

Projections of future meteorological drought and wet periods in the Amazon

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Future intensification of Amazon drought resulting from climate change may cause increased fire activity, tree mortality, and emissions of carbon to the atmosphere across large areas of Amazonia. To provide a basis for addressing these issues, we examine properties of recent and future meteorological droughts in the Amazon in 35 climate models participating in the Coupled Model Intercomparison Project Phase 5 (CMIP5). We find that the CMIP5 climate models, as a group, simulate important properties of historical meteorological droughts in the Amazon. In addition, this group of models reproduces observed relationships between Amazon precipitation and regional sea surface temperature anomalies in the tropical Pacific and the North Atlantic oceans. Assuming the Representative Concentration Pathway 8.5 scenario for future drivers of climate change, the models project increases in the frequency and geographic extent of meteorological drought in the eastern Amazon, and the opposite in the West. For the region as a whole, the CMIP5 models suggest that the area affected by mild and severe meteorological drought will nearly double and triple, respectively, by 2100. Extremes of wetness are also projected to increase after 2040. Specifically, the frequency of periods of unusual wetness and the area affected by unusual wetness are projected to increase after 2040 in the Amazon as a whole, including in locations where annual mean precipitation is projected to decrease. Our analyses suggest that continued emissions of greenhouse gases will increase the likelihood of extreme events that have been shown to alter and degrade Amazonian forests.

Amazon Basin | climate | precipitation extremes | CMIP5 | drought

The responses of tropical forests to severe droughts exert strong influences on the global carbon cycle (1, 2). During periods of extended soil water stress, changes in forest physiology and structure reduce the capacity of forests to cycle and store carbon (3–5). In the 2000s, for example, more than half of the Amazon experienced droughts that were severe enough to cause increased tree mortality and reduced tree growth (6). In response to these droughts, 1–2% of the carbon stocks of Amazonian forests were committed to the atmosphere (6, 7), while large amounts were combusted due to widespread fires. Although similar droughts have occurred for millennia (8), and forests have apparently recovered from such events (9), climate change could intensify hydrological extremes over the basin (10). Together with warmer climatic conditions, an increase in the frequency and severity of droughts could push the Amazon region into a new climate envelope (11), potentially releasing to the atmosphere a large part of the 120 Pg of carbon stored in these forests (12). These effects on the carbon stocks of the Amazon could be even more pronounced if forest fires become more common in the region.

There is disagreement about the potential responses of Amazon forests to climate change (13). Earlier versions of climate–vegetation models projected that as climate changed, many forests growing in southeast Amazonia would be replaced by savanna-like ecosystems within the next 50–100 y (14). This shift in vegetation dominance would result mostly from warm and dry climatic conditions (15). However, other projections are less grim. Instead of

widespread changes in vegetation states, some models project that increases in air temperature are likely to cause losses in forest carbon stocks but also that increased atmospheric CO₂ concentration would promote forest growth and associated carbon accumulation (16). The net result of these two opposing forces appears in some studies to be approximately neutral, although positive vegetation responses to high CO₂ concentration remain poorly understood (17).

Interestingly, assessments of the potential future trajectories of Amazonian forests using dynamic global vegetation models (DGVMs) driven by global climate models (e.g., ref. 16) show smaller effects than are seen in field observations and experiments. Field-based studies suggest that severe hydrological droughts tend to reduce both forest growth rates (via reduced photosynthesis) and carbon stocks (via increased tree mortality) (18). At least two factors account for the relatively small effects of hydrological droughts seen in simulations. First, most ecosystem models lack a mechanism to represent short-term carbon losses resulting from severe drought events (4). Powell et al. (19), for instance, showed that commonly used DGVMs were unable to represent the spike in drought-induced tree mortality observed in two large-scale throughfall exclusion experiments conducted in east Amazonia. Based on these results, the authors argued that DGVMs must strive to improve vegetation responses (e.g., mortality) to extreme, relatively short-term weather events.

