. In other words, fires would be less sensitive to any given year anomalous temperatures were not for compounding effect of the multiyear trend. In dry conditions, fires are driven mainly by the severity of precipitation deficit and the added effect of temperature anomalies is similar regardless of recent trends. Higher evapotranspiration rates in wet and warm as opposed to wet and cool conditions are consistent with increased fire probability. High temperature leads to high atmospheric vapor pressure deficit and ET rates, and regardless of changes in precipitation, a warming trend can induce vegetation water stress and greater susceptibility to fires. This has important implications for Indonesia, as near-term climate simulations point to a continuing increase in temperature, while precipitation variability remains largely unchanged. Our findings add yet another layer of complexity to fire manage-

ment, suggesting that fire prevention measures should no longer be restricted to dry years. In addition, further understanding of how human activities and various land use interact with increasingly higher temperature could help identify effective interventions to prevent and mitigate fire occurrence and spread in Indonesia. On longer timescale, strategies to reduce GHG emission through forest restoration and conservation should take into account the effect of a warmer environment on fires, as currently observed mild fire seasons associated with wet and cool conditions will become rare events in Indonesia.

References

Abatzoglou J T and Williams A P 2016 Impact of anthropogenic climate change on wildfire across western US forests *Proc. Natl Acad. Sci.* **113** 11770–5

Aiken S R 2004 Runaway fires, smoke-haze pollution, and unnatural disasters in Indonesia *Geogr. Rev.* **94** 55–79

Aldersley A, Murray S J and Cornell S E 2011 Global and regional analysis of climate and human drivers of wildfire *Sci. Total Environ.* **409** 3472–81

Aragão L E O C, Malhi Y, Barbier N, Lima A, Shimabukuro Y, Anderson L and Saatchi S 2008 Interactions between rainfall, deforestation and fires during recent years in the Brazilian Amazonia *Philos. Trans. R. Soc. B* **363** 1779–85

Belsley D A 1991 A guide to using the collinearity diagnostics *Comp. Sci. Econ. Manag.* **4** 33–50

Berg A et al 2015 Interannual coupling between summertime surface temperature and precipitation over land: processes and implications for climate change* *J. Clim.* **28** 1308–28

Boden T A, Marland G and Anderes R J 2016 *Global, Regional, and National Fossil Fuel CO₂ Emissions* (Oak Ridge, TN: US Department of Energy, Oak Ridge National Laboratory)

Brando P M et al 2014 Abrupt increases in Amazonian tree mortality due to drought–fire interactions *Proc. Natl Acad. Sci.* **111** 6347–52

Breshears D D, Adams H D, Eamus D, McDowell N, Law D J, Will R E, Williams A P and Zou C B 2013 The critical amplifying role of increasing atmospheric moisture demand on tree mortality and associated regional die-off *Front. Plant Sci.* **4** 266

Burnham K P and Anderson D R 1998 *Introduction Model Selection and Inference* (New York: Springer) pp 1–31

Ceccato P N, Jaya I N S, Qian J, Tippett M K, Robertson A W and Someshwar S 2010 Early warning and response to fires in Kalimantan, Indonesia *Tech. Rep.* 10–14 (https://academiccommons.columbia.edu/catalog/ac:130695)

Chen C-C, Lin H-W, Yu J Y and Lo M-H 2016 The 2015 Borneo fires: what have we learned from the 1997 and 2006 El Niños? *Environ. Res. Lett.* **11** 104003

Chen Y, Randerson J T, Morton D C, DeFries R S, Collatz G J, Kasibhatla P S, Giglio L, Jin Y and Marlier M E 2011 Forecasting fire season severity in South America using sea surface temperature anomalies *Science* **334** 787–91

Corlett R T 2016 The impacts of droughts in tropical forests *Trends Plant Sci.* **21** 584–93

Fan Y and Van den Dool H 2008 A global monthly land surface air temperature analysis for 1948–present *J. Geophys. Res. Atmos.* **113** D01103

FAO 2015 *Global Forest Resources Assessment 2015* How have the world's forests changed?

Fernandes K et al 2011 North Tropical Atlantic influence on western Amazon fire season variability *Geophys. Res. Lett.* **38** L12701

Fernandes K, Giannini A, Verchot L, Baethgen W and Pinedo-Vasquez M 2015 Decadal covariability of Atlantic SSTs and western Amazon dry-season hydroclimate in observations and CMIP5 simulations *Geophys. Res. Lett.* **42** 6793–801

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

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

Giglio L, Randerson J T and Werf G R 2013 Analysis of daily, monthly, and annual burned area using the fourth-generation global fire emissions database (GFED4) *J. Geophys. Res. Biogeosciences* **118** 317–28

Greene A M, Goddard L and Cousin R 2011 Web tool deconstructs variability in twentieth-century climate *Eos, Trans. Amer. Geophys. Union* **92** 397–8

Greene A M, Hellmuth M and Lumsden T 2012 Stochastic decadal climate simulations for the Berg and Breede water management areas, western Cape province, South Africa *Water Resour. Res.* **48** W06504

Gutiérrez-Vélez V H, Uriarte M, DeFries R, Pinedo-Vásquez M, Fernandes K, Ceccato P, Baethgen W and Padoch C 2014 Land cover change interacts with drought severity to change fire regimes in Western Amazonia *Ecol. Appl.* **24** 1323–40

