Dear Prof. Nicola Maher,

We are resubmitting the revised manuscript of esd-2019-46 by Hideo Shiogama et al. Based on the advice of the reviewers, we changed the title to "Historical and future anthropogenic warming effects on droughts, fires and fire emissions of CO2 and PM2.5 in equatorial Asia when 2015-like El Niño events occur".

>Thank you for the submission of this interesting manuscript to this special issue.
>While the reviews were generally positive, I am asking for major revisions to your manuscript.
>In particular the reviewers raised concerns about the context of your study in relation to previous
> work, particularly Lestari et al. (2014).

We explain the probabilistic event attribution approach, the difference between Lestari et al. (2014) and the present study, and why 100 member ensembles are necessary in lines 54-95 and 263-266. Because the 10 member ensembles of Lestari et al. (2014) are too small to examine how historical climate changes affected the probability of extreme events, we use 100 member ensembles [lines 74-76].

>There was also some confusion around the implications section, abstract and presentation
> which require revision to make the manuscript clearer and the results more understandable.
> I look forward to reading the revised manuscript.

Because our descriptions of experimental designs were not enough in the original manuscript, the reviewers were confused. Therefore we have added many sentences to explain our experiments and logics.

To help the reviewers, we have highlighted the changes in red colours in the clean version of the manuscript. We hope the revised manuscript satisfies you and the reviewers.

Best regards,
Hideo Shiogama

Reply to reviewer #1

Thank you very much for your helpful comments. Based on your comments, we have improved the manuscript.

The title of the study is confusing. Is it about historical and future anthropogenic warming effects on the year 2015? — could future anthropogenic warming have an impact on a past year?

Based on the advice of the other reviewers, we changed the title to "Historical and future anthropogenic warming effects on droughts, fires and fire emissions of CO_2 and PM2.5 in equatorial Asia when 2015-like El Niño events occur". We investigated the historical anthropogenic warming effects on the 2015 event and also assessed how future warming can affect droughts, fire and emissions when 2015-like El Niño events occur in 1.5, 2.0 and 3.0 degree Celsius warmed climates. [lines 16-22, 59-95 and section 3].

Equally confusing is the abstract. For instance, "we suggest that historical anthropogenic warming increased the chances of meteorological droughts exceeding the 2015 observations in the EA area : : :.." (line 15-29). What does it mean exactly? Which period are those claims referring to?

Please note that we compare factual condition simulations (Hist) and counterfactual natural forcing condition simulations (Nat). In both ensembles, the SST is prescribed as that the 2015-like El Niño occurs. In the Nat ensembles, anthropogenic warming from the preindustrial to the present is removed from the SST data. By comparing these two large-member ensembles, we suggest that historical anthropogenic warming increased the probability of meteorological droughts exceeding a given threshold when the 2015 El Niño event occurred. [lines 16-18, 59-78, 146-159]

The abstract lacks fundamental clarity, so does the paper. It seems to me that the authors have not sorted out a coherent logic chain to tell a concrete story. Instead, the paper presents a series of model results without a clear rationale to make sense of it. Last but not least, several figures of this paper have been documented by previous studies as cited in the paper (in slight variations); I do not see added value from the duplication. Therefore, I recommend rejecting this paper in its current form.

Our explanations were not enough in the original manuscript. Therefore we have added many explanations of the experimental designs and our logics as mentioned below. We hope that these explanations help the reviewers and readers to better understand our results.

For example, in lines 59-78, we explain the probabilistic event attribution approach as follows: "Although Lestari et al. (2014) showed the anthropogenic effects on the *historical trends in droughts,* it is not clear how historical climate changes affected the *particular drought event of 2015.* Because extreme events can occur by natural variability alone, it is difficult in principle to attribute a particular event to anthropogenic climate change. However, comparisons of observations and large ensemble simulations can help us evaluate the degree to which human influence has affected the probability of a particular event (Allen 2003). Such an approach is called probabilistic event attribution (PEA) (Pall et al. 2011, Shiogama et al. 2013). In the PEA approach, two large ensemble simulations (e.g., 100 members) are generally performed. The first is historical simulations of an AGCM driven by the historical values of anthropogenic (e.g., greenhouse gases) and natural forcing (solar and volcanic activities) agents and by the observed sea surface temperature (SST) and sea ice concentration (SIC). The second is counterfactual natural runs driven by preindustrial anthropogenic and historical natural forcing agents and by the observed values of SST and SIC cooled according to estimates of anthropogenic warming (Stone et al. 2019) (see section 3 for more details). Note that the components of interannual variations in the SST data are not modified in the natural forcing ensemble. Therefore, for example, we can assess how anthropogenic warming affected the probabilities of drought events exceeding the observed value in the 2015 major El Niño year by comparing the distributions of members in historical and natural forcing ensembles. In this study, based on the PEA approach, we examine whether historical climate changes increased not only the probabilities of drought but also those of fire and fire emissions of CO_2 and $PM_{2.5}$ during the June-November dry season of 2015. Because the 10 member ensembles of Lestari et al. (2014) are too small to estimate probabilities of extreme events, we use 100 member ensembles of Shiogama et al. (2014). The lower computing costs of AGCM than AOGCM enable us to perform large ensembles, which are necessary for PEA."

In lines 79-95 we explain our future experiments and their relationships to the Paris Agreement goals and the emission gaps as follows: "Although Lestari et al. (2014) and Yin et al. (2016) showed increases in droughts and fires in the future projection ensembles of AOGCMs, it is not clear how future anthropogenic warming affects droughts and fire when events like the 2015 El Niño occur in a future warmer climate. It is important to investigate changes in extreme events at 1.5ºC and 2.0ºC warming levels to inform stakeholders after that the Paris Agreement set the 2°C long-term climate stabilization goal and moreover state pursuing 1.5 °C for stabilization (United

Nations Framework Convention on Climate Change 2015), but Lestari et al. (2014) and Yin et al. (2016) did not perform such analyses. In this study, we examine how the probabilities of drought, fire and fire emissions of CO_2 and $PM_{2.5}$ would change when major El Niño events like 2015 occur under 1.5ºC and 2.0ºC warmed climates. We analyse large (100-member) ensembles of the MIROC5 AGCM under the Half a degree Additional warming, Prognosis and Projected Impacts (HAPPI) project, which was initiated in response to the Paris agreement (Mitchell et al., 2016, 2017, 2018; Shiogama et al., 2019). These MIROC5 HAPPI ensembles have been used, for example, to study the changes in extreme hot days (Wehner et al., 2018), extreme heat-related mortality (Mitchell et al., 2018), tropical rainy season length (Saeed et al., 2018) and global drought (Liu et al., 2018) at 1.5ºC and 2.0ºC global warming. There is a significant "emissions gap", which is the gap between where we are likely to be and where we need to be (United Nations Environment Programme 2018). The current mitigation policies of nations would lead to global warming of approximately 3.2°C (with a range of 2.9-3.4°C) by 2100 (United Nations Environment Programme 2018). Therefore, it is worthwhile to compare changes in extreme events and impacts in cases where the 1.5ºC and 2.0ºC goals are achieved or not. Therefore, we perform and analyse a large ensemble of a 3.0ºC warmed climate."

It seems that you believe that Fig. 2 is a duplication. We do not insist to say Fig. 2 is a new result [lines 126-128]. Our main aims are that we combine those empirical functions (not new) with the large ensemble simulations of droughts to assess the climate change effects on fire and emissions when 2015-like El Nino events occur at the warming levels of the present, the Paris agreement goals and the current mitigation trajectory (new results).

Please see a few technical issues below (not an exhaustive list):
Line 47: "this study has three aims." What is its relevance given the studies mentioned in the previous paragraph?

We explain the relationships between the previous studies (Lestari et al. 2014 and Yin et al. 2016) and this study in lines 59-95 and 263-266.

Line 48: A higher-level introduction of the "probabilistic event attribution approach" is necessary for the readers to understand the concept. While technical details could refer to published papers, the general principle should be properly introduced.

We introduce further details of the "probabilistic event attribution approach" in lines 59-78 and 146-159.

Line 55-56: On what temporal horizon? This point is not clear at all. After reading the entire paper, it appears to me that the warming scenarios (1.5, 2.0, or 3.0 C) is defined regarding the reference year 2100. However, the simulated results in 2015 are discussed. This setting is problematic since the emission changes in each scenario are not linear across the century, what does it mean when comparing the first few years? The starting and ending point of the simulations are not clearly stated. The use of those simulations is not adequately justified.

We added SST anomalies of 1.5, 2.0, or 3.0 °C warmer climate (relative to the preindustrial) scenarios at the end of the 21^{st} century taken from the RCP experiments of the CMIP5 AOGCMs for the observed 2006-2016 SST (HaISST) data. By using these experiments, we can investigate changes in droughts and fires when 2015-like El Nino events occur at the given future warmed levels, such as the 1.5°C and 2.0°C goals of the Paris Agreement. The computing cost of AGCM is lower than AOGCMs, which enables us to perform large ensembles (100 members for each experiment) that are necessary to estimate changes in the probabilities of extreme events. Please see lines 79-95 and 160-188 for more details.

Line 64: It will be helpful to state clearly how many ensemble members for each scenario, covering which period, based on what emission trajectory.

We state the ensemble numbers (100 for each experiment), period (11 or 10 years) and emission scenarios in section 3.

Line 77: “Although socio-economic factors are important for fire activities, we only examine the effects of climate change in this study.” “climate change” here refers to simulated climate given different forcing scenarios, which by definition accounts for socio-economic factors. Maybe, the authors are referring to local land-use change impact? It is important to make those distinctions to make sense of the results.

We rewrote the sentence to “Although conversions of forest and peatlands to agriculture and plantations of oil palm are also important factors for fire activities (Marlier et al., 2013, 2015; Kim et al., 2015), we do not examine the effects of land use change in this study. ” [lines 104-105]

Section 2. Compared to the papers cited here, I do not see any new contribution from this section. It just shows what has been done, without any new data or insight.

Our main results are that we combine those empirical functions with the estimated probability functions of droughts based on the large ensembles to assess the historical and future warming effects on the probabilities of fire and emissions. We do not say that section 2 presents new results, but we do show the empirical functions here in order to use them in the following sections. [lines 114-129 and 215-221]

Line 118: "Please note that both the Hist and Nat ensembles have the same spatial SST patterns as the 2015 El NinÌCˇ o event". How so?

Please see lines 146-159 for the details regarding the experimental design.

Line 124: If the simulation periods are 2006-2015, how come are they future simulations???

As mentioned above, we simulated extreme events when 2015-like El Nino events occur in the given future warming levels. [lines 18-22, 79-95 and 160-188]

Line 136: Why is showing sea ice (Fig. 5) relevant to this study? Similarly, it is not clear about the role of results showing in Figure 4 to Figure 7.

This is the second paper in which the 3°C runs of the HAPPI project have been performed. Although the first paper (Lo et al. 2019, using the different AGCM) briefly described the experimental design, it could not show the SST and ice patterns due to the limited space of paper. Therefore, we wanted to show the SST and sea ice patterns in Figs. 4-5 of the original manuscript. However, it is not necessary to include these figures in the main text. We have moved those to the supplementary material (Supplementary Figs. 2-4).

Figures 6 and 7 of the original manuscript (Figs. 4-5 of the current manuscript) are necessary in the main text to explain that the differences in the described SST between Niño 3.4 and the 30°S-30°N ocean clearly affect the vertical motion and precipitation anomalies in the EA region. Fig. 7 (Fig. 5 of the current version) is used to investigate why the precipitation anomalies of 1.5°C are slightly larger than those of 2.0°C. [lines 195-203]

Line 169: Are you comparing fire and fossil fuel emissions from Japan? Not clear.

We included this comparison because it was highlighted that the fire emissions of EA exceeded the fossil fuel emissions from Japan when the massive 2015 fire event occurred (e.g., Field et al. 2016). However, readers other than Japanese readers may be not interested in this comparison. Therefore, we have omitted this paragraph.

Line 192-194: By now, it is still difficult to understand what do they mean.
Line 192-212: The conclusion is far reached.
We hope that the additional explanations of the probabilistic event attribution approach and the experimental design mentioned above help you to understand our results and why we have reached these conclusions.

Line 197: “somewhat”?
We rephrased “somewhat” to “tended to increase” [line 259].

Reply to the reviewer #2

Thank you very much for your helpful comments. Based on your comments, we have improved the manuscript.

General comments:

The authors present a policy-relevant study of changes in precipitation deficits and fire metrics in equatorial Asia (EA) during a 2015-like El Niño event and in a decadal average sense at 1.5_, 2_, and 3_C warming levels. Results are based on a factual counterfactual probabilistic event attribution approach in a MIROC5 AGCM large ensemble framework. The following questions are explored:

• Did historical climate change increase the probability of the 2015 event?

• How will probabilities of drought, fire and fire emissions change when a major El Niño event similar to the one in 2015 occurs in 1.5_C, 2.0_C, 3.0_C climate.

Authors find that historical anthropogenic forcing has increased the likelihood of a drier than-2015 El Niño-driven precipitation deficit in the EA from 2% to 9%. At 1.5_C of warming, a drier event is 82% likely to occur. At 2_C of warming, the probability of a drier event drops to 67% likely (for reasons that are not entirely clear) but increases to 93% at 3_C of warming. This increased risk of drier conditions during El Niño events has ramifications for burned area extent, CO2 and particulate emissions in the regions.

