Earth's Future

RESEARCH ARTICLE
10.1029/2020EF001608

Implications of CMIP6 Projected Drying Trends for 21st Century Amazonian Drought Risk

L. A. Parsons[1,2]

[1]Department of Atmospheric Sciences, University of Washington, Seattle, WA, USA, [2]Nicholas School of the Environment, Duke University, Durham, NC, USA

Key Points:

- Coupled Modeling Intercomparison Project, Phase 6, models show better agreement that the Amazon will receive less future rainfall
- Model simulations indicate that if global warming continues unabated, recent particularly warm and severe droughts will become more common
- Climate models that simulate a more "El Niño-like" future tropical Pacific tend to also simulate more drying over Amazonia

Supporting Information:

- Supporting Information S1

Correspondence to:
L. A. Parsons,
luke.parsons@duke.edu

Citation:
Parsons, L. A. (2020). Implications of CMIP6 projected drying trends for 21st century Amazonian drought risk. *Earth's Future*, *8*, e2020EF001608. https://doi.org/10.1029/2020EF001608

Received 1 MAY 2020
Accepted 24 SEP 2020
Accepted article online 29 SEP 2020

Author Contributions:
Conceptualization: L. A. Parsons
Formal analysis: L. A. Parsons
Funding acquisition: L. A. Parsons
Investigation: L. A. Parsons
Methodology: L. A. Parsons
Project administration: L. A. Parsons
Resources: L. A. Parsons
Supervision: L. A. Parsons
Validation: L. A. Parsons
Visualization: L. A. Parsons
Writing - original draft: L. A. Parsons
Writing – review & editing: L. A. Parsons

Abstract

Recent exceptionally hot droughts in Amazonia have highlighted the potential role of global warming in driving changes in rainfall and temperatures in the region. The previous generation of global climate models projected that eastern Amazonia would receive less future precipitation while western Amazonia would receive more precipitation, but many of these models disagreed on future precipitation trends in the region. Here Coupled Modeling Intercomparison Project, Phase 6 (CMIP6) models are used to examine the shifting risk of eastern Amazonian droughts under high and low future greenhouse gas emissions scenarios. This new generation of models shows better agreement that most of the Amazonian basin will receive less future rainfall, with particularly strong agreement that eastern and southern Amazonia will dry in the 21st century. These models suggest that global warming may be increasing the likelihood of exceptionally hot drought in the region. With unabated global warming, recent particularly warm and severe droughts will become more common by midcentury, but reducing the rate of greenhouse gas emissions can make extremely hot and dry years less common in the future. Simulated future rainfall changes in Amazonia under high greenhouse gas emissions are associated with changes in the tropical Pacific, but many climate models struggle to reproduce observed trends in the tropical Pacific. These shortcomings highlight the need to improve confidence in global climate models' ability to simulate observed trends in the tropics, even if more CMIP6 models agree on the sign of future rainfall trends.

Plain Language Summary

Recent exceptionally hot droughts in Amazonia have highlighted the potential role of global warming in driving changes in rainfall and temperatures in the region. The previous generation of global climate models projected that eastern Amazonia would receive less future rainfall while western Amazonia would receive more rainfall. Here the latest climate model simulations are used to examine future rainfall and temperature changes over tropical South America. The new generation of climate models shows that most of the Amazonian basin will receive less future rainfall, with particularly strong agreement that eastern and southern Amazonia will dry in the future if the planet continues to rapidly warm. These models suggest that global warming has already increased the likelihood of exceptionally hot drought in the region, and by midcentury under unabated global warming, recent particularly warm and severe droughts will become more common. Reducing future greenhouse gas emissions decreases these warming and drying trends but does not eliminate them. However, many climate models have traditionally struggled to reproduce several key climate features in the tropics.

1. Introduction

The Amazonian rainforest provides important ecosystem services both locally and globally (Malhi et al., 2008; Lenton et al., 2008). Yet, the composition of the Amazonian rainforest is vulnerable to human land use as well as climate variability and global climate change (Malhi et al., 2009; Marengo et al., 2018; Nepstad et al., 1994). A combination of warming and rainfall deficits, driven by both climate variability and change, will likely cause future ecosystem stress and thus potentially limit the ability of this region to continue to store carbon (Brienen et al., 2015; Hubau et al., 2020; Phillips et al., 2009; Tian et al., 1998). Decreased seasonal precipitation and warming are already contributing to drought and vegetation stress in this region (Dai, 2013; Jimenez-Munoz et al., 2016; Lewis et al., 2011; Marengo et al., 2018; Saatchi et al., 2013). Specifically, fires during droughts in tropical South America can clear tropical rainforest and grassland, leading to carbon emissions to the atmosphere (Aragão et al., 2018). Recent work has also shown that rainfall deficits can increase fire risk, leading to self-amplified forest loss (Boers et al., 2017; Brando et al., 2014; Zemp et al., 2017), and drought-deforestation feedbacks can grow in strength with cumulative deforestation (Staal et al., 2020). Furthermore, deforestation can reduce evapotranspiration, amplifying regional drought (Lovejoy & Nobre, 2018; Xu et al., 2020; Zemp et al., 2017).

Superimposed on future rainfall changes (Duffy et al., 2015), the region may also need to cope with multiyear droughts arising from natural background climate variability (Parsons et al., 2018). The paleoclimate records suggest that the Amazonian ecosystem was able to persist during moderate droughts in the preindustrial climate (Bush et al., 2016), but it is uncertain if future climate change, combined with other anthropogenic stressors and natural hydroclimatic variability, will trigger unprecedented ecosystem stress in this "climate change hot spot" (Davidson et al., 2012; Diffenbaugh & Giorgi, 2012). The region is expected to warm quickly as the globe warms (Soares et al., 2019), but action that will limit future global climate change may significantly reduce the most detrimental impacts of climate change locally (Lehner et al., 2017).

The previous generation of climate models (Coupled Model Intercomparison Project Phase 5, or CMIP5; Taylor et al., 2012) indicated that northeastern Amazonia may dry while western Amazonia may receive increasing rainfall as the globe warms (Duffy et al., 2015). Recent work has shown that the new CMIP Phase 6 (CMIP6; Eyring et al., 2016) simulations agree on the sign of future rainfall trends in Amazonia, with droughts projected to increase in duration and intensity with global warming (Ukkola et al., 2020). Specifically, CMIP6 models show drying across western Amazonia, and most CMIP6 models agree on future decreases in soil moisture and runoff across most of Amazonia in low, medium, and high greenhouse gas emissions scenarios (Cook et al., 2020).

Studies of observed rainfall and temperature indicate that climate change may already be driving "enhanced" (particularly hot and arid) drought in the region; 2016 was the warmest year in Amazonia since 1950 (Marengo et al., 2018), and the recent 2015–2016 drought in eastern Amazonia was at least 1.5°C warmer than the drought associated with the 1997–1998 El Niño event (Jimenez-Munoz et al., 2016, hereafter JM16). Yet, the risk of this type of recent hot drought has not been investigated in state-of-the-art climate models, and recent preliminary studies of future drought changes in CMIP6 (e.g., Cook et al., 2020; Ukkola et al., 2020) have relied on limited numbers of these new model simulations (e.g., 10–13 models). Given the severity of recent seasonal droughts in the region and the apparent increase in model agreement in terms of future drying in the region, here instrumental records and an expanded suite of CMIP6 simulations are used to examine recent and future trends in rainfall and temperatures, with a focus on the likelihood of the risk of a 2015–2016 type drought under shifting precipitation and temperature baselines.

2. Data and Methods

2.1. Choice of Season and Drought Metric

Surface air temperature, rainfall, and soil moisture variability and trends over tropical Central and South America in October–March (ONDJFM) are examined (e.g., Satyamurty et al., 2010; Wang et al., 2018), with a specific focus on northeastern Amazonia (10°S to 8°N, 60–50°W, outlined in Figure 1). Although many CMIP6 models project drying across much of tropical South America (Cook et al., 2020; Ukkola et al., 2020), this study focuses on northeastern Amazonia due to the impact of recent drought in this region in observations (JM16), as well as the robust drying response in CMIP6 models in this region under climate change (Cook et al., 2020, also discussed here). Furthermore, although abnormally low rainfall can occur during various months throughout the year, here the focus is on ONDJFM due to the impacts of El Niño events during the ONDJFM time period (e.g., JM16).