The second explanation relates to the ability of climate models to represent basic drought conditions. Climate model results drive ecosystem models and provide insights into processes that exert strong influences on the structural dynamics of tropical forests (e.g., drought-induced tree mortality and forest fires).

Although several studies have demonstrated a strong association between historical droughts and anomalies in sea surface

Significance

Recent severe droughts in the Amazon basin have increased interest in future climatological and ecological conditions of this region. Future changes in drought and wet periods could have enormous impacts on forest structure, biomass, and composition, but our ability to predict changes in the hydrological regime remains highly uncertain. We evaluate an ensemble of state-of-the-art climate models and demonstrate their accuracy in simulating processes influencing drought in Amazonia. These models provide projections of future properties of drought and wet periods, and indicate that different portions of the Amazon Basin undergo contrasting hydrological futures but will share a tendency toward more hydrological extremes.

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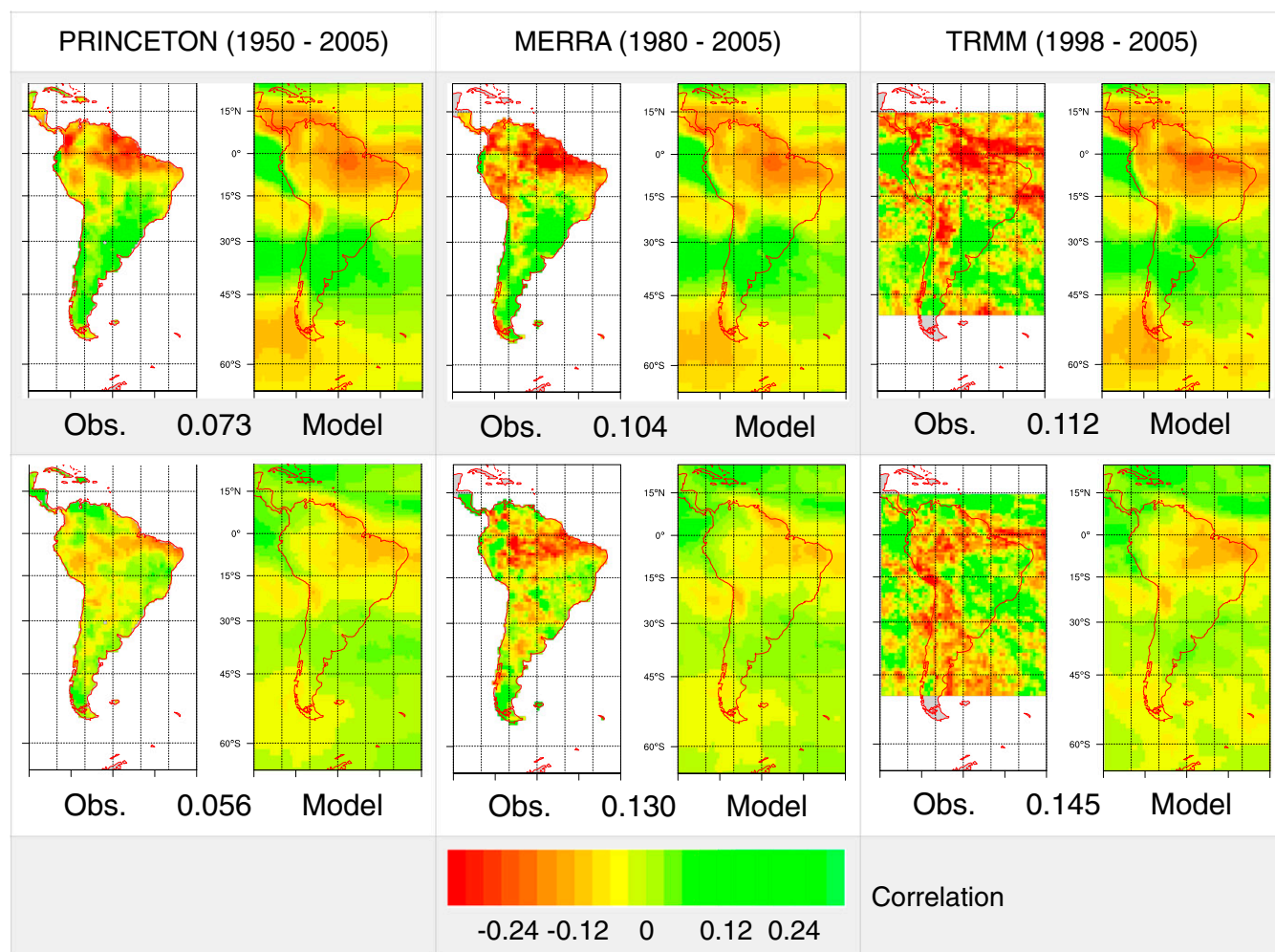


