

Implications of CMIP6 projected drying trends for 21st century Amazonian drought risk

Luke A Parsons¹

¹University of Washington

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Abstract

Recent exceptionally hot droughts in Amazonia have highlighted the potential role of global warming in driving elevated fire risk and forest dieback. The previous generation of global climate models projected that eastern Amazonia would receive less future rainfall while western Amazonia would receive more rainfall, but many of these models disagreed on the sign of 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 climate change. This new generation of models shows better agreement that the entire Amazonian basin will receive less future rainfall, with particularly strong agreement that eastern Amazonia will dry in the 21 century. These models suggest that global warming may be increasing the likelihood of exceptionally hot drought in the region, and by mid-century with unabated global warming, recent particularly warm and severe droughts will become more common. However, Amazonia is a region with a relatively sparse instrumental record that makes it difficult to test the ability of model simulations to reproduce observed long-term rainfall trends, and climate models have traditionally struggled to reproduce satellite-era observed trends in the region. These shortcomings highlight the need to improve confidence in global climate models'; ability to simulate future drought, even if more CMIP6 models agree on the sign of future rainfall trends.

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3 **21st century Amazonian drought risk**
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6 **L. A. Parsons**¹

7 ¹Department of Atmospheric Sciences, University of Washington, Seattle, WA

8 Corresponding author: Luke Parsons (lakp@uw.edu)

9
10 **Key Points:**

- 11 • Coupled Modeling Intercomparison Project, Phase 6 models show better agreement that
12 the Amazon will receive less future rainfall
- 13 • These simulations indicate that if global warming continues unabated, recent particularly
14 warm and severe droughts will become more common
- 15 • CMIP6 models that simulate more drying over Amazonia tend to simulate a more 'El
16 Nino like' tropical Pacific
17

18 **Abstract**

19 Recent exceptionally hot droughts in Amazonia have highlighted the potential role of global
20 warming in driving elevated fire risk and forest dieback. The previous generation of global
21 climate models projected that eastern Amazonia would receive less future rainfall while western
22 Amazonia would receive more rainfall, but many of these models disagreed on the sign of future
23 precipitation trends in the region. Here Coupled Modeling Intercomparison Project, Phase 6
24 (CMIP6) models are used to examine the shifting risk of eastern Amazonian droughts under
25 climate change. This new generation of models shows better agreement that the entire
26 Amazonian basin will receive less future rainfall, with particularly strong agreement that eastern
27 Amazonia will dry in the 21st century. These models suggest that global warming may be
28 increasing the likelihood of exceptionally hot drought in the region, and by mid-century with
29 unabated global warming, recent particularly warm and severe droughts will become more
30 common. However, Amazonia is a region with a relatively sparse instrumental record that makes
31 it difficult to test the ability of model simulations to reproduce observed long-term rainfall
32 trends, and climate models have traditionally struggled to reproduce satellite-era observed trends
33 in the region. These shortcomings highlight the need to improve confidence in global climate
34 models' ability to simulate future drought, even if more CMIP6 models agree on the sign of
35 future rainfall trends.

36

37 **Plain Language Summary**

38 Recent exceptionally hot droughts in Amazonia have highlighted the potential role of global
39 warming in driving elevated fire risk and forest dieback. The previous generation of global
40 climate models used in the Intergovernmental Panel on Climate Change Fifth Assessment Report
41 (IPCC AR5) projected that eastern Amazonia would receive less future rainfall while western
42 Amazonia would receive more rainfall. Here climate models used in the upcoming IPCC Sixth
43 Assessment Report (IPCC AR6) are used to examine future rainfall and temperature changes
44 over tropical South America. The new generation of CMIP6 models shows better agreement that
45 the entire Amazonian basin will receive less future rainfall, with particularly strong agreement
46 that eastern Amazonia will dry in the future if the planet continues to warm. These models
47 suggest that global warming has already increased the likelihood of exceptionally hot drought in
48 the region, and by mid-century under business-as-usual warming, recent particularly warm and
49 severe droughts will become more common. However, climate models traditionally struggle to
50 reproduce several key observed rainfall metrics in this region.

51 **1 Introduction**

52 The Amazonian rainforest is a biodiversity hotspot (Mittermeier et al., 1998) that
53 provides important ecosystem services both locally and globally (Malhi et al., 2008; Lenton et
54 al., 2008). Yet, the composition of the Amazonian rainforest is vulnerable to human land use as
55 well as climate variability and global climate change (Nepstad et al., 1994; Malhi et al., 2009;
56 Marengo et al., 2018). A combination of warming and rainfall deficits, driven by both climate
57 variability and change, will likely cause future ecosystem stress, and thus potentially limit the
58 ability of this region to continue to store carbon (Tian et al., 1998; Phillips et al., 2009).
59 Decreased seasonal precipitation and warming are already contributing to drought and vegetation
60 stress in this region (Marengo et al., 2018; Lewis et al., 2011; Dai et al., 2013; Jimenez-Munoz et

61 al., 2016; Saatchi et al., 2013). Specifically, fires during droughts in tropical South America can
62 clear tropical rainforest and grassland, leading to carbon emissions to the atmosphere (Aragao et
63 al., 2018); recent work has shown that rainfall deficits can increase fire risk, leading to self-
64 amplified forest loss and a possible deforestation tipping point (Brando et al., 2014; Zemp et al.,
65 2017; Boers et al., 2017) .

