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ORIGINAL ARTICLE

Attributing the 2015/2016 Amazon basin drought to anthropogenic influence

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Abstract

Droughts in the Amazon region have the potential to generate severe socio-environmental impacts in addition to having the ability to interfere with the long-term carbon cycle, thus affecting global climate. The 2015/2016 drought that occurred in this region, associated with an El Niño, was considered a record-breaking event in terms of unprecedented warming and the largest extent of the drought affected areas. Anthropogenic influence on the probability and intensity of this drought was assessed using two ensembles of the Met Office's HadGEM3-GA6 model. One ensemble was driven only with natural forcings and the other also included anthropogenic forcings. This analysis found that the intensity and probability of the 2015/2016 Amazon drought likely increased due to anthropogenic influence. The reliability of the model to represent the precipitation of the study area was assessed by comparing it with the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) product ($R^2 = 0.81$). Results indicate that anthropogenic forcings altered the drought intensity of 2015/2016 in the Amazon and increased the risk of this event by about four times with a confidence interval ranging from 2.7 to 4.7. We conclude that anthropogenic emissions threaten the functioning of the Amazon forest due to increased likelihood of extreme droughts.

KEYWORDS
Amazon, attribution, climate change, drought, ENSO

1 | INTRODUCTION

Climate change can lead to changes in regional climate and climate variability including altered seasonal and diurnal cycles, and the frequency of extremes (Intergovernmental Panel on Climate Change, 2014). Climate extremes such as droughts can be harmful to both human and natural systems. An example of this are droughts that occur in the Amazon region, which in addition to severely harming local communities can impact global climate. The societal impacts of the Amazonian drought events are largely due to an increase in wildfires which results in respiratory diseases (Smith and Nelson, 2011), reduction of agricultural production and disruption in the transport of goods and people (Anderson et al., 2018; Aragão et al., 2018). These drought events increase tree mortality and decrease the CO_2 uptake by the forest due to photosynthesis suppression with significant post-drought impacts on the forest above-ground biomass (Anderson et al., 2018; Doughty et al., 2015; Feldpausch et al., 2016; Koren et al., 2018; Yang et al., 2018). These impacts lead Amazonia to shift to being a carbon source instead of being a carbon sink. In addition, this can directly affect the long-term global climate due to the emissions from drought-induced tree deaths (Lewis et al., 2011). Furthermore, Amazonia is responsible for 15% of the freshwater discharge that reaches the oceans. Changes in this can modify the global carbon cycle and consequently affect global climate (Bernstein et al., 2008; Molinier et al., 1996; Solomon & IPCC, 2007).

Climate in the Amazon basin has a strong relationship with the El Niño-Southern Oscillation (ENSO) which is associated with dry conditions in this region. In the 21st century, the Amazon region has been affected by significant droughts every 5–6 years (Aragão et al., 2018; Marengo et al., 2011; Silva Junior et al., 2019). Specifically, the 2015/2016 drought has been identified to be not only anomalously warmer, but also larger in extent when compared with the previous 1982/1983 and 1997/1998 droughts events (Jiménez-Muñoz et al., 2016). During this drought event, a region of approximately 400,000 km^2 of primary forest showed photosynthetic capacity four times smaller than the regions that were not affected by this drought event (Anderson et al., 2018; Koren et al., 2018; van Schaik et al., 2018). Furthermore, during 2016, there was an observed increase in fire pixel occurrence in western Amazonia and in the northern fringes of the basin (Silva Junior et al., 2019).

Extreme and anomalous events such as the 2015/2016 Amazon drought produce social and scientific demand to understand if this event was induced or modified by human activities (Van Loon et al., 2016). Decision makers can then use this information to plan strategies for adaptation or to support carbon emissions reduction policies. In recent years, there has been an increase in the number of studies that seek to understand the contribution of anthropogenic forcings to extreme hydro-meteorological events (Chen et al., 2019; de Abreu et al., 2019; Pall et al., 2011). In general, attribution of extreme events is made by comparing the probability of the event in a scenario that simulates the real climatic conditions observed and another that has human influences removed. This concept has already been applied to several studies (de Abreu et al., 2019; Pall et al., 2011; Shiogama et al., 2013; Stott et al., 2004) and specifically for the Amazon region, Shiogama et al. (2013) studied the drought that occurred in 2010 in the south of that region using the MIROC5 model. In this study, we aim to analyse whether the Amazonian 2015/2016 (October 2015 to February 2016) drought event was modified in terms of intensity and occurrence probability by anthropogenic influences, using event attribution methods based on climatic simulations of the Met Office HadGEM3-GA6-based model.

