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Variability of fire carbon emissions in equatorial Asia and its nonlinear sensitivity to El Niño — Source link

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Key Points:

- As constrained by atmospheric inversion, 0.5 +/- 0.17 Pg carbon was emitted from the equatorial Asia peat fires in 2015
- Fire carbon emissions increase exponentially with cumulative water deficit; possible to forecast it with a lead time of 2 months
- We infer a future fire carbon loss ranging from 12 to 25 Pg by 2100 in the absence of actions to limit peat burning based on climate projections

Supporting Information:

- Supporting Information S1

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Variability of fire carbon emissions in equatorial Asia and its nonlinear sensitivity to El Niño

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Abstract The large peatland carbon stocks in the land use change-affected areas of equatorial Asia are vulnerable to fire. Combining satellite observations of active fire, burned area, and atmospheric concentrations of combustion tracers with a Bayesian inversion, we estimated the amount and variability of fire carbon emissions in equatorial Asia over the period 1997–2015. Emissions in 2015 were of 0.51 ± 0.17 Pg carbon—less than half of the emissions from the previous 1997 extreme El Niño, explained by a less acute water deficit. Fire severity could be empirically hindcasted from the cumulative water deficit with a lead time of 1 to 2 months. Based on CMIP5 climate projections and an exponential empirical relationship found between fire carbon emissions and water deficit, we infer a total fire carbon loss ranging from 12 to 25 Pg by 2100 which is a significant positive feedback to climate warming.

1. Introduction

Equatorial Asia (EQAS) tropical peatlands accumulated over thousands of years hold about 70 Pg of organic carbon (C) [*Page et al.*, 2011], a large pool comparable to the forest biomass of the entire Amazon [*Saatchi et al.*, 2011]. Fires are typically lit by humans as a management tool in EQAS, but the burning often goes out of control during dry years, especially in areas where peatland drainage for agriculture and palm plantation has lowered the water table [*van der Werf et al.*, 2008]. Abnormally large fires occur during El Niño droughts, causing negative health, ecological, and economic impacts [*Field et al.*, 2009; *Marlier et al.*, 2015]. An iconic example is the extreme Indonesian fire event associated with the 1997 El Niño, which was estimated to release 0.8–2.6 Pg C to the atmosphere [*Page et al.*, 2002]. In the dry season of 2015, the El Niño index reached again an extremely high value comparable to that of 1997/1998 [*NOAA*, 2016]. Various media reported a significant positive fire anomaly in Indonesia in September and October 2015. Yet a robust estimation of the fire carbon loss is challenging given the large uncertainties in the detection of peat fires due to the low-temperature anomaly of smoldering and underground burning and the blocking of heavy smoke [*Tansey et al.*, 2008]. Considerable uncertainties also lie in the estimation of burning depth and fuel consumption [*Page et al.*, 2002; *van der Werf et al.*, 2008, 2010; *Ballhorn et al.*, 2009; *Konecny et al.*, 2015].

Atmospheric observations of carbon fuel combustion tracers, i.e., carbon monoxide (CO), carbon dioxide (CO_2), methane (CH_4), and formaldehyde (CH_2O), are thus valuable to provide additional top-down constraints to the regional fire carbon emissions using inverse modeling. Among these tracers, CO is particularly useful in tracking biomass burning emissions, because it shows significant regional enhancement over pyrogenic sources, its average lifetime of 2 months allows atmospheric transport models to track the fire pollution plumes, and it is one of the best observed tracers with its spatial-temporal variations well quantified over the recent 15 years from space [*Yin et al.*, 2015]. Here using a sophisticated multitracer 4-D Var Bayesian inversion system, this study aims at (1) quantifying the variability of fire emissions in the EQAS over the last 19 years, (2) documenting how fire carbon emissions respond to climate variability covering records of two extreme El Nino events, and (3) estimating future fire carbon emissions in the coming century.