Fig. 1. Correlation coefficients between monthly SST anomalies in the Niño 3.4 region (*Top*) or the region in the North Atlantic identified by Yoon and Zeng (29) (*Bottom*) and local precipitation anomalies. In each panel, the left-hand map shows the observed correlation, based on HadISST monthly SSTs and one of three observed precipitation datasets, indicated above *Top*; the right-hand map shows the multimodel mean correlation based on CMIP5 results for the same period. The number at the bottom of each panel is the RMS difference between the simulated field of coefficients and that based on observations, calculated over the Amazon basin. The outline of the basin is visible in Fig. 2.

temperature (SST) [the El Niño–Southern Oscillation (ENSO) and the Atlantic Multidecadal Oscillation (AMO) (20–22)], it has been unclear whether this association holds in projections of future climate, if climate models can reasonably represent basic drought properties, or whether models project increases in drought frequency and intensity. For example, previous studies (e.g., refs. 10 and 23) have reported that climate change is likely to cause increases in average air temperature and could alter average precipitation patterns over the Amazon basin, but they have not quantified how the rate of short-term extreme dry or wet periods will shift as the climate changes.

Here we confront these issues by asking how well the latest generation of climate models (24) simulate observed relationships between SST anomalies and Amazon drought, and what these models suggest about the future of meteorological drought in the region.

Results

Model Evaluation. The Coupled Model Intercomparison Project Phase 5 (CMIP5) models have been extensively evaluated elsewhere (e.g., ref. 25); we focus on aspects relevant to meteorological drought in the Amazon. Assessing how well the models reproduce observed relationships between SST anomalies in specific regions

and Amazon drought addresses physical mechanisms that produce drought, and increases confidence in their representation of Amazon drought mechanisms. This bears more directly on the credibility of future drought projections than does the ability to reproduce historical drought properties, which might be simulated accurately without capturing the underlying physical processes. We also assess the ability of CMIP5 models to capture the pronounced seasonal cycle of precipitation in the Amazon (*Supporting Information*). Yin et al. (26) also evaluate the performance of these models in simulating Amazon precipitation, focusing more on the performance of individual models and of atmospheric and land surface processes.

We describe how well the CMIP5 models reproduce observed relationships between area-averaged SST anomalies in specific ocean regions and precipitation anomalies throughout the Amazon. This analysis included 29 CMIP5 models for which both SST and precipitation data were available. Relationships involving SSTs in regions used to measure ENSO (e.g., Nino 3.4) are relatively well established (27, 28). Yoon and Zeng (29) pointed out a similar relationship involving SSTs in a region in the North Atlantic. In both regions, region-wide SST anomalies show negative correlations with Amazon precipitation anomalies. The CMIP5 models, as a group, have skill at reproducing these relationships (Fig. 1),