Drought metrics can account for supply of moisture from the atmosphere (e.g., rainfall and standardized precipitation index), atmospheric-centric supply and demand (e.g., Palmer Drought Severity Index, PDSI), or plant-centric supply and demand (e.g., soil moisture and water budget; Swann, 2018). Precipitation is chosen as the primary metric to study the impacts of climate change on drought as it related to "atmospheric supply." Precipitation trends are also compared to trends in simulated 10-cm soil moisture anomalies because soil moisture in Earth system models accounts for supply from the atmosphere, atmospheric demand, and plant responses to changing future atmospheric CO_2 concentrations (Swann et al., 2016). Although near-surface soil water can respond differently than deeper soil water to drought (Berg et al., 2017), CMIP6 simulations show similar projected trends in surface and full column soil moisture in tropical

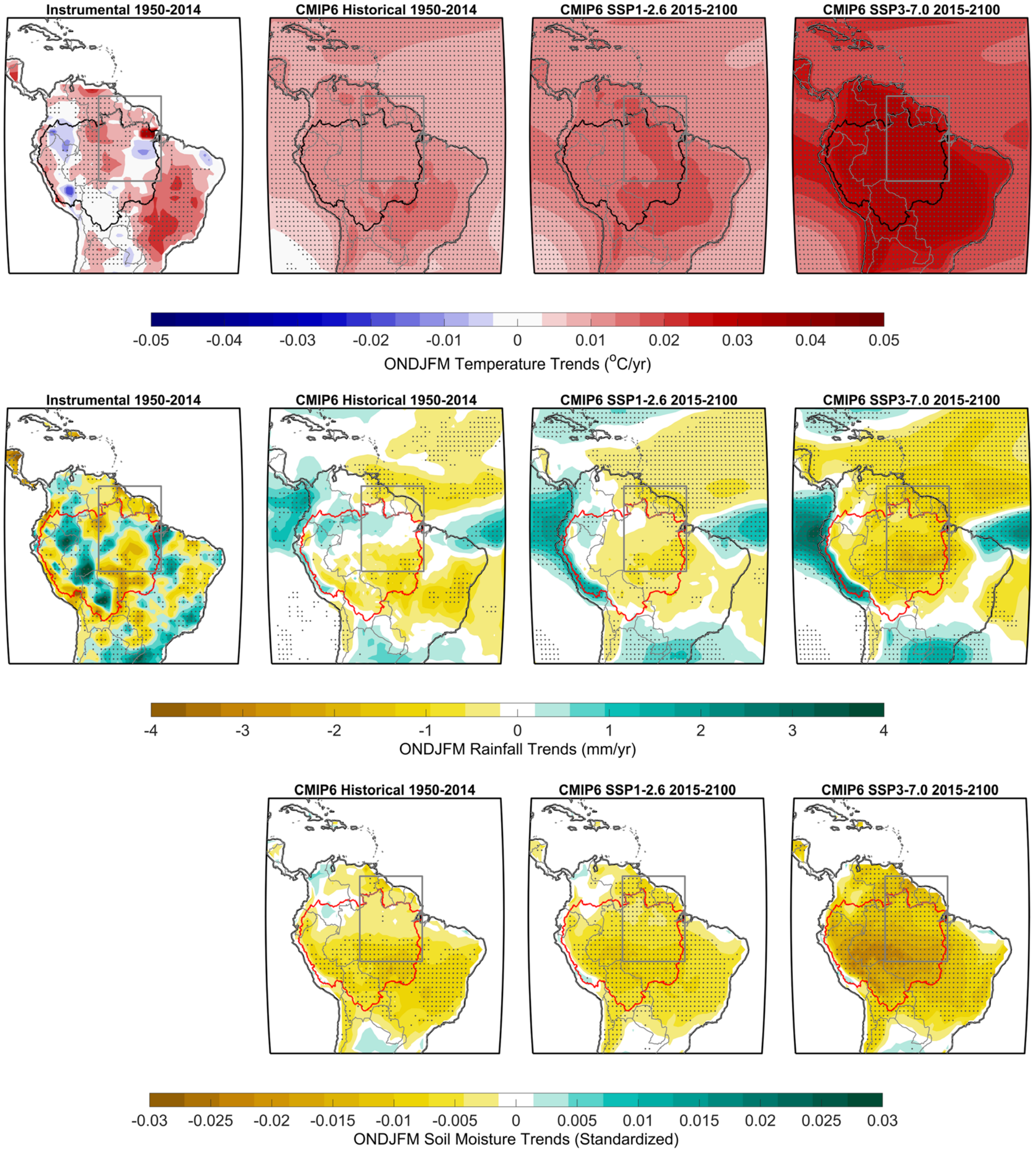

Figure 1. Average temperature (top row), rainfall (middle row), and 10-cm soil moisture (bottom row) trends in instrumental data 1950–2014 (left), climate model historical simulations 1950–2014 (center left), SSP1-2.6 warming scenario 2015–2100 (center right), and SSP3-7.0 warming scenario 2015–2100 (right). Gray box outlines the Eastern Amazonian region used to make time series shown in text (10°S to 8°N, 60–50°W), black/red line outlines the Amazonian basin, and light gray lines show country borders. Stippling shows where all instrumental data agree on sign of trend (left) or where more than 17 out of 22 model simulations (>75%) agree on the sign of the trend (center, right).

South America (Cook et al., 2020). Other drought metrics are not considered, such as PDSI, because they can provide conflicting answers about responses of drought to warming or overestimate aridification from warming (e.g., Swann et al., 2016; Trenberth et al., 2014). Although ONDJFM trends are examined here, trends in individual months are shown in Figures S1 (precipitation) and S2 (soil moisture) in the supporting information. Droughts are complex phenomena with various characteristics including intensity, duration, frequency, onset, demise, and areal extent. Here, implications of ONDJFM mean precipitation, soil moisture, and temperature trends on droughts are examined. The work presented here does not explore the length of the dry or onset of rainy season (Fu et al., 2013; Marengo et al., 2011, 2017; Saeed et al., 2018) as the issue of drought duration and severity has already been addressed in Ukkola et al. (2020).

2.2. Instrumental Data

The station-based Global Precipitation Climatology Centre (GPCC) Version 2018 (Schneider et al., 2011), University of Delaware (UDEL) Version 5.01 (Willmott & Matsuura, 2001), and National Oceanic and Atmospheric Administration (NOAA) Precipitation Reconstruction over Land (PRECL; Chen et al., 2002) are used to examine past rainfall variability and trends. When showing time series covering the 1979–2018 time period, the station-based data are supplemented with Climate Prediction Center Merged Analysis of Precipitation (CMAP) data set, which blends satellite and gauge-based data from 1979 to the present (Xie & Arkin, 1997). Past surface air temperature variability over land is also examined using Goddard Institute of Space Studies (GISS) surface temperature analysis (GISTEMP; Lenssen et al., 2019), Climate Research Unit (CRU) Air Temperature Anomalies Version 4.2.0 (CRUTEMv4; Jones et al., 2012), and UDEL temperature Version 5.01 (Willmott & Matsuura, 2001). Linear trends in each temperature and rainfall data set are calculated over the 1950–2014 time period, and the average of these trends are shown in Figure 1. Stippling in Figure 1 shows where all rainfall (GPCC, UDEL, and PRECL) or temperature data (GISTEMP, CRUTEM4, and UDEL) agree on the sign of trend over this time period. Varying the time period over which this trend is calculated (e.g., 1950–2010 or 1950–2017) does not noticeably change these results.

In all instrumental time series (e.g., Figures 2 and 3), data are normalized to the mean and interannual variability (standard deviation, hereafter σ) of the 1950–2000 time period (hereafter "baseline") using the mean and σ from all data sets that have coverage over this time period. Baseline mean and σ results are presented in section 3.1. An anomalously "hot" season is defined as a year when ONDJFM mean temperatures are at least 2 σ above the baseline, and anomalously dry seasons are defined as ONDJFM precipitation anomalies at least 1.5 σ below the baseline period. These thresholds are based on anomalously high temperatures and drought conditions experienced in this region during recent El Niño events (1982–1983, 1997–1998, and 2015–2016; JM16; Figure 2).