2 | MATERIALS AND METHODS

The methodology consists of three main stages:

1. Event characterization: Delimiting the study area and analysing the impact of the 2015/2016 drought event. We used precipitation data to determine which region of the Amazon was most affected by the drought event in 2015/2016.
2. Model evaluation: Analysing the performance of the Met Office HadGEM3-GA6-based model. We evaluate the capability of this model to represent the main atmospheric patterns related to the occurrence of drought events in the Amazon region.
3. Event attribution: Attributing changes in the risk of the Amazonian 2015/2016 drought event to anthropogenic influences. We compared the probability of the occurrence of this event in a scenario that removes human influences with a scenario that represents the conditions actually observed to quantify the anthropogenic influence in the 2015/2016 drought event.

2.1 | Event characterization

In this study, we focus on the northern Amazon. This region was selected not only because of the extreme drought and high temperatures in 2015/2016, but also because in other drought events the impact on vegetation was greatest in this region (Anderson et al., 2018; Jiménez-Muñoz et al., 2016). The 2015/2016 drought event started during the 2015 wet season (April–September), then evolved and reached its peak intensity during the dry season (October 2015 to February 2016). The onset and peak of this drought event occurred when the most intense sea surface temperature (SST) variation associated with El Niño were recorded in recent decades (Jiménez-Muñoz et al., 2016).

We delimited the study area by analysing the drought impact by determining the yearly anomaly of maximum water deficit (AWD). The water deficit (WD) indicates when drought led to a negative impact in the photosynthetic capacity of the old growth forests. For this, we used the forest evapotranspiration threshold of 100 mm/month (da Rocha et al., 2004; von Randow et al., 2004). This means that when the precipitation is lower than 100 mm/month, the vegetation enters into water stress. This methodology was proposed by Aragão et al. (2007) for the study of fire patterns in the Amazon during drought events. First, we calculated the WD (Equation 1) using the monthly precipitation and then selected the period with potentially higher impact, defined here as October 2015 to February 2016.

$$\mathrm{WD}_t\ (i,j) = \min(0,\ \mathrm{WD}_{t-1}(i,j) - \mathrm{E}(i,j) + \mathrm{P}_t(i,j)), \tag{1}$$

where subscript t is month, and i and j are latitude and longitude, respectively. WD is the water deficit, E is the evapotranspiration (100 mm/month; Aragão et al., 2007) and P is the monthly precipitation. The time series used for this research covers the period ranging from January 1981 to December 2018. AWD was then calculated according to the following equation:

$$\mathrm{AWD}_t\ (i,j) = \frac{\mathrm{WD}_t(i,j) - \mu(\mathrm{WD}(i,j))}{\sigma(\mathrm{WD}(i,j))}, \tag{2}$$

where μ(WD) and σ(WD) are the mean and standard deviation of the *WD(i,j)*, respectively, from, in our case, 1981 to 2018.

The density of the network of rain gauges in the Amazon region is quite low, despite the efforts of several government institutions to expand it. In addition, in most of the cases the collection of precipitation data is still carried out in a traditional way, which means that local technicians of the country's hydro-meteorological services take notes and report them. One of the main consequences of this method is that it results in additional errors in the time series of precipitation (Paca et al., 2020). Remote sensing products can be a solution for both problems and therefore we chose use the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS; Funk et al., 2015) precipitation products as an observational precipitation reference. The CHIRPS data set is a precipitation product that was originally developed for drought analysis and presents daily to seasonal time scales with a spatial resolution of 0.05° with quasi-global coverage (50° S–50° N, 180° E–180° W), starting from 1981 onwards. We selected this product due to its high accuracy and spatio-temporal resolution for the Amazon region, in addition to having been widely applied in several studies related to this region (Anderson et al., 2018; Cavalcante et al., 2020; Espinoza et al., 2019; Haghtalab et al., 2020; Paca et al., 2020; Paccini et al., 2018; Segura et al., 2020; Wongchuig Correa et al., 2017).