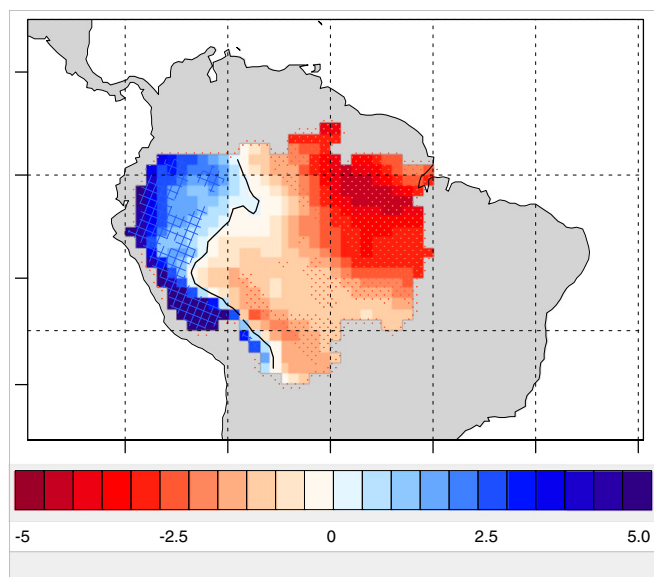


Fig. 2. Linear trends in simulated multimodel mean annual mean precipitation in the Amazon, 1950–2099. The black line denotes zero trend; we perform some analyses separately for locations with negative and positive trends. Hatching (dots) indicate regions where $>2/3$ of models have a positive (negative) trend. Units are millimeters per day per century.

although the skill level varies greatly among individual models. Because the phasing of internal variability is random in climate projections, the multimodel mean results shown in Fig. 1 are simply the multimodel mean correlation coefficient, rather than the correlation coefficient based on multimodel mean results. In case the correlation coefficients depend on the length of the data record, for each observational dataset, we calculated simulated correlation coefficients for a period the same length as the observed dataset.

To assess how well individual models perform relative to an estimate of observational uncertainty, we compared RMS differences in spatial patterns of correlation coefficients between individual models and observations to RMS differences among observational datasets, which capture structural uncertainties in the observations. This analysis was performed for the period of overlap of all three observational datasets (1998 through 2005),

and, of the 29 models analyzed, 5 and 17 have RMS differences that are less than the smallest of the interobservational differences for the North Atlantic and El Niño region SSTs, respectively. Thus, by this measure of model performance, a significant number of individual models are performing at a level comparable to apparent observational uncertainties. Also, as we find elsewhere (and as is common in climate model evaluations generally), the model mean result compares more closely to observations than the result of any individual model.

Projected Average Precipitation. Our results for projected future drought and periods of unusual wetness are best understood in the context of projected changes in mean precipitation, by region and by season. Although mean annual precipitation (MAP) averaged over the Amazon basin is projected to remain largely unchanged, this results from a cancellation of significant regional and seasonal trends (Figs. 2 and 3). Geographically, MAP is projected to increase in the western Amazon and to decrease in the eastern part of the region (Fig. 2). Seasonally, projections indicate that the wettest months (December–April) may become slightly wetter, the driest months (July–September) get drier, and autumnal transition months (September–November) experience strong, drying trends (Fig. 3).

Projected regional and seasonal changes may be explained by differential warming of regional SSTs. Yoon and Zeng (29) showed that SSTs in both the eastern tropical Pacific and a specific region of the North Atlantic anticorrelate with precipitation in the Amazon as a whole. More localized analysis shows that the Pacific SSTs correlate most strongly with precipitation in the eastern Amazon, and the North Atlantic SSTs correlate with precipitation more in the western Amazon. We find that SSTs in the Pacific region are projected to warm relatively rapidly, whereas those in the North Atlantic region identified by ref. 29 warm relatively slowly (*Supporting Information*). Based on observed the relationships just described, this would suggest that projected precipitation should increase in the western Amazon and decrease in the east, as is, in fact, the case. In addition, Yoon and Zeng (29) show that the Pacific region SSTs correlate with rainy season precipitation; hence, relatively rapid warming in this region could contribute to a wetter rainy season.