2.3. Climate Model Data

Monthly 2-m surface air temperature (tas), precipitation (pr), and 10-cm soil moisture (mrsos) from 22 CMIP6 models are used. To be included in this analysis, CMIP6 model output for all three variables from the historical (1850–2014), Shared Socio-Economic Pathway (SSP) 3–7.0 (2015–2099; Riahi et al., 2017), and SSP1-2.6 experiments (2015–2099; Eyring et al., 2016) had to be available at the time of analysis (Table S1). The historical runs are driven by estimates of recent anthropogenic (land use, greenhouse gas, aerosol, ozone) and natural (solar, orbital, volcanic) forcing. The SSP scenarios are concentration-driven experiments from hypothetical future socioeconomic pathways (Riahi et al., 2017). The SSP3-7.0 simulations are from a high-end emissions scenario from the Scenario Model Intercomparison Project (ScenarioMIP; O'Neill et al., 2016). The SSP3-7.0 scenario reaches ~7.0-W/m^2 radiative forcing by the year 2100 in a "regional rivalry" future, with high levels of deforestation (Popp et al., 2017). By contrast, the SSP1-2.6 simulations are from a low-end emissions scenario that focuses on a "sustainable" future and reaches ~2.6-W/m^2 radiative forcing by 2100 (O'Neill et al., 2016). CMIP6 results are compared to output from 32 CMIP5 historical (1861–2005) and RCP8.5 simulations (2006–2,100; CMIP5 models listed in Table S1). CMIP6 SSP3-7.0 results have been compared to CMIP6 SSP5-8.5 results, and the main conclusions are nearly identical (not shown). In section 4 and the supporting information, results from SSP3-7.0 are also compared to results from idealized 1%CO_2 simulations, in which CO_2 concentrations in the atmosphere are increased at a rate of 1%/year, and there are no prescribed land use changes (Eyring et al., 2016).

All model data are linearly interpolated to the GPCC 1° × 1° spatial grid resolution for creating multimodel means. Many CMIP5 models underestimate rainfall over tropical South America (e.g., Yin et al., 2013) and have several biases related to simulation of climate over Amazonia (e.g., Moghim et al., 2017). Although daily model data are often bias corrected (e.g., Cannon et al., 2015), return values for extreme events can be corrupted in the process. Furthermore, there is no relationship among mean state bias or variability bias in ONDJFM rainfall and future rainfall changes in the region in CMIP6 models (not shown). Therefore, to avoid issues associated with bias correction, CMIP6 model time series of eastern Amazonian rainfall, soil moisture, and temperatures are shown as anomalies relative to the ONDJFM mean and interannual variability (standard deviation, hereafter σ) 1950–2000 "baseline." Soil moisture is standardized to the mean and standard deviation of the baseline period in each CMIP6 model prior to analysis (e.g., Cook et al., 2020). An anomalously "hot" year is defined as a year when ONDJFM mean temperatures are at least

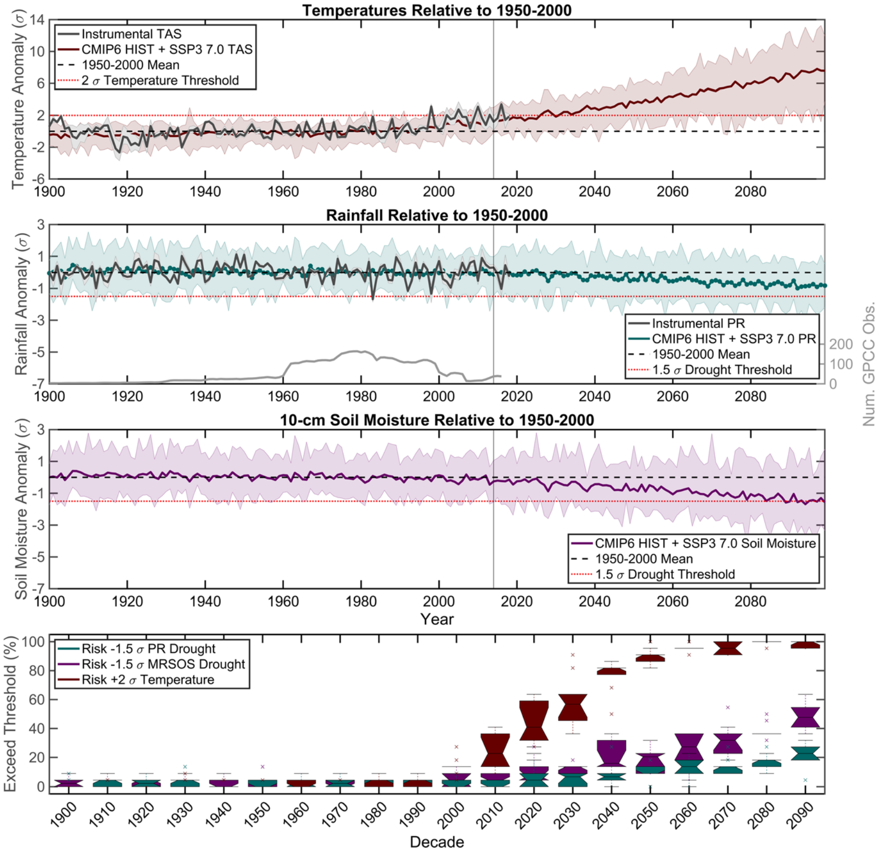

Figure 2. Top three panels show normalized October–March temperature (top), rainfall (upper middle), and 10-cm soil moisture (lower middle), anomalies from the 1950–2000 time period in eastern Amazonia (10°S to 8°N, 60–50°W) in instrumental data (gray) and CMIP6 historical and SSP3-7.0 simulations (temperature: red, precipitation: teal, soil moisture: purple). Thick light gray line on bottom of middle panel shows number of station observations in eastern Amazonia. Dark colored lines in top three panels show multimodel mean in the historical and SSP3-7.0 simulations, and shading shows model spread. Dashed black line shows the 1950–2000 mean, red dotted line shows the heat and drought thresholds, light gray lines show spread of instrumental data, and dark gray lines show mean of instrumental data. Vertical line shows the end of the historical simulations and the start of the SSP simulations. Boxplots in bottom panel show the percent of years per decade that fall outside the baseline (1950–2000) range of temperature and drought variability. Red boxplots show the spread in the percent of models per decade that exceed a 2 σ temperature threshold, and teal and purple boxplots show the spread in the percent of models per decade that simulate droughts 1.5 σ below the baseline. See section 2 for more information about instrumental data.

2 σ above the baseline for each model, and anomalously dry years are defined as ONDJFM precipitation or soil moisture anomalies that are at least 1.5 σ below the baseline period for each model. In section 3.3, "likelihood" or "risk" of anomalously hot and dry years by decade is presented; this likelihood is based on the percent of model years per decade across all models that cross this baseline threshold. Baseline mean and standard deviation results are presented in section 3.1.

2.4. Comparison With Sea Surface Temperature Variability and Trends

Variability in sea surface temperatures (SSTs) in the tropical Atlantic and Pacific from the NOAA Extended Reconstructed SST Version 5 (ERSSTv5) data set (Huang et al., 2017) is compared to rainfall and temperature variability over land. Specifically, the ONDJFM El Niño–Southern Oscillation (ENSO) index (Niño3.4 region: 5°S to 5°N, 170–120°W), and the Tropical North Atlantic (TNA) index (6°N to 22°N, 80–15°W; Yoon & Zeng, 2010) are compared with ONDJFM rainfall and temperature over tropical South America over the 1950–2014 time period after removing the linear trend from each grid point over this time period. Maps of correlations show the average correlation between the ERSSTv5 Niño3.4 index and each