66 Superimposed on future rainfall changes (Duffy et al., 2017), the region will also need to
67 cope with multi-year droughts arising from natural background climate variability (Parsons et al.,
68 2018). The paleoclimate records suggests that the Amazonian ecosystem was able to persist
69 during moderate droughts in the pre-industrial climate (Bush et al., 2016), but it is uncertain if
70 future climate change, combined with other anthropogenic stressors and natural hydroclimatic
71 variability, will trigger unprecedented and rapid forest dieback in this ‘climate change hotspot’
72 (Davidson et al., 2012; Diffenbaugh and Giorgi, 2012). The region is expected to warm quickly
73 as the globe warms (Soares et al., 2019), but action that will limit future global climate change
74 may significantly reduce the most detrimental impacts of climate change locally (Lehner et al.,
75 2017).

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

85 Studies of observed rainfall and temperature indicate that climate change may already be
86 driving ‘enhanced drought’ in the region; 2016 was the warmest year in Amazonia since 1950
87 CE (Marengo et al., 2018), and the recent 2015-2016 drought in eastern Amazonia was at least
88 1.5°C warmer than the drought associated with the 1997-1998 El Niño event (Jimenez-Munoz et
89 al., 2016; hereafter JM16). Yet, the risk of this type of recent ‘enhanced hot’ drought (JM16) has
90 not been investigated in state-of-the-art climate models, and recent preliminary studies of future
91 drought changes in CMIP6 (e.g., Cook et al., 2020; Ukkola, 2020) have relied on limited
92 numbers of these new model simulations (e.g., 10-13 models). Given the severity of recent
93 seasonal droughts in the region and the apparent increase in model agreement in terms of future
94 drying in the region, here instrumental records and an expanded suite of CMIP6 climate and
95 Earth system model simulations are used to examine recent and future trends in rainfall and
96 temperatures, with a focus on the likelihood of the risk of a 2015-2016 type ‘enhanced drought’
97 event (JM16) under a shifting precipitation baseline.

98 **2 Data and Methods**

99 2.1 Choice of season and drought metric

100 Surface air temperature variability and rainfall variability and trends over tropical Central
101 and South America in October-March (ONDJFM) is examined (e.g., Satyamurty et al., 2010;
102 Wang et al., 2018), with a specific focus on northeastern Amazonia (10°S-8° N, 60°W-50° W,
103 outlined in Figure 1). Although many CMIP6 models project drying across much of tropical

104 South America (Ukkola, 2020; Cook et al., 2020), this study focuses on northeastern Amazonia
105 due to the impact of recent drought in this region in observations (JM16), as well as the robust
106 drying response in CMIP6 models in this region under climate change (Cook et al., 2020, also
107 discussed here). Furthermore, although abnormally low rainfall can occur during various months
108 throughout the year, here the focus is on ONDJFM due to the impacts of El Niño events during
109 the time period (e.g., JM16). Precipitation is chosen to study the impacts of climate change on
110 drought because many other drought metrics, such as Palmer Drought Severity Index (PDSI) or
111 precipitation minus evaporation (P-E), can provide conflicting answers about responses of
112 drought to warming or overestimate aridification from warming (e.g., Trenberth et al., 2014;
113 Swann et al., 2016). Furthermore, droughts are complex phenomena with various characteristics
114 including intensity, duration, frequency, onset, demise, and areal extent. Here, implications of
115 seasonal precipitation and temperature trends on seasonal droughts are examined as the issue of
116 drought duration and severity have already been addressed in Ukkola, 2020.

117 2.2 Instrumental Data

118 The station-based Global Precipitation Climatology Centre (GPCC) version 2018
119 (Schneider et al., 2011), University of Delaware (UDEL) version 5.01 (Willmott and Matsuura,
120 2001), and National Oceanic and Atmospheric Administration (NOAA) Precipitation
121 Reconstruction over Land (Chen et al., 2002; PRECL) are used to examine past rainfall
122 variability and trends. When showing time series covering the 1979-2018 CE time period, the
123 station-based data are supplemented with Climate Prediction Center Merged Analysis of
124 Precipitation (CMAP) data set, which blends satellite and gauge-based data from 1979 CE to the
125 present (Xie and Arkin, 1997). Past surface air temperature variability over land is also examined
126 using Goddard Institute of Space Studies (GISS) surface temperature analysis (GISTEMP;
127 Lenssen et al., 2019), Climate Research Unit (CRU) Air Temperature Anomalies version 4.2.0
128 (CRUTEMv4; Jones et al., 2014), and University of Delaware (UDEL) temperature version 5.01
129 (Willmott and Matsuura, 2001). Linear trends in each temperature and rainfall dataset are
130 calculated over the 1950-2014 CE time period and the average of these trends are shown in
131 Figure 1. Stippling in Figure 1 shows where all rainfall (GPCC, UDEL, PRECL) or temperature
132 data (GISTEMP, CRUTEM4, UDEL) agree on the sign of trend over this time period. Varying
133 the time period over which this trend is calculated (e.g., 1950-2010 or 1950-2017 CE) does not
134 noticeably change these results.