The paper could be a valuable addition to the current body of literature on extreme events in warmer climates and the figures presented are clear and easy to interpret. There is care taken to connect findings to policy considerations whenever possible, particularly possible underestimates of EA CO_2 emissions under climate change scenarios. However, the interesting findings would benefit from additional detail on the method, model experimental framework, relationships between relevant processes, and, most critically, on the value-add gained by using a 100-member large ensemble as opposed to 10-member ensembles. Addressing the specific comments below should more than adequately clarify and strengthen conclusions.

Thank you very much for the helpful comments. Please see the section below for our detailed responses to your specific comments.

Specific comments:

I recommend omitting the phrase: “the year” from the title.

Thank you. We changed the title to “Historical and future anthropogenic warming effects on droughts, fires and fire emissions of CO_2 and $PM_{2.5}$ in equatorial Asia when 2015-like El Niño events occur”.

Abstract On what is the statement “caused” based on? [L14] What is the dry season in Equatorial Asia (i.e., in terms of months)? [L15] The acronym PM2.5 is not yet defined [L21]

Based on previous studies and the analyses of Figs. 1-3 (e.g., Fig. 3c shows the -0.89 correlation between the Nino3.4 SST and precipitation anomalies), we stated “caused”, but this terms may be too strong. We rephrased it to “contributed to”. [line 15]

The dry season is June-November. [line 16]

We define acronym PM2.5 in lines 23-24.

Introduction It would be helpful to explicitly define when EA dry season occurs: : : Is the EA region the same as the SEA SREX region? If not, the specific latitude and longitude boundaries should be given. [L32-34]

We define the EA dry season (June-November) in line 37. We apologize that the EA region shown in the original Fig. 1 was incorrect. Actually, we use the definition of the EA region of GFED4s. We show the EA region in Fig. 1g and explain it in the caption of Fig. 1 and line 37.

Could you explain the ENSO phenomenon and how and why it “enhanced severe drought" to help guide readers? How did the 2015 drought compare to other ENSO events? This can be done through an explanation of the relationship between Walker circulation and convection and by including relevant citations on how the 2015 event compares to other El Nino in terms of effect on EA climate. [L32-34]

We explain the relationships between the 2015 El Niño and drought in lines 36-44 and 139-145.

Is the whole EA region considered tropical peatland? Can that qualification be defined (i.e. what is tropical peatland) and can it be explained why the region is susceptible to biomass burning? [L33]

We have improved these sentences as follows: “Parts of the EA region are tropical peatlands that contain tremendous amounts of soil organic carbon (Page et al., 2011) and huge biomass

(Baccini et al., 2012, 2017; Saatchi et al., 2011). Coupled with anthropogenic land-use change (e.g., expansion of oil palm plantations on peatlands), the severe drought increased fire activities in forests and peatlands" [lines 45-47]

Can you elaborate more on the findings of Lestari et al. 2014? It will help readers understand how this new study extends the findings. [L43]
I also recommend the following edit: "We use a probabilistic event attribution approach similar to Lestari et al. (2014), but our results are based on 100-member large ensembles of the MIROC5 AGCM with and without anthropogenic warming as opposed to 10-member ensembles." Then, a statement should be made about why the large ensembles were necessary and important to use. Justifying and highlighting the importance of large ensembles is a key point, especially for a special journal edition dedicated to large ensembles. [L48-50]

We explain the probabilistic event attribution approach, the difference between Lestari et al. (2014) and the present study, and why 100 member ensembles are necessary in lines 54-95 and 263-266. Because the 10 member ensembles of Lestari et al. (2014) are too small to examine how historical climate changes affected the probability of extreme events, we use 100 member ensembles [lines 74-76].

Question 1: Did historical climate change increase the probability of the 2015 event? How is historical climate change defined? Is it with respect to a certain base period? How is "change" defined in the presence of natural variability? [L47]
Can you elaborate on the probabilistic event attribution approach used in this study? It will help readers who are not familiar with detection and attribution techniques understand the opportunities and limitations of these approaches. How were they used in these cited papers? What were some of the key findings? [L48-54]

Historical climate change increased the probability of the 2015 drought event. We explain more details of the event attribution approach in lines 59-78 and 146-159, which should help readers understand how we define "historical change". On the other hand, we shorten the text mentioning the previous event attribution papers to prevent the paragraph from being too long [lines 76-78].

Question 2/3: Could these two sections be combined into one section about risk at 1.5, 2.0, and 3.0_C warming? [L55]

We combine those paragraphs regarding the risks at 1.5, 2.0, and 3.0°C warming into one paragraph. [lines 79-95].

Just a small comment but can the connection between the initiation of the HAPPI project and the Paris agreement be smoothed out a little? Was the HAPPI project initiated in response to or to inform the Paris agreement? [L56-61]

The HAPPI project was initiated in response to the Paris agreement. [line 87]

In regards to "Although socio-economic factors (e.g., conversions of forest and peatlands to agriculture and plantations of oil palm) are also important for fire activities (Marlier et al., 2013, 2015; Kim et al., 2015), we only examine the effects of climate change in this study." Does this mean land-use change is not considered? What are the relevant "effects of climate change" on these events (i.e. warmer mean temperature, circulation changes, changes in ENSO?)

We rewrote those sentences to "Although conversions of forest and peatlands to agriculture and plantations of oil palm are also important factors for fire activities (Marlier et al., 2013, 2015; Kim et al., 2015), we do not examine effects of land use change in this study." [lines 104-105]

Empirical functions: Can you elaborate on your observational dataset choices? Why did you choose the reanalysis products you use? How are the enhanced fire fraction, fire CO2 emissions and fire $PM_{2:5}$ emissions computed in the Global Fire Emissions Database?

ERA Interim reanalysis (ERA-I) data (Dee et al., 2011) are used for temperature and vertical circulation. GPCP is precipitation data that merge rain gauge stations, satellites, and sounding observations to estimate monthly rainfall on a 2.5-degree global grid from 1979 to present. Because these datasets have been used by an enormous number of atmospheric circulation studies, we also analyze these data. [lines 39-40]

By combining satellite information on fire activity and vegetation productivity, GFED4s provide monthly burned area, fire carbon and dry matter (DM) emissions. We can also compute aerosol emissions by multiplying DM by the provided factors. [lines 110-114]

Could a figure demonstrating the relationship between burned area, CO2 emissions, and particulate emissions be included? Is there a linear relationship between burned area and emissions?

Supplementary Figure 1 shows the relationships between fires and fire emissions in the EA area of the GFED4s during 1997-2016. Clear linear relationships are shown. [line 114]

What are the empirical functions used for in this study?

We use the relationships in Figs. 2a-c as the empirical functions to estimate fire and emissions from the simulated precipitation. [lines 119-129 and 214-221]

Model simulations: Can you provide a further description of the MIROC5 AGCM? I.e. what is the horizontal resolution of the atmosphere? What observed SSTs specifically were used, particularly for the "natural" SST? How was the "long-term anthropogenic signal" defined and removed?

The MIROC5 AGCM has a 160 km horizontal resolution [line 132]. We used the HadISST data for the observed SST [lines 133-134]. We explain the long-term signal of SST and the Nat SST in lines 153-159.

Most importantly, what fire model is used? How is it related to the land surface state and coupled to the atmosphere? What triggers a fire in the model? How are CO_2 and $PM_{2:5}$ concentrations determined for a given event? [L103-121]

The MIROC5 model has no fire module. Therefore, we used the empirical functions of Fig. 2 to estimate fire and emissions from the simulated precipitation. [lines 128-129 and 214-221]

What are the "corresponding standard deviation values"? [L108]

Here, the observed $\triangle P$ and $\triangle\omega 500$ are divided by their own standard deviation values. The $\triangle P$ and $\triangle\omega 500$ of each ensemble member are also divided by their own standard deviation values. [lines 134-136]

Throughout the study, the descriptions of the figures are a little brief. In this case: "The precipitation and vertical motion anomalies are closely related to the Nino 3.4 SST (an index of El Niño Southern Oscillation) in the observations, and the MIROC5 model represents these relationships well (Figs. 3c-e)." How are they related (i.e., subsidence and reductions in rainfall during an El Niño)? What does "represent these relationships well" mean (i.e., significantly correlated with observations)? [L108-110]

We have improved the descriptions in lines 139-145:
"The precipitation and vertical motion anomalies are closely related to the Nino 3.4 SST (an index of El Niño Southern Oscillation) in the observations (correlations are -0.89 and 0.76, respectively) (Figs. 3c-d). There is also a high correlation value between $\triangle$P and $\triangle\omega$500 (-0.87) (Fig. 3e). It is suggested that El Niño (La Niña) accompanies descending wind (ascending wind) in the EA area (Fig. 3d), leading to negative (positive) $\triangle$P (Figs. 3e and 3c). The MIIROC5 model well represents these relationships between Niño 3.4, $\triangle$P and $\triangle\omega$500 in the observations (Figs. 3c-e), i.e., the regression lines of MIROC5 in Figs. 3c-e are close to those in the observations."

How were "prescribed long-term warming anomalies in SST" defined? From Figure 4, I can see that there are spatial differences in warming, where do they come from?
These details are likely important to the overall interpretation of the results and it would benefit the reader not to have to search for methodological descriptions in other studies or elsewhere in the paper. [L125-126]

We explain more details of the experimental designs of future simulations and how to add the SST anomalies in Fig. 4 to the observed data in lines 79-95 and 160-188.

The colorbar seems to be saturated in the bottom panel of Figure 4 over much of the Northern hemisphere, could the scale be adjusted to accommodate the 3_C mean difference? Is there a difference between the respective Figure 5 top and middle panels?

We changed the color scale in Supplementary Fig. 2. Supplementary Fig. 4 shows the sea ice differences.

Could you detail how these results were reached using the cumulative density functions? Particularly, how did the use of large ensembles affect the results? Does the "chance of exceedance" change with fewer members? [L154-158]

To help readers understand our results, we add "2% (1-4%) in Nat to 9% (6-14%) in Hist", "(in the 1.5°C and 2.0°C runs)" and "(in the 3.0°C runs)" in lines 206, 211 and 213.

The large ensemble simulations enable us to estimate the probabilities of drought exceeding the observed value [line 204]. We cannot robustly examine the probabilities using only the 10 members (10 samples) of Lestari et al. (2014) [lines 74-75].

Can you comment on why the chance of precipitation reduction exceedance more probable in the 1.5_ scenario than the 2_ scenario? [L157]

We explain this in lines 195-203.

“2015 CO2 emission of Japan due to fossil fuel consumptions" is a missing a citation [L168-169]

We included this comparison because it was highlighted that the fire emissions of EA exceeded the fossil fuel emissions from Japan when the massive 2015 fire event occurred (e.g., Field et al. 2016). However, readers other than Japanese readers may be not interested in this comparison. Therefore, we have omitted this paragraph.

I am sorry I may have missed something, but what is the AIM/CGE model used for? Was it introduced in the methods section? [L179-180]

AIM/CGE is the one of integrated assessment models (economic models) that produced emissions data for the SSP scenarios of CMIP6. In this paragraph, we suggest that additional fire CO_2 emissions due to climate change should be considered in emission scenarios that are used for the next CMIP7 future projection experiments. We have improved this paragraph [lines 228-248].

Reply to the reviewer #3

Thank you very much for your helpful comments. Based on your comments, we have improved the manuscript.

General comments: This study examines global warming impacts on fire activities, focusing on the burned area and fire emissions of CO_2 and PM2.5 over equatorial Asia. Considering June-November 2015 when a strong El-Nino induced a large decrease in precipitation over the area, the authors examine changes in the probabilities of droughts and fire activities due to anthropogenic influences using the MIROC5 AGCM large ensemble (100 members) simulations. They find increased probabilities of the droughts and fire activities as global warming become stronger. In particular, they show that 3.0 degree warming that represents the current mitigation policies would bring severe droughts and increased fire activities due to the intensified El Nino at near 100% chance. I find this paper overall well written, providing interesting and policy-relevant results. However, there are a few issues, mostly related to uncertainty factors, which need to be improved through revision.

Thank you. Please see our replies to the following comments.

Major points: 1. Model dependency: It would be useful to discuss limitations of the atmospheric model experiments and its possible impacts on the results. Particularly, precipitation changes in the future warming simulations are shown to be critical for determining changes in fire burned area and CO_2 and PM2.5 emissions (Fig. 8), but atmospheric models tend to have large biases in precipitation over the Tropics partly related to the omission of air-sea coupling. It seems that normalized precipitation is used to overcome this problem but some justification would be needed with showing precipitation bias of the model. In addition, future projections of precipitation look highly dependent on the SST change patterns (Fig. 4). Uncertainty in these SST change patterns needs to be discussed as well.

Unfortunately, MIROC5 is only one model that produced all the Nat, Hist, 1.5°C, 2°C and 3°C ensembles. Therefore, we cannot use the other HAPPI models for this study. With a simple bias correction (i.e., dividing precipitation anomalies by their standard deviation values), the MIROC5 model has very good hindcast skill regarding interannual variability in the EA-averaged $\triangle P$ and $\triangle\omega500$ (correlation values between the model and observations are ~0.9) [lines 134-145]. We also suggest that our future projections are consistent with previous studies that have analyzed the CMIP5 ensemble: Lestari et al. (2014) and Yin et al. (2016) also showed that the coupled model ensembles of CMIP5 projected future drying trends and enhanced fire carbon emissions [lines 263-266]. We also add a caveat in lines 280-282.

2. New findings: New results compared to previous studies are not clearly explained, in particular, in view of Lestari et al. (2014). What advances have been achieved by increasing ensemble size? Adding more information on this would be helpful, such as how to construct ensembles and how uncertainty is assessed with the large ensemble simulations.