2.2 | Model evaluation

We have used a multi-decadal ensemble of the Met Office HadGEM3-GA6-based attribution framework with ENDGame dynamics at a spatial resolution of N216 (around 60 km), with 85 vertical levels (Ciavarella et al., 2018; Walters et al., 2017). The land surface model is JULES version GL6.0. We used this data set at a monthly temporal resolution. The model encompasses two types of simulations. In the first one ('natural'), the model is driven with only natural forcings, such as solar variability and volcanic eruptions, and has the estimated impact of anthropogenic forcings removed from the HadISST observed SST and sea ice patterns (Rayner et al., 2003) using the method described in Pall et al. (2011) and Christidis et al. (2012). The second ensemble ('historical') is forced by both natural forcings and anthropogenic forcings (including greenhouse gases, aerosols and changes in land use and land cover (LULC) and by HadISST observed SST and sea ice patterns). An ensemble of 15 multi-decadal simulations (from 1960 to 2013) was produced for each of the natural and historical scenarios, designed primarily for model validation. The differences in the realizations of individual ensemble members were produced by a unique random number seed given to a stochastic physics scheme (Ciavarella et al., 2018). For use in attribution assessments, ensemble simulations were extended and expanded to 105 members for 2014/2015 period and to 525 members from 2016 onwards. For this last period, we only had access to monthly rainfall during the dry season (October to February).

The Met Office HadGEM3 model performance analysis was conducted in two ways. First, we evaluate the capability of this model to represent the atmospheric patterns from the historical and natural simulations related to the occurrence of drought events in the Amazon region. This was done by calculation of velocity potential (VP) from the simulations and the European Centre for Medium Range Weather Forecasts (ECMWF) Interim Reanalysis (ERA-Interim; Dee et al., 2011). We validated the precipitation from the model by comparing it with the CHIRPS precipitation product through the Pearson correlation Index (R^2)

and percentage of the absolute bias (AB), which was calculated through Equation (3).

$$AB_t = 100 \times \frac{\sum_{t=1}^{n} \frac{|Pob_t - Psim_t|}{Pob_t}}{n} \quad (3)$$

where subscript t is the analysed month and n is the number of months in the time series. Pob and Psim are the precipitation from CHIRPS and the historical simulation, respectively.

2.3 | Event attribution

The event attribution method used in this study is the risk ratio (RR), which is the ratio between the probability of an event, larger than a defined threshold, in the historical ensemble compared to the natural ensemble. We determined this threshold through analysis of the standardized seasonal precipitation time series, which is the area averaged precipitation of the dry season (October to February) divided by mean of this time series for 1981 to 2010. We then expressed the standardized seasonal precipitation as a percentage to facilitate the interpretation of the results. Standardizing precipitation reduces the impact of bias in HadGEM3-GA6. The threshold used to define the drought event was defined as the average of the standardized seasonal precipitation of the two lowest standardized seasonal precipitation values from CHIRPS prior to 2015/2016 which were 1982/1983 and 1991/1992. This approach avoids overselection for the observed threshold and was based on the methods used by Dalagnol et al. (2021) and de Abreu et al. (2019). We also tested the sensibility of the RR to threshold values. The sensitivity of the RR to precipitation threshold was evaluated considering two other thresholds for standardized precipitation. These are CHIRPS precipitation drier by one or two standard deviations and then normalized by the mean.

The probability of occurrence was calculated by fitting the precipitation data from each ensemble, and the observations, to a Gamma probability distribution function, which is commonly used for this kind of analysis (McKee et al., 1993; Stagge et al., 2015). From the Gamma distribution, we computed the probability of exceeding the threshold. We analysed several different time periods from the natural and historical ensembles relative to the defined threshold. First, we considered the period 1981 to 2018 (15 members) and 2015/2016 (105 members). Then we analysed scenarios related only to periods subsequent to the occurrence of the 2015/2016 drought event. In this case, we analysed 2016/2017 and 2017/2018 both with 525 members. The confidence interval of the RR was calculated using the bootstrap method (Efron & Tibshirani, 1994) generating 10^4 samples for each set of average precipitation from October 2015 to February 2016 for the natural and historical ensemble members by sampling with replacement. We fit a Gamma distribution to each of these bootstrap samples to calculate the RR and then use the 5%–90% empirical distribution to quantify the uncertainty in the original RR calculation.