Herawati H and Santoso H 2011 Tropical forest susceptibility to and risk of fire under changing climate: a review of fire nature, policy and institutions in Indonesia *For. Policy Econ.* **13** 227–33

Huijnen V et al 2016 Fire carbon emissions over maritime Southeast Asia in 2015 largest since 1997 *Sci. Rep.* **6** 26886

Koster R, Schubert S and Suarez M 2009 Analyzing the concurrence of meteorological droughts and warm periods, with implications for the determination of evaporative regime *J. Clim.* **22** 3331–41

Labat D, Ronchail J and Guyot J L 2005 Recent advances in wavelet analyses: part 2—Amazon, Parana, Orinoco and Congo discharges time scale variability *J. Hydrol.* **314** 289–311

Lestari R K, Watanabe M, Imada Y, Shiogama H, Field R D, Takemura T and Kimoto M 2014 Increasing potential of biomass burning over Sumatra, Indonesia induced by anthropogenic tropical warming *Environ. Res. Lett.* **9** 104010

Levine J S 1999 The 1997 fires in Kalimantan and Sumatra, Indonesia: gaseous and particulate emissions *Geophys. Res. Lett.* **26** 815–8

Malhi Y and Wright J 2004 Spatial patterns and recent trends in the climate of tropical rainforest regions *Philos. Trans. R. Soc.* B **359** 311–29

Marlier M E, DeFries R S, Voulgarakis A, Kinney P L, Randerson J T, Shindell D T, Chen Y and Faluvegi G 2013 El Niño and health risks from landscape fire emissions in Southeast Asia *Nat. Clim. Change* **3** 131–6

Mathworks 2015a *MATLAB and Econometrics Toolbox Release 2015b* (Natick, MA: The MathWorks, Inc.)

Mathworks 2015b *MATLAB and Statistics and Machine Learning Toolbox Release 2015b* (Natick, MA: The MathWorks, Inc.)

Moritz M A, Parisien M-A, Batllori E, Krawchuk M A, Van Dorn J, Ganz D J and Hayhoe K 2012 Climate change and disruptions to global fire activity *Ecosphere* **3** 1–22

Mu Q, Zhao M and Running S W 2011 Improvements to a MODIS global terrestrial evapotranspiration algorithm *Remote Sens. Environ.* **115** 1781–1800

Murdiyarso D and Adiningsih E S 2007 Climate anomalies, Indonesian vegetation fires and terrestrial carbon emissions *Mitig. Adapt. Strat. Glob. Change* **12** 101–12

NOAA 2016 Historical ENSO National Weather Service (www.cpc.noaa.gov)

Page S E, Siegert F, Rieley J O, Boehm H-D V, Jaya A and Limin S 2002 The amount of carbon released from peat and forest fires in Indonesia during 1997 *Nature* **420** 61–5

Pechony O and Shindell D T 2010 Driving forces of global wildfires over the past millennium and the forthcoming century *Proc. Natl Acad. Sci.* **107** 19167–70

Raftery A E 1995 Bayesian model selection in social research *Sociol. Methodol.* **25** 111–63

Schamm K, Ziese M, Becker A, Finger P, Meyer-Christoffer A, Schneider U, Schröder M and Stender P 2014 Global gridded precipitation over land: a description of the new GPCC first guess daily product *Earth Syst. Sci. Data* **6** 49–60

Schneider U, Becker A, Finger P, Meyer-Christoffer A, Ziese M and Rudolf B 2014 GPCC's new land surface precipitation climatology based on quality-controlled *in situ* data and its role in quantifying the global water cycle *Theor. Appl. Climatol.* **115** 15–40

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

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

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

Todd M C and Washington R 2004 Climate variability in central equatorial Africa: influence from the Atlantic Sector *Geophys. Res. Lett.* **31** L23202

Trenberth K E and Shea D J 2005 Relationships between precipitation and surface temperature *Geophys. Res. Lett.* **32** L14703

Uriarte M, Pinedo-Vasquez M, DeFries R S, Fernandes K, Gutierrez-Velez V, Baethgen W E and Padoch C 2012 Depopulation of rural landscapes exacerbates fire activity in the Western Amazon *Proc. Natl Acad. Sci.* **109** 21546–50

van der Werf G R *et al* 2008a Climate regulation of fire emissions and deforestation in equatorial Asia *Proc. Natl Acad. Sci.* **105** 20350–5

Van Der Werf G R, Randerson J T, Giglio L, Gobron N and Dolman A 2008b Climate controls on the variability of fires in the tropics and subtropics *Glob. Biogeochem. Cycles* **22** GB3028

Westerling A and Bryant B 2008 Climate change and wildfire in California *Clim. Change* **87** 231–49

Wilks D S 2011 *Statistical Methods in the Atmospheric Sciences* (New York: Academic)

Williams A P *et al* 2013 Temperature as a potent driver of regional forest drought stress and tree mortality *Nat. Clim. Change* **3** 292–7

Wu R, Chen J and Wen Z 2013 Precipitation-surface temperature relationship in the IPCC CMIP5 models *Adv. Atmos. Sci.* **30** 766–78

Zhao M and Running S W 2010 Drought-induced reduction in global terrestrial net primary production from 2000 through 2009 *Science* **329** 940–3

Zhao M, Running S W and Nemani R R 2006 Sensitivity of moderate resolution imaging spectroradiometer (MODIS) terrestrial primary production to the accuracy of meteorological reanalyses *J. Geophys. Res. Biogeosci.* **111** G01002