135 In all instrumental time series (e.g., Figure 2), data are normalized to the mean and
136 standard deviation (σ) of the 1950-2000 CE time period (hereafter 'baseline) using the mean and
137 σ from all datasets that have coverage over this time period. The instrumental October-March
138 1950-2000 CE mean rainfall is 1230 mm (+/- 19 mm), and σ is 214mm (+/- 19mm). The
139 October-March mean UDEL temperature over the baseline period is 22.4°C, and the average
140 temperature σ across all three instrumental data sources is 0.34°C (+/-0.03°C). GISTEMP and
141 CRUTEM4 provide temperatures as anomalies, so their mean 1950-2000 CE temperatures are
142 not presented here. An anomalously 'hot' season is defined as a year when October-March mean
143 temperatures are at least 2- σ above the baseline, and anomalously dry seasons are defined as
144 October-March precipitation anomalies at least 1.5 σ below the baseline period. These thresholds
145 are based on anomalously high temperatures and drought conditions experienced in this region
146 during recent El Niño events (1982-1983, 1997-1998, 2015-2016; JM16; Figure 2).

147 2.3 Climate Model Data

148 Surface air temperature (tas) and precipitation (pr) from 25 models from Phase 6 of the
149 Coupled Model Intercomparison Project (CMIP6) model simulations are used (Table S1).
150 Precipitation and temperatures are examined using monthly data from the historical and Shared
151 Socio-Economic Pathway (SSP) 3-7.0 experiments (Eyring et al., 2016; Riahi et al., 2017). The
152 historical runs are driven by observed transient forcing (land use change, greenhouse gas,
153 aerosol, ozone). The SSP simulations are high-end emissions scenarios from the Scenario Model
154 Intercomparison Project (ScenarioMIP). These scenarios are concentration-driven experiments
155 determined from hypothetical future socioeconomic pathways (Riahi et al., 2017). The SSP3-7.0
156 scenario reaches $\sim 7.0 \text{ W/m}^2$ radiative forcing by 2100 in a 'regional rivalry' scenario (O'Neill et
157 al., 2016). CMIP6 temperature and rainfall trends are compared to output from 32 CMIP5
158 historical and RCP8.5 simulations (CMIP5 models listed in Table S1). CMIP6 SSP3-7.0 results
159 have been compared to CMIP6 SSP5-8.5 results, and the main conclusions are nearly identical
160 (not shown).

161 CMIP6 model time series of eastern Amazonian rainfall and temperatures are shown as
162 anomalies relative to the October-March mean and standard deviation (σ) 1950-2000 CE
163 'baseline'. In the CMIP6 historical simulations 1950-2000 CE, the mean October-March rainfall
164 over eastern Amazonia is 926 mm (± 222 mm), and σ is 180mm (± 36 mm). The October-
165 March mean temperature is 22.4°C (± 1.1 °C), and σ is 0.60°C (± 0.19 °C). The CMIP6 models
166 show a slightly wetter mean as compared to the CMIP5 simulations, which Yin et al., 2013
167 reported displayed a 'dry bias'; the CMIP5 (Table S1) mean 1950-2000CE October-March
168 rainfall is 846 mm (± 274 mm). However, the intent of this work is not to provide a detailed
169 analysis of the causes for CMIP5 and CMIP6 differences in these models (e.g., Cook et al.,
170 2020), but instead to discuss the implications of a drying a warming trend for the region.

171 2.4 Comparison with sea-surface temperature variability

172 Variability of sea-surface temperatures in the tropical Atlantic and Pacific is also
173 compared to rainfall and temperature variability over land. Specifically, the El Niño Southern
174 Oscillation (ENSO) index, calculated from the National Oceanic and Atmospheric
175 Administration (NOAA) Extended Reconstructed Sea Surface Temperature version 5
176 (ERSSTv5) dataset (Huang et al., 2017), is compared with rainfall and temperature variability
177 over land. The October-March Niño3.4 index (5°S-5° N, 170°-120° W), and the Tropical North
178 Atlantic index (6°S-22° N, 80°W-15° W) is compared with October-March rainfall and
179 temperature over tropical South America over the 1950-2014 CE time period after removing the
180 linear trend from each grid point over this time period. Maps of correlations show the average
181 correlation between the ERSSTv5 Niño3.4 index and each precipitation dataset (GPCC, UDEL,
182 PRECL) and temperature dataset (GISTEMP, CRUTEM4, UDEL), with stippling showing
183 where all datasets agree on the sign of the correlation (Figure S2, Figure S3).

184 The CMIP6 historical and SSP3-7.0 rainfall and temperature over South America are also
185 compared with the Niño3.4 index (5°S-5° N, 170°-120° W) and Tropical North Atlantic index
186 (6°S-22° N, 80°W-15° W). Specifically, the Niño3.4 index and TNA index are correlated in each
187 CMIP6 model with rainfall and temperature over tropical South America separately over the
188 1950-2014 CE and 2015-2100 CE after removing the linear trend from each grid point over these
189 time periods (Figure S2, Figure S3). Maps of correlations in Figures S2 and S3 show the average

190 correlation among all CMIP6 simulations over the relevant time periods, with stippling showing
191 where >90% models agree on sign of correlation.