2. Materials and Methods

In this study, we analyzed the fire dynamics in EQAS based on bottom-up satellite-derived ground fire data and atmospheric carbon combustion tracer concentrations since the early 2000s. Using a global multitracer

(CH_4–CH_2O–CO) atmospheric inversion, we calculated a top-down estimate of the EQAS fire carbon emissions for the period of 2002–2015 and extended it back to 1997 based on the strong correlation between bottom-up and top-down estimates. Further, we analyzed the correlation between fire emissions and climate over the last 19 years and estimated future fire carbon emissions by 2100 based on climate projections from the model ensembles of Coupled Model Intercomparison Project Phase 5 (CMIP5). Three types of observational data sets are used: (1) ground fire features, (2) atmospheric tracer concentrations, and (3) climate proxies (Table S1 in the supporting information). In addition, future climate projections from CMIP5 are analyzed (Table S3).

2.1. Ground Fire Feature Analysis

Moderate Resolution Imaging Spectroradiometer (MODIS) daily active fire products, MOD14A1 from Terra and MYD14A1 from Aqua with local pass time of 10:30 and 13:30 [*Giglio et al.*, 2006], are analyzed. The lowest detection confidence level of active fires was chosen because smoldering fires could be classified as lower confidence due to their lower burning temperatures. The ratios of peat fires to total fire counts are calculated based on the high-resolution peat distribution map [*Wahyunto and Subagjo*, 2003, 2004] for the three main islands, Sumatra, Borneo, and West Papua, where over 90% of the EQAS peats are distributed (Figure S1). We also analyzed two burned area products—MCD45A1 [*Roy et al.*, 2008] and MCD64A1 [*Giglio et al.*, 2013]. These data sets are complemented by the Global Fire Emissions Database (GFED4), which provides not only a bottom-up estimate of burned area but also fire type and emissions of various tracers from 1997 to 2015 [*Randerson et al.*, 2015]. Last, emission estimates from Global Fire Assimilation System (GFAS) based on fire radiative power are also analyzed, covering the recent period from 2003 to 2015 [*Kaiser et al.*, 2012].

2.2. Atmospheric Inversion

Fire CO emissions in this study are quantified for the period from 2002 to 2015 using a global multitracer (CH_4–CH_2O–CO) atmospheric Bayesian inversion system as detailed in *Yin et al.* [2015, and references therein]. Satellite total column retrievals of CO from the Measurements Of Pollution In The Troposphere (MOPITT) (available for a full year since 2002) [*Deeter et al.*, 2014] and CH_2O from the Ozone Monitoring Instrument (OMI) (available since 2004) [*González Abad et al.*, 2015] are assimilated jointly with surface in situ measurements of CH_4 and methyl chloroform (MCF). Very limited surface stations are located within or around the EQAS region, providing only background constraints to the regional budgets. The results of CH_4 and MCF from surface stations are thus not addressed in this paper.

The inversion optimizes prior CO emissions compiled from biomass burning emissions from GFED4 (or GFAS for sensitivity tests; Table S2), fossil fuel emission inventory from MACCity [*Lamarque et al.*, 2010], and ocean biogenic emissions from model climatology (see details in [*Yin et al.*, 2015]). Fire attribution of the optimized total CO emissions is empirically estimated based on the interannual variation (IAV) of the posterior fluxes and the relative fire contribution according to the prior information (details in the supporting information). Fire total carbon (TC) emissions are then estimated from fire CO emissions using the ratio of emission factors between TC and CO. Three burning types are differentiated—peat, deforestation, and agriculture—with average TC:CO ratios of 2.81, 5.28, and 4.7, respectively, following GFED [*van der Werf et al.*, 2010]. A Monte Carlo approach is used to estimate the uncertainty of the TC emissions, accounting for the propagation of errors in the CO inversion as described by *Chevallier et al.* [2007] and in the fire emission partitioning and emission factor ratios (arbitrarily set as 30%) (Text S2). Then, fire carbon emissions of the pre-MOPITT period (1997–2001) are estimated using the linear regression between the annual bottom-up and top-down estimates of the period from 2002 onward.