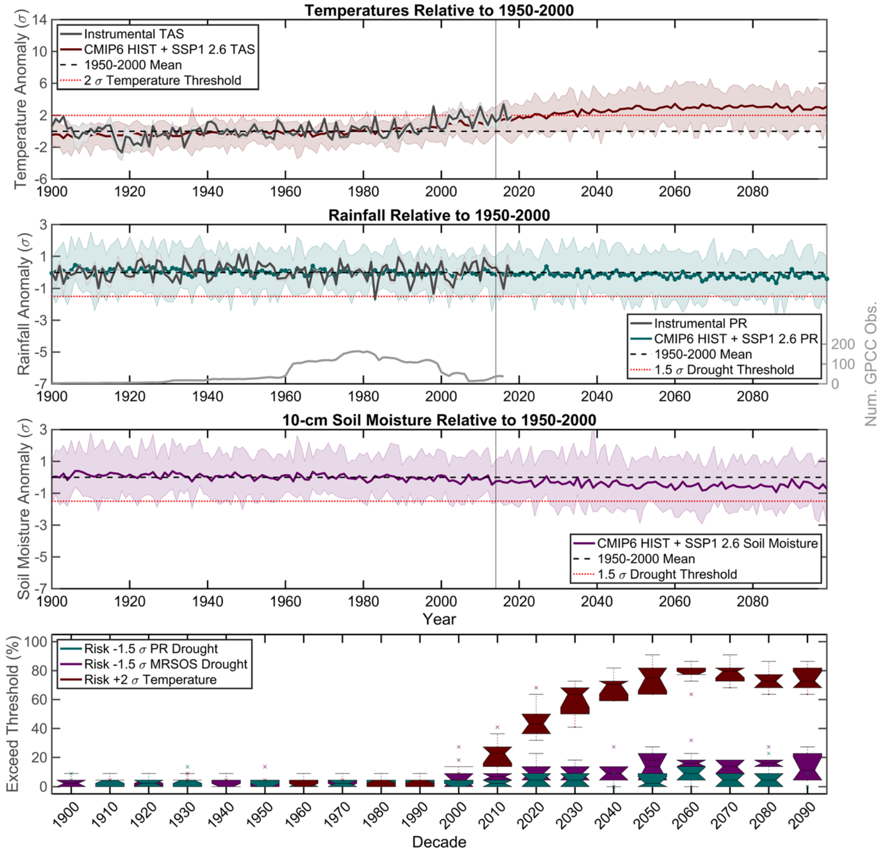

Figure 3. As in Figure 2, but for the SSP1-2.6 simulations.

precipitation data set (GPCC, UDEL, and PRECL) and temperature data set (GISTEMP, CRUTEM4, and UDEL) in Figures S3 and S4.

The CMIP6 historical and SSP3-7.0 rainfall and temperature over South America are also compared with the Niño3.4 index (5°S to 5°N, 170–120°W) and TNA index (6°N to 22°N, 80–15°W). Specifically, the Niño3.4 index and TNA index are correlated in each CMIP6 model with rainfall and temperature over tropical South America separately over the 1950–2014 and 2015–2100 after removing the linear trend from each grid point over these time periods (Figures S3 and S4). Maps of correlations in Figures S3 and S4 show the average correlation among all CMIP6 simulations over the relevant time periods, with stippling showing where >90% models agree on sign of correlation. Most CMIP6 simulations agree on the sign and spatial correlation patterns associated with the Niño3.4 and TNA indices.

Additionally, 21st century surface temperature trends in the tropical Pacific are compared to trends in Amazonian rainfall in CMIP5 RCP8.5 and CMIP6 SSP3-7.0 simulations 2015–2099. Specifically, eastern Amazonian rainfall trends are compared to (1) trends in mean surface temperature over the Niño3.4 region and (2) west-east tropical Pacific temperature trend differences (e.g., Yeh et al., 2012).

3. Results

3.1. Eastern Amazonian “Baseline” in Instrumental and CMIP6 Data

The instrumental ONDJFM 1950–2000 “baseline” mean rainfall is 1,230 mm (±19 mm across data sets), and interannual variability (σ) is 214 mm (±19 mm across data sets). The ONDJFM mean UDEL temperature over the baseline period is 22.4°C, and the average temperature σ across all three instrumental data sources is 0.34°C (±0.03°C across data sets). GISTEMP and CRUTEM4 provide temperatures as anomalies, so their mean 1950–2000 temperatures are not presented here. In the CMIP6 historical simulations 1950–2000, the “baseline” mean ONDJFM rainfall over eastern Amazonia is 892 mm (±207 mm across models), and interannual variability (σ) is 177 mm (±31 mm across models). The ONDJFM mean temperature is 22.7°C (±1.1°C across models), and interannual variability (σ) is 0.61°C (±0.16°C across models).

3.2. Trends in Amazonian Temperature and Drought

Instrumental data and CMIP6 simulations show similar warming trends 1950–2014 over northern Amazonia and much of southeastern Brazil (Figure 1). However, the CMIP6 multimodel mean shows a more widespread, homogeneous warming pattern than the instrumental data; this result is perhaps not surprising given that ensemble mean of climate model simulations tend to maximize forced variability (Knight, 2009), whereas the instrumental data represent a combination of internal variability and forced change. All CMIP6 models show a continued warming trend across the region in SSP3-7.0 projections, with a decrease in warming in SSP1-2.6 (Figure 1).

Instrumental precipitation data show a drying trend over much of eastern Amazonia and northern tropical South America, and a positive rainfall trend in much of western and northwestern Amazonia 1950–2014 (Figure 1). These results are similar to findings presented by Wang et al. (2018), who show that the December–May season in northwestern Amazonia experienced increasing rainfall 1979–2015. CMIP6 historical simulations show decreasing precipitation over northern South America and much of southern Amazonia and a slightly positive rainfall trend over northwestern Amazonia in the ONDJFM mean (trends in individual months shown in Figure S1).

In the SSP3-7.0 global warming scenario, >75% of models show a drying trend over much of southwestern, eastern, and northern tropical South America. The geographic extent of this future drying trend is decreased in SSP1-2.6, with a weaker drying trend in eastern and southern Amazonia in the multimodel mean, but general agreement in the sign of the trend in the southeast. The CMIP6 SSP3-7.0 and SSP1-2.6 simulations show increasing future rainfall in NE Brazil, but there is less agreement on the sign of this trend. All but 2 months show future decreasing rainfall across much of Amazonia in CMIP6 SSP3-7.0 projections (Figure S1). The soil water variable from CMIP6 SSP1-2.6 and SSP3-7.0 simulations shows a drying trend across most of tropical South America, with particularly strong soil water decreases in southwestern Amazonia in the ONDJFM mean (Figure 1), but these trends in soil water are apparent in all months (Figure S2).

3.3. Climate Change and the Shifting Risk of Amazonian Drought

Instrumental records of Amazonian rainfall and surface air temperatures extending to the early twentieth century can be used to put recent droughts in a longer-term context. Instrumental data show that recent ONDJFM seasonal droughts associated with El Niño events have been 2–3 σ warmer than the 1950–2000 baseline (section 2.2), with recent multiyear temperatures either at or near this 2 σ level (Figure 2). Recent low-rainfall seasons also appear more frequent than the midtwentieth century, with multiple seasons since 1980 showing rainfall deficits at least 1.5–2 σ below the baseline. Instrumental data in the early twentieth century in this region are sparse (Figure 2), so the magnitudes of temperature and rainfall anomalies before midcentury should be interpreted with caution.

Given the lack of station data in the early twentieth century, CMIP6 simulations are used to examine the shifting frequency of 2 σ seasonal temperature anomalies and −1.5 σ rainfall extremes. CMIP6 historical simulations indicate that years with temperatures at least 2 σ above the baseline in Amazonia were incredibly rare before the late 20th century and early 21st century warming. However, these models show that greenhouse gas driven warming is already increasing the frequency of these events (Figures 2 and 3). Specifically, under the SSP3-7.0 scenario, by 2030 the average temperature in CMIP6 is 2 σ warmer than the baseline. Under unabated emissions, by midcentury, the coolest ONDJFM will be as warm as the isolated anomalously hot years of the recent past. By the end of the 21st century under unabated emissions, the multimodel average ONDJFM is 6–8 σ (~3.6–4.8°C) above the baseline. Some CMIP6 models project years with ONDJFM mean temperatures that are 12–20 σ (~7–12°C) above the baseline, while the CMIP6 simulations showing the least warming indicate that end of century ONDJFM periods will be at least as warm as the hottest droughts during El Niño events in the late 20th century and early 21st century under SSP3-7.0. By contrast, under the SSP1-2.6 scenario, temperatures increase until ~2040 (around 2–3 σ above the baseline in the multimodel mean), with some CMIP6 models projecting ONDJFM periods in the middle and end of the century that are up to 6 σ (~3.6°C) above the baseline (top panel, Figure 3).

Although all models show warming in the SSP3-7.0 scenario that exceeds internal variability (top panel, Figure 2), future rainfall trends do not exceed the envelope of 20th century variability in all CMIP6 SSP3-7.0 simulations (upper middle panel, Figure 2). However, decreasing rainfall in almost all SSP3-7.0 model simulations increases the likelihood of ONDJFM precipitation deficits similar in magnitude to recent observed droughts. CMIP6 SSP3-7.0 simulations show an average decrease in precipitation of ~0.5 σ (~90 mm) relative to 1950–2000 by 2040; around this time, these simulations project regular 1.5–2 σ (~250–350 mm) ONDJFM rainfall deficits every year. By the end of the 21st century, the multimodel mean ONDJFM in eastern Amazonia receives as much rainfall as a typical ONDJFM in a drought in the twentieth century, and particularly dry ONDJFM periods in some model projections approach 3–4 σ (~500–700 mm) below the baseline if global warming is left unchecked. Soil moisture shows similar drying trends that approach 1 σ below the baseline in the multimodel mean by the end of the century under SSP3-7.0 (lower middle panel, Figure 2). By contrast, in the SSP1-2.6 simulations, rainfall and soil moisture trends are less pronounced in eastern Amazonia (middle panels, Figure 3), with soil moisture still showing decreases in SSP1-2.6 through the 21st century.