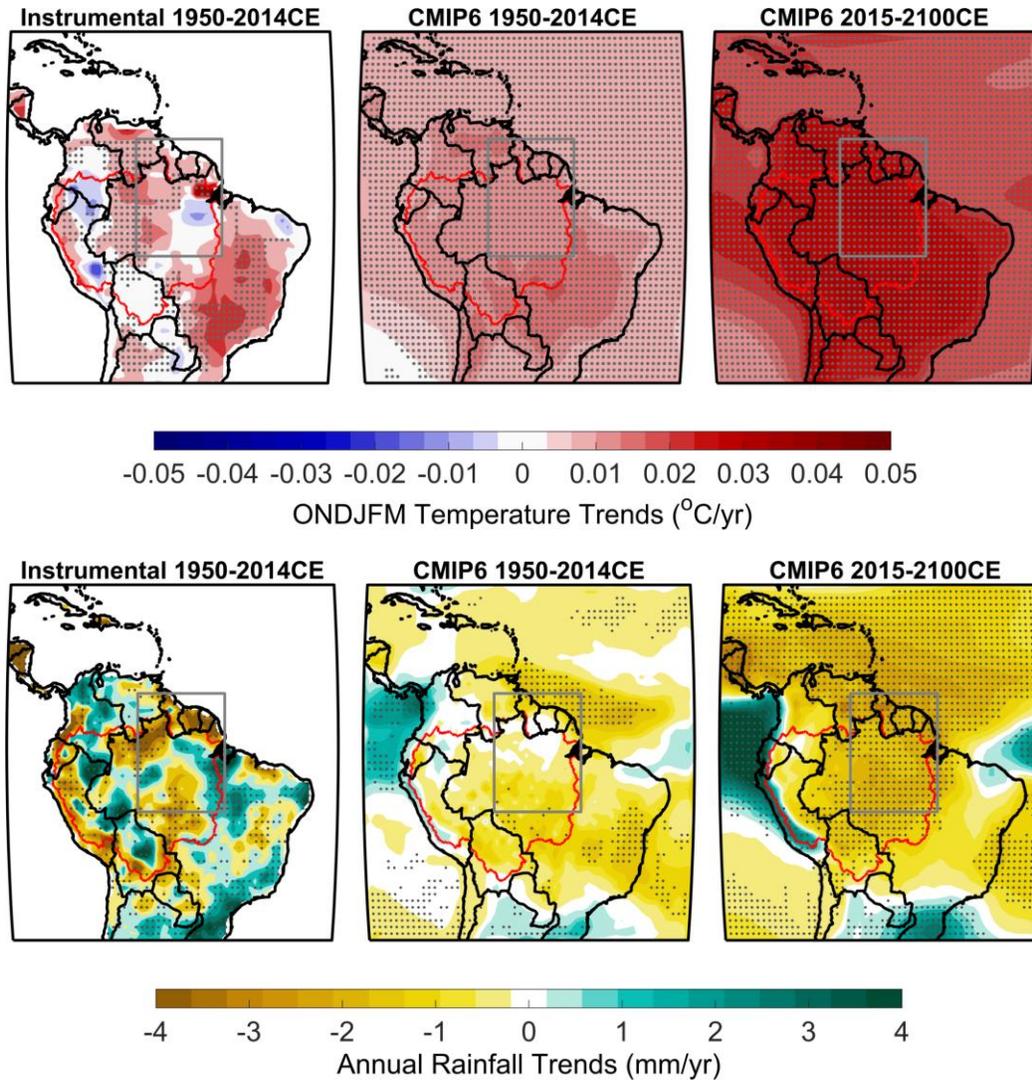
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193 **3 Results**

194 3.1 Trends in Amazonian Temperature and Rainfall

195 Instrumental data and CMIP6 simulations show similar warming trends 1950-2014 CE
196 over northern Amazonia and much of southeastern Brazil (Figure 1). However, the CMIP6
197 multi-model mean shows a more widespread, homogeneous warming pattern than the
198 instrumental data; this result is perhaps not surprising given that ensemble mean of climate
199 model simulations tend to maximize forced variability (Knight et al., 2009). All CMIP6 models
200 show a continued warming trend across the region (Figure 1) in the warming projections from
201 the Shared Socio-Economic Pathway (SSP) 3-7.0 simulations).

202 Instrumental precipitation data show a drying trend over much of eastern Amazonia and
203 northern tropical South America, and a positive rainfall trend in much of western Amazonia
204 1950-2014 CE (Figure 1). CMIP6 models show a drying trend over northern South America and
205 much of southern Amazonia. However, under the SSP3-7.0 global warming scenario, >75% of
206 models show that the drying trend expands over much of southwestern, eastern, and northern
207 tropical South America. All but two months show future drying trends across much of Amazonia
208 in CMIP6 projections (Figure S1). CMIP6 models show a different response to warming as
209 compared to the CMIP5 21st century warming projections, which suggested that much of western
210 Amazonia will become more wet while eastern Amazonia will receive less rainfall (Duffy et al.,
211 2015; Cook et al., 2020).



214 **Figure 1.** Temperature (top) and rainfall (bottom) trends in instrumental data 1950-2014 CE
 215 (left) climate model historical simulations 1950-2014 CE (middle), and in the SSP3-7.0 warming
 216 scenario 2015-2100 CE (right). Grey box outlines the Eastern Amazonian region used to make
 217 all time series shown in text (10°S - 8°N , 60°W - 50°W), red line outlines the Amazonian basin,
 218 and black lines show country borders. Precipitation and temperature trend maps show average
 219 trends across instrumental and model data (Methods). Stippling on maps shows where all
 220 instrumental data agree on sign of trend (left) or where more than 19 out of 25 model simulations
 221 ($>75\%$) agree on the sign of the trend (middle, right).