Although Lestari et al. (2014) showed anthropogenic effects on the historical trends of droughts, it is not clear how historical climate changes affected the *particular drought event of 2015*. Based on probabilistic event attribution, we investigated whether historical climate changes affected the 2015 event. Because the 10 member ensembles of Lestari et al. (2014) are too small to estimate the probabilities of extreme events, we use 100 member ensembles of Shiogama et al. (2014). The computing cost of AGCM is lower than AOGCM, which enables us to perform such large ensembles that are necessary for PEA. [lines 59-78 and 204]

Although Lestari et al. (2014) and Yin et al. (2016) showed increases in droughts and fires in the future projection ensembles of AOGCMs, it is not clear how future anthropogenic warming affects droughts and fire when 2015-like El Niño events occur in a future warmer climate. It is important to investigate changes in extreme events at 1.5ºC and 2.0ºC warming levels to inform stakeholders, as the Paris Agreement set the 2°C long-term climate stabilization goal and is pursuing 1.5 °C to reach stabilization (United Nations Framework Convention on Climate Change 2015), but Lestari et al. (2014) and Yin et al. (2016) did not perform such analyses. In this study, we examine how the probabilities of drought, fire and fire emissions of CO_2 and $PM_{2.5}$ would change when major events like the 2015 El Niño occur under 1.5ºC, 2.0ºC and 3.0ºC warmed climates. [lines 79-95 and 263-266].

We added details of the experimental designs in section 3. We also explain how uncertainty is assessed with the large ensemble simulations below.

Also, the empirical relation between precipitation and fire activities is used to estimate future changes in fire activities and the authors consider its uncertainty somehow in their analysis. I think this part is important and more details needs be provided on its uncertainty ranges and associated impacts on main results. See my specific points below.

L141-144: This way of sampling looks important to capture uncertainty arising from internal variability, and showing resulting spreads in P and omega responses in Fig. 7 would be interesting. Also, it would be useful to explain here how to construct CDF using 1000 samples and estimate probabilities exceeding the observed value and its 10-90% confidence intervals. L161: “1000 random samples of the regression factors in Eq. 1”. Please provide details given its importance. Also see my major comment.

We explain how to construct the CDFs and estimate the uncertainty ranges by using the large ensembles and the resampling techniques as follows.

“We also estimate the 10%-90% confidence intervals of the fitting curves by applying a 1000-time random sampling of the observed data: we randomly resample 20-year samples from the original 20-year (1997-2016) data and compute a and b; we repeat the random resampling process 1000-times; we consider that the 10%-tile and 90%-tile values of the 1000 regression lines indicate the 10%-90% confidence intervals. ” [123-126]

“Here, we use the cumulative histograms of 100×10=1000 samples of △P to estimate the probabilities of △P. The values in parentheses indicate the 10-90% confidence interval estimated by applying the 1000-time resampling: we randomly resample 100×10 data from the original 100×10 samples of △P and compute the probabilities of drought exceeding the 2015 observed value; we repeat the random resampling process 1000-times and consider the 10%-tile and 90%-tile values of the 1000 estimates of probability as the 10-90% bounds.” [lines 206-210]

“ We consider uncertainties by combining randomly resampled △P and resampled regression factors of Eq. 1: (i) we compute the regression factors of Eq. 1 using randomly resampled data (the same as the process used to estimate the uncertainty ranges of the regression lines); (ii) we randomly resample 100×10 data from the original 100×10 samples of △P; (iii) we use the regression factors of (i) and the 100×10 △P samples of (ii) to compute the 1000 estimates of fire or emissions and estimate the probability of exceeding the observed values; (iv) the processes of (i)-(iii) are repeated 1000-times; and (v) the 10%-tile and 90%-tile values of the 1000 estimates of the probabilities of exceeding the observed values are considered to be the 10-90% bounds.” [lines 215-221]

3. Implications: The last part on implications is rather confusing and hard to follow. I would suggest rephrasing it for better understanding. For example, it is unclear what are exactly

compared between MIROC5-based estimations and diverse SSP scenarios: fire CO_2 emissions due to climate change versus land use CO_2 emissions? From this comparison, the authors seem to suggest that additional fire CO_2 emissions due to climate change should be considered in SSP scenarios, but this interpretation is not that clear at the present form. I am wondering if it can be made more specific by suggesting how much increase in CO_2 emissions should be added, for example.

We improved this paragraph [lines 228-248]. Currently, it is not easy to compute fire CO_2 emissions due to future drying in AIM/CGE because we have to develop a new fire module considering climate change effects on fire for AIM/CGE. The development of such a new module is an issue for subsequent CMIP7 activity.

Specific points: Title: “year 2015” sounds a bit strange to be connected with “future” warming effects. How about saying “2015-like” or similar instead.

We changed the title to “Historical and future anthropogenic warming effects on droughts, fires and fire emissions of CO_2 and $PM_{2.5}$ in equatorial Asia when 2015-like El Niño events occur”

L87-88: How is the EA box selected? I think it can be adjusted (e.g., narrower in zonal direction) to better capture the P decrease area. Or it doesn’t matter since only land is considered? Please clarify this.

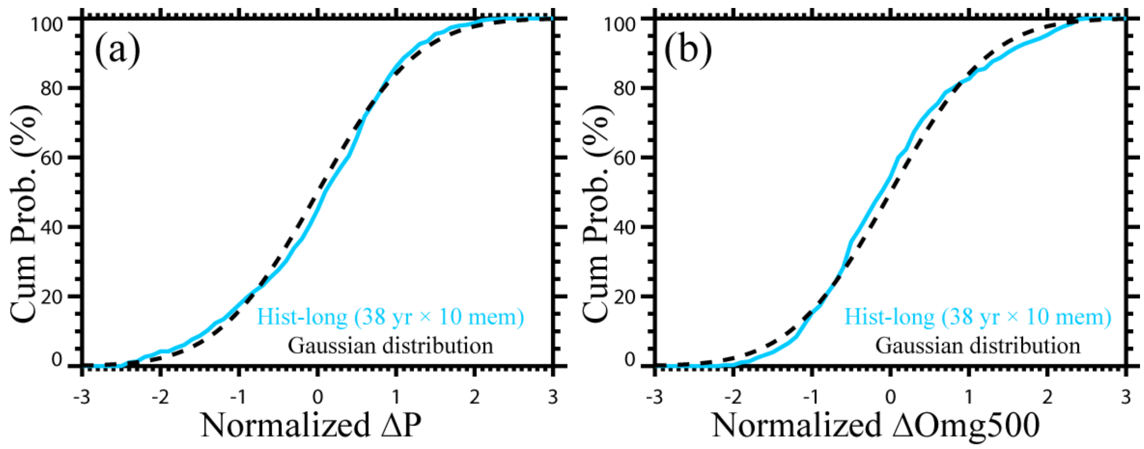
We apologize that the EA region shown in the original Fig. 1 was incorrect. Actually, we use the definition of the EA region of GFED4s. We show the EA region in Figure 1g and explain it in the caption of Figure 1 and lines 36-37.

L91-92: In line with “precipitation anomalies and accumulated water deficits”, wouldn’t it be better to use accumulated precipitation like SPI?

We use the June-November mean precipitation, which is the accumulated precipitation during the dry season divided by the period length. Therefore, we substantially use the accumulated precipitation anomalies.

L93, L108: “divided by standard deviation”. Can we assume normality for precipitation and omega anomalies? Area averaged 6-month mean values might be okay but a quick check would be useful.

The following figure shows the cumulative distribution functions of normalized precipitation and omega anomalies and those of Gaussian distribution. It is suggested that the area-averaged 6-month mean values have a Gaussian distribution.



L115: I would suggest providing more details on how "long-term anthropogenic signals were removed" as SST patterns are important for determining precipitation responses to El Nino.

Anthropogenic SST changes were estimated by taking the ensemble mean differences between the all-forcing historical runs and the natural-forcing historical runs of the CMIP5 ensembles. The multi-model averaged anthropogenic signals were subtracted from the HadISST data, and the Nat sea ice was estimated by using empirical functions between observed sea ice concentrations and surface temperature. [lines 153-159]

L122: "100 member ensembles during 2006-2015 with 1.5 degree and 2.0 degree warming". Do it mean that ensemble runs are performed only for Plus15 and Plus20 or there are 100-member HIST runs for 2006-2015 as well?

We performed 100 member runs of 2006-2016 for each of Hist, Nat, Plus15 and Plus20 [lines 158-159, 160-161 and 166-167]. The Plus30 are 100 member runs of 2006-2015 [line 176].

L150-153: Why stronger El Nino (and P responses) are simulated in 1.5 degree warming simulations than 2.0 degree ones? Some discussion needs to be provided. Does it occur in all

1000 samples? Do other HAPPI models share this or is this a characteristic of MIROC5?

All the HAPPI models share the SST anomalies that were taken from the CMIP5 model ensembles [lines 160-175]. It is not clear why the ensemble average of the CMIP5 RCP2.6 runs (i.e., the prescribed SST anomalies of the 1.5 ºC runs) has a larger SST difference between the Niño 3.4 region and the tropical ocean mean than that of the weighted sum of RCP2.6 and RCP4.5 (the 2.0 ºC runs) [lines 201-203]. The differences in the prescribed SST warming contrasts between the 1.5°C and 2°C runs cause the difference between the blue and green CDFs in Fig. 6a [195-212].

L163-164: Please explain how to assess significance of this change.

By comparing the uncertainty bounds of future changes with the uncertainty bounds of Hist and Nat, we assess the significance of changes.

L169: Why is the emission of Japan used as reference here?

We included this comparison because it was highlighted that the fire emissions of EA exceeded the fossil fuel emissions from Japan when the 2015 massive fire event occurred (e.g., Field et al. 2016). However, readers other than Japanese readers may be not interested in this comparison. Therefore, we omitted this paragraph.

L172: First sentence. This needs to be mentioned clearly above and also in figure captions to avoid confusing.
L172-188: This paragraph and Fig. 9 are hard to follow with many skips and limited explanations. Please consider rephrasing it. See my major comment above.

We have improved our explanations in lines 228-248.

L196: “82%, 68%, and 93%”. Please add uncertainty ranges or indicate these are ensemble means or medians. Same for L204.

We add the uncertainty ranges in lines 254, 256 and 261-263.

L199-202: Model dependency issue is here. How representative is MIROC5 projected precipitation in the future? Any comparison with other models would be useful. See my major comment above.

Please see our responses to your major comments.

L205: “additional changes”. Are these significant?

Although the differences between 2.0°C and 3.0°C are not statistically significant for the burned area and the CO_2 and $PM_{2.5}$ emissions, the 50th percentile values of probabilities exceeding the 2015 observations first reach approximately 100% in the 3.0°C runs. [lines 270-272]

L209: “modifying fire CO2 emissions scenarios”. Can authors suggest how much modification is needed? See my major comment above.

Currently, it is not easy to compute fire CO2 emissions due to future drying in AIM/CGE because we have to develop a new fire module considering climate change effects on fire for AIM/CGE. The development of such a new module is an issue for subsequent CMIP7 activity.

Fig. 1: Line 342: “left panels” should be “right panels”.

We corrected this issue in the caption of Fig. 1.

Fig. 2: There seems to be a stronger case than 2015, perhaps 1998? Where is 1982 that has also a stronger P decrease in Fig. 3? It may affect fitted curves.

We apologize that the explanations of the original manuscript were not corrected. Although we used 1979-2016 GPCP data, GFED4s covered only 1997-2016. Thus, Fig. 2 shows the scatter plots between precipitation and GFED4s during 1997-2016, not 1979-2016. We corrected this mistake in lines 116-119 and the caption of Fig. 2. Therefore, 1982 is not included in this figure. The 1997 case (the 1997-1998 El Nino) is stronger than 2015 case. We indicate 1997 in Fig. 2.

Fig. 3: Indicating 2015 case in time series and scatter plots would be useful. Is there any underestimation or overestimation by models in P and omega responses?

We indicate the 2015 case in Fig. 3. The model estimates P and omega responses well [lines 136-145].

Fig. 6: It's not clear why difference from NAT is shown even for future changes. Is this for 2015 or using all years?

We show differences from NAT because the mixing of differences from Hist for future changes and that from NAT for Hist may confuse readers. These figures are for 2015 (caption of Fig. 4).

Fig. 7: Is this also for 2015? Related to my major comment on model dependency issue, are these are supported by other coupled models?

This figure is for 2015. Please see our responses to your major comments.

Fig. 9: Difficult to understand. How is the CDF of CO_2 emissions (red curves) estimated? Are these CO_2 emissions only due to increased fire over equatorial Asia?

We improved the descriptions in lines 228-248.