The bottom panel in Figure 2 illustrates the shifting risk of droughts by decade in the historical and SSP3-7.0 simulations, with boxplots showing the percent of years per decade across all CMIP6 simulations that cross the baseline temperature and drought thresholds. Starting in the first decade of the 21st century, at least 10% of CMIP6 simulations cross the 2 σ heat threshold per decade, and by midcentury, all CMIP6 SSP3-7.0 simulations show that ONDJFM temperatures will cross this threshold at some point each decade. In addition to projecting large temperature increases, CMIP6 SSP3-7.0 simulations show an increasing risk of rainfall deficits 1.5 σ below the baseline as well; in the coming decades (2020–2050), between 0% and 20% of models cross this rainfall deficit threshold per decade. By midcentury, at least 10% of models cross this drought threshold at least once per decade, and by 2080, on average at least one in five models show 1.5 σ droughts at least once per decade in SSP3-7.0. If 10-cm soil moisture is used as a drought metric, by midcentury, there is a 20–40% drought risk that increases to ~40–60% by the end of the century (bottom panel, Figure 2). The bottom panel in Figure 3 illustrates the shifting risk of droughts by decade in the historical and SSP1-2.6 simulations. Even if global warming is slowed, eastern Amazonia is projected to experience an increased number of years in the 21st century with temperatures that are 2 σ above the baseline. Rainfall trends in SSP1-2.6 are less apparent, so precipitation drought risk remains nearly constant in SSP1-2.6. By contrast, soil moisture decreases slightly more than rainfall in SSP1-2.6, with an ~10–20% drought risk per decade by the middle of the 21st century (bottom panel, Figure 3).

3.4. Amazonian Drought and Tropical SSTs

SST anomaly patterns in both the tropical Pacific and tropical Atlantic are associated with temperature and rainfall variability over northern South America (Kousky et al., 1984; Ropelewski & Halpert, 1987; Yoon & Zeng, 2010). The instrumental data and CMIP6 simulations agree on the general spatial patterns of the relationships of these ocean regions with temperature and rainfall variability over tropical South America (Figures S3 and S4). Seasonal droughts in southern Amazonia and positive rainfall trends in northern Amazonia have been linked to the tropical North Atlantic (Wang et al., 2018; Yoon & Zeng, 2010), but recent particularly warm droughts in central and eastern Amazonia have occurred during strong El Niño events (JM16), and rainfall changes over Amazonia could be driven by changes in Walker circulation (Barichivich et al., 2018). Indeed, CMIP6 simulations project a strengthening relationship among temperature and rainfall variability over tropical South America and variability in the tropical Pacific (Figure S3) and the tropical North Atlantic (Figure S4) in the 21st century.

CMIP5 and CMIP6 models appear to show qualitatively similar relationships with the tropical Pacific and Atlantic, yet CMIP6 models more consistently simulate drying in Amazonia in the 21st century warming projections across the Amazonian basin in most seasons (Figures 1 and S1), whereas CMIP5 models show less agreement in future rainfall trends (Figures 4 and S5). Although a relationship between 21st century trends in the Niño3.4 index and trends in Amazonian rainfall is found (Figure 5), future global warming could independently cause increasing temperatures in the tropical Pacific while causing decreasing rainfall over Amazonia. Therefore, west-east tropical Pacific temperature trend differences are compared to determine if the tropical Pacific becomes more “El Niño like” or “La Niña like” in the 21st century in CMIP5 and CMIP6 simulations. Most CMIP6 models analyzed here indicate that the tropical Pacific will become

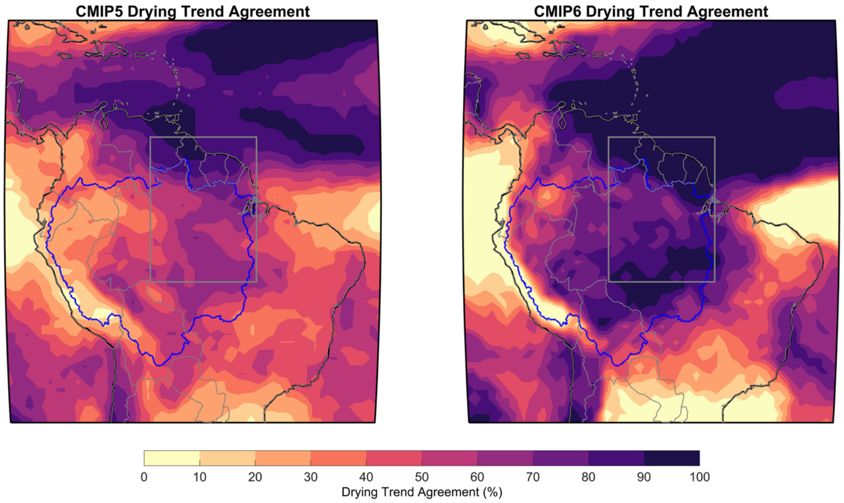

Figure 4. Agreement in sign of drying trend in CMIP5 RCP 8.5 ($N = 32$) and CMIP6 SSP3-7.0 ($N = 22$) 21st century warming simulations. Blue line outlines the Amazonian basin.

more "El Niño like" (stronger warming in the eastern Pacific relative to the western Pacific) in the future. In fact, CMIP6 models that simulate a more pronounced "El Niño-like" future tropical Pacific tend to simulate more drying over Amazonia (Figure 5). Therefore, shifts in Walker circulation related to a decreasing tropical Pacific SST gradient could explain much of the CMIP6 agreement in future drying trends over Amazonia. A similar comparison in 32 CMIP5 models indicates that the previous generation of models shows a similar relationship between the tropical Pacific SST and Amazonian rainfall. Specifically, several

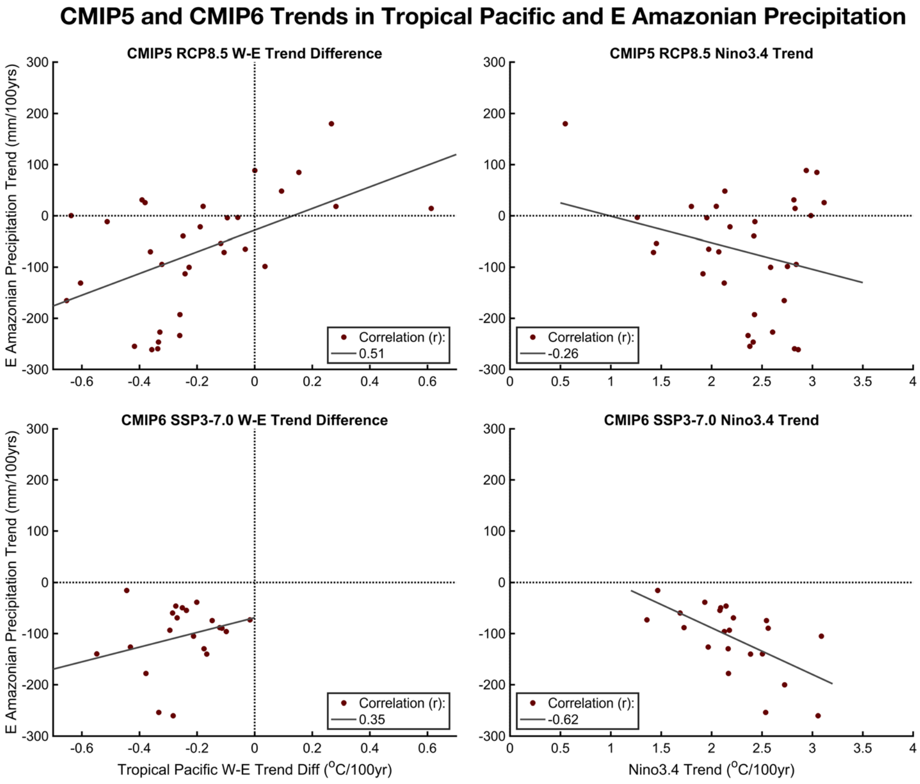

Figure 5. Relationship between October–March temperature trends in the tropical Pacific and eastern Amazonian rainfall 2015–2099 in CMIP5 RCP8.5 (top) and CMIP6 SSP3-7.0 simulations (bottom). Difference in western tropical Pacific and eastern tropical Pacific temperature trends (section 2) and eastern Amazonian rainfall trends (left) and Niño3.4 temperature trends and eastern Amazonian rainfall trends (right).