222 3.2 Climate Change and the Shifting Risk of Amazonian Drought

223 Instrumental records of Amazonian rainfall and surface air temperatures extending to the
 224 early 20th century can be used to put recent ‘enhanced droughts’ in a longer-term context (JM16).
 225 Instrumental data show that recent October-March seasonal droughts associated with El Niño
 226 events have been 2-3 standard deviations (σ) warmer than the 1950-2000 CE baseline (Methods),
 227 with recent multi-year temperatures either at or near this 2σ level (Figure 2). Recent low-rainfall
 228 seasons also appear more frequent than the mid 20th century, with multiple seasons since 1980

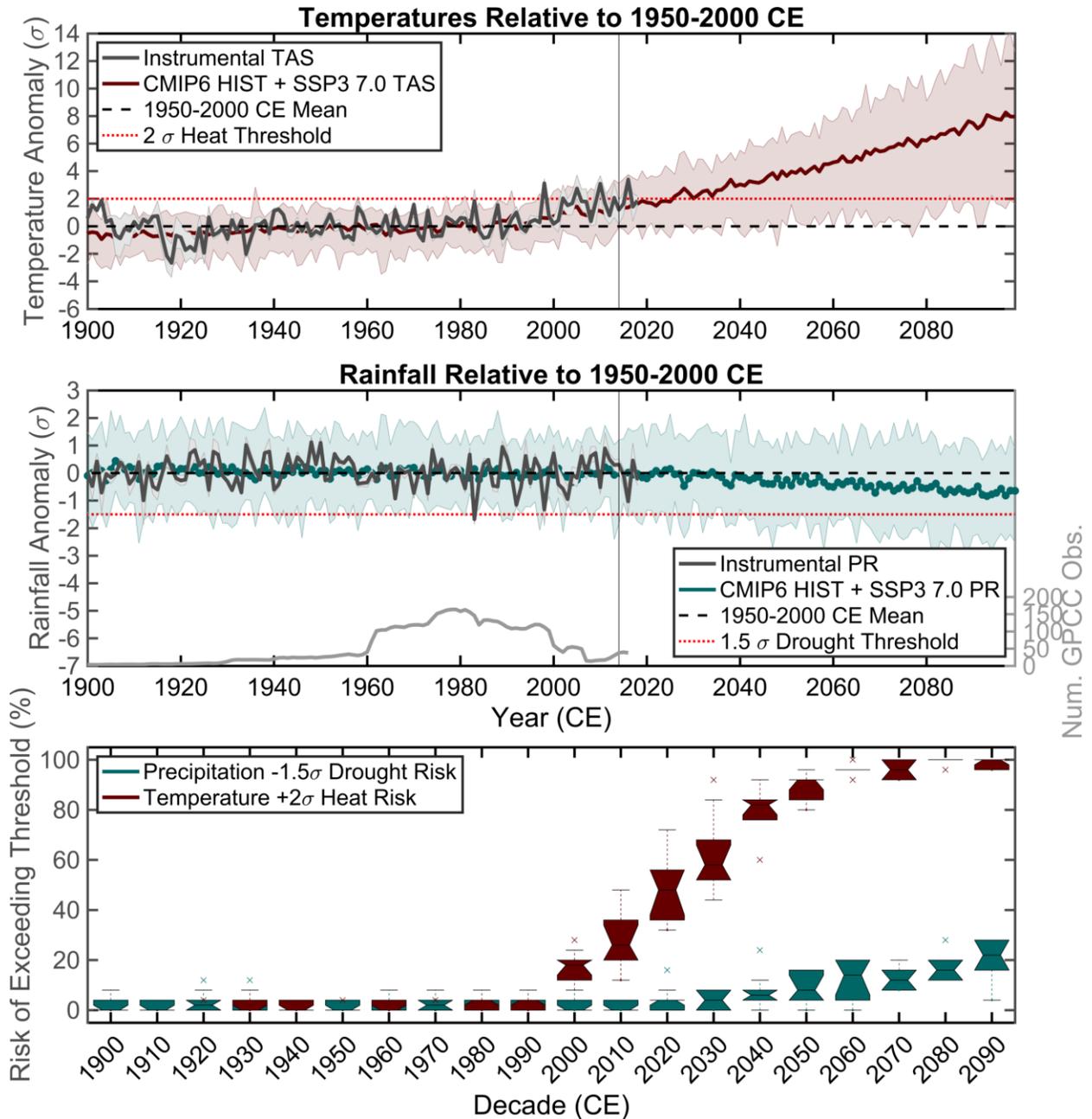
229 CE showing rainfall deficits at least 1.5-2 σ below the baseline. Although recent droughts appear
230 abnormal, the time period ~1900-1940 CE also experienced several warm seasons nearly 2 σ
231 above the 1950-2000 CE mean, and there were multiple dry events of lower magnitude during
232 this time period (Figure 2). Given the lack of station data in the early 20th century (Figure 2),
233 CMIP6 simulations are used to examine the shifting frequency of 2- σ seasonal temperature
234 anomalies and -1.5 σ rainfall extremes.