Historical and future anthropogenic warming effects on droughts, fires and fire emissions of CO_2 and $PM_{2.5}$ in equatorial Asia when 2015-like El Niño events occur

Hideo Shiogama[1, 2], Ryuichi Hirata[1], Tomoko Hasegawa[3], Shinichiro Fujimori[4], Noriko Ishizaki[1], Satoru Chatani[1], Masahiro Watanabe[2], Daniel Mitchell[5], Y. T. Eunice Lo[5]

[1]National Institute for Environmental Studies, 16-2 Onogawa, Tsukuba, Ibaraki 305-8506, Japan
[2]Atmosphere and Ocean Research Institute, University of Tokyo, 5-1-5 Kashiwanoha, Kashiwa, Chiba 277-8564, Japan
[3]College of Science and Engineering, Ritsumeikan University, 1-1-1 Noji-higashi, Kusatsu, Shiga 525-8577, Japan
[4]Department Environmental Engineering, Graduate School of Engineering, Kyoto University, Kyoto 615-8540 Japan
[5]School of Geographical Sciences, University of Bristol, University Road, Bristol BS8 1SS, United Kingdom

Corresponding author: Hideo Shiogama (shiogama.hideo@nies.go.jp)

Abstract. In 2015, El Niño contributed to severe droughts in equatorial Asia (EA). The severe droughts enhanced fire activities in the dry season (June-November), leading to massive fire emissions of CO_2 and aerosols. Based on large event attribution ensembles of the MIROC5 atmospheric global climate model, we suggest that historical anthropogenic warming increased the chances of meteorological droughts exceeding the 2015 observations in the EA area. We also investigate changes in drought in future climate simulations, in which prescribed sea surface temperature data have the same spatial patterns as the 2015 El Niño with long-term warming trends. Large probability increases in stronger droughts than the 2015 event are projected when events like the 2015 El Niño occur in the 1.5°C and 2.0°C warmed climate ensembles according to the Paris Agreement goals. Further drying is projected in the 3.0°C ensemble according to the current mitigation policies of nations.

We combine these experiments and empirical functions among precipitation, burned area, and fire emissions of CO_2 and fine (<2.5 micrometers) particulate matter ($PM_{2.5}$). Increases in the chances of burned areas and the emissions of CO_2 and $PM_{2.5}$ exceeding the 2015 observations due to past anthropogenic climate change are not significant. In contrast, there are significant increases in the burned area and CO_2 and $PM_{2.5}$ emissions even if the 1.5°C and 2.0°C goals are achieved. If global warming reaches 3.0°C, as is expected from the current mitigation policies of nations, the chances of burned area, CO_2 and $PM_{2.5}$ emissions exceeding the 2015 observed values become approximately 100%, at least in the single model ensembles.

We also compare changes in fire CO_2 emissions due to climate changes and the land-use CO_2 emission scenarios of five shared socioeconomic pathways, where the effects of climate change on fire are not considered. There are two main implications. First, in a national policy context, future EA climate policy will need to consider these climate change effects regarding both mitigation and adaptation aspects. Second, the consideration of fire increases would change global CO_2 emissions and the mitigation strategy, which suggests that future climate change mitigation studies should consider these factors.

1 Introduction

In 2015/2016, a major El Niño event (strongest since 1997/1998) enhanced severe drought in equatorial Asia (EA, the area denoted in Fig. 1g) during the dry season (June-November). Figures 1a-c indicate the observed June-November 2015 mean anomalies in surface air temperature ($\triangle$T), vertical pressure velocity at the 500-hPa level ($\triangle\omega_{500}$) and precipitation ($\triangle$P) relative to the 1979-2016 averages. ERA Interim reanalysis (ERA-I) data (Dee et al., 2011) are used for $\triangle$T and $\triangle\omega_{500}$. Global

Precipitation Climatology Project (GPCP) data (Adler et al., 2003) are analysed for △P. The largely positive △T over the eastern tropical Pacific Ocean (i.e., El Niño) is related to substantial downward motion anomalies (weakening of Walker circulation) and negative precipitation anomalies over the EA region (the area shown in Fig. 1g). The negative precipitation anomalies in June-November 2015 were the third largest since 1979 (the first and second largest anomalies are 1997 and 1982) (see section 2).

Parts of the EA region are tropical peatlands that contain tremendous amounts of soil organic carbon (Page et al., 2011) and huge biomass (Baccini et al., 2012, 2017; Saatchi et al., 2011). Coupled with anthropogenic land-use change (e.g., expansion of oil palm plantations on peatlands), severe drought increased fire activities in forests and peatlands, leading to wide-ranging disasters in the economy (at least 16.1 billion USD for Indonesia), ecology and human health (Taufik et al., 2017; World Bank 2016, Hartmann et al., 2018). The fires enhanced the emissions of CO_2 and aerosols (Yin et al., 2016; Field et al., 2016; Koplitz et al., 2016). The estimated 2015 CO_2-equivalent biomass burning emissions for all Indonesia (1.5 billion metric tons CO_2) were between the 2013 annual fossil fuel CO_2 emissions of Japan and India (Field et al., 2016). The massive emissions of ozone precursors and aerosols, including fine (<2.5 micrometers) particulate matter ($PM_{2.5}$), caused severe haze across much of EA (Field et al., 2016), resulting in the excess deaths of approximately 100,300 people (Koplitz et al., 2016).

In a previous study (Lestari et al., 2014), we suggested that recent fire events in Sumatra were exacerbated by human-induced drying trends based on analyses of two sets of historical simulations of the MIROC5 atmospheric global climate model (AGCM) (Watanabe et al., 2010) with and without anthropogenic warming. Lestari et al. (2014) and Yin et al. (2016) projected future increases in the frequencies of droughts and fires based on analyses of the coupled atmosphere-ocean global climate model (AOGCM) ensembles of the Coupled Model Intercomparison Project Phase 5 (CMIP5) (Taylor et al., 2012).

Although Lestari et al. (2014) showed the anthropogenic effects on the *historical trends in droughts*, it is not clear how historical climate changes affected the *particular drought event of 2015*. Because extreme events can occur by natural variability alone, it is difficult in principle to attribute a particular event to anthropogenic climate change. However, comparisons of observations and large ensemble simulations can help us evaluate the degree to which human influence has affected the probability of a particular event (Allen 2003). Such an approach is called probabilistic event attribution (PEA) (Pall et al. 2011, Shiogama et al. 2013). In the PEA approach, two large ensemble simulations (e.g., 100 members) are generally performed. The first is historical simulations of an AGCM driven by the historical values of anthropogenic (e.g., greenhouse gases) and natural forcing (solar and volcanic activities) agents and by the observed sea surface temperature (SST) and sea ice concentration (SIC). The second is counterfactual natural runs driven by preindustrial anthropogenic and historical natural forcing agents and by the observed values of SST and SIC cooled according to estimates of anthropogenic warming (Stone et al. 2019) (see section 3 for more details). Note that the components of interannual variations in the SST data are not modified in the natural forcing ensemble. Therefore, for example, we can assess how anthropogenic warming affected the probabilities of drought events exceeding the observed value in the 2015 major El Niño year by comparing the distributions of members in historical and natural forcing ensembles. In this study, based on the PEA approach, we examine whether historical climate changes increased not only the probabilities of drought but also those of fire and fire emissions of CO_2 and $PM_{2.5}$ during the June-November dry season of 2015. Because the 10 member ensembles of Lestari et al. (2014) are too small to estimate probabilities of extreme events, we use 100 member ensembles of Shiogama et al. (2014). The lower computing costs of AGCM than AOGCM enable us to perform large ensembles, which are necessary for PEA. These PEA experiments of MIROC5 have been used for many attribution studies of single extreme events (e.g., Shiogama et al., 2014, Kim et al., 2018, Hirota et al., 2018).

Although Lestari et al. (2014) and Yin et al. (2016) showed increases in droughts and fires in the future projection ensembles of AOGCMs, it is not clear how future anthropogenic warming affects droughts and fire when events like the 2015 El Niño occur in a future warmer climate. It is important to investigate changes in extreme events at 1.5ºC and 2.0ºC warming levels to inform stakeholders after that the Paris Agreement set the 2°C long-term climate stabilization goal and moreover state pursuing 1.5 °C for stabilization (United Nations Framework Convention on Climate Change 2015), but Lestari et al. (2014) and Yin et al. (2016) did not perform such analyses. In this study, we examine how the probabilities of drought, fire and fire emissions of CO_2 and $PM_{2.5}$ would change when major El Niño events like 2015 occur under 1.5ºC and 2.0ºC warmed climates. We analyse large (100-member) ensembles of the MIROC5 AGCM under the Half a degree Additional warming, Prognosis and Projected Impacts (HAPPI) project, which was initiated in response to the Paris agreement (Mitchell et al., 2016, 2017, 2018; Shiogama et al., 2019). These MIROC5 HAPPI ensembles have been used, for example, to study the changes in extreme hot days (Wehner et al., 2018), extreme heat-related mortality (Mitchell et al., 2018), tropical rainy season length (Saeed et al., 2018) and global drought (Liu et al., 2018) at 1.5ºC and 2.0ºC global warming. There is a significant "emissions gap", which is the gap between where we are likely to be and where we need to be (United Nations Environment Programme 2018). The current mitigation policies of nations would lead to global warming of approximately 3.2°C (with a range of 2.9-3.4°C) by 2100 (United Nations Environment Programme 2018). Therefore, it is worthwhile to compare changes in extreme events and impacts in cases where the 1.5ºC and 2.0ºC goals are achieved or not. Therefore, we perform and analyse a large ensemble of a 3.0ºC warmed climate.

By using the above ensembles, we answer the following questions:

(a) Has historical climate change significantly affected the probabilities of drought, fire and fire emissions of CO_2 and $PM_{2.5}$?

(b) How do the probabilities of drought, fire and fire emissions in 2015-like major El Niño years change if we can limit global warming to 1.5ºC and 2.0ºC? Adaptation investments are necessary to reduce the associated impacts.

(c) If we overshoot the 1.5ºC and 2.0ºC goals to the current trajectory of 3.0ºC, how will drought, fire and fire emissions be altered? Comparisons of the results of 3.0ºC and 2.0ºC/1.5ºC indicate the potential benefits of mitigation efforts to achieve the goals of the Paris Agreement.

Although conversions of forest and peatlands to agriculture and plantations of oil palm are also important factors for fire activities (Marlier et al., 2013, 2015; Kim et al., 2015), we do not examine the effects of land use change in this study. In sections 2 and 3, we describe the empirical functions and model simulations used in this study, respectively. In section 4, we examine changes in precipitation, fire and fire emissions. Finally, section 5 contains the conclusions.

2 Empirical functions

In the EA region, the negative precipitation anomalies are associated with the enhanced fire fraction, fire CO_2 emissions and fire $PM_{2.5}$ emissions estimated from the Global Fire Emissions Database (GFED4s) (van der Werf et al., 2017) (Figs. 1d-f). By combining satellite information on fire activity and vegetation productivity, GFED4s provide monthly burned area, fire carbon and dry matter (DM) emissions. We can also compute aerosol emissions by multiplying DM by the provided factors. The CO_2 and $PM_{2.5}$ emissions increase linearly as the burned areas expand (Supplementary Fig. 1). Previous studies found that fire activities and related emissions have non-linear relationships with precipitation anomalies and accumulated water deficits (Lestari et al., 2014; Spessa, et al. 2015; Yin et al., 2016; Field et al., 2016). Figure 2 shows the empirical relationships between the EA averaged precipitation anomalies (GPCP) and the EA cumulative burned area and fire CO_2 and $PM_{2.5}$ emissions (GFED4s) during 1997-2016. Here, we remove the 1979-2016 average from precipitation and divide the anomalies by their standard deviation value. As precipitation decreases, the burned area, fire CO_2 and $PM_{2.5}$ emissions increase exponentially. We estimate the fitting curves (solid curves in Fig. 2) by using the following equation:

$$\ln(y) = a + b\Delta P, \qquad \text{(Eq. 1)}$$

where y is the burned area, CO_2 emissions or $PM_{2.5}$ emissions, and a and b are the intercept and regression coefficient, respectively. The coefficients of determination (R^2) are higher than 0.7. We also estimate the 10%-90% confidence intervals of the fitting curves by applying a 1000-time random sampling of the observed data: we randomly resample 20-year samples from the original 20-year (1997-2016) data and compute *a* and *b*; we repeat the random resampling process 1000-times; we consider that the 10%-tile and 90%-tile values of the 1000 regression lines indicate the 10%-90% confidence intervals. These non-linear relationships are consisted with previous studies (Lestari et al., 2014; Spessa, et al. 2015; Yin et al., 2016; Field et al., 2016). We use the relationships in Figs. 2a-c as empirical functions to estimate fire and emissions from the AGCM simulations of precipitation in section 4.

3 Model simulations

The MIROC5 AGCM (Watanabe et al. 2010) has a 160 km horizontal resolution. We perform 10-member long-term (1979-2016) historical simulations (Hist-long) of the MIROC5 AGCM forced by the observed sea surface temperature (SST) (HadISST, Rayner et al., 2003) and anthropogenic and natural external forcing factors (Shiogama et al., 2013; 2014). Here, the observed $\triangle$P ($\triangle\omega_{500}$) is divided by their standard deviation value. The $\triangle$P and $\triangle\omega_{500}$ of each ensemble member are also divided by their own standard deviation values. The correlations of the 1979-2016 time series of $\triangle$P and $\triangle\omega_{500}$ between the observations and the ensemble averages of the MIROC5 simulations are 0.90 and 0.87, respectively (Figs. 3a-b). When we apply "dividing by the standard deviation value" as a simple bias correction technique, it is found that the MIROC5 model has good hindcast skill regarding interannual variability in the EA-averaged $\triangle$P and $\triangle\omega_{500}$. The precipitation and vertical motion anomalies are closely related to the Nino 3.4 SST (an index of El Niño Southern Oscillation) in the observations (correlations are -0.89 and 0.76, respectively) (Figs. 3c-d). There is also a high correlation value between $\triangle$P and $\triangle\omega_{500}$ (-0.87) (Fig. 3e). It is suggested that El Niño (La Niña) accompanies descending wind (ascending wind) in the EA area (Fig. 3d), leading to negative (positive) $\triangle$P (Figs. 3e and 3c). The MIIROC5 model well represents these relationships between Niño 3.4, $\triangle$P and $\triangle\omega_{500}$ in the observations (Figs. 3c-e), i.e., the regression lines of MIROC5 in Figs. 3c-e are close to those in the observations.