2.3. Future Emission Estimates

Correlation between the monthly fire TC emissions and climate variability over the major emission regions over the last 19 years are analyzed, including precipitation, temperature, evapotranspiration, and multivariate El Niño–Southern Oscillation (ENSO) index (MEI). Future climate projections of precipitation and evapotranspiration from 24 models in the CMIP5 ensembles [*Taylor et al.*, 2012] and from seven models that have been bias corrected for the climate forcing variables (precipitation and surface air temperature) [*Hempel et al.*, 2013] are used to estimate future cumulative fire TC emissions (see model list in Table S3). The empirical relationship found between the fire TC emissions and accumulative water deficit are applied to estimate the amplitude of future fire carbon emissions (Text S3).

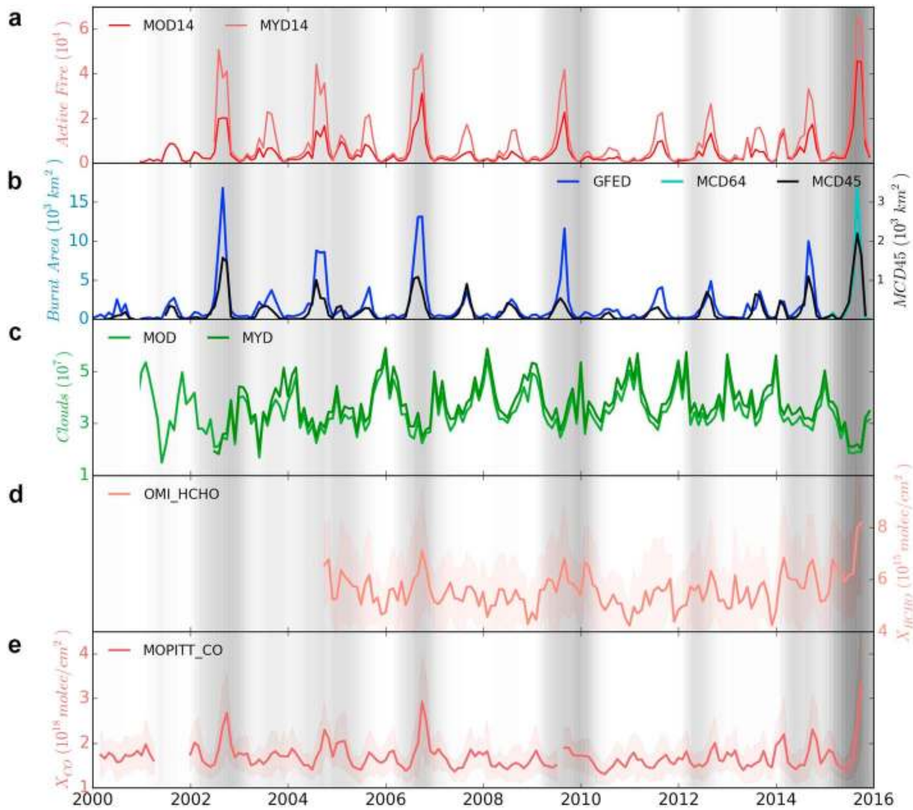

Figure 1. Time series of monthly fire-related proxies from 2000 to 2015. (a) Active fire counts derived from MODIS in the morning (MOD14) and the afternoon (MYD14). (b) Burned area estimated by two MODIS data sets (MCD45 and MCD64). A different scale is used for MCD45—right *y* axis. (c) Cloud counts associated with MODIS active fires. (d) Atmospheric column concentration of CH_2O (X_{CH2O}) over EQAS from OMI. (e) Atmospheric column concentration of CO (X_{CO}) over EQAS from MOPITT. Grey shades in the background show the bimonthly multivariate ENSO index—the darker the color, the higher the value.