Projected Drought and Wet Periods. We use the Standardized Precipitation Index (SPI) (30) to assess spatial–temporal changes in precipitation variability. Because the SPI is based solely on

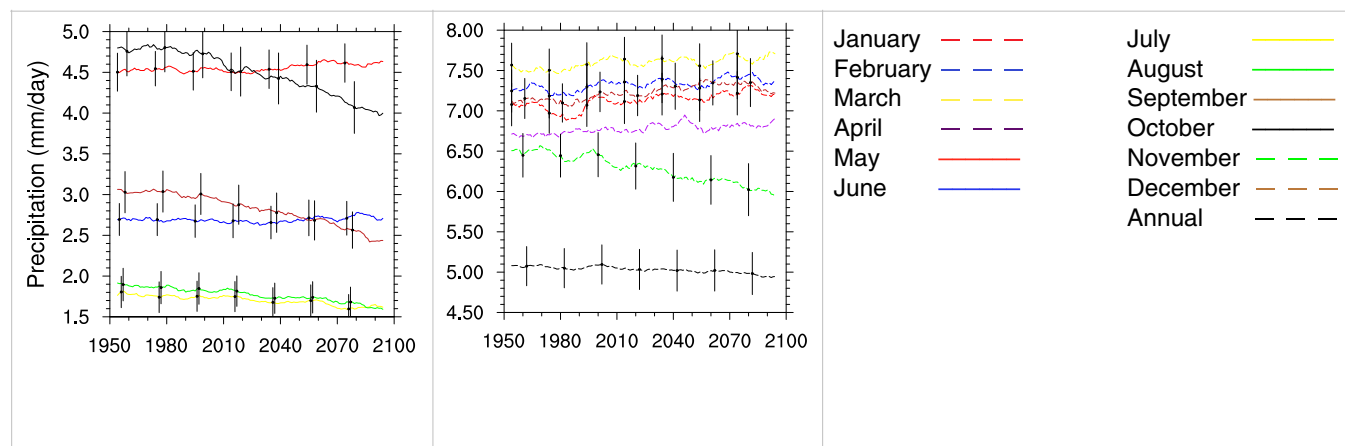


Fig. 3. Projected changes in the seasonal cycle of precipitation in the Amazon. Each curve shows monthly mean precipitation for one month of the year, as a multimodel mean of 35 CMIP5 models, and is smoothed by applying a 10-y running mean. Error bars measure of intermodel agreement (the SE across 35 CMIP models based on smoothed results), and are displayed every 20 y. Vertical axis units are millimeter per day. Note that the error bars are temporally offset from one another for clarity.

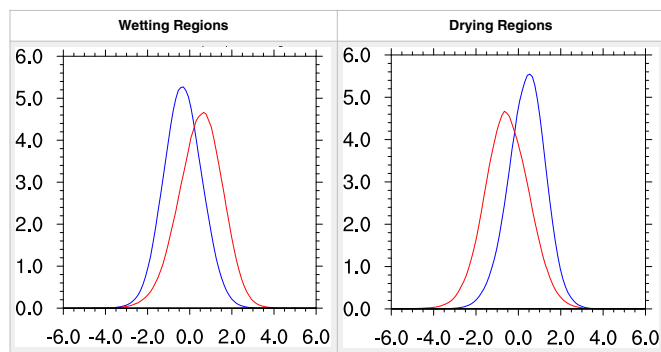


Fig. 6. Probability density functions of simulated 12-mo SPI values, in regions where annual mean precipitation is projected to increase (*Left*) and decrease (*Right*). These regions are shown in Fig. 2. In both “wetting” and “drying” regions, interannual variability in precipitation, as measured by the variance of 12-mo SPI, is projected to increase. Red curve, results for 2071–2100; blue curves, results for 1950–1979.

an increasing trend in periods of unusual wetness. These projections derive from CMIP5 models that, as a group, capture well-established positive relationships between Amazon droughts and SST, as well as some basic drought properties. In addition to an intensification of the hydrological cycle, the CMIP5 models project increased dry-season length due to reduced precipitation in autumnal transition months.

The recent droughts in 2005 and 2010 in some ways are analogs for projected future conditions. First, droughts of similar intensity (with SPI values less than -2) are projected to greatly increase in frequency; hence the impacts of these recent droughts may offer some insight into future drought impacts. Second, both the 2005 and 2010 droughts were accompanied by unusual wetness in the northeast part of the basin; the CMIP5 models project increased frequency of extreme wetness in the same region (21).

