Amplification of wildfire area burnt by hydrological drought in the humid tropics

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Borneo's diverse ecosystems, which are typical humid tropical conditions, are deteriorating rapidly as the area is experiencing recurrent large-scale wildfires, affecting atmospheric composition[1–4] and influencing regional climate processes[5,6]. Studies suggest that climate-driven drought regulates wildfires[2,7–9], but these overlook subsurface processes leading to hydrological drought, an important driver. Here, we show that models which include hydrological processes better predict area burnt than those solely based on climate data. We report that the Borneo landscape[10] has experienced a substantial hydrological drying trend since the early 20th century, leading to progressive tree mortality, more severe than in other tropical regions[11]. This has caused massive wildfires in lowland Borneo during the last two decades, which we show are clustered in years with large areas of hydrological drought coinciding with strong El Niño events. Statistical modelling evidence shows amplifying wildfires and greater area burnt in response to El Niño/Southern Oscillation (ENSO) strength, when hydrology is considered. These results highlight the importance of considering hydrological drought for wildfire prediction, and we recommend that hydrology should be considered in future studies of the impact of projected ENSO strength, including effects on tropical ecosystems, and biodiversity conservation.

Host for 10,000 plant species in its lowland rainforest alone[10] and ca. 5000 vascular plants in mountainous regions[12], Borneo's ecosystems are deteriorating at an alarming rate. An important cause is large-scale wildfires, which frequently coincide with prolonged ENSO-driven droughts. Impacts in Borneo are exemplary for other biodiversity hotspots in the humid tropics (e.g. the Amazon[5,8]). Future droughts in wet tropical regions will likely increase in frequency and severity[13], and hence the fire risk[5]. Therefore, a better understanding of fire area burnt of tropical humid ecosystems during droughts is urgently required. Direct and indirect impacts of ENSO-drought driven wildfires have already been investigated[1–3,14], but possible long-term drying trends and the associated amplification of ENSO-driven droughts, as well as the area burnt by wildfires and the underlying hydrological mechanism have not been quantified yet. We show that including hydrology improves predictions of area burnt, which so far typically are based on meteorology only. This is essential to predict future fire extent particularly during strong during ENSO-driven droughts.

How does hydrological drought drive wildfire? In the humid tropical environment of Borneo, groundwater dynamics is a key hydrological variable to understand the mechanism of the drought-fire link (Fig. 1). The groundwater table fluctuation influences hydrological drying of fuels and the organic soil. The deeper the groundwater table is, the more fire-prone, the humid tropics become[15–18]. Climate variability related to ENSO-drought[2,7] is the main driver of wildfire in Borneo, by reducing groundwater recharge that feeds the groundwater table, which creates dry conditions for usually human-induced fire ignition. Once the fire is lit, it can escape in an uncontrolled way mainly during a prolonged (hydrological) drought, which happens during a strong El Niño event. Human activities through land-use change and associated drainage and land-clearing immediately following deforestation or long fallow periods create favourable conditions for the fires and amplify the hydrological drying processes in the above-ground fuels and the underlying organic soil (Fig. 1). In regions with few observations, like Borneo, a water balance model can help us to understand the hydrological drought-fire mechanism. We selected groundwater recharge as a key hydrological variable that integrates precipitation, actual evapotranspiration and changes in soil moisture content (Fig. 1). Hence, it is expected to be a stronger explanatory factor to characterize drought than just the precipitation anomaly (meteorological drought) or the soil moisture anomaly. We hypothesize that periods with low groundwater recharge will create conditions for a greater area burnt.