3 | RESULTS AND DISCUSSION

3.1 | Event characterization

Previous studies indicate that, in general, old growth forests in the Amazon region suffer water stress when rainfall is lower than evapotranspiration, estimated to be 100 mm/month. This WD can lead to a reduction in photosynthetic capacity or even increased vegetation mortality, therefore leading to a reduction of the CO_2 uptake rates. In this study, we characterize the drought events that occurred in the Amazon region using the yearly AWD (Figure 1), which is an index that quantifies this vegetation water stress. Drought events occurred frequently in Amazonia, and since 1981, there have been at least five relevant drought events (1983, 1995, 1997, 2005, and 2010). However, all were less intense than the 2015/2016 event (Figure 1). The study area was delimited by analysing the spatial variation of AWD and then identifying the region most commonly affected by drought events (purple rectangle, Figure 1a). Figure 1b shows the time series of AWD of the study area. It is even more clear in this figure the outstanding intensity of the 2015/2016 drought event, which was at least twice as intense as the other drought events that occurred in the study area.

3.2 | Model evaluation

The attribution of an extreme meteorological event to climate change requires complex simulations and their outputs should be reliable enough to represent the main climatic patterns related to the occurrence of the extreme event analysed. Thus, we evaluated the performance of the HadGEM3-GA6 model. First, we compared the 200 hPa VP difference between El Niño and La Niña from ERA-Interim reanalysis and simulations, and results are presented in Figure 2. We also analysed the difference between historical and natural ensemble for 2015/2016 (Figure 3). There is a general agreement of the model with the reanalysis, with increased VP in the western Pacific Ocean, implying anomalous descent, and negative values from the Central to the Eastern Pacific Ocean, implying anomalous ascent and these features are associated with a