235 CMIP6 historical simulations confirm the instrumental-based analysis, which shows that
236 isolated warm years in Amazonia have occurred before the recent late 20th century and early 21st
237 century warming. However, these models show that greenhouse gas driven warming is already
238 increasing the frequency of these events (Figure 2). Specifically, by 2030 CE the average
239 temperature in CMIP6 is 2 σ warmer than the baseline. Under unabated emissions, by mid-
240 century, the coolest October-March seasons will be as warm as the isolated heat events of the
241 recent past. By the end of the 21st century under unabated emissions, the average October-March
242 season is 6-8 σ (3.6-4.8°C) above the baseline, with the warmest seasons 12-20 σ (7.2-12°C)
243 above the baseline, and the coolest seasons at least as warm as the hottest droughts during El
244 Niño events in the late 20th century and early 21st century.

245 Although all models show warming in the SSP3-7.0 scenario that exceeds internal
246 variability, future rainfall trends do not exceed the envelope of 20th century variability in all
247 CMIP6 simulations (Figure 2). However, a drying trend in almost all models increases the
248 likelihood of seasonal droughts similar in magnitude to recent observed droughts. CMIP6
249 simulations show an average decrease in precipitation of ~0.5 σ relative to 1950-2000 CE by
250 2040 CE; around this time, these simulations project regular 1.5-2 σ seasonal rainfall deficits
251 relative to the baseline every year. By the end of the 21st century if global warming is left
252 unchecked, the average year in eastern Amazonia receives as much rainfall as a typical drought
253 year in the 20th century, and particularly dry seasons approach 3-4 σ below the baseline.

254 The bottom panel in Figure 2 shows the shifting risk of these 'enhanced' droughts by
255 decade. Starting in the 21st century, at least 10% of CMIP6 simulations cross the 2- σ heat
256 threshold per decade, and by mid-century, all CMIP6 SSP3-7.0 simulations show that seasonal
257 temperatures will cross this threshold at some point each decade. In addition to projecting large
258 temperature increases, CMIP6 simulations show an increasing risk of rainfall deficits 1.5 σ
259 below the baseline as well; in the coming decades (2020-2050 CE), between 0 and 20% of
260 models cross this rainfall deficit threshold per decade. By mid-century, at least 10% of models
261 show cross this drought threshold at least once per decade, and by 2080 CE, on average at least
262 one in five models show 1.5 σ droughts at least once per decade.

263



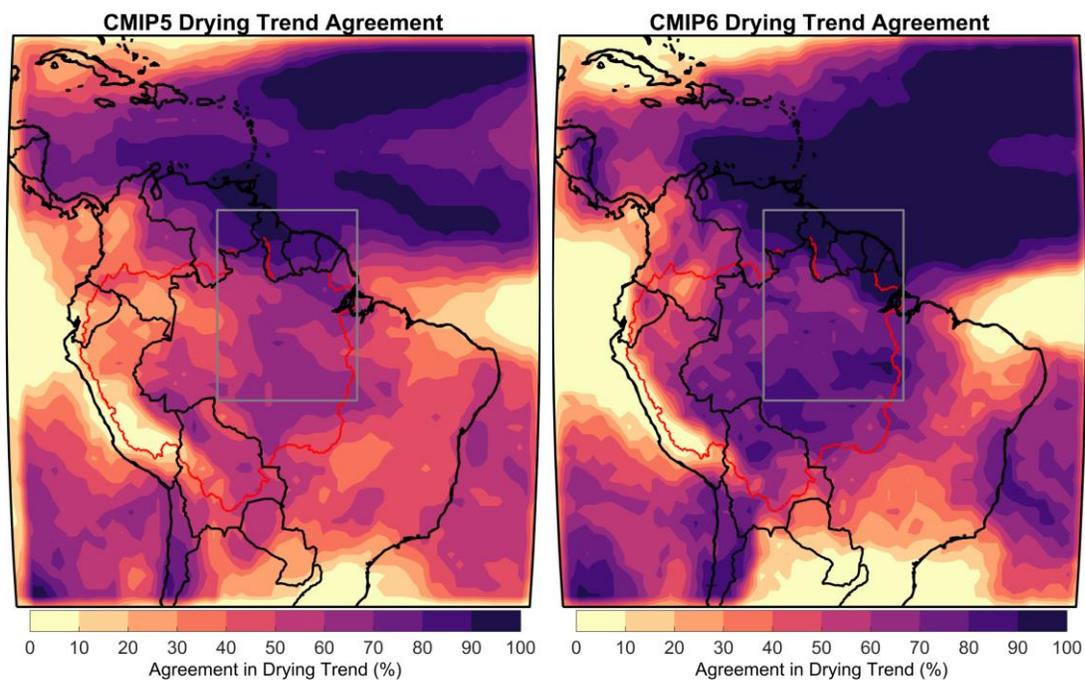
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265 **Figure 2.** Top two panels show October-March temperature (top) and rainfall (middle)
 266 anomalies from the 1950-2000 CE time period in eastern Amazonia (10°S - 8°N , 60°W - 50°W) in
 267 instrumental data (grey) and CMIP6 historical and SSP3-7.0 simulations (blue). Thick light grey
 268 line on bottom of middle panel shows number of station observations in eastern Amazonia.
 269 Boxplots in bottom panel show the percent of years per decade that fall outside the baseline
 270 (1950-2000 CE) range of temperature and rainfall variability. Dashed black line shows the 1950-
 271 2000 CE mean, red dotted line shows the heat and drought thresholds, light grey lines show
 272 spread of instrumental data, and dark grey lines show mean of instrumental data. Vertical line
 273 shows the end of the historical simulations and the start of the SSP simulations. Dark blue lines
 274 show multi-model mean temperature and rainfall in the historical and SSP3-7.0 simulations, and

275 light blue lines show CMIP6 maxima and minima. See Methods for more information about
 276 instrumental data. Red boxplots show the spread in the percent of models per decade that exceed
 277 a $2\text{-}\sigma$ temperature threshold, and teal boxplots show the spread in the percent of models per
 278 decade that simulate droughts 1.5σ below the baseline.