To investigate whether historical anthropogenic climate change affected the precipitation anomalies during the 2015 El Niño event, we analyse the outputs of two large ensembles of factual historical forcing (Hist) and counterfactual natural forcing (Nat) of MIROC5 for June-November 2015 (Shiogama et al. 2013, 2014). These simulations are called "probabilistic event attribution" experiments, which contribute to "the International Climate and Ocean: Variability, Predictability and Change (CLIVAR) C20C+ Detection and Attribution Project (Stone et al. 2019)". The Hist ensemble is forced by historical anthropogenic and natural external forcing factors plus observational data of SST and sea ice (HadISST, Rayner et al., 2003). The Nat ensemble is forced by historical natural forcing factors and hypothetical "natural" SST and sea ice patterns where long-term anthropogenic signals were removed. Anthropogenic SST changes were estimated by taking the ensemble mean differences between the all-forcing historical runs and the natural-forcing historical runs of the CMIP5 AOGCMs. The multimodel averaged anthropogenic signals were subtracted from the HadISST data, and the Nat sea ice was estimated by using empirical functions between observed sea ice concentrations and surface temperature (Stone et al. 2019). Please note that both the Hist and Nat ensembles have 2015 El Niño components in the spatial patterns of SST, but the prescribed long-term warming anomalies in SST are different from each other. We performed 100 member runs of the 2006-2016 period for both Hist and Nat. Please see Shiogama et al. (2013; 2014) and Stone et al. (2019) for details regarding the experimental design.

We also analyse the 100 member ensembles of 11-year simulations with 1.5ºC and 2.0ºC warming relative to preindustrial levels. We performed those experiments as a contribution to the HAPPI project (Mitchell et al. 2016, 2017, 2018; Shiogama et al. 2019). Since the ensemble-averaged global warming of the CMIP5 Representative Concentration Pathway 2.6 (RCP2.6) experiments is 1.55ºC, for the 1.5ºC runs, we used the RCP2.6 anthropogenic forcing agents (e.g., greenhouse gases) at 2095 and the ensemble mean 2091-2100 averaged SST anomalies of the RCP2.6 runs of the CMIP5 AOGCMs. The SST anomalies

(Supplementary Fig. 2, top panel) are changes in the CMIP5 multimodel mean SST for each month, between the decadal average of 2091-2100 RCP2.6 and the decadal average of 2006-2015 RCP8.5. We added those SST anomalies to the 2006-2016 observed SST data of HadISST. To estimate the sea ice concentration, we applied a linear sea ice-SST relationship estimated from observations (Supplementary Figs. 3-4) (Mitchell et al., 2017). For the 2.0ºC runs, we used the weighted sum of RCP2.6 and RCP4.5 (0.41×RCP2.6 + 0.59×RCP4.5) of the well-mixed greenhouse gas concentrations in 2095 and the ensemble mean 2091-2100 averaged SST anomalies of the CMIP5 AOGCM ensembles (Supplementary Fig. 2, middle panel) because the weighted sum of the global mean temperature change values of the ensemble-averaged CMIP5 RCP2.6 and RCP4.5 runs is 2.0ºC. Please see Mitchell et al. (2017) for details regarding the experimental design. Notably, these future simulations have the same components as the 2015 El Niño event in terms of the spatial patterns of SST, but the prescribed long-term warming anomalies in SST have been added. Therefore, we can investigate drought events when events like the 2015 El Niño occur under 1.5ºC and 2.0ºC warmed climates relative to preindustrial levels.

Furthermore, we run the 100-member 3.0ºC ensemble (10-year simulations based on the 2006-2015 HadISST data) as an extension of the HAPPI project. Following the original HAPPI methodology, we add SST and sea ice concentration anomalies that represent additional warming in a 3°C warmer world compared to preindustrial values. The SST anomalies (Supplementary Fig. 2, bottom panel) are changes in the CMIP5 multimodel mean SST for the decadal average of 2006-2015 in RCP8.5 and the decadal average of 2091-2100 in a combined scenario of RCP4.5 and RCP8.5, i.e., 0.686×RCP4.5 + 0.314×RCP8.5 (Lo et al. 2019). The CMIP5 multimodel mean global mean temperature in 2091-2100 is approximately 3°C warmer than the 1861-1880 mean in this combined scenario; hence, this scenario describes 3°C global warming above preindustrial levels. For the sea ice concentration anomalies, we find the coefficients of this linear relationship from pre-existing 1.5°C and 2°C SST and sea ice anomalies. We apply this relationship to the 3°C SST anomalies to estimate the sea ice concentration anomalies, which are then added to the observed 2006-2015 data (see Mitchell et al., 2017). Supplementary Figs. 3-4 show the sea ice concentrations in both hemispheres in the 1.5°C, 2°C and 3°C experiments. The same weightings for RCP4.5 and RCP8.5 in the combined scenario equivalent to 3°C warming are also applied to greenhouse gas concentrations. This study is the first to report results from the HAPPI extension (i.e., the 3°C runs) using MIROC5.

To compute the normalized values of EA-averaged $\triangle$P and $\triangle\omega_{500}$ of the Hist, Nat, 1.5ºC, 2.0ºC and 3.0ºC runs, we subtract a long-term mean value of a given single member of Hist-long and divide anomalies by the standard deviation value of that Hist-long member. This normalization process enables us to produce 100×10=1000 samples of normalized $\triangle$P and $\triangle\omega_{500}$ data for each of the Hist, Nat, 1.5ºC, 2.0ºC and 3.0ºC ensembles.

4 Changes in precipitation, fire and fire emissions

The difference patterns of surface air temperature (≈ prescribed SST difference patterns over the ocean) in Hist-Nat, 1.5ºC-Nat, 2.0ºC-Nat and 3.0ºC-Nat have greater warming in the Niño 3.4 region than the tropical (30ºS-30ºN) ocean averaged values (Fig. 4). The relatively higher warming in the Niño 3.4 region accompanies downward motion anomalies in the EA region (Fig. 5a), enhancing negative precipitation anomalies when El Niño occurs (Figs. 5b). Notably, the prescribed SST difference between the Niño 3.4 region and the tropical ocean mean is larger in the 1.5ºC runs than in the 2.0ºC runs. As a result, the amplitude of negative precipitation in the 1.5ºC runs is slightly greater than that in the 2.0ºC runs, as mentioned below, at least in these ensembles. It is not clear why the ensemble average of the CMIP5 RCP2.6 runs (i.e., the prescribed SST anomalies of the 1.5 ºC runs) has a larger SST difference between the Niño 3.4 region and the tropical ocean mean than that of the weighted sum of RCP2.6 and RCP4.5 (the 2.0 ºC runs).

The large ensemble simulations enable us to estimate the probabilities of drought exceeding the observed value. Historical anthropogenic climate change has significantly increased the chance of $\triangle$P being more negative than the observed value from

2% (1-4%) in Nat to 9% (6-14%) in Hist (Fig. 6a). Here, we use the cumulative histograms of 100×10=1000 samples of △P to estimate the probabilities of △P. The values in parentheses indicate the 10-90% confidence interval estimated by applying the 1000-time resampling: we randomly resample 100×10 data from the original 100×10 samples of △P and compute the probabilities of drought exceeding the 2015 observed value; we repeat the random resampling process 1000-times and consider the 10%-tile and 90%-tile values of the 1000 estimates of probability as the 10-90% bounds. Even if the 1.5°C and 2.0°C goals of the Paris Agreement are achieved (in the 1.5°C and 2.0°C runs), the chance of exceeding the observed value significantly increases from 9% (6-14%) in Hist to 82% (76-87%) and 67% (60-74%), respectively. In the current trajectory of 3.0°C warming (in the 3.0°C runs), the chance of exceeding the observed value becomes 93% (89-96%).

By combining the △P of MIROC5 (Fig. 6a) and the empirical relationships in Fig. 2, we assess the historical and future changes in burned area and fire emissions of CO_2 and $PM_{2.5}$ (Figs. 6b-d). We consider uncertainties by combining randomly resampled △P and resampled regression factors of Eq. 1: (i) we compute the regression factors of Eq. 1 using randomly resampled data (the same as the process used to estimate the uncertainty ranges of the regression lines); (ii) we randomly resample 100×10 data from the original 100×10 samples of △P; (iii) we use the regression factors of (i) and the 100×10 △P samples of (ii) to compute the 1000 estimates of fire or emissions and estimate the probability of exceeding the observed values; (iv) the processes of (i)-(iii) are repeated 1000-times; and (v) the 10%-tile and 90%-tile values of the 1000 estimates of the probabilities of exceeding the observed values are considered to be the 10-90% bounds. Historical anthropogenic drying has increased the probability of exceeding the observed values of the burned area (from 5% (0-18%) to 23% (3-52%)), CO_2 emissions (from 5% (0-15%) to 23% (3-47%)), and $PM_{2.5}$ emissions (from 2% (0-5%) to 24% (3-49%)), but these changes are not statistically significant due to the large uncertainties. In the 1.5°C, 2.0°C and 3.0°C runs, the chances of exceeding the observed values significantly increase for the burned area (93% (66-99%), 81% (50-95%) and 98% (84-100%), respectively), CO_2 emissions (92% (72-98%), 81% (55-93%) and 98% (86-100%), respectively), and $PM_{2.5}$ emissions (93% (70-98%), 81% (54-94%) and 98% (85-100%), respectively).

We contextualize the estimated fire CO_2 emissions within the future emissions scenarios. Although the above analyses focus on the year when the 2015-like El Niño events occurred, long-term mean fire CO_2 emissions are also important for mitigation policies. Here, we use simulated June-November mean precipitation anomalies of 11 years (2006-2016), instead of using only the 2015 data, and the empirical function of Fig. 2b to estimate the cumulative probability function of fire CO_2 emissions in the EA area in the 2.0°C runs (Fig. 7). The fire CO_2 emissions of the 11-year period including both El Niño and non-El Niño years (Fig. 7) are much less than those in the major El Niño year (Fig. 6c) due to small fire CO_2 emissions in the non-El Niño years (Fig. 2). However, these fire CO_2 emissions can have substantial implications for mitigation policies. The vertical lines in Fig. 7 are the year 2100 land-use CO_2 emission scenarios including fire emissions for the East and South East Asia regions except China and Japan in the five shared socioeconomic pathway (SSP) scenarios from the Asia-Pacific Integrated Model/Computable General Equilibrium (AIM/CGE) (Fujimori et al., 2012). AIM/CGE is one of the integrated assessment models (economic models) that produced the emissions data of SSP scenarios for the Coupled Model Intercomparison Project Phase 6 and the 6th assessment report of the Intergovernmental Panel on Climate Change (Riahi et al. 2017, Fujimori et al. 2017). The chances of exceeding the emissions of SSP1, 2, 3, 4 and 5 are 77% (70-84%), 34% (28-39%), 13% (10-18%), 37% (31%-41%) and 77% (70-84%), respectively. Although these probability values highly depend on the SSP scenarios, the results are substantial in all the SSP scenarios. Because the CO_2 emissions in the AIM/CGE model include a wider area and other emission sources than the EA fire emissions, this comparison is conservative. In the SSP simulations of AIM/CGE, fire CO_2 emissions are computed by using functions of land-cover changes, and climate change effects on fires are not considered. Therefore, it is suggested that implementing climate change effects on fire CO_2 emissions in integrated assessment models can significantly affect SSP land-use CO_2 emissions and studies of mitigation pathways, which in turn would be highly relevant to national and global climate policies. We suggest that additional fire CO_2 emissions due to climate change should be considered in possible CMIP7 activities.

5 Conclusions

By applying the probabilistic event attribution approach based on the MIROC5 AGCM ensembles, we suggested that historical anthropogenic warming significantly increased the chance of severe meteorological drought exceeding the 2015 observations in the EA area during the 2015 major El Niño year (from 2% (1-4%) in Nat to 9% (6-14%) in Hist). By performing and analysing the HAPPI (1.5°C and 2.0°C warming) and HAPPI extension (3.0°C warming) runs, we showed that the probabilities of drought exceeding the 2015 observations will largely increase (82% (76-87%), 67% (60-74%), and 93% (89-96%), respectively).

Drying trends tend to exacerbate fire activities. By combining these experiments and the empirical functions, we also implied that historical anthropogenic drying had tended to increase the chances of the burned area, CO_2 emissions and $PM_{2.5}$ emissions exceeding the 2015 observations, but those changes were not statistically significant. In contrast, if the 2.0°C goal is achieved, the chances of exceeding the observed values will substantially increase for the burned area (from 23% (3-52%) in Hist to 81% (50-95%) for 2.0°C), CO_2 emissions (from 23% (3-47%) to 81% (55-93%)) and $PM_{2.5}$ emissions (from 24% (3-49%) to 81% (54-94%)). Lestari et al. (2014) and Yin et al. (2016) also showed that the AOGCM ensemble of CMIP5 projected future long-term trends of drying and enhanced fire carbon emissions. We further suggest that the risks of drought and fire significantly increase when events like the 2015 El Niño occur in future warmer climates even if the 1.5°C and 2.0°C goals are achieved. The impacts of these changes on droughts, fire and fire emissions should be reduced by adaptation investments.

If we cannot limit global warming to 2.0°C and it reaches 3.0°C as expected from the current "emissions gap" (United Nations Environment Programme 2018), the chances of exceeding the observed values further increase for the burned area, CO_2 emissions and $PM_{2.5}$ emissions. Although the differences between 2.0°C and 3.0°C are not statistically significant for the burned area and the CO_2 and $PM_{2.5}$ emissions, the 50th percentile values of probabilities exceeding the 2015 observations first reach approximately 100% in the 3.0°C runs. These additional changes relative to 2.0°C indicate the effects of the failures of mitigation policies. Conversely, these changes indicate the potential benefits of limiting the current trajectory of 3°C global warming to the Paris Agreement goals.