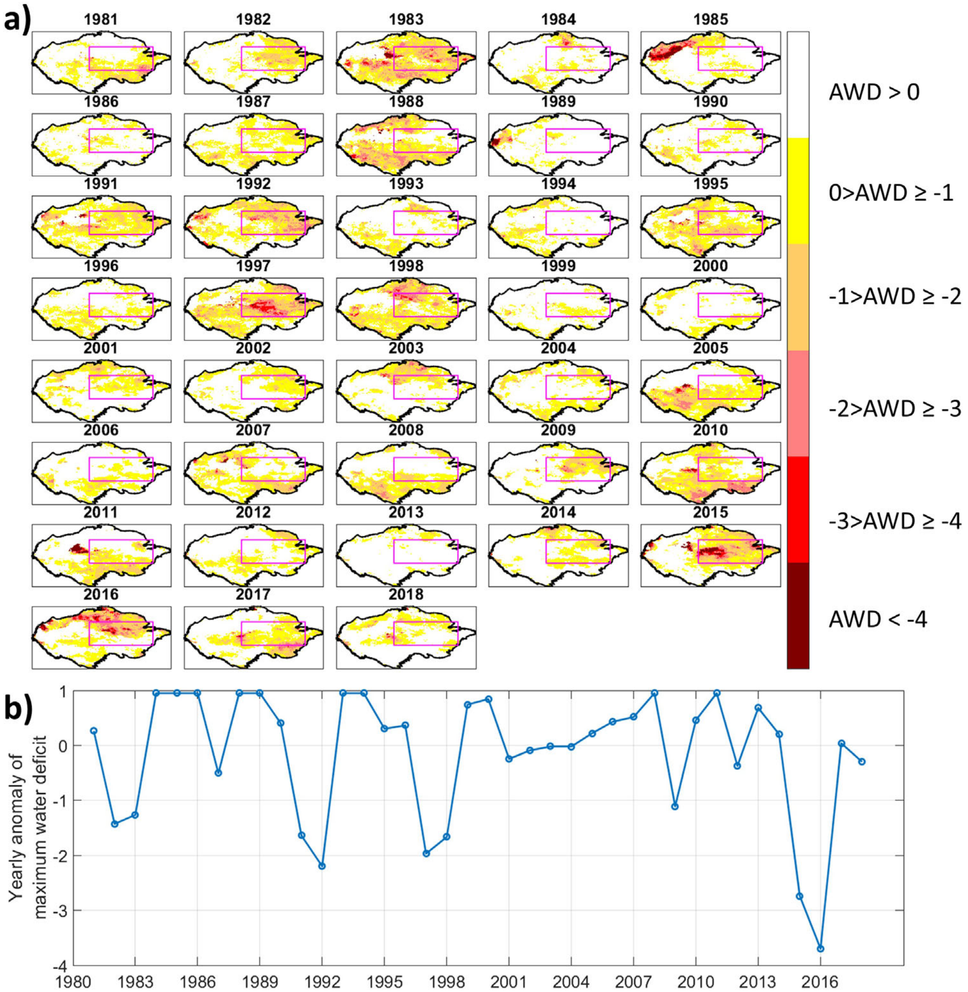

FIGURE 1 (a) Spatial variation of yearly anomaly of maximum water deficit (AWD) for the Amazon basin and location of the study area (purple rectangle 2° N to 8° S and 65° W to 50° W); (b) time series of AWD for the study area

weakened Walker circulation over the tropical Pacific associated with El Niño events (e.g. Cai et al., 2020). Another important feature is anomalous upper level positive VP anomalies over the Amazon which suggests anomalous descent in the region associated with El Niño events although VP anomalies based on reanalysis are relatively weak. As shown in Figure 2, there is a statistically significant over-estimation of VP anomalies associated with El Niño relative to La Niña events in the Amazon, which suggests stronger anomalous upper level divergence, and therefore stronger anomalous descent, in the region for the historical and natural ensembles than in reanalysis. Also, the composites in natural simulations show lower values of VP anomalies in the central and eastern Pacific Ocean, indicating a weaker anomalous circulation associated with El Niño in the natural than historical simulations, but there is no statistically significant difference in the Amazon (Figure 2a). Physical explanations for the model reanalysis and for the changes in the response to El Niño between the historical and natural ensembles are beyond the scope of this paper. Speculating, these differences between model and reanalysis could be due to the parameterization of convection in HadGEM-GA6 and how the latent heating is vertically distributed.

For the 2015/2016 drought event, VP differences between the two ensembles are more evident over the tropical Pacific and the Amazon (Figure 3). Over the tropical Pacific, positive VP anomalies over the western tropical Pacific and negative anomalies over the eastern tropical Pacific in the upper level are similar to those associated with El Niño events and suggest that anthropogenic forcings also induce a weakened Walker circulation. The historical ensemble has higher values than natural in the Amazon, indicating that the anthropogenic forcings also induce anomalous upper divergence and therefore anomalous descent in the region. These results suggest an anthropogenic influence on the large-scale tropical divergence circulation and circulation over the Amazon. Physically, this could be due to a wetter atmosphere, in response, to anthropogenic warming meaning larger changes in latent

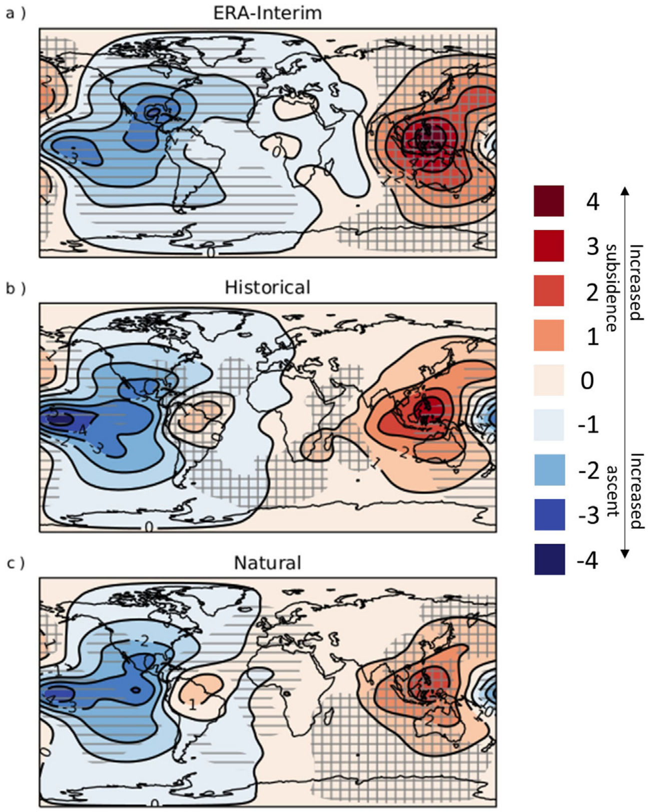

FIGURE 2 October–February velocity potential (10^6 m^2/s) composite difference between El Niño and La Niña years at 200 hPa for (a) ERA-Interim reanalysis; (b) historical ensemble; (c) natural ensemble. Hatching shows where El Niño composites are significantly different from La Niña years for (a), where historical is significantly different from Era-Interim for (b) and where natural is significantly different from historical for (c). Horizontal lines and cross-hatching indicate decreased and increased significance at the 10% level, respectively. Positive values (red colours) are associated with increased subsidence while negative values (blue colours) are associated with increased ascent