Figure 1: The mechanisms of the drought-fire link are explained through the dynamics of the groundwater table fluctuation, which responds to soil moisture (a), capillary rise (b) and groundwater recharge (c) driven by weather changes. During a period with no rainfall (meteorological drought), soil moisture is depleted (soil moisture drought) to fulfil the evapotranspiration flux, hence groundwater recharge is reduced or even becomes negatives (capillary rise, b). Short meteorological drought is characterised by low fire risk. When the meteorological drought lasts longer, the continuous capillary rise accelerates groundwater table decline (hydrological drought), until a depth where the capillary rise becomes insufficient to feed soil moisture (layer 2). Then the soil moisture flux (a) is affected, which leads to drying out the organic topsoil and the above-ground fuels stimulating drought stress. This stress leads to shedding of leaves by the evergreen forest and to accumulation of dry litter on the forest floor (fuel layer). Further persistent moisture depletion will ease ignition in layer 1 (usually human-induced) and subsequent spreading of fire. The combined effect of drying out the above-ground fuels and hydrological drought leads to low moisture in the organic soil (layer 2), which substantially favours peat smouldering combustion (extremely high fire risk). Human activities through land clearing change land use, and wetland canalisation accelerate the (hydrological) drying process (in layers 1 and 2) by providing abundant fuels and lowering of groundwater tables. Moreover, the dryer soil increases accessibility, which makes land management activities easier to carry out.

Has hydrological drought become more severe and hence created conditions for more extended wildfires? First, to explore the spatially-distributed hydrological drought in Borneo, we analysed time-series of monthly climate data provided by the Climatic Research Unit (CRU[19]) for the period 1901-2015. We simulated the transient monthly water balance (Eq. 1) to derive groundwater recharge at the 0.5° latitude/longitude grid scale. Subsequently, we applied the threshold approach with the 80th percentile[20] to derive hydrological drought, i.e. drought in groundwater recharge across Borneo. Here we report that there has been a drying trend in Borneo since the early 20th century, as indicated by the proportion of the annual area in drought (Extended Data Fig. 1) expressed as the annual maximum and annual mean (see Methods, Eqs. 3 and 4). The monthly groundwater recharge has been derived as follows:

$rch = pre - eta \pm ds$ (1)

where: *rch* is monthly recharge, *pre* is monthly precipitation, *eta* is monthly actual evapotranspiration, and *ds* is change in monthly soil moisture [units: mm].

Does hydrological drought amplify wildfire? To explore the link between hydrological drought and fire in Borneo, we analysed the monthly fire area burnt from the Global Fire Emission Dataset (GFED4[21]) for the period 1996-2015 with a 0.25° spatial resolution. This fire area burnt has been aggregated to 0.5° grid cells. We classified years in this period into drought and non-drought years. A drought year is defined as a year with prolonged and spatially extensive hydrological drought events (see Methods). Our analysis illustrates that wildfires occur annually, i.e. also in non-drought years, but that amplification of wildfires occurs during drought years. In drought years, maximum area burnt is significantly larger (Fig. 2a), namely by almost 10 times relative to non-drought years. The larger the area in drought the higher the annual area burnt. Furthermore, very large fire extents (i.e. area burnt >10,000 ha) were hardly detected for non-drought years, while 14 times as many events occurred during drought years (Fig. 2b). Additionally, our grid-scale analysis shows that large-scale wildfire is mainly widespread in the eastern and southern parts of Borneo during drought years (Fig. 2c), where prolonged hydrological drought events are more likely to occur (Extended Data Fig. 2). This finding proves that hydrological drought amplifies wildfires in terms of area burnt and frequency of very large wildfire events.

Figure 2: Area burnt by wildfires in Borneo during drought and non-drought years for the period 1996-2015; (a) Relation between the annual maximum of area burnt and the percentage of the annual maximum area in drought. The graph indicates that area burnt increases substantially during drought years; (b) Frequency of area burnt by very large wildfires (>10,000 ha); (c). Spatial distribution of the maximum value of wildfire area burnt at 0.5° spatial resolution. The figures clearly show that during hydrological drought years, fire area burnt expands. The unit of area burnt is in ha (natural logarithmic).