CMIP5 models that simulate a more "La Niña-like" future tropical Pacific also simulate positive future rainfall trends over Amazonia (Figure 5).

4. Discussion and Conclusions

There is better agreement in projected future rainfall trends in CMIP6 models in many regions such as Amazonia (e.g., Cook et al., 2020; Ukkola et al., 2020), but these results should be interpreted with caution for several reasons. Most CMIP6 models show future drying in Amazonia, but the local details of this drying pattern can vary from model to model (Figure S6). Future work could further examine the causes of increased CMIP6 agreement in rainfall trends in the region, as well as why certain models appear to show increasing future rainfall in parts of tropical South America (Figure S6). Additionally, treating individual model simulations from a Modeling Intercomparison Project as independent can be problematic because multiple, similar models from the same modeling centers are often included (Table S1), and models from different centers often share similar components (e.g., Knutti et al., 2013). Also, climate models from different modeling centers can agree on the sign of a projected precipitation trend, but this agreement could be based on the same systematic bias that appears in multiple models (e.g., Tierney et al., 2015).

Simulated future rainfall changes in eastern Amazonia are weakly associated with simulated future changes in the tropical Pacific in both CMIP5 and CMIP6 models (Figure 5), but future changes in the tropical Pacific are uncertain. Recent work has shown that climate models show considerable tropical Pacific biases, so future trends in tropical Pacific gradients and their potential impacts on tropical rainfall could be incorrect (e.g., Coats & Karnauskas, 2017; Seager et al., 2019). Furthermore, climate model simulations may underestimate dry-season length (Marengo et al., 2017) as well as the risk of multiyear droughts in Amazonia (Parsons et al., 2018).

Nonetheless, if CMIP6 simulations of future drying in the American Tropics are accurate, these results are especially relevant given recent developments in Amazonia related to land management, drought, and fires. Drought is one among several important drivers of deforestation (e.g., environmental law enforcement, prices of commodities, and international market pressures), so climate change will be one of many factors influencing future forest loss (Nepstad et al., 2014). Nevertheless, the Amazonian forest can be particularly vulnerable to forest fire and land clearing during drought (Le Page et al., 2017; Nepstad et al., 2008), especially along forest edges where drying, fire intensity, and grass invasion are greatest (Balch et al., 2015).

Furthermore, forest cover and evapotranspiration are critical for water cycling over tropical South America, and observation and modeling studies have shown that drought-deforestation feedbacks can grow in strength with cumulative deforestation (Staal et al., 2020), leading to biogeophysical feedbacks on drought (Bagley et al., 2014). To test if the drying trend in CMIP6 simulations is caused by high levels of deforestation in the SSP3-7.0 simulations (Popp et al., 2017), the SSP3-7.0 precipitation results have been compared to drying trends in idealized 1%CO_2 simulations, which do not include land use changes (Figure S7). Although there is stronger drying in the SSP3-7.0 simulations per degree of global warming, the geographic patterns of precipitation trends are similar in these two modeling experiments, suggesting that changes in land cover may influence future rainfall trends in these models, but the pattern of decreasing precipitation is not purely due to prescribed land-use changes in the SSP3-7.0 simulations (Figure S7).

Here the focus has been on ONDJFM rainfall in eastern Amazonia, but CMIP6 SSP3-7.0 simulations show strong agreement in future decreases in precipitation across southern Amazonia in the months of August through November (Figure S1). The months of September–November mark the end of the dry season in southern Amazonia, and delays in the end of the dry season are associated with a prolonged fire season (Fu et al., 2013). Fire risk is associated with interactions among land use change and dry-air spells during the dry season (e.g., Brando et al., 2020; Morton et al., 2013), so future decreases in dry-season and end of dry-season rainfall (Figure S1) and soil moisture (Figure S2) along the forest edge in southern Amazonia could have consequences for southern Amazonia fire season.

Although projections of decreasing precipitation can appear dire for ecosystem resilience, the sensitivity of the Amazonian forest to drought and climate change is a nuanced issue. For example, impacts of decreasing rainfall on tropical plants may be lessened by the "water savings" these plants will experience under high CO_2 conditions (Swann et al., 2016). However, these savings are unlikely to eliminate all stress on plants during particularly dry years (Swann, 2018), and decreasing soil moisture (e.g., Cook et al., 2020) suggests that even with high CO_2 water savings, there is less available soil moisture in both low and high emissions scenarios (Figure 1). Furthermore, even if the forest proves to be sensitive to a warming and drying climate under higher CO_2 conditions, the ecosystem response will likely be spatially heterogeneous, with local soil type, plant trait diversity, and vegetation interactions controlling the resilience of the forest (Levine et al., 2016; Sakschewski et al., 2016). Nonetheless, significant local land management efforts combined with global efforts to curtail carbon emissions would likely help make this region less vulnerable to warming, drought, fire, and land use conversion (Marengo et al., 2018). Forest dieback driven by these combined stressors would, in turn, have major implications for regional carbon sequestration, local biodiversity, and the global climate system.

Data Availability Statement

Observation-based gridded temperature and precipitation data were provided by the NOAA/OAR/ESRL PSD, Boulder, Colorado, USA, from their Web site at https://www.esrl.noaa.gov/psd/ website. Coupled Model Intercomparison Project Phase 6 (CMIP6) and Phase 5 (CMIP5) data were downloaded from the World Climate Research Programme (WCRP) Earth System Grid Federation (ESGF) website (https://esgf-node.llnl.gov/). HadCRUT data are freely available from this site (https://crudata.uea.ac.uk/cru/data/temperature/).

Acknowledgments

The author thanks the Washington Research Foundation for their funding support through the WRF Postdoctoral Fellowship. The author also thanks T. Ault, A. Swann, D. Frierson, G. Hakim, E. Steig, R. C. J. Wills, and J. Overpeck for input and support. The author also thanks two anonymous reviewers for helpful comments that improved the manuscript.

References

Aragão, L. E., Anderson, L. O., Fonseca, M. G., Rosan, T. M., Vedovato, L. B., Wagner, F. H., et al. (2018). 21st century drought-related fires counteract the decline of Amazon deforestation carbon emissions. *Nature Communications*, *9*, 536.

Bagley, J. E., Desai, A. R., Harding, K. J., Snyder, P. K., & Foley, J. A. (2014). Drought and deforestation: Has land cover change influenced recent precipitation extremes in the Amazon? *Journal of Climate*, *27*(1), 345–361.

Balch, J. K., Brando, P. M., Nepstad, D. C., Coe, M. T., Silvério, D., Massad, T. J., et al. (2015). The Susceptibility of Southeastern Amazon Forests to Fire: Insights from a Large-Scale Burn Experiment. *BioScience*, *65*(9), 893–905. https://doi.org/10.1093/biosci/biv106

Barichivich, J., Gloor, E., Peylin, P., Brienen, R. J. W., Schöngart, J., Espinoza, J. C., & Pattnayak, K. C. (2018). Recent intensification of Amazon flooding extremes driven by strengthened Walker circulation. *Science Advances*, *4*(9), eaat8785. https://doi.org/10.1126/sciadv.aat8785

Berg, A., Sheffield, J., & Milly, P. C. (2017). Divergent surface and total soil moisture projections under global warming. *Geophysical Research Letters*, *44*, 236–244. https://doi.org/10.1002/2016GL071921

Boers, N., Marwan, N., Barbosa, H. M., & Kurths, J. (2017). A deforestation-induced tipping point for the South American monsoon system. *Scientific Reports*, *7*, 41489.

Brando, P. M., Balch, J. K., Nepstad, D. C., Morton, D. C., Putz, F. E., Coe, M. T., et al. (2014). Abrupt increases in Amazonian tree mortality due to drought–fire interactions. *Proceedings of the National Academy of Sciences*, *111*(17), 6347–6352. https://doi.org/10.1073/pnas.1305499111

Brando, P. M., Soares-Filho, B., Rodrigues, L., Assunção, A., Morton, D., Tuchschneider, D., et al. (2020). The gathering firestorm in southern Amazonia. *Science Advances*, *6*(2), eaay1632.