heating of the atmosphere during El Niño and La Niña events. This then increases the changes in the Walker circulation in response to El Niño/La Niñas.

We also analysed the performance of the model through its capability to represent precipitation at different time scales (monthly climatology, annual mean, and dry season). The number of members of the Met Office HadGMEGA6 model is not constant over time, so to standardize the performance analysis we used the 15 multi-decadal historical ensemble for 1981 to 2018 (see Subsection 2.2). In general, the model represents reasonably well precipitation in the study area over a range of time scales (Figure 4a–d). Figure 4a shows that the model tends to overestimate precipitation in the dry (October to February) and wet seasons (April to June). The consequence of this pattern is more evident in Figure 4b, in which it shows that there was in general an overestimation of the interannual variability of precipitation. Nevertheless, the model shows a high correlation with the observed data for all time scales and even at monthly time scales (Figure 4c), the AB was lower than 18%. At the dry season time scale (Figure 4d), which is the most relevant for analysing the drought patterns occurrence in the study area, it can be seen that the AB was below 10% and associated with a correlation close to 0.8. The overall rainfall variability at different time scales for historical simulation was well correlated with CHIRPS as seen in Figure 4, although simulations tend to overestimate ENSO influences in Amazonia. It is expected that the accuracy of the model can be further improved through bias correction methods. Furthermore, the low AB in the estimation of precipitation in most time scales implies that the ensemble simulates well enough the atmospheric drivers for the precipitation time series and therefore it is suitable for drought analysis and attribution. The gaps in Figure 4c are because we only had access to monthly precipitation for the dry season (October to February) for the period after 2016.

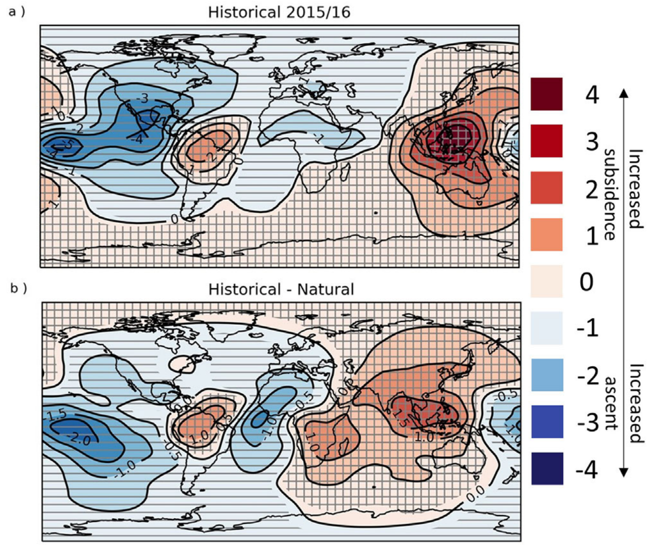

FIGURE 3 October–February velocity potential (10^6 m/s) difference between 2015/2016 drought event and climatology (1980 to 2010) at 200 hPa for (a) historical simulation; (b) historical minus natural simulation. Hatching shows where the event is significantly different from the climatology for (a) and where historical is significantly different from natural for (b). Horizontal lines and cross-hatching indicate decreased and increased significance at the 10% level, respectively. Positive values (red colours) are associated with increased subsidence while negative values (blue colours) are associated with increased ascent

3.3 | Event attribution

The threshold for calculating the RR uses standardized seasonal precipitation (Figure 4d) which is expressed as