Wildfires are usually explained through the occurrence and severity of meteorological drought (i.e. below-normal precipitation[5,7–9]). However, so far no model to predict wildfire area burnt has been developed that includes hydrology. There are indications that by integrating hydrological variables, fire occurrence is better identified[17,22]. To develop a predictive model for wildfire area burnt, we explored statistical relationships between the fire area burnt (response *Y*) from GFED4[21] and independent predictors (*X*), which were obtained and derived from water balance components (Eq. 1), fire weather system indices (FWI), and ENSO (see Methods) for the period 1996-2015. Three different approaches were used to establish statistical relationships (i.e. models): a linear approach, non-linear approach with local regression (loess[23]), and non-linear approach with random forest[24]. We note that all data sources are independently derived, with the GFED4 derived from remotely-sensed data; FWI from the Global Fire Weather Database (GFWED)[25], ENSO derived from sea surface temperature at the Pacific Ocean; and CRU climate data derived from interpolated station climate data. We clearly distinguished between models that are solely based on climate (i.e. precipitation, FWI, and ENSO) and models that also integrate hydrological variables, such as groundwater recharge, as predictors. In total, over 300 statistical relationships have been investigated. Our analysis shows that non-linear models using loess better predict area burnt than the two other approaches for any combination of predictors used in this study (Extended Data Fig. 3).

To what extent does hydrology contribute to the quantification of the area burnt by wildfire? To assess whether statistical models integrating hydrology perform better than models using climate only, we clustered the predictive models into two ensembles of models (see Methods), i.e. climate-oriented models (CLIM) and hydroclimate-oriented models (H-CLIM). We applied three different goodness-of-fit criteria (see Methods) for the assessment of model performance. Our model assessment (Extended Data Fig. 4) shows that H-CLIM performed better in terms of any goodness-of-fit (GOF) measure used; the median of all GOF values is employed as a measure in hydrology[26]. Furthermore, the variance of the residuals for the ensemble of H-CLIM models is significantly lower (30%, $\alpha=0.01$) than that of CLIM. The reduced variance provides additional evidence that by integrating hydrological variables, model uncertainty is significantly reduced.

Does hydrology matter for the prediction of wildfire area burnt under various ENSO strengths? To understand how the wildfire area burnt is attributable to the warm phase of ENSO (El Niño) and to how much hydrology adds, we applied both model ensembles (CLIM and H-CLIM) to estimate the mean and the maximum of the area burnt per grid cell for 1950-2015. For each year El Niño strength was assigned to one of the four classes (i.e. weak, moderate, strong and very strong, see Methods). Our analysis shows that the mean annual area burnt predicted by the H-CLIM model ensemble was larger than that predicted by the CLIM model ensemble for any El Niño strength (Fig. 3, upper row). The predicted area burnt is at least 15% greater. In particular, for years with a very strong El Niño the difference in area burnt between CLIM and H-CLIM ensembles is large. The predicted maximum annual area burnt is even 154-275% larger for strong and very strong ENSO conditions when hydrology is integrated (Fig. 3, lower row). If climate-oriented models (i.e. CLIM ensemble) are applied for predicting area burnt (specifically under extreme El Niño events in the future), the estimate tends to substantially underestimate the possible very large area burnt that may occur. Because extreme El Niño events are more frequently projected in the future[27,28], promoting prolonged dry seasons and impacting wildfire area burnt, use of the appropriate prediction tools that integrate all drivers with hydrology being one of the most important, is crucial.

This research improves the assessment of wildfire area burnt in humid tropical ecosystems. So far, climate-driven prolonged drought is used as the only driver for wildfire occurrence and strength in the humid tropics, such as the Amazon[5,8] and Borneo[2,5,7]. Our findings provide a promising direction to improved prediction of area burnt in other humid tropical areas beyond Borneo for various El Niño strengths. Hydrological drought has never been considered, so far, as indicator for strategic policy formulation, and the results indicate that the approach offers a powerful tool to improve planning and strategies to adapt to climate change. Most practically, such a tool may be adopted in the ambitious government effort to restore 2 million hectares of degraded peatland by 2020, among others by rewetting drained peatlands.

Figure 3: Predicted area burnt for various El Niño strengths (see Methods) using two model ensembles (CLIM and H-CLIM). For each ensemble, two different predictions are provided, namely the mean (upper) and maximum values of all grid cells for 1950-2015 (lower). It appears that predicted area burnt by using the CLIM model ensemble is substantially smaller than that by applying the H-CLIM model ensemble except for the moderate El Niño strength. By including hydrological processes, a greater area burnt is predicted; the CLIM model ensemble tends to underestimate the area burnt.