Forest-based climate mitigation has a key role in meeting the goals of the Paris Agreement (Grassi et al., 2017). We also suggested that changes in fire CO_2 emissions due to future warming can increase the need for modifying fire CO_2 emission scenarios for future climate projections. Although we focused on the influences of climate change on fires, land use and land cover changes are also important factors. To avoid fire intensification due to drying climates, effective land management policies for protecting forests and peatlands are necessary (Marlier et al., 2015; Kim et al., 2015; Koplitz et al., 2016; World Bank 2016).

This study is based on the single model ensembles using the particular SST anomaly patterns. It is worthwhile to compare multi model simulations using multiple estimates of warming patterns in SST to investigate the uncertainties. It remains for future work.

Data availability.

The data of MIROC5 model, ERA-I, GPCP and GFED4s used in this article can be download from https://portal.nersc.gov/c20c/ , https://www.ecmwf.int/en/forecasts/datasets/reanalysis-datasets/era-interim , https://www.esrl.noaa.gov/psd/data/gridded/data.gpcp.html , and https://www.globalfiredata.org/data.html , respectively. The data of AIM/CGE can be accessed by contacting the corresponding author.

.

Author contributions.

HS, RH, TH, SF and SC designed the analysis. HS performed the analysis and wrote the first draft of the paper. HS, YTEL and DM proposed and performed the HAPPI extension runs. All authors contributed to the interpretation of the results and to the writing of the paper.

Competing interests.

The authors declare that they have no conflict of interest.

Acknowledgements

We thank the reviewers and the editor for their useful comments. The MIROC5 simulations were performed using the Earth Simulator at JAMSTEC and the NEC SX at NIES.

Financial support.

This study was supported by ERTDF 2-1702 (Environmental Restoration and Conservation Agency, Japan) and TOUGOU (MEXT, Japan). This research used the science gateway resources of the National Energy Research Scientific Computing Center, a DOE Office of Science User Facility supported by the Office of Science of the U.S. Department of Energy under contract no. DE-AC02-05CH11231.

References

Adler, R. F., Huffman, G. J., Chang, A., Ferraro, R., Xie, P.-P., Janowiak, J., Rudolf, B., Schneider, U., Curtis, S., Bolvin, D., Gruber, A., Susskind, J., Arkin, P. and Nelkin, E.: The Version-2 Global Precipitation Climatology Project (GPCP) Monthly Precipitation Analysis (1979–Present), J. Hydrometeorol., 4(6), 1147–1167, doi:10.1175/1525-7541, 2003.

Allen, M. R., 2003: Liability for climate change. Nature, 421, 891−892, 2003.

Baccini, A., Goetz, S.J., Walker, W.S., Laporte, N.T., Sun, M., Sulla-Menashe, D., Hackler, J., Beck, P. S. A., Dubayah, R., Friedl, M. A., Samanta, S., Houghton, R. A.: Estimated carbon dioxide emissions from tropical deforestation improved by carbon-density maps. Nature Climate Change, 2, 182-185, 2012.

Baccini, A., Walker, W., Carvalho, L., Farina, M., Sulla-Menashe, D., Houghton, R.A.: Tropical forests are a net carbon source based on aboveground measurements of gain and loss. Science, 358, 230-233, 2017.

Dee, D. P., Uppala, S. M., Simmons, A. J., Berrisford, P., Poli, P., Kobayashi, S., Andrae, U., Balmaseda, M. A., Balsamo, G., Bauer, P., Bechtold, P., Beljaars, A. C. M., van de Berg, L., Bidlot, J., Bormann, N., Delsol, C., Dragani, R., Fuentes, M., Geer, A. J., Haimberger, L., Healy, S. B., Hersbach, H., Hólm, E. V., Isaksen, L., Kållberg, P., Köhler, M., Matricardi, M., Mcnally, A. P., Monge-Sanz, B. M., Morcrette, J. J., Park, B. K., Peubey, C., de Rosnay, P., Tavolato, C., Thépaut, J. N. and Vitart, F.: The ERA-Interim reanalysis: Configuration and performance of the data assimilation system, Q. J. R. Meteorol. Soc., doi:10.1002/qj.828, 2011.

Field, R. D., van der Werf, G. R., Fanin, T., Fetzer, E. J., Fuller, R., Jethva, H., Levy, R., Livesey, N. J., Luo, M., Torres, O. and Worden, H. M.: Indonesian fire activity and smoke pollution in 2015 show persistent nonlinear sensitivity to El Niño-induced drought, Proc. Natl. Acad. Sci., doi:10.1073/pnas.1524888113, 2016.

Fujimori, S., Hasegawa, T., Masui, T., Takahashi, K., Herran, D. S., Dai, H., Hijioka, Y. and Kainuma, M.: SSP3: AIM implementation of Shared Socioeconomic Pathways, Glob. Environ. Chang., doi:10.1016/j.gloenvcha.2016.06.009, 2017.

Fujimori, S., Masui, T. and Matsuoka, Y.: AIM/CGE [basic] manual. Center for Social and Environmental Systems Research, NIES, Tsukuba, Japan, 2012.

Grassi, G., House, J., Dentener, F., Federici, S., Den Elzen, M. and Penman, J.: The key role of forests in meeting climate targets requires science for credible mitigation, Nat. Clim. Chang., doi:10.1038/nclimate3227, 2017.

Hartmann, F., Merten, J., Fink, M., Faust, H.: Indonesia’s Fire Crisis 2015: A Twofold Perturbation on the Ground, Pacific Geographies #49, 4-11, doi:10.23791/490411, 2018

Hirota, N., Ogura, T., Tatebe, H., Shiogama, H., Kimoto, M. and Watanabe, M.: Roles of shallow convective moistening in the eastward propagation of the MJO in MIROC6, J. Clim., doi:10.1175/JCLI-D-17-0246.1, 2018.

Kim, P. S., Jacob, D. J., Mickley, L. J., Koplitz, S. N., Marlier, M. E., DeFries, R. S., Myers, S. S., Chew, B. N. and Mao, Y. H.: Sensitivity of population smoke exposure to fire locations in Equatorial Asia, Atmos. Environ., 102, 11-17, doi:10.1016/j.atmosenv.2014.09.045, 2015.

Kim, Y. H., Min, S. K., Stone, D. A., Shiogama, H. and Wolski, P.: Multi-model event attribution of the summer 2013 heat wave in Korea, Weather Clim. Extrem., doi:10.1016/j.wace.2018.03.004, 2018.

Koplitz, S. N., Mickley, L. J., Marlier, M. E., Buonocore, J. J., Kim, P. S., Liu, T., Sulprizio, M. P., DeFries, R. S., Jacob, D. J., Schwartz, J., Pongsiri, M. and Myers, S. S.: Public health impacts of the severe haze in Equatorial Asia in September-October 2015: Demonstration of a new framework for informing fire management strategies to reduce downwind smoke exposure, Environ. Res. Lett., doi:10.1088/1748-9326/11/9/094023, 2016.

Lestari, R. K., Watanabe, M., Imada, Y., Shiogama, H., Field, R. D., Takemura, T. and Kimoto, M.: Increasing potential of biomass burning over Sumatra, Indonesia induced by anthropogenic tropical warming, Environ. Res. Lett., doi:10.1088/1748-9326/9/10/104010, 2014.

Liu, W., Sun, F., Ho Lim, W., Zhang, J., Wang, H., Shiogama, H. and Zhang, Y.: Global drought and severe drought-Affected populations in 1.5 and 2 °C warmer worlds, Earth Syst. Dyn., doi:10.5194/esd-9-267-2018, 2018.

Lo, Y.T.E, Mitchell, D.M., Gasparrini, A., Vicedo-Cabrera, A.M., Ebi, K.L., Frumhoff, P. C., Millar, R.J., Roberts, W., Sera, F., Sparrow, S., Uhe, P., Williams, G: Increasing mitigation ambition to meet the Paris Agreement's temperature goal avoids substantial heat-related mortality in U.S. cities. Science Advances, 5(6), eaau4373, DOI: 10.1126/sciadv.aau4373, 2019

Marlier, M. E., Defries, R. S., Kim, P. S., Gaveau, D. L. A., Koplitz, S. N., Jacob, D. J., Mickley, L. J., Margono, B. A. and Myers, S. S.: Regional air quality impacts of future fire emissions in Sumatra and Kalimantan, Environ. Res. Lett., doi:10.1088/1748-9326/10/5/054010, 2015.

Marlier, M. E., Defries, R. S., Voulgarakis, A., Kinney, P. L., Randerson, J. T., Shindell, D. T., Chen, Y. and Faluvegi, G.: El Niño and health risks from landscape fire emissions in southeast Asia, Nat. Clim. Chang., doi:10.1038/nclimate1658, 2013.

Mitchell, D., James, R., Forster, P. M., Betts, R. A., Shiogama, H. and Allen, M.: Realizing the impacts of a 1.5 °C warmer world, Nat. Clim. Chang., doi:10.1038/nclimate3055, 2016.

Mitchell, D., AchutaRao, K., Allen, M., Bethke, I., Beyerle, U., Ciavarella, A., Forster, P. M., Fuglestvedt, J., Gillett, N., Haustein, K., Ingram, W., Iversen, T., Kharin, V., Klingaman, N., Massey, N., Fischer, E., Schleussner, C. F., Scinocca, J., Seland, Ø., Shiogama, H., Shuckburgh, E., Sparrow, S., Stone, D., Uhe, P., Wallom, D., Wehner, M. and Zaaboul, R.: Half a degree additional warming, prognosis and projected impacts (HAPPI): Background and experimental design, Geosci. Model Dev., doi:10.5194/gmd-10-571-2017, 2017.

Mitchell, D., Heaviside, C., Schaller, N., Allen, M., Ebi, K. L., Fischer, E. M., Gasparrini, A., Harrington, L., Kharin, V., Shiogama, H., Sillmann, J., Sippel, S. and Vardoulakis, S.: Extreme heat-related mortality avoided under Paris Agreement goals, Nat. Clim. Chang., doi:10.1038/s41558-018-0210-1, 2018.

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

Pall, P., T. Aina, D. A. Stone, P. A. Stott, T. Nozawa, A. G. J. Hilberts, D. Lohmann, and M. R. Allen: Anthropogenic greenhouse gas contribution to flood risk in England and Wales in autumn 2000. Nature, 470, 382−385, 2011.

Rayner, N. A., D. E. Parker, E. B. Horton, C. K. Folland, L. V. Alexander, D. P. Rowell, E. C. Kent, and A. Kaplan: Global analyses of sea surface temperature, sea ice, and night marine air temperature since the late nineteenth century. J. Geophys. Res., 108, 4407, 2003.

Riahi, K., van Vuuren, D. P., Kriegler, E., Edmonds, J., O'Neill, B. C., Fujimori, S., Bauer, N., Calvin, K., Dellink, R., Fricko, O., Lutz, W., Popp, A., Cuaresma, J. C., KC, S., Leimbach, M., Jiang, L., Kram, T., Rao, S., Emmerling, J., Ebi, K., Hasegawa, T., Havlik, P., Humpenöder, F., Da Silva, L. A., Smith, S., Stehfest, E., Bosetti, V., Eom, J., Gernaat, D., Masui, T., Rogelj, J., Strefler, J., Drouet, L., Krey, V., Luderer, G., Harmsen, M., Takahashi, K., Baumstark, L., Doelman, J. C., Kainuma, M., Klimont, Z., Marangoni, G., Lotze-Campen, H., Obersteiner, M., Tabeau, A. and Tavoni, M.: The Shared Socioeconomic Pathways and their energy, land use, and greenhouse gas emissions implications: An overview, Glob. Environ. Chang., doi:10.1016/j.gloenvcha.2016.05.009, 2017.

Saatchi, S.S., Harris, N.L., Brown, S., Lefsky, M., Mitchard, E.T., Salas, W., Zuttaa, B.R., Buermann, W., Lewis, S. L., Hagen, S., Petrova, S., White, L., Silman, M., Morel, A.: Benchmark map of forest carbon stocks in tropical regions across three continents. Proc Natl Acad Sci U S A, 108: 9899-904, 2011.

Saeed, F., Bethke, I., Fischer, E., Legutke, S., Shiogama, H., Stone, D. A. and Schleussner, C. F.: Robust changes in tropical rainy season length at 1.5 °c and 2 °c, Environ. Res. Lett., doi:10.1088/1748-9326/aab797, 2018.

Shiogama, H, T Hasegawa, S Fujimori, D Murakami, K Takahashi, K Tanaka, S Emori, I Kubota, M Abe, Y Imada, M Watanabe, D Mitchell, N Schaller, J Sillmann, E Fischer, J. F. Scinocca, I. Bethke, L Lierhammer J. Takakura, T. Trautmann,

P. Döll, S. Ostberg, H. M. Schmied, F. Saeed, C.-F. Schleussner: Limiting global warming to 1.5ºC will lower increases in inequalities of four hazard indicators of climate change. Environ. Res. Lett., submitted, 2019

Shiogama, H., Watanabe, M., Imada, Y., Mori, M., Ishii, M. and Kimoto, M.: An event attribution of the 2010 drought in the South Amazon region using the MIROC5 model, Atmos. Sci. Lett., doi:10.1002/asl2.435, 2013.