Our analyses reveal that CMIP5 models project contrasting behavior in precipitation between eastern and western Amazonian regions. Although the specific mechanisms driving such differences should be explored, they may result from differential warming in Atlantic vs. Pacific ocean SSTs (23). Below-average SSTs in the Pacific tend to trigger periods of extreme wetness in the western Amazon. We observed strong associations between Amazon drought and SST in CMIP5 model simulations. Assuming that this association will hold in the future, an increase in the amplitude of ENSO or AMO could explain the projected increases in drought and extreme wetness in the eastern and western Amazon basin, respectively.

By 2100, the CMIP5 simulations project roughly a tripling of the area experiencing meteorological droughts in Amazonia (for both 3-mo and 12-mo droughts), and there is reason to suspect that they may underestimate future drought intensity and extent. The projected changes in the CMIP5 simulations described here are driven by increases in atmospheric greenhouse gases and other human forcings. However, other important processes, which are highly uncertain and poorly represented in CMIP5 models, could also intensify Amazon droughts. For example, rainfall in the eastern Amazon has a strong dependency on regional evapotranspiration, so a reduction in tree cover due to deforestation could reduce precipitation (32). This suggests that if processes related to changes in land use and land cover (including feedbacks on climate) were better represented in more of the CMIP5 models, drought intensity could be even more frequent than projected here (33). Furthermore, our analysis does not consider effects of warming or CO_2 on evapotranspiration and soil moisture.

Previous field-based studies and modeling exercises suggest that the projected increases in drought frequency and severity described above could exert strong influences on the ecology and productivity of Amazonian forests. For example, two rainfall exclusion experiments found that soil water stress caused reduced tree growth and triggered a fourfold increase in mortality of large trees (5), which store most of the aboveground carbon in tropical forests. Two recent Amazon droughts had similar effects on the ecology of tropical forests, when mortality increased to levels that were large enough to transform tropical forests from carbon sink to source (6). By altering forest microclimate and fuel dynamics, droughts also tend to increase forest flammability (1). In the 2000s, for example, more than 85,000 km^2 of primary forests burned, mostly in the drought years of 2005, 2007, and 2010 (34, 35). It is important to note that our study focuses on precipitation; increases in temperature could worsen the severity and effects of droughts (36–38).

Historical droughts altered the ecology of Amazonian forests (39). However, it remains unclear whether the future changes in drought intensity and frequency that CMIP5 models project will have influences similar to past changes. We still lack quantitative analyses of the effects of historical droughts compared with future projections. Without such studies, it is difficult to define what constitutes a dangerous or catastrophic change in drought frequency and intensity for the stability of Amazonian forests. Likewise, it is important to consider the combined effects of reduced precipitation and increased temperatures, which together can reduce the capacity of tropical forests to cycle and store carbon. The eastern Amazon, in particular, may experience increases of air temperature between 4°C and 5°C , and this portion of the basin is already close to the lower rainfall limit for moist tropical forests (40), so minor changes could have important consequences. Further research on these types of thresholds is needed now to inform policy development processes.