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Methods

Soil water balance model. Borneo has been subdivided into 270 grid cells (0.5°). For each grid cell, we applied a simple soil water balance model[29,30] to simulate transient soil water storage, actual evapotranspiration, and groundwater recharge (Eq. 1), with as input precipitation and reference potential evapotranspiration from the CRU dataset[19]. For a detailed explanation about the soil water balance model, readers may refer to Ref. 28 and 29.

The recharge simulation identifies droughts using the land use from 2007 as reference[31] and the climate variability as reflected in the monthly climate data from 1901 to 2015. Land use in 2007 included 2.3% of the area classified as oil palm plantation. In 2010, this increased to 4% of Borneo[32] and is projected to increase in the coming decades[33]. The emphasis in this study is on climate variability rather than on land use change, although the latter may influence wildfires as well[34] through providing favourable conditions. Likely, the area burnt will increase and the importance of hydrology will become even more distinct, if more peatland is converted into large-scale plantations.

Area in hydrological drought. Drought events were derived from time series of groundwater recharge using the threshold level approach, where the threshold is taken to be the 80th percentile of the cumulative duration curve[20] of groundwater recharge. Drought was defined as the period when the recharge is continuously below this threshold value. We applied different monthly variable thresholds for each grid cell, representative for its own soil-hydrological properties and given precipitation. Deficit in groundwater recharge (*def*) is the hydrological drought characteristic we used in this study. Then we also counted the proportion of grid cells for Borneo, for which the monthly recharge was below the threshold, and we defined this proportion as the area in drought[30].The monthly percentage area in drought (AD_m) for the whole of Borneo for month m and year i is calculated as follows:

$$AD_{m,i} = 100 * \frac{1}{Ng}\sum_{g=1}^{Ng} def_{g,m,i} \qquad (2)$$

where: $def_{g,m}$ describes whether a grid cell g for month m and year i is in drought (0: no drought, 1: drought), N_g is number of grid cells covering Borneo.

For each year i, two metrics of area in drought were used, namely the annual max (AD_mx) and annual mean (AD_ave):

$$AD\_mx_i = \max(AD_{m,i}) \qquad (3)$$
$$AD\_ave_i = \mathrm{mean}(AD_{m,i}) \qquad (4)$$

Where: AD_mx_i and AD_ave_i describe the annual maximum and annual mean area in drought, which are the maximum area occurring in one of the months in a year and the mean of the areas in drought derived from the 12 monthly values for each year.

Drought and non-drought years. Drought was defined as the period with a deficit in the groundwater recharge over a large area. This definition was introduced to avoid taking into account droughts that cover only a small area [35]. Borneo is well-known as an ENSO-driven drought region[2,36], therefore we defined a drought year as a year with a warm ENSO event (*classification is available at http://ggweather.com/enso/oni.htm)*. Our analysis shows that in warm ENSO years, hydrological drought occurred extensively throughout Borneo in more than 50% of the area. For example, during the ENSO-drought in 2015, 50% of Borneo experienced hydrological drought for 2-consecutive months. There were seven warm ENSO years, i.e. 1997-98, 2002, 2004, 2006, 2009, and 2015. For a non-warm ENSO year, we assumed that at least 40% of Borneo had to be in drought to be selected as a drought year. This drought should occur as an uninterrupted event for at least two consecutive months. Under this definition, only one year was identified as a drought year, i.e. 2014. In total we identified eight out of 20 as drought years in the period for which observed area burnt was available (1996-2015, Extended Data Table 1).