279 4 Discussion and Conclusions

280 Sea-surface temperature anomaly patterns in both the tropical Pacific and tropical
 281 Atlantic can help drive temperature and rainfall variability over northern South America (Yoon
 282 and Zeng, 2010; Kousky et al., 1984; Ropelewski and Halpert, 1987). Although seasonal
 283 droughts in southern Amazonia have been linked to the tropical North Atlantic (Yoon and Zeng,
 284 2010), recent particularly warm droughts in central and eastern Amazonia have occurred during
 285 strong El Niño events (JM16). Future rainfall changes over Amazonia could be driven by a
 286 warming tropical Pacific (Barichivich et al., 2012). Indeed, CMIP6 simulations project a
 287 strengthening relationship between the tropical Pacific (Figure S2) and the tropical North
 288 Atlantic (Figure S3) in the 21st century over tropical South America.



289

290 **Figure 3.** Agreement in sign of drying trend in CMIP5 RCP 8.5 (N=32) and CMIP6 SSP3-7.0
 291 (N=25) 21st century warming simulations.

292

293 CMIP5 and CMIP6 models appear to show qualitatively similar relationships with the
 294 tropical Pacific and Atlantic, yet CMIP6 models more consistently simulate drying in Amazonia
 295 in the 21st century warming projections across the Amazonian basin in most seasons (Figure 1;
 296 Figure S1), whereas CMIP5 models show less agreement in future rainfall trends (Figure 3;
 297 Figure S4). Although a relationship between 21st century trends in the Niño3.4 index and trends
 298 in Amazonian rainfall is found (Figure 4), future global warming could independently cause
 299 increasing temperatures in the tropical Pacific while causing decreasing rainfall over Amazonia.

300 Therefore, west-east tropical Pacific temperature trend differences are compared to determine if
301 the tropical Pacific becomes more 'El Niño like' or 'La Niña like' in the 21st century. CMIP6
302 models that simulate a more 'El Niño like' future tropical Pacific (stronger warming in the
303 eastern Pacific relative to the western Pacific) tend to simulate more drying over Amazonia
304 (Figure 4). Most CMIP6 models analyzed here indicate that the tropical Pacific will become
305 more 'El Niño like' in the future; shifts in Walker circulation related to decreasing tropical
306 Pacific SST gradient could explain much of the CMIP6 agreement in future drying trends over
307 Amazonia. A similar comparison in 32 CMIP5 models indicates that the previous generation of
308 models shows a similar relationship between the tropical Pacific SST and Amazonian rainfall.
309 Specifically, several CMIP5 models simulate a more 'La Niña like' future tropical Pacific and
310 minimal or no increasing rainfall trends over Amazonia (Figure 4).

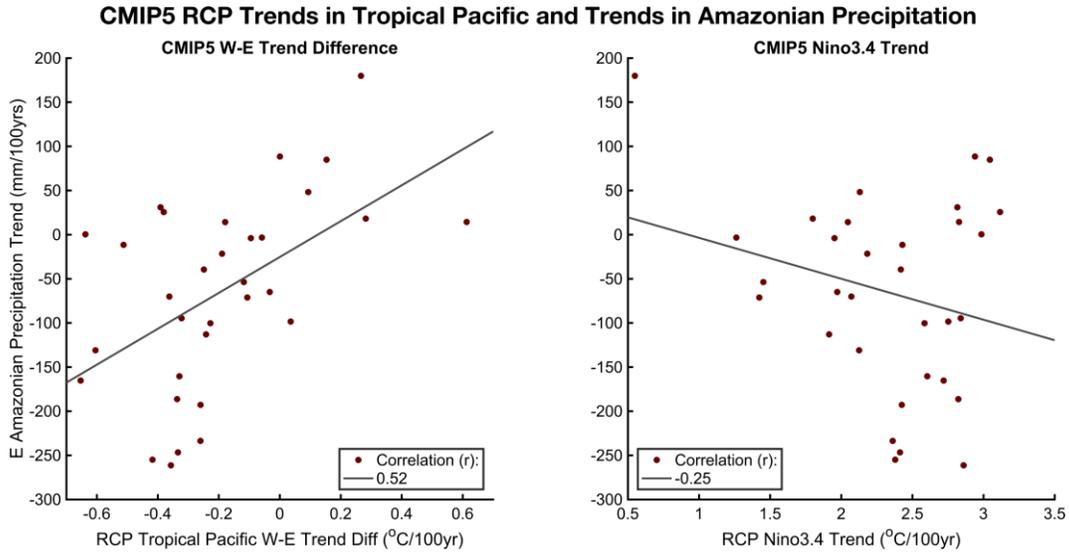
311 Although there is better agreement in projected future rainfall trends in CMIP6 models in
312 many regions (e.g., Cook et al., 2020; Ukkola et al., 2020), these results should be interpreted
313 with caution for several reasons. Most CMIP6 models show future drying in Amazonia, but the
314 local details of this drying pattern can vary from model to model (Figure S5). Future work
315 should examine the causes of increased CMIP6 agreement in rainfall trends in the region, as well
316 as why certain models, such as INM-CM4-8 and INM-CM5-0, appear to show increasing future
317 rainfall in many parts of tropical South America (Figure S5). Additionally, treating individual
318 model simulations from a Modeling Intercomparison Project as independent can be problematic
319 because multiple, similar models from the same modeling centers are often included (Table S1),
320 and models from different centers often share similar components (e.g., Knutti et al., 2013).
321 Also, climate models from different modeling centers can agree on the sign of a projected
322 precipitation trend, but this agreement could be based on the same systematic bias that appears
323 across models (e.g., Tierney et al., 2015).