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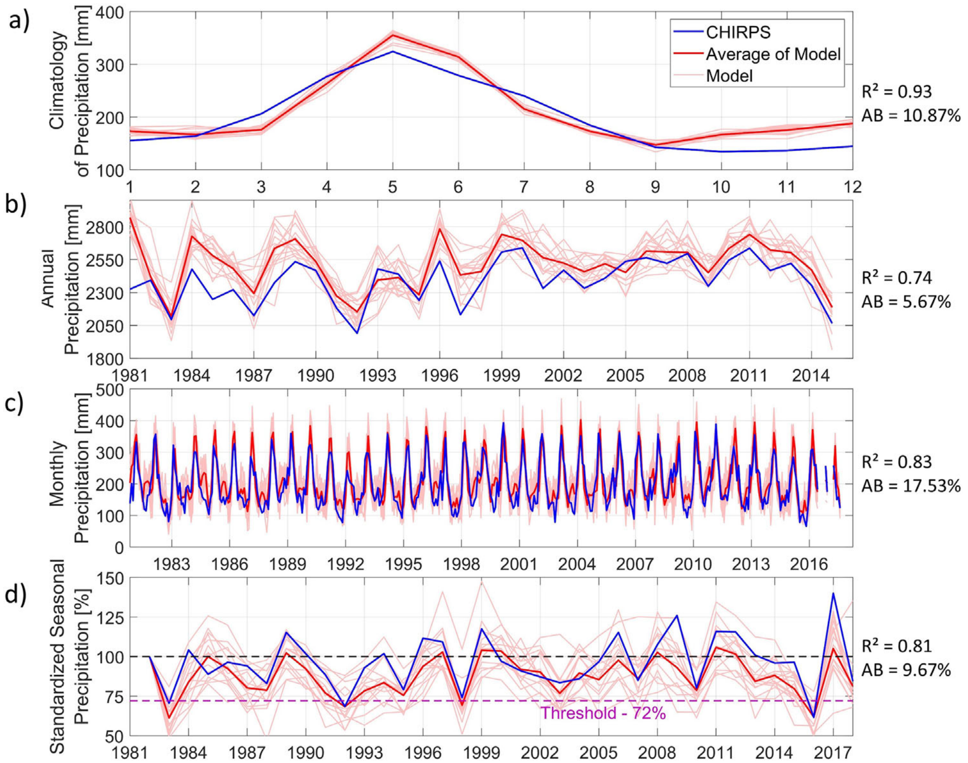
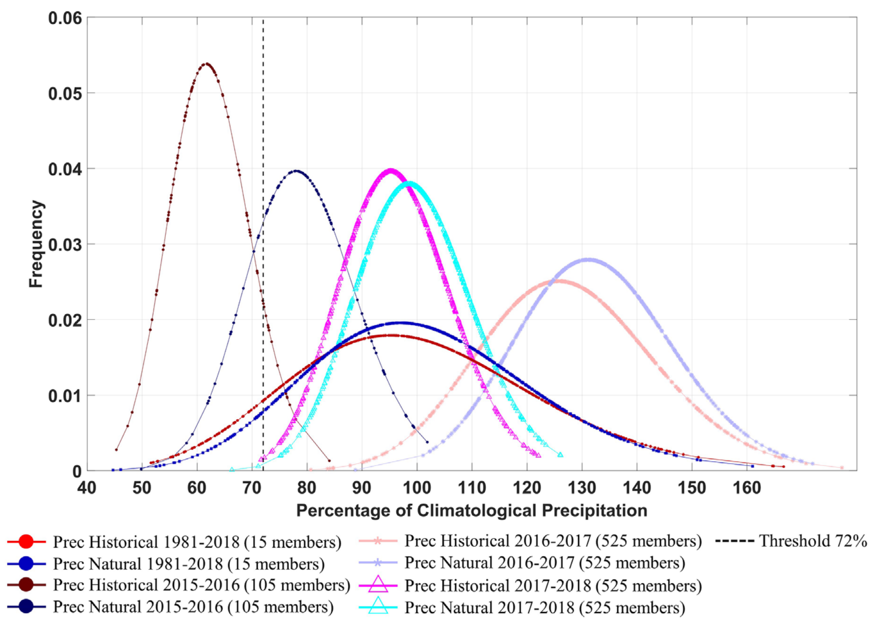


FIGURE 4 Comparison between CHIRPS precipitation and HadGEM-GA6 simulated precipitation in the study area. (a) Seasonal evolution of climatological monthly mean, (b) time series of annual mean, (c) time series of monthly mean and (d) time series of seasonal mean (October to February). AB is percentage of the absolute bias and R^2 is the Pearson correlation index. The dashed purple line is the threshold that was used for the risk ratio calculation. The black dashed line in (d) shows the 100% standardized seasonal precipitation