Statistical analysis. We used three different statistical approaches to predict monthly area burnt (*response Y*) given by independent predictors (*X*). There were two types of predictors, namely predictors based only on climate information (e.g. precipitation, fire weather system indices, and an El Niño/ ENSO indicator), and predictors including hydrological information (e.g. groundwater recharge) to complement climate predictors (Extended Data Table 2). From the water balance components (Eq. 1), predictors were derived, such as the total two consecutive months with deficit recharge, and FWI (Extended Data Fig. 3). We used the Oceanic Niño Index (ONI, *data available at http://ggweather.com/enso/oni.htm*) as an ENSO predictor. Subsequently, three statistical approaches were explored, namely linear models, non-linear models using loess (local regression fitting[23]), and random forest[24] as predictive models. The period 1996-2015 was used for model calibration, as data on area burnt were available from GFED4[21].

We hypothesise that wildfires occur during a drought, when prolonged below normal precipitation occurs. A threshold of 100 mm/month is commonly used to detect drought events in the forest ecosystem in Borneo[37–39]. Here, we used low groundwater recharge instead to detect drought-fire connectivity. The prediction of area burnt was performed when the groundwater recharge is below 20 mm/month. This number reflects soil moisture depletion and groundwater drawdown due to limited water input. Furthermore, we applied the Nash-Sutcliffe Efficiency (NSE) criterion to assess model performance. NSE indicates the fraction of the variance of the observations explained by the model and is widely applied in hydrology[26,40]. The assessment confirmed that by using the loess approach, the area burnt is better identified than by using other models (Extended Data Fig 3).

To assess whether hydrological predictors perform better than climate ones, we clustered the loess models into two groups, i.e. a climate-oriented ensemble (CLIM) and a hydroclimate-oriented ensemble (H-CLIM). Here, we have chosen the Kling-Gupta Efficiency (*KGE*)[40], as a combined measure of bias, correlation and scale between observed and model data, and the *RMSE*-observation standard deviation ratio (*RSR* [26]) to complement the *NSE* criterion to assess model performance. Moreover, we tested the variance of the residuals for both groups of ensembles with the chi-square test (using $\alpha=0.01$) to evaluate their performance. We used the R statistical computing language[41] to perform all statistical analyses. Finally, we utilized the ggplot2 package[42] to visualize data and information.

Model selection procedures. To identify the best explanatory statistical relationships, we used criteria widely used in hydrology[26] for a monthly time step simulation. The performance of a statistical model is considered acceptable if the NSE >=0.5 and the RSR <0.7. The KGE should greater than 0.5, as well. By applying these criteria we found 24 models that performed well in which all of them belong to HCLIM. To reduce the number of models in the ensemble, we added that the variance of the chosen model should be below the 80^{th} percentile of all models' variance. By applying this selection procedure, we identified 13 ensemble members that performed well for H-CLIM. On other hand, for CLIM we selected the best 13 models with full record length (1950-1995) as model ensemble. These best-performing models are labelled in the Extended Data Fig. 5.

There are not many independent data for the area burnt to verify that the ensemble of H-CLIM models performs better than the CLIM one. During the very strong El-Nino of 1982/1983[43], wildfires (incl. land and forest) occurred over an area of 3.5 million ha. The CLIM model ensemble deviated by 60% from the actual area burnt reported, whereas the difference for H-CLIM was only 14%. This means that the CLIM models very likely underestimate the area burnt.

ENSO classes. We used the ONI for the period 1950-2015 to categorize the years as very strong, strong, moderate, or weak El Niño years (*classification is available at http://ggweather.com/enso/oni.htm)*. Based on El Niño strength, we classified the years 1982-83 and 1997-98 as very strong El Niño years, while 1965-66 and 1972-73 were categorized as strong El Niño years. The years 1991-92 and 2009-10 represent moderate El Niño years. Years 1976-77 and 2006-07 are the best examples of weak El Niño events. Finally, we applied both the CLIM and H-CLIM model ensemble members to estimate wildfire area burnt for these different ENSO classes.

Data availability. The authors declare that the data supporting the findings of this study can be found in the corresponding references. Specifically, the data are available online: climate (https://crudata.uea.ac.uk/cru/data/hrg/), fire area burnt (ftp://fuoco.geog.umd.edu/gfed4/monthly/, user/password: fire/burnt), and fire weather system indices (ftp://ftp.nccs.nasa.gov/v2.0, user: GlobalFWI). The statistical models that support the findings of this study are available from the corresponding author upon request

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