3. Results and Discussion

3.1. Anomaly of Surface Fire Counts and Burned Area

In September–October 2015, active fire counts [*Giglio et al*., 2006] reached the highest values observed by the Moderate Resolution Imaging Spectroradiometer (MODIS) instruments since 2000 (Figure 1a). The 2015 fire counts are 2.7 and 2.4 times the decadal average as observed in the morning and afternoon, respectively (Figure 1a). Positive fire anomalies in 2015 occurred mainly in southeast Sumatra, southern Borneo, and West Papua, where most EQAS peatlands locate [*Wahyunto and Subagjo*, 2003, 2004] (Figures 2a and 2b). The 2015 fire anomaly is also embedded in a progressive increase of peat burning from 2007 onward (Figure S2). Over peat-rich ecosystems, fire counts remained similar between the morning and afternoon, whereas in other ecosystems, more fires occurred in the afternoon (Figure S2). The fire persistence index, defined as the ratio between continuously detected daily fires and the total fire counts over a year, shows a similar interannual variation (IAV) as the peat fire proportion [*van der Werf et al*., 2008] and the ratio of morning-to-afternoon fire counts, confirming that peat fires are more persistent and continue to burn for days once ignited.

The MODIS burned areas, derived from surface reflectance change, also show positive fire anomalies in 2015 (Figure 1b). The 2015 burned areas estimated by the two products listed above, MCD45 [*Roy et al*., 2008] and MCD64 [*Giglio et al*., 2013], are 2.7 and 2.1 times the decadal average, respectively. The GFED4 burned area, which is based on MCD64 and extends back to 1997 from other satellites, further shows that the 2015 burned area was 30% lower than that of 1997. The two burned area data sets have a similar IAV, but MCD64 finds systematically 5–10 times more burned area than MCD45, in line with previous studies suggesting that MCD45 is low biased due to a greater cloud and aerosol contamination [*Roy et al*., 2008]. The differences