Shiogama, H., Watanabe, M., Imada, Y., Mori, M., Kamae, Y., Ishii, M., Kimoto, M.: Attribution of the June–July 2013 heat wave in the southwestern United States. SOLA, 10, 122−126, doi:10.2151/sola.2014-025, 2014

Spessa, A. C., Field, R. D., Pappenberger, F., Langner, A., Englhart, S., Weber, U., Stockdale, T., Siegert, F., Kaiser, J. W. and Moore, J.: Seasonal forecasting of fire over Kalimantan, Indonesia, Nat. Hazards Earth Syst. Sci., doi:10.5194/nhess-15-429-2015, 2015.

Stone, D. A., Christidis, N., Folland, C., Perkins-Kirkpatrick, S., Perlwitz, J., Shiogama, H., Wehner, M. F., Wolski, P., Cholia, S., Krishnan, H., Murray, D., Angélil, O., Beyerle, U., Ciavarella, A., Dittus, A., Quan, X. W. and Tadross, M.: Experiment design of the International CLIVAR C20C+ Detection and Attribution project, Weather Clim. Extrem., doi:10.1016/j.wace.2019.100206, 2019.

Taufik, M., Torfs, P. J. J. F., Uijlenhoet, R., Jones, P. D., Murdiyarso, D. and Van Lanen, H. A. J.: Amplification of wildfire area burnt by hydrological drought in the humid tropics, Nat. Clim. Chang., doi:10.1038/nclimate3280, 2017.

Taylor, K. E., Stouffer, R. J. and Meehl, G. A.: An Overview of CMIP5 and Experimental Design, Bull. Am. Meteorol. Soc., doi:10.1175/BAMS-D-11-00094, 2012.

United Nations Environment Programme: Emissions Gap Report 2018, 2018

United Nations Framework Convention on Climate Change: Adoption of the Paris Agreement FCCC/CP/2015/L.9/Rev.1, 2015

Watanabe, M., Suzuki, T., O'Ishi, R., Komuro, Y., Watanabe, S., Emori, S., Takemura, T., Chikira, M., Ogura, T., Sekiguchi, M., Takata, K., Yamazaki, D., Yokohata, T., Nozawa, T., Hasumi, H., Tatebe, H. and Kimoto, M.: Improved climate simulation by MIROC5: Mean states, variability, and climate sensitivity, J. Clim., doi:10.1175/2010JCLI3679.1, 2010.

Van Der Werf, G. R., Randerson, J. T., Giglio, L., Van Leeuwen, T. T., Chen, Y., Rogers, B. M., Mu, M., Van Marle, M. J. E., Morton, D. C., Collatz, G. J., Yokelson, R. J. and Kasibhatla, P. S.: Global fire emissions estimates during 1997-2016, Earth Syst. Sci. Data, 9(2), 697–720, doi:10.5194/essd-9-697-2017, 2017.

Wehner, M., Stone, D., Mitchell, D., Shiogama, H., Fischer, E., Graff, L. S., Kharin, V. V., Lierhammer, L., Sanderson, B. and Krishnan, H.: Changes in extremely hot days under stabilized 1.5 and 2.0 °c global warming scenarios as simulated by the HAPPI multi-model ensemble, Earth Syst. Dyn., doi:10.5194/esd-9-299-2018, 2018.

World Bank: The cost of fire: an economic analysis of Indonesia's 2015 fire crisis (English). Indonesia sustainable landscapes knowledge; note no. 1. Washington, D.C. : World Bank Group, 2016

Yin, Y., Ciais, P., Chevallier, F., van der Werf, G. R., Fanin, T., Broquet, G., Boesch, H., Cozic, A., Hauglustaine, D., Szopa, S. and Wang, Y.: Variability of fire carbon emissions in equatorial Asia and its nonlinear sensitivity to El Niño, Geophys. Res. Lett., doi:10.1002/2016GL070971, 2016.

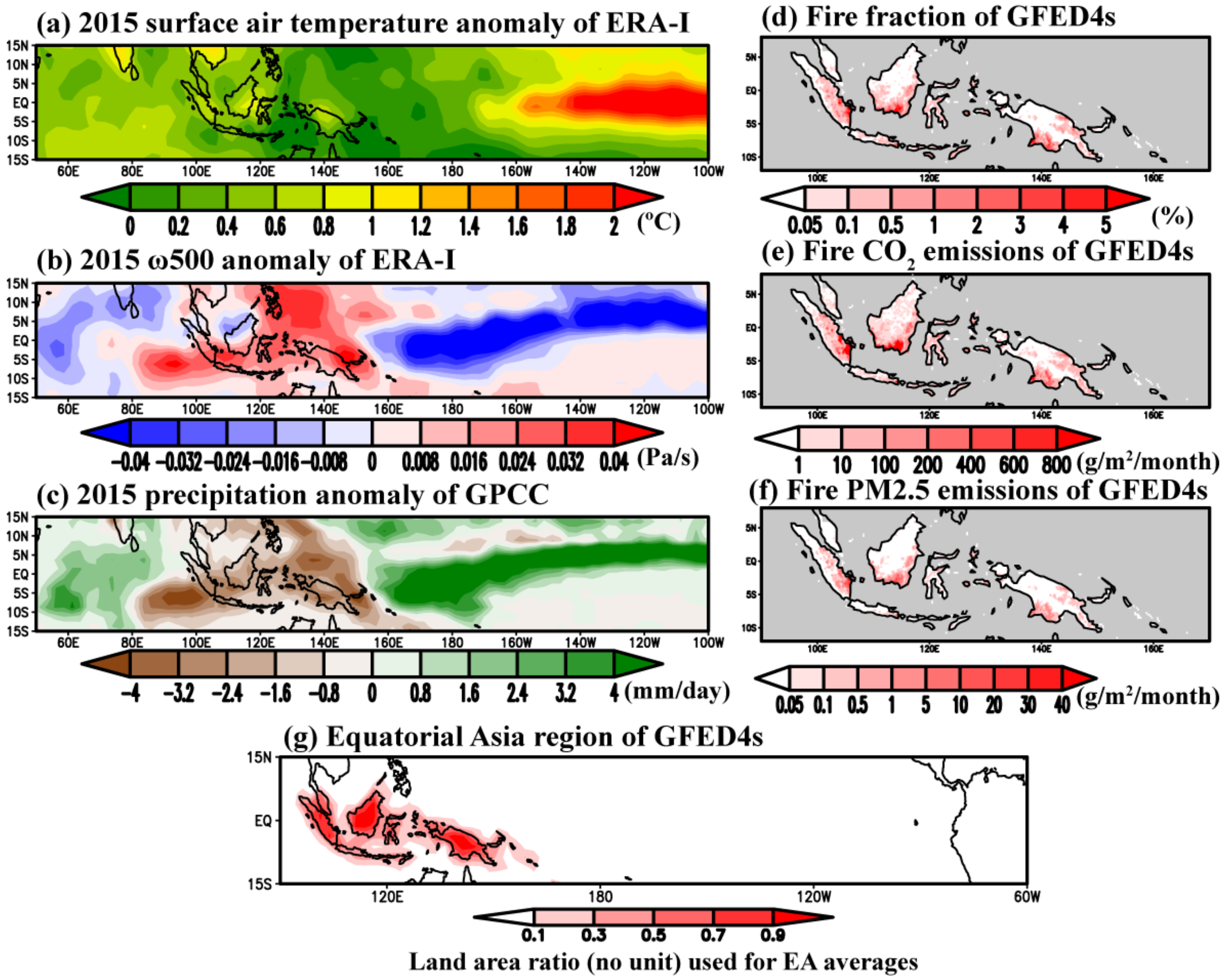


Figure 1: The observed climate conditions and fires. The June-November 2015 averaged anomalies of (a) surface air temperature (°C) and (b) vertical pressure velocity at the 500-hPa level (Pas^{-1}, downward motions are positive) from ERA Interim reanalysis data (Dee et al. 2011) relative to the 1979-2016 mean. (c) The June-November 2015 averaged anomalies of precipitation from GPCP (Adler et al. 2003) (mm/day). The right panels indicate (d) fire fraction (%), (e) fire CO2 emissions (gm^{-2} $month^{-1}$) and (f) fire $PM_{2.5}$ emissions from GFED4s (van der Werf et al. 2017) during June-November 2015. (g) The red area indicates the EA region of the GFED4s. We use this definition of the EA area. Shading shows the land area ratio (no unit) used for weighting in the computation of EA averages.

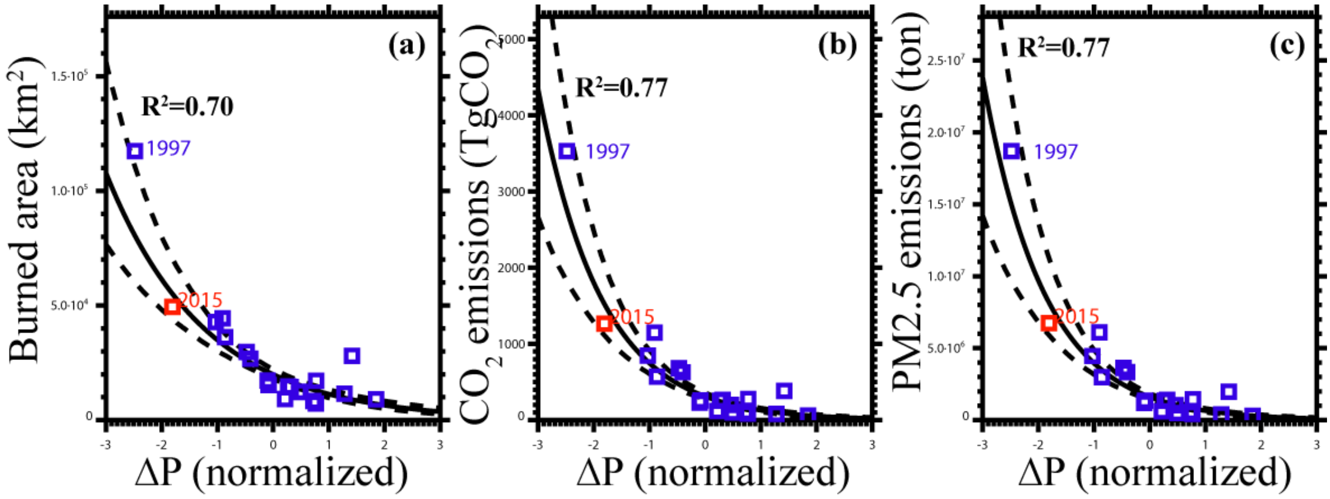


Figure 2: Empirical relationships between observed precipitation anomalies and fires and fire emissions in the EA area during 1997-2016. The horizontal axes are the normalized June-November mean precipitation anomalies (no unit) of the GPCP. The vertical axes denote (a) burned area (km^2), (b) CO_2 emissions ($TgCO_2$) and (c) $PM_{2.5}$ emissions (ton) of GFED4s. The year 2015 values are indicated by red squares. Solid and dashed lines indicate the best estimates and 10-90% confidence intervals of the fitting curves from Eq. 1, respectively.

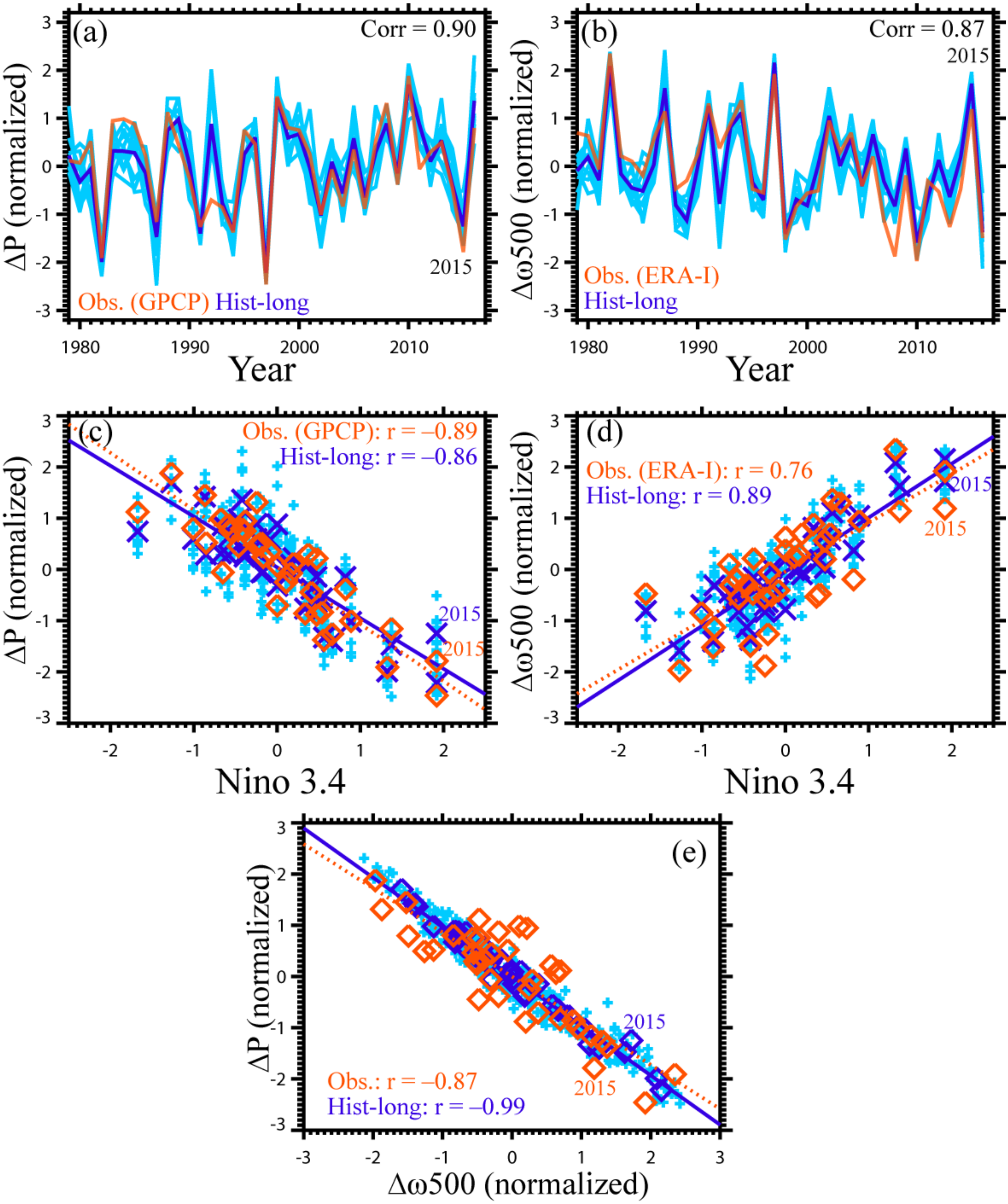


Figure 3: Evaluations of the MIROC5 simulations of the EA averaged precipitation and vertical air motions. Top panels show the normalized June-November mean time series of (a) ΔP (no unit) and (b) $\Delta\omega_{500}$ (no unit). Red lines are the observations. Light blue lines are the 10 ensemble members of Hist-long, and blue lines are the ensemble mean. The other panels are scatter plots of (c) ΔP and the Nino 3.4 index (°C), (d) $\Delta\omega_{500}$ and the Nino 3.4 index and (e) ΔP and $\Delta\omega_{500}$. Red diamonds are the observed values. Small light blue crosses are the 10 ensemble members of Hist-long, and large blue diamonds indicate the ensemble mean values. The red and blue lines indicate the regression lines of the observations and the ensemble averages of Hist-long, respectively.