FIGURE 5 Probability distribution function for fitted Gamma distributions of natural and historical scenarios of October to February standardized precipitation in the study region



a percentage. This figure also shows the event attribution threshold that was defined considering the years 1982/1983 and 1991/1992 (see Subsection 2.3). We consider that there should be a reduction in precipitation by at least 28% (threshold of 72% indicated by the purple dashed line in Figure 4d) in relation to climatology (average value for the period 1981/2018) for a drought event to be considered extreme. Figure 5 shows the probability distributions for both the natural and historical ensembles based on fits to Gamma distributions. For the entire 1980 to 2018 period, there was a small precipitation reduction due to anthropogenic influences. For 2015/2016 (105 members), we obtain an RR value of 3.7 with 97.5% confidence intervals of 2.7 and 4.7. This suggests that the probability of a severe drought event is almost four times higher in the historical scenario and within 2.5 times to five times more likely.

Gamma distribution fits for the both 525-member ensembles in 2016/2017 and 2017/2018 show a shift to drier conditions in the historical ensembles. They both show large year-to-year changes in the distributions suggesting that interannual variability has a large impact on the hydro-climate of the Amazon. This increased risk of drought events due to anthropogenic forcing, together with the similarity of the VP anomalies between the historical and natural simulations (Figure 3) to those associated with El Niño events suggest that the increased drought occurrence was due to the natural climatic variability enhanced by anthropogenic influence.

To test sensitivity of the RR to precipitation threshold, we considered two other thresholds for standardized precipitation. These are CHIRPS precipitation drier by one or two standard deviations and then normalized by the mean. These thresholds are 82% and 65%, respectively, with the 2015/2016 drought being close to the drier threshold. The RRs for these thresholds are 1.6 (1.4–1.7) and 10.3 (6.2–20.5) suggesting that RR increases with the magnitude of Amazonian drought. This happens because, in 2015/16, the historical distribution, relative to natural, shifted to being drier and so dry events in the tail of the distribution are more common in historical than in natural. It also suggests that our finding of significant increases in the risk of drought, due to anthropogenic climate change, are insensitive to the threshold used.

4 | CONCLUSIONS

In this study, we analysed if anthropogenic forcings changed the probability and intensity of the 2015/2016 (October 2015 to February 2016) Amazonia drought event, which was the most severe drought in the past few decades. We compare a historical scenario with a natural one in which the major anthropogenic forcings after the industrial revolution are not considered (e.g. changes in greenhouse gas emissions, aerosol emissions and land use/land cover pattern). We show that although the model presents some bias related to the intensification of the El Niño effect in the atmospheric circulation pattern, in general it well represents the spatial–temporal variation of the precipitation of the Amazon region at different time scales. The results presented in this study highlighted the potential of anthropogenic influence in the intensification of droughts in the Amazon. We show that the occurrence likelihood of the 2015/2016 drought event has been increased by almost four times due to anthropogenic influence.

The physical mechanism for the risk enhancement appears to be a stronger response to the 2015/2016 El Niño in the historical ensemble than in the natural ensemble over Amazonia driving descent over this region. In both model and observations, precipitation over Amazonia is strongly correlated with ENSO. Mechanistically, during El Niño events the equatorial Pacific is anomalously warm, which leads to anomalous ascending motion here, while subsidence increases over the west tropical Atlantic and east Amazon basin, as an anomalous Walker circulation. However, the enhanced response to ENSO, due to anthropogenic warming, seen in HadGEM-GA6 would benefit from further investigation, using other models, as the circulation in HadGEM-GA6 appears to show a stronger response to El Niño than does ERA-Interim.

Finally, these results suggest serious concern about the long-term cumulative impacts of climate change. Extreme droughts in the Amazon region have the potential to reduce the greenhouse gas capture capacity of the biome and, therefore, intensify the effects of climate change. This in turn can increase the frequency of extreme droughts in this region, thus creating a vicious cycle. This study was part of the scientific effort to elucidate more issues related to climate change, which can support the planning of policies to reduce the emission of greenhouse gases and mitigate the impacts resulting from climate change.

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