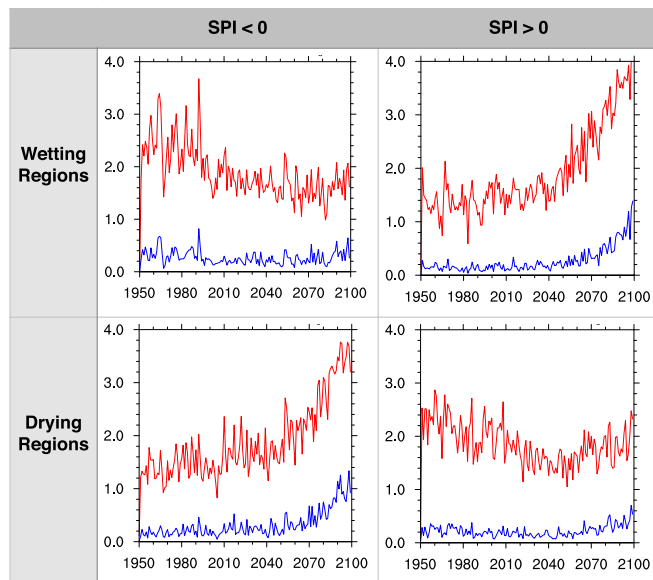


Fig. 7. Simulated frequency of drought or unusual wetness, as measured by months per year when the absolute value of SPI exceeds specified thresholds. Shown are results in locations projected to experience an increase (*Top*) or decrease (*Bottom*) in annual mean precipitation. (*Left*) Results for drought and (*Right*) results for periods of unusual wetness. Red curves show results for $\text{SPI} < -1$ (*Left*) or $\text{SPI} > 1$ (*Right*). Blue curves show results for $\text{SPI} < -2$ (*Left*) or $\text{SPI} > 2$ (*Right*).

Methods

We analyzed results from simulations performed with up to 35 climate models participating in CMIP5 (24). Each simulation spanned the years 1950 through 2099. For 1950 through 2005, estimates of historical climate forcings (atmospheric greenhouse gas concentrations, etc.) were used. After 2006, forcings corresponded to the Representative Concentration Pathway 8.5 scenario, which assumes a relatively rapid buildup of atmospheric greenhouse gases. We used one simulation from each model; whenever possible, this was the r1i1p1 simulation. All model results used are reported as monthly means, and are regridded to a $1^\circ \times 1^\circ$ latitude by longitude grid before analysis (these are available

from gdo-dcp.ucllnl.org/downscaled_cmip_projections/dcpInterface.html). Most analyses were restricted to the Amazon watershed; exceptions include evaluation of simulated correlations with SST. We find that the CMIP5 models have demonstrable skill in representing observed relationships between SST anomalies in specific regions in the North Atlantic and tropical Pacific oceans, as well as in simulating basic properties of observed Amazon drought (*Supporting Information*).

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Supporting Information

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SI Model Evaluation

Our evaluation of the CMIP5 climate models is limited to its ability to simulate meteorological drought in the Amazon; more comprehensive evaluations of CMIP5 models have been performed and reported on elsewhere. For example, a thorough review is provided by ref. 41. Beyond this, Orlowsky and Seneviratne (42) looked at drought on a global domain.

We discussed in the *Results* the ability of the CMIP5 models to reproduce observed relationships between SST anomalies in specific regions and precipitation anomalies in the Amazon; here we discuss how we weight the different models, and examine their ability to reproduce observed properties of meteorological Amazon droughts. We start by intercomparing the different observational datasets used in this study.

We compared CMIP5 results to three different observation-based datasets of precipitation in the Amazon (Table S1). Because we are interested in understanding intraregional variations, we selected datasets having relatively fine spatial resolution. The first of these is the precipitation field used to produce the Modern Era Retrospective Analysis (MERRA) Land reanalysis product (gmao.gsfc.nasa.gov/research/merra/merra-land.php); it is based on correcting the precipitation from the MERRA reanalysis using satellite and station data, as described by ref. 43. The second is monthly precipitation from the Princeton global meteorological forcing dataset (44). The third is the Tropical Rainfall Measurement Mission (TRMM) 3B43 data product, which is based upon satellite retrievals and in situ data. Evaluation of the TRMM 3B43 results in the mountainous regions of Peru is discussed by ref. 45.

Significant disagreements among these three datasets exist in parts of the study area. Because we use these datasets in part to evaluate simulated correlations between SST anomalies and precipitation anomalies, we compared the three datasets by looking at correlations among them (Fig. S2). These show poor agreement in parts of South America, including parts of the Amazon. None of the three datasets can be identified as an outlier relative to the others. These regions of poor agreement should be kept in mind when using the observation-based datasets to evaluate models. Below we show additional evidence for disagreements among observation-based datasets, in the form of evaluations in which the CMIP5 models, as a group, appear to have different biases (even biases of different signs) compared with different observation-based datasets.