324 Future changes in the tropical Pacific are uncertain, and recent work has shown that
325 CMIP5 models show considerable tropical Pacific biases, so future trends in tropical Pacific
326 gradients and their potential impacts on tropical rainfall could be incorrect (e.g., Seager et al.,
327 2019). Furthermore, climate model simulations may underestimate dry-season length (Marengo
328 et al., 2017) as well as the risk of multi-year droughts in Amazonia (Parsons et al., 2017), so the
329 potential for multi-year dry periods superimposed on background warming and potential drying
330 trends in CMIP6 projections should be considered (Marengo et al., 2018). Recent work has also
331 shown that the December-May season may in fact have experienced increasing rainfall trends
332 1979-2015 CE in northwestern Amazonia (Fu et al., 2013). CMIP6 historical simulations do
333 simulate positive rainfall trends in northeastern Amazonia (1950-2014 CE) in several of these
334 months (Figure S1), although these trends are apparent in the October-March seasonal average as
335 well (Figure 1). Additionally, the work presented here has not explored the length of the dry or
336 onset of rainy season (Marengo et al., 2011; 2017; Fu et al., 2013; Ukkola et al., 2020), or how
337 temperature and rainfall changes can impact other drought metrics in CMIP6 projections such as
338 soil moisture content (e.g., Cook et al., 2020).

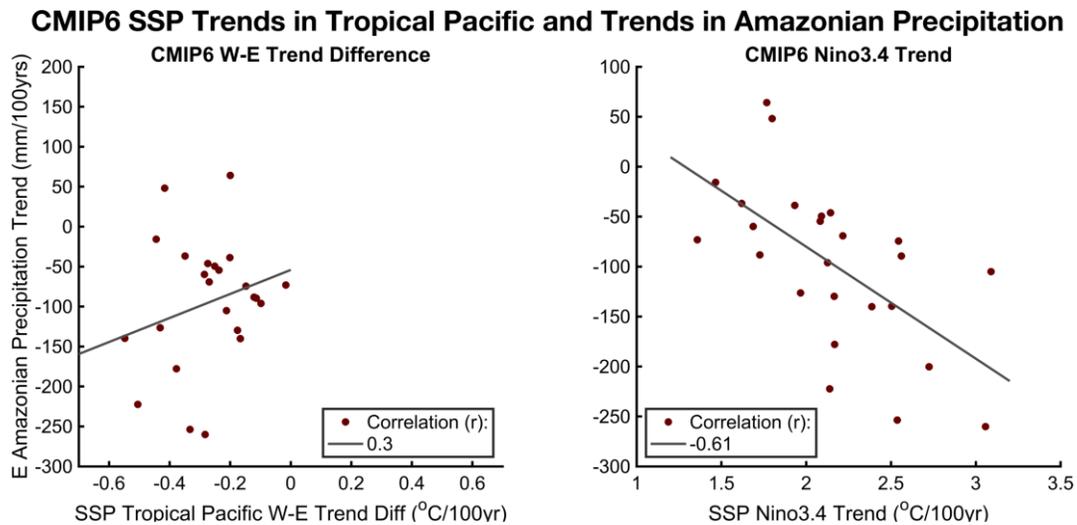
339 Nonetheless, if CMIP6 simulations of future drying in the America Tropics are accurate,
340 these results are especially relevant given recent developments in Amazonia related to land
341 management, drought, and fires. The Amazonian forest appears to be particularly vulnerable to
342 forest fire and land clearing during drought (Nepstad et al., 2008; Le Page et al., 2017),
343 particularly for forest edges where drying, fire intensity, and grass invasion are greatest (Balch et
344 al., 2015). Given that rainfall deficits on their own can increase fire risk and forest dieback, this

345 region appears susceptible to self-amplified forest loss and a possible deforestation tipping point
 346 (Brando et al., 2014; Zemp et al., 2017; Boers et al., 2017). Without significant local land
 347 management efforts combined with global efforts to curtail carbon emissions, this region appears
 348 increasing vulnerable to warming, drought, fire, and land use conversion (Marengo et al., 2018).
 349 Forest dieback driven by these combined stressors would, in turn, have major implications for
 350 regional carbon sequestration and biodiversity and the global climate system.

351



352



353

354 **Figure 4.** Relationship between October-March temperature trends in the tropical Pacific and
 355 eastern Amazonian rainfall in CMIP5 RCP8.5 (2006-2099 CE) and CMIP6 SSP3-7.0 simulations
 356 (2015-2099 CE). Difference in western tropical Pacific and eastern tropical Pacific temperature
 357 trends (Methods) and eastern Amazonian rainfall trends (left) and Niño3.4 temperature trends
 358 and eastern Amazonian rainfall trends (right).

359

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