Brienen, R. J., Phillips, O. L., Feldpausch, T. R., Gloor, E., Baker, T. R., Lloyd, J., et al. (2015). Long-term decline of the Amazon carbon sink. *Nature*, *519*(7543), 344–348.

Bush, M. B., Correa-Metrio, A., McMichael, C. H., Sully, S., Shadik, C. R., Valencia, B. G., et al. (2016). A 6900-year history of landscape modification by humans in lowland Amazonia. *Quaternary Science Reviews*, *141*, 52–64.

Cannon, A. J., Sobie, S. R., & Murdock, T. Q. (2015). Bias correction of GCM precipitation by quantile mapping: How well do methods preserve changes in quantiles and extremes? *Journal of Climate*, *28*(17), 6938–6959.

Chen, M., Xie, P., Janowiak, J. E., & Arkin, P. A. (2002). Global land precipitation: A 50-yr monthly analysis based on gauge observations. *Journal of Hydrometeorology*, *3*, 249–266.

Coats, S., & Karnauskas, K. B. (2017). Are simulated and observed twentieth century tropical Pacific sea surface temperature trends significant relative to internal variability? *Geophysical Research Letters*, *44*, 9928–9937. https://doi.org/10.1002/2017GL074622

Cook, B. I., Mankin, J. S., Marvel, K., Williams, A. P., Smerdon, J. E., & Anchukaitis, K. J. (2020). Twenty-first century drought projections in the CMIP6 forcing scenarios*, Earth's Future*, *8*, e2019EF001461. https://doi.org/10.1029/2019EF001461

Dai, A. (2013). Increasing drought under global warming in observations and models. *Nature Climate Change*, *3*, 52–58.

Davidson, E. A., de Araújo, A. C., Artaxo, P., Balch, J. K., Brown, I. F., C. Bustamante, M. M., et al. (2012). The Amazon basin in transition. *Nature*, *481*(7381), 321–328. https://doi.org/10.1038/nature10717

Diffenbaugh, N. S., & Giorgi, F. (2012). Climate change hotspots in the CMIP5 global climate model ensemble. *Climatic Change*, *114*, 813–822.

Duffy, P. B., Brando, P., Asner, G. P., & Field, C. B. (2015). Projections of future meteorological drought and wet periods in the Amazon. *Proceedings of the National Academy of Sciences*, *112*, 13,172–13,177.

Eyring, V., Bony, S., Meehl, G. A., Senior, C. A., Stevens, B., Stouffer, R. J., & Taylor, K. E. (2016). Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6) experimental design and organization. *Geoscientific Model Development*, *9*(5), 1937–1958. https://doi.org/10.5194/gmd-9-1937-2016

Fu, R., Yin, L., Li, W., Arias, P. A., Dickinson, R. E., Huang, L., et al. (2013). Increased dry-season length over southern Amazonia in recent decades and its implication for future climate projection. *Proceedings of the National Academy of Sciences*, *110*(45), 18,110–18,115. https://doi.org/10.1073/pnas.1302584110

Huang, B., Thorne, P. W., Banzon, V. F., Boyer, T., Chepurin, G., Lawrimore, J. H., et al. (2017). Extended Reconstructed Sea Surface Temperature, version 5 (ERSSTv5): Upgrades, validations, and intercomparisons. *Journal of Climate*, *30*, 8179–8205.

Hubau, W., Lewis, S. L., Phillips, O. L., Affum-Baffoe, K., Beeckman, H., Cuní-Sanchez, A., et al. (2020). Asynchronous carbon sink saturation in African and Amazonian tropical forests. *Nature*, *579*(7797), 80–87.

Jimenez-Munoz, J. C., Mattar, C., Barichivich, J., Santamaria-Artigas, A., Takahashi, K., Malhi, Y., et al. (2016). Record-breaking warming and extreme drought in the Amazon rainforest during the course of El Nino 2015–2016. *Scientific Reports*, *6*, 33130.

Jones, P. D., Lister, D. H., Osborn, T. J., Harpham, C., Salmon, M., & Morice, C. P. (2012). Hemispheric and large-scale land-surface air temperature variations: An extensive revision and an update to 2010. *Journal of Geophysical Research*, *117*, D05127. https://doi.org/10.1029/2011JD017139

Knight, J. R. (2009). The Atlantic Multidecadal Oscillation inferred from the forced climate response in coupled general circulation models. *Journal of Climate*, *22*, 1610–1625.

Knutti, R., Masson, D., & Gettelman, A. (2013). Climate model genealogy: Generation CMIP5 and how we got there. *Geophysical Research Letters*, *40*, 1194–1199. https://doi.org/10.1002/grl.50256

Kousky, V. E., Kagano, M. T., & Cavalcanti, I. F. (1984). A review of the Southern Oscillation: Oceanic-atmospheric circulation changes and related rainfall anomalies. *Tellus A*, *36*, 490–504.

Le Page, Y., Morton, D., Hartin, C., Bond-Lamberty, B., Pereira, J. M. C., Hurtt, G., & Asrar, G. (2017). Synergy between land use and climate change increases future fire risk in Amazon forests. *Earth System Dynamics (Online)*, *8*.

Lehner, F., Coats, S., Stocker, T. F., Pendergrass, A. G., Sanderson, B. M., Raible, C. C., & Smerdon, J. E. (2017). Projected drought risk in 1.5°C and 2°C warmer climates. *Geophysical Research Letters*, *44*, 7419–7428. https://doi.org/10.1002/2017GL074117

Lenssen, N. J., Schmidt, G. A., Hansen, J. E., Menne, M. J., Persin, A., Ruedy, R., & Zyss, D. (2019). Improvements in the GISTEMP uncertainty model. *Journal of Geophysical Research: Atmospheres*, *124*, 6307–6326. https://doi.org/10.1029/2018JD029522

Lenton, T. M., Held, H., Kriegler, E., Hall, J. W., Lucht, W., Rahmstorf, S., & Schellnhuber, H. J. (2008). Tipping elements in the Earth's climate system. *Proceedings of the National Academy of Sciences of the United States of America*, *105*, 1786–1793.

Levine, N. M., Zhang, K., Longo, M., Baccini, A., Phillips, O. L., Lewis, S. L., et al. (2016). Ecosystem heterogeneity determines the ecological resilience of the Amazon to climate change. *Proceedings of the National Academy of Sciences*, *113*(3), 793–797. https://doi.org/10.1073/pnas.1511344112

Lewis, S. L., Brando, P. M., Phillips, O. L., van der Heijden, G. M. & Nepstad, D. (2011). The 2010 Amazon drought. *Science*, *331*, 554.

Lovejoy, T. E., & Nobre, C. (2018). Amazon tipping point. *Science Advances*, *4*.

Malhi, Y., Aragao, L. E. O. C., Galbraith, D., Huntingford, C., Fisher, R., Zelazowski, P., et al. (2009). Exploring the likelihood and mechanism of a climate-change-induced dieback of the Amazon rainforest. *Proceedings of the National Academy of Sciences of the United States of America*, *106*, 20,610–20,615.

Malhi, Y., Roberts, J. T., Betts, R. A., Killeen, T. J., Li, W., & Nobre, C. A. (2008). Climate change, deforestation, and the fate of the Amazon. *Science*, *319*, 169–172.

Marengo, J. A., Fisch, G. F., Alves, L. M., Sousa, N. V., Fu, R., & Zhuang, Y. (2017). Meteorological context of the onset and end of the rainy season in Central Amazonia during the 2014–15 Go-Amazon Experiment. *Atmospheric Chemistry and Physics Discussions*. https://doi.org/10.5194/acp-2017-22

Marengo, J. A., Souza, C. A., Thonicke, K., Burton, C., Halladay, K., Betts, R. A., & Soares, W. R. (2018). Changes in climate and land use over the Amazon Region: Current and future variability and trends. *Frontiers in Earth Science*, *6*, 228.

Marengo, J. A., Tomasella, J., Alves, L. M., Soares, W. R., & Rodriguez, D. A. (2011). The drought of 2010 in the context of historical droughts in the Amazon region. *Geophysical Research Letters*, *38*, L12703. https://doi.org/10.1029/2011GL047436

Moghim, S., McKnight, S. L., Zhang, K., Ebtehaj, A. M., Knox, R. G., Bras, R. L., et al. (2017). Bias-corrected data sets of climate model outputs at uniform space–time resolution for land surface modelling over Amazonia. *International Journal of Climatology*, *37*(2), 621–636.