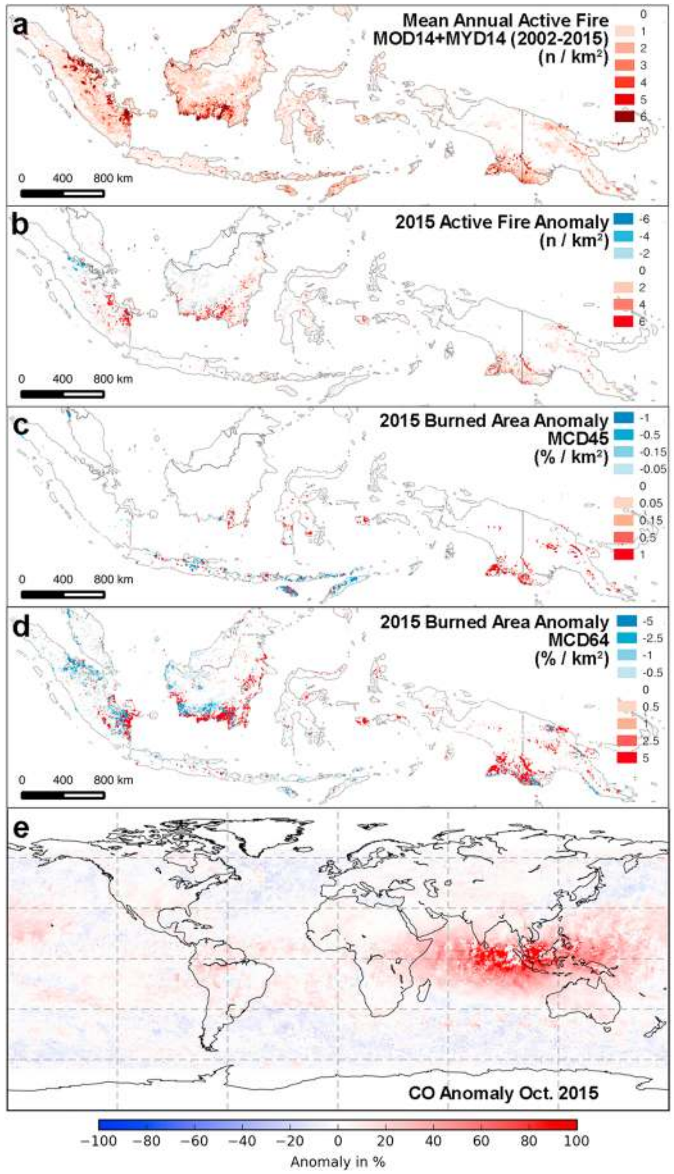

Figure 2. Spatial distribution of fire anomaly in 2015. (a) Mean annual active fire counts from both the morning (MOD14) and the afternoon (MYD14). (b) Active fire anomaly. (c) Burned area anomaly in MCD45 compared to its multiyear average (2003–2015). (d) Burned area anomaly in MCD64 compared to its multiyear average (2003–2015). (e) MOPITT X_{CO} anomaly in October 2015 compared to its multiyear October average (2002–2015).

in the magnitude and spatial distribution of fire anomalies between the two burned area data sets illustrate the large uncertainties in identifying EQAS fire emissions with bottom-up fire observation alone (Figures 2c and 2d). The uncertainty in peat burning depth could further complicate bottom-up fire emission estimates from burned area [*Ballhorn et al.*, 2009; *Konecny et al.*, 2015]. Moreover, cloud cover significantly decreased after 2013, when the El Niño state started to build up (Figure 1c), which increases the probability of fire detection by satellite and may bias the interpretation of fire trends based on burned area and active fire. Thus, a top-down approach is useful to quantify the amount and variability of regional fire carbon emissions from atmospheric tracer signals.

3.2. Anomaly of Atmospheric Tracer Concentrations

Abnormally high column concentrations of CO were observed by MOPITT over the EQAS region in 2015 (Figure 2e). The average regional enhancement of CO was ~63 ppb (parts per billion, 10^{-9}), i.e., 66% higher

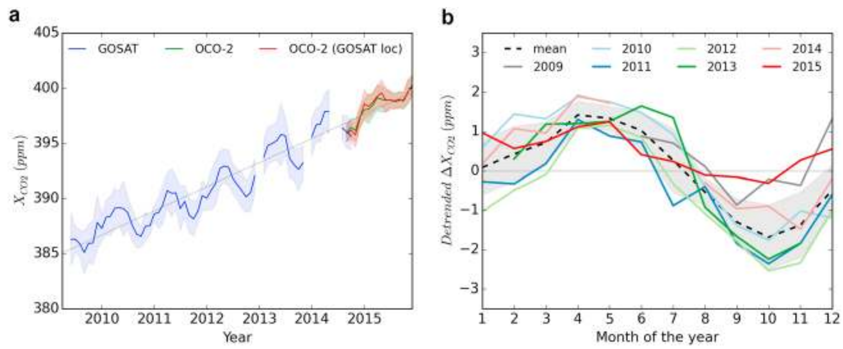

Figure 3. The concentration of CO_2 total column (X_{CO2}) over EQAS observed by GOSAT and OCO-2. (a) Regional X_{CO2} concentration from April 2009 to December 2015. (b) The seasonal cycle of the detrended X_{CO2} for each year.

than the decadal average dry season level (June to October) (Figure 1e). The peaks in CO column concentrations echo with high active fire counts. The OMI satellite retrievals of CH_2O—whose sources are direct surface emission and oxidation of volatile organic compounds—also showed a positive anomaly of ~100 ppt (parts per trillion, 10^{-12}) in 2015, 34% higher than the mean decadal dry season level (Figure 1d). The peaks in both CO and CH_2O concentrations provide evidence for abnormally high fire emissions during El Niño years (2002, 2006, 2009, and 2015), as shown in Figure 1.

The total column concentrations of CO_2 (X_{CO2}) as observed by the Greenhouse Gases Observing Satellite (GOSAT) [*Cogan et al*., 2012] and Orbiting Carbon Observatory (OCO-2) [*Crisp et al*., 2012] also show significant positive enhancements in 2015 compared to the detrended mean seasonal cycle (2009–2015) (Figure 3; see Figure S3 for comparison with other regions). The magnitude of the regional X_{CO2} enhancement is around 1.2 ppm (parts per million, 10^{-6}) in September and reached 1.6 ppm in November 2015. A direct attribution of this X_{CO2} anomaly to EQAS fire emission is complicated because of the additional and uncertain contribution from terrestrial and oceanic CO_2 fluxes induced by the El Niño climate anomaly. Therefore, we chose to use measurements of CO to infer fire emissions, because CO is a more direct proxy tracer of fire carbon emissions and the time series of CO observations are longer than those of X_{CO2}.