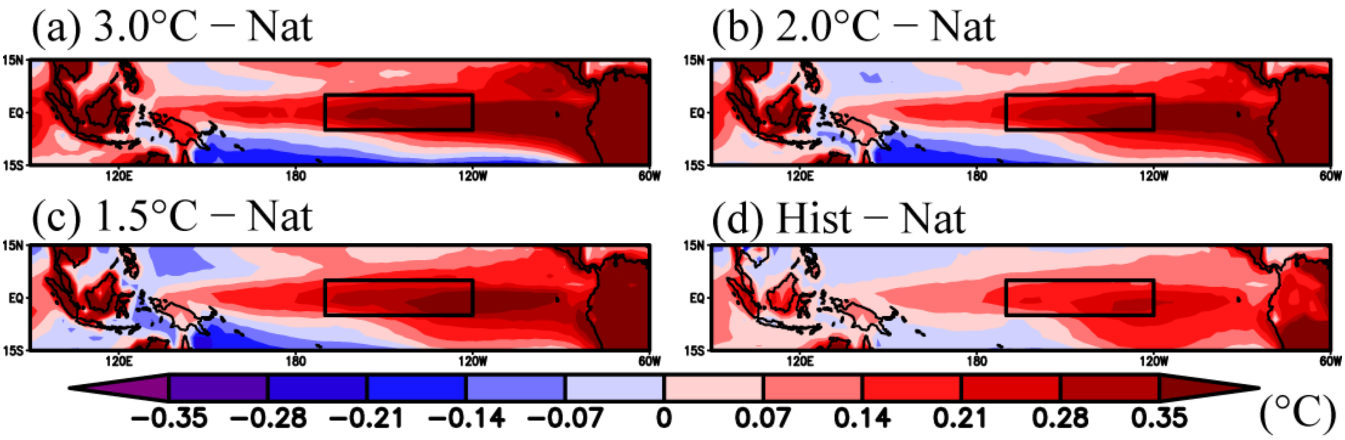


Figure 4: Surface air temperature warming patterns in 2015. (a) △T differences between 3.0 ºC and Nat (ºC). The 30ºS-30ºN ocean averaged value is omitted. The black box indicates the Nino 3.4 region. The other panels are the same as panel (a) but for (b) 2.0 ºC minus Nat, (c) 1.5 ºC minus Nat and (d) Hist minus Nat.

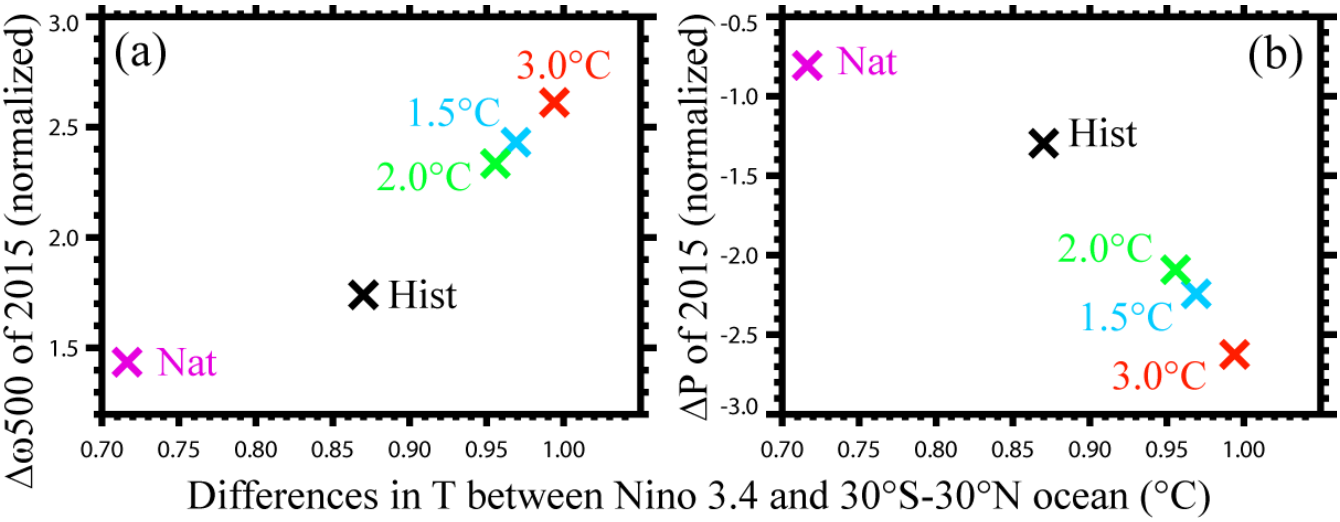


Figure 5: Relationships between Niño 3.4 warming and EA vertical motion and precipitation anomalies of the ensemble mean. The horizontal axes show differences in the 2015 T anomalies between the Niño 3.4 area and the 30ºS-30ºN ocean (ºC). The vertical axes are (a) $\triangle\omega_{500}$ (no unit) and (b) $\triangle$P (no unit) for the year 2015. Crosses denote the ensemble averages of Nat (purple), Hist (black), 1.5ºC (light blue), 2.0ºC (green) and 3.0ºC (red).

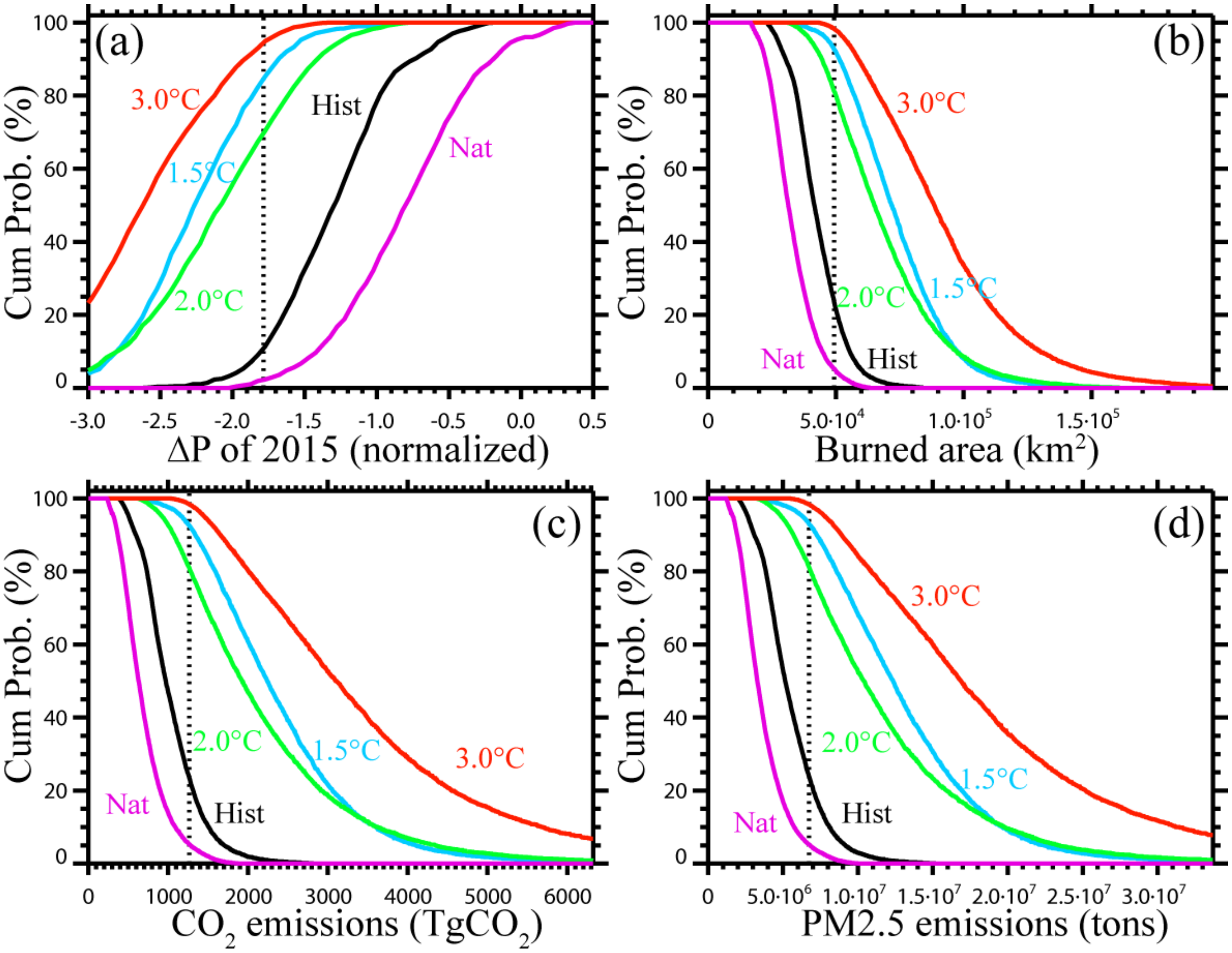


Figure 6. Changes in the cumulative probability functions. (a) The vertical axis indicates the probability (%) of △P being lower than a given horizontal value (no unit). Solid lines denote the 50% values of the 1000 random samples of the Nat (purple), Hist (black), 1.5ºC (light blue), 2.0ºC (green) and 3.0ºC (red) ensembles. The vertical dotted line is the observed 2015 value. The other panels show the probabilities of exceeding the given horizontal values for (b) the burned area (km^2), (c) CO_2 emissions ($TgCO_2$) and (d) $PM_{2.5}$ emissions (tons).

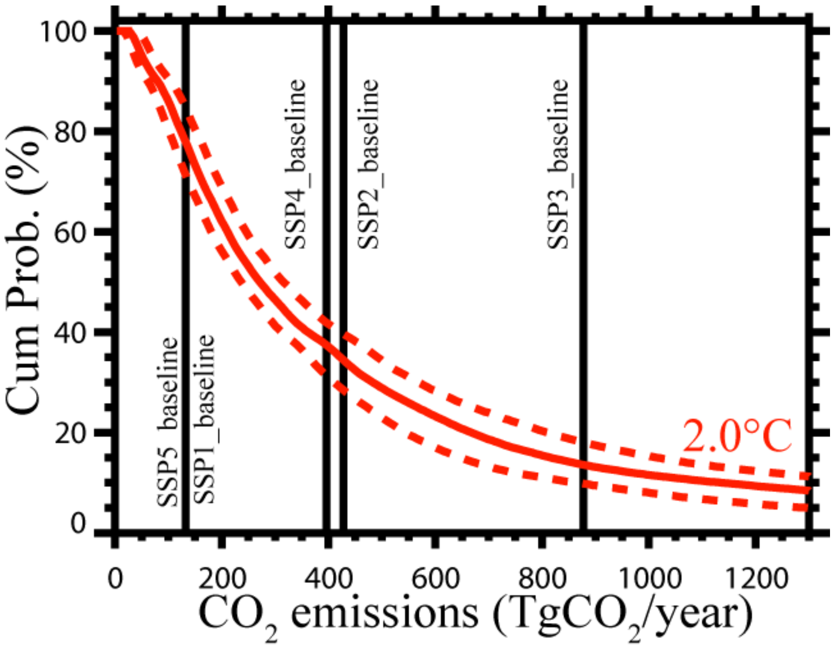


Figure 7: The red curves are the cumulative probability function of CO_2 emissions ($TgCO_2$/year) during June-November of 2006-2016 for the 2.0ºC runs. Solid and dashed lines denote the 50% values and the 10-90% confidence intervals, respectively. The vertical lines indicate the year 2100 annual land-use CO_2 emission scenarios (including fire emissions) for the East and South East Asia regions, except China and Japan for the 5 SSP baseline scenarios of the AIM/CGE model.