Morton, D. C., Le Page, Y., DeFries, R., Collatz, G. J., & Hurtt, G. C. (2013). Understorey fire frequency and the fate of burned forests in southern Amazonia. *Philosophical Transactions of the Royal Society, B: Biological Sciences*, *368*(1619), 20120163.

Nepstad, D., McGrath, D., Stickler, C., Alencar, A., Azevedo, A., Swette, B., et al. (2014). Slowing Amazon deforestation through public policy and interventions in beef and soy supply chains. *Science*, *344*(6188), 1118–1123. https://doi.org/10.1126/science.1248525

Nepstad, D. C., Decarvalho, C. R., Davidson, E. A., Jipp, P. H., Lefebvre, P. A., Negreiros, G. H., et al. (1994). The role of deep roots in the hydrological and carbon cycles of Amazonian forests and pastures. *Nature*, *372*, 666–669.

Nepstad, D. C., Stickler, C. M., Filho, B. S., & Merry, F. (2008). Interactions among Amazon land use, forests and climate: Prospects for a near-term forest tipping point. *Philosophical Transactions of the Royal Society, B: Biological Sciences*, *363*, 1737–1746.

O'Neill, B. C., Tebaldi, C., Vuuren, D. P. V., Eyring, V., Friedlingstein, P., Hurtt, G., et al. (2016). The Scenario Model Intercomparison Project (ScenarioMIP) for CMIP6. *Geoscientific Model Development*, *9*, 3461–3482.

Parsons, L. A., LeRoy, S., Overpeck, J. T., Bush, M., Cárdenes-Sandí, G. M., & Saleska, S. (2018). The threat of multiyear drought in Western Amazonia. *Water Resources Research*, *54*, 5890–5904. https://doi.org/10.1029/2017WR021788

Phillips, O. L., Aragao, L. E. O. C., Lewis, S. L., Fisher, J. B., Lloyd, J., Lopez-Gonzalez, G., et al. (2009). Drought sensitivity of the Amazon rainforest. *Science*, *323*(5919), 1344–1347. https://doi.org/10.1126/science.1164033

Popp, A., Calvin, K., Fujimori, S., Havlik, P., Humpenöder, F., Stehfest, E., et al. (2017). Land-use futures in the shared socio-economic pathways. *Global Environmental Change*, *42*, 331–345.

Riahi, K., Van Vuuren, D. P., Kriegler, E., Edmonds, J., O'neill, B. C., Fujimori, S., et al. (2017). The shared socioeconomic pathways and their energy, land use, and greenhouse gas emissions implications: An overview. *Global Environmental Change*, *42*, 153–168.

Ropelewski, C. F., & Halpert, M. S. (1987). Global and regional scale precipitation patterns associated with the El Niño/Southern Oscillation. *Monthly Weather Review*, *115*, 1606–1626.

Saatchi, S., Asefi-Najafabady, S., Malhi, Y., Aragao, L. E. O. C., Anderson, L. O., Myneni, R. B., & Nemani, R. (2013). Persistent effects of a severe drought on Amazonian forest canopy. *Proceedings of the National Academy of Sciences of the United States of America*, *110*, 565–570.

Saeed, F., Bethke, I., Fischer, E., Legutke, S., Shiogama, H., Stone, D. A., & Schleussner, C. (2018). Robust changes in tropical rainy season length at 1.5 °C and 2 °C. *Environmental Research Letters*, *13*, 064024.

Sakschewski, B., von Bloh, W., Boit, A., Poorter, L., Peña-Claros, M., Heinke, J., et al. (2016). Resilience of Amazon forests emerges from plant trait diversity. *Nature Climate Change*, *6*(11), 1032–1036. https://doi.org/10.1038/nclimate3109

Satyamurty, P., de Castro, A. A., Tota, J., da, S. G., & Manzi, A. O. (2010). Rainfall trends in the Brazilian Amazon Basin in the past eight decades. *Theoretical and Applied Climatology*, *99*, 139–148.

Schneider, U., Becker, A., Finger, P., Meyer-Christoffer, A., Rudolf, B., & Ziese, M. (2011). *Monthly land-surface precipitation from rain-gauges built on GTS-based and historic data* (Vol. 10). Deutscher Wetterdienst: Global Precipitation Climatology Centre (GPCC).

Seager, R., Cane, M., Henderson, N., Lee, D., Abernathey, R., & Zhang, H. (2019). Strengthening tropical Pacific zonal sea surface temperature gradient consistent with rising greenhouse gases. *Nature Climate Change*, *9*, 517.

Soares, W. R., Marengo, J. A., & Nobre, C. A. (2019). Assessment of warming projections and probabilities for Brazil. In C. Nobre, J. Marengo, & W. Soares (Eds.), *Climate change risks in Brazil*. Cham: Springer. https://doi.org/10.1007/978-3-319-92881-4_2

Staal, A., Flores, B. M., Aguiar, A. P. D., Bosmans, J. H., Fetzer, I., & Tuinenburg, O. A. (2020). Feedback between drought and deforestation in the Amazon. *Environmental Research Letters*, *15*(4), 044024.

Swann, A. L. (2018). Plants and drought in a changing climate. *Current Climate Change Reports*, *4*(2), 192–201.

Swann, A. L., Hoffman, F. M., Koven, C. D., & Randerson, J. T. (2016). Plant responses to increasing CO_2 reduce estimates of climate impacts on drought severity. *Proceedings of the National Academy of Sciences*, *113*(36), 10,019–10,024.

Taylor, K. E., Stouffer, R. J., & Meehl, G. A. (2012). An overview of CMIP5 and the experiment design. *Bulletin of the American Meteorological Society*, *93*, 485–498.

Tian, H., Melillo, J. M., Kicklighter, D. W., McGuire, A. D., Helfrich, J. V., Moore, B., & VoÈroÈsmarty, C. J. (1998). Effect of interannual climate variability on carbon storage in Amazonian ecosystems. *Nature*, *396*, 664–667.

Tierney, J. E., Ummenhofer, C. C., & deMenocal, P. B. (2015). Past and future rainfall in the Horn of Africa. *Science Advances*, *1*(9), e1500682.

Trenberth, K. E., Dai, A., Van Der Schrier, G., Jones, P. D., Barichivich, J., Briffa, K. R., & Sheffield, J. (2014). Global warming and changes in drought. *Nature Climate Change*, *4*(1), 17–22.

Ukkola, A. M., De Kauwe, M. G., Roderick, M. L., Abramowitz, G., & Pitman, A. J. (2020). Robust future changes in meteorological drought in CMIP6 projections despite uncertainty in precipitation. *Geophysical Research Letters*, *47*, e2020GL087820. https://doi.org/10.1029/2020GL087820

Wang, X., Li, X., Zhu, J., & Tanajura, C. A. (2018). The strengthening of Amazonian precipitation during the wet season driven by tropical sea surface temperature forcing. *Environmental Research Letters*, *13*, 094015.

Willmott, C. J. & Matsuura, K. (2001). Terrestrial air temperature and precipitation: Monthly and annual time series (1950–1999) Version 1.02*, Center for Climatic Research, University of Delaware, Newark*.

Xie, P., & Arkin, P. A. (1997). Global precipitation: A 17-year monthly analysis based on gauge observations, satellite estimates, and numerical model outputs. *Bulletin of the American Meteorological Society*, *78*, 2539–2558.

Xu, X., Jia, G., Zhang, X., Riley, W. J., & Xue, Y. (2020). Climate regime shift and forest loss amplify fire in Amazonian forests. *Global Change Biology*, *26*(10), 5874–5885. https://doi.org/10.1111/gcb.15279

Yeh, S., Ham, Y., & Lee, J. (2012). Changes in the tropical Pacific SST trend from CMIP3 to CMIP5 and its implication of ENSO. *Journal of Climate*, *25*, 7764–7771.

Yin, L., Fu, R., Shevliakova, E., & Dickinson, R. E. (2013). How well can CMIP5 simulate precipitation and its controlling processes over tropical South America? *Climate Dynamics*, *41*, 3127–3143.

Yoon, J., & Zeng, N. (2010). An Atlantic influence on Amazon rainfall. *Climate Dynamics*, *34*, 249–264.

Zemp, D. C., Schleussner, C., Barbosa, H. M., Hirota, M., Montade, V., Sampaio, G., et al. (2017). Self-amplified Amazon forest loss due to vegetation-atmosphere feedbacks. *Nature Communications*, *8*, 14681.