3.3. Fire Carbon Emission and Climate Variability

We inferred the optimized CO emissions (posterior estimate) that best fit atmospheric CO (MOPITT) and CH_2O (OMI) satellite measurements using the inversion summarized in section 2.2 from 2002 to 2015. For the year 2015, the inversion shows lower CO emissions from Sumatra but higher emissions from Borneo compared to the prior (Figure S4). The optimized EQAS CO emission in 2015 is 134 ± 19 Tg (with 122 Tg CO attributed to fire emissions), accounting for 10.5% of the global CO emissions. The top-down estimates of the regional emissions show a similar IAV as the bottom-up fire data sets (GFED and GFAS) (Figure 4a). We extended the TC emission estimates to the pre-MOPITT period using linear regression between the annual bottom-up (average of the three data sets shown in Figure 4a) and top-down estimates of 2002 onward as shown in

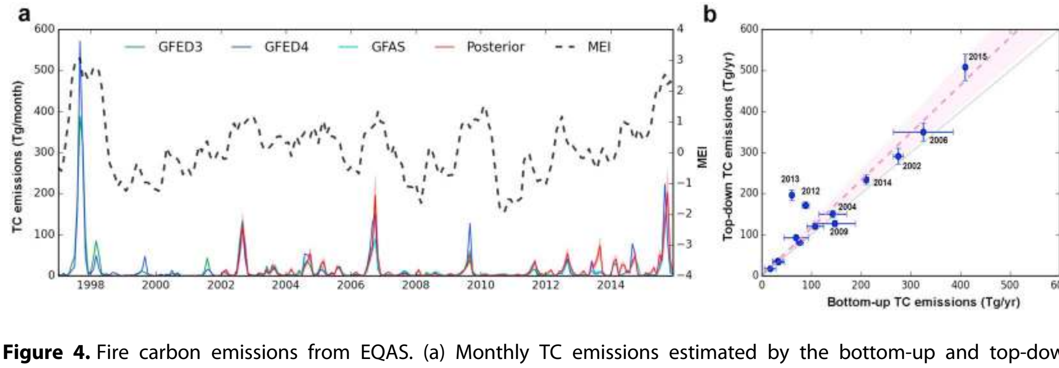

Figure 4. Fire carbon emissions from EQAS. (a) Monthly TC emissions estimated by the bottom-up and top-down approaches. The dashed line shows the dynamics of multivariate ENSO index. (b) Scatter of the annual TC emissions obtained by the bottom-up and top-down approaches from 2002 to 2015. Shaded areas show 2σ uncertainty ranges.

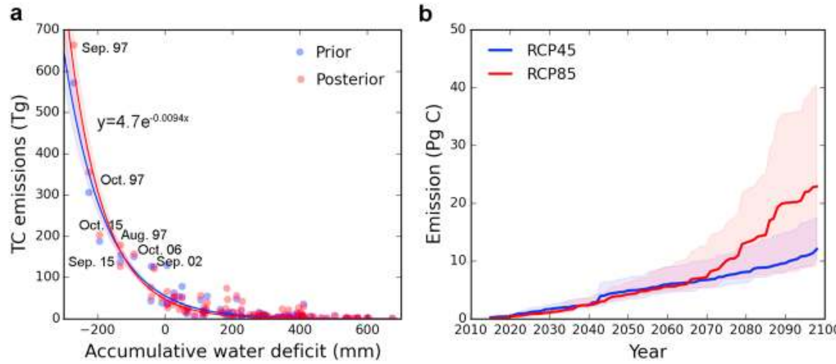

Figure 5. (a) Monthly fire carbon emissions as a function of the cumulative water deficits of 4 months. (b) Future projections of fire carbon emissions based on future climate projections of seven bias-corrected CMIP5 models and the empirical relationship in Figure 5a. Solid lines represent the model median; shaded areas represent the range between the 25th and 75th quantiles of the model ensembles.

Figure 4b ($R^2 = 0.92$). The inversion approach gives an emission of 0.51 ± 0.17 Pg C in 2015, which is less than half of the emissions inferred during the 1997 El Niño (1.21 ± 0.45 Pg C). Considering a 30% lower burned area of 2015 with regard to 1997, the greater decrease in fire carbon emissions indicates lower fuel combustion per area in 2015. The EQAS cumulative fire emission since 1997 is of 4 ± 1.3 Pg C.

The water deficit in the dry season of 2015 was less acute than in 1997 (−165 mm versus −210 mm); the MEI in 2015 is also lower compared to 1997 (2.31 versus 2.69). The rainfall anomaly also suggests a longer drought season and a larger rainfall deficit in 1997 compared to 2015, for the fire concentrated regions in southern Sumatra and Borneo as well as for the entire EQAS (Figure S5). Monthly TC emissions are found to increase exponentially with cumulative water deficit (precipitation minus evapotranspiration) (Figure 5a). Exponentially increasing TC emissions are also observed with decreasing cumulative precipitation or increasing ENSO index during the fire season (Figures S6a and S6b). The best exponential fit is obtained using 4 months cumulative water deficit preceding the fire season (June to October), suggesting that using the cumulative water deficit is more robust for TC emission estimates compared to using precipitation or ENSO index as predictors. Cumulative precipitation or water deficit preceding the fire season with a lead time of 1 to 2 months could also effectively forecast the amount of fire emissions (Figures S6c and S6d), which may contribute to an early warning for EQAS peat fire management.

3.4. Future Fire Emission Projection

The frequency of extreme El Niño events simulated by climate models is projected to nearly double in the coming decades [*Cai et al*., 2014]. Climate models also indicate an increase in severe drought events in the EQAS region, with the potential to increase fire emissions [*Lestari et al*., 2014]. Based on future climate model projections from CMIP5 and the empirical relationship found between fire TC emission and cumulative water deficit shown in Figure 5a, we estimated a total cumulative peat fire carbon loss of 25 ± 20 Pg C in EQAS by 2100 following the current climate warming trajectory (Representative Concentration Pathway RCP 8.5) [*Meinshausen et al*., 2011] (13 ± 9 Pg C in RCP 4.5) (Figure 5b and Text S3). The large uncertainty reflects the spread of climate model projections. Our simple method to estimate future emissions ignores exhaustion of peat stocks prone to burning and future changes in human drivers such as policies of fire management and peat conservation [*van der Werf et al*., 2008; *Carlson et al*., 2012; *Busch et al*., 2015]. Nevertheless, it shows the magnitude of the peat carbon deposits that are at stake under future climate change.

4. Conclusions

Satellite observations of ground fire features and atmospheric pollutant concentrations provided us new insights into fire dynamics and fire-associated carbon losses in the EQAS, where massive land use change due to agriculture and palm plantation are taking place over the carbon-rich peat soils in recent decades [*Carlson et al*., 2012; *Margono et al*., 2014]. The strong nonlinear relationship found between fire emissions and cumulative water deficit suggests a high future risk of peat carbon loss due to fire given that future climate projections indicate a twofold increase in the frequency of extreme El Niño [*Cai et al*., 2014]. In the absence of actions to limit peat burning, our results show that peat fire CO_2 emissions to the atmosphere will act as a positive feedback on climate change, whose magnitude is one quarter of the permafrost feedback [*Schuur et al*., 2015]. However, such process is not yet represented in current Earth system models. Offsetting this long-term carbon source will require stronger mitigation measures to keep climate warming below 2°C as stated in the UN Paris Climate Agreement.

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Erratum

In the originally published version of this paper, the author acknowledged “JPL/MIT OCO-2 for CO_2 retrievals.” This has since been corrected to “JPL/Caltech OCO-2 for CO_2 retrievals.”