Referring to correlation coefficients between area mean SSTs and gridded precipitation (shown in Fig. 1), we calculated a skill score for each model based on the RMS differences between its patterns of simulated correlation coefficients and the patterns based upon observations. For each model, six RMS errors were found, one corresponding to each panel in Fig. 1. We then found a single skill score for each model based on a weighted mean of these six RMS errors, with the weight proportional to the number of years each was based on. To produce a skill score that ranges from a minimum possible value of zero to a maximum of 1, the skill score was defined as

$$\text{skill} = 0.5 * (2 - \langle \text{RMSE} \rangle)$$

where $\langle \text{RMSE} \rangle$ is the weighted average of RMS errors found as described above. The skill scores calculated in this way for 29 CMIP5 models range from 0.915 to 0.948; i.e., intermodel differences in skill are small compared with the maximum possible range. The skill score calculated as just described based on multi-

model mean correlation coefficients is 0.956, slightly higher than that of any individual model. This indicates some tendency for errors to cancel when many models are averaged together, and is consistent with previous findings that model mean results or median model results agree better with observations than any single model does; this is especially true when “agreement” is based on a broad set of metrics (46). Tebaldi and Knutti (46) also point out that superior skill in multimodel mean results is found in fields beyond climate and weather.

We turn now to evaluating properties of simulated droughts in the historical period. We used two metrics of drought properties, both based upon the SPI. To evaluate the spatial coherence of drought within the Amazon, we calculated the SD in time of the area within the Amazon having 12-mo SPI < -1 (mild drought) and 12-mo SPI < -2 (severe drought). This measure is arrived at as follows: In the limiting case that droughts were much smaller than the region and uncorrelated from location to location, then the fraction of the region having SPI < -1 and SPI < -2 would be constant in time (at 16% and 2.3%, respectively, which follows from the definition of SPI). At the other extreme, if every drought affected the entire region, then the fractional area affected would be as high as 100% at times, while still averaging 16% and 2.3%, respectively. Hence the SD in time of the fractional area affected by drought measures the spatial coherence of drought within the region.

We calculated this measure based on monthly time series of 12-mo and 3-mo SPI (each month's value of SPI based on the previous 12 mo or 3 mo) for each of the observational datasets. To evaluate the models, we calculated the same measure for each model over the interval of years corresponding to each observational dataset. We display the results for 12-mo SPI in Fig. S3.

The impression gained from this evaluation exercise (Fig. S3) depends on which observations the models are compared with. In particular, the models, as a group, seem to be biased high (implying overly coherent droughts) compared with the Princeton dataset, and biased low compared with TRMM. Compared with MERRA, individual models have significant biases but the set of biases is much more closely centered around zero. This is true for both mild and severe droughts (SPI < -1 and SPI < -2). Hence it appears that differences among observational datasets limit our ability to assess this aspect of model performance.

We use a simple measure of drought duration, the temporal autocorrelation of SPI at lag 6 mo, based on monthly time series of 12-mo SPI. As with spatial coherence, we calculated this measure for each of the observational datasets, and for each of the models over the same interval of years as each observational dataset. For each observational dataset, we compared the observation-based value to the set of model values (Fig. S4). In contrast to Fig. S3, we saw no tendency for the models to have systematically different biases against different observational datasets. We also saw no clear bias in the CMIP5 models as a group. It is also noteworthy that in every panel in both Fig. S3 and Fig. S4, the range of model values relative to observed (i.e., the limits on the horizontal axis) is greater for SPI of -2 than for SPI of -1 . This probably occurs because more severe droughts are more rare, which results in less robust comparisons between models and observations.

As discussed in the *Discussion*, projected trends in regional SST (Fig. S5) may be the proximate drivers of projected changes in hydrological variability.

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Figs. S6–S9 show results obtained for shorter droughts (3-mo SPI) but otherwise identical to results shown in Figs. 4–7, re-

spectively. The reader is referred there for details of the analysis. Results for 3-mo SPI are generally similar to those for 12-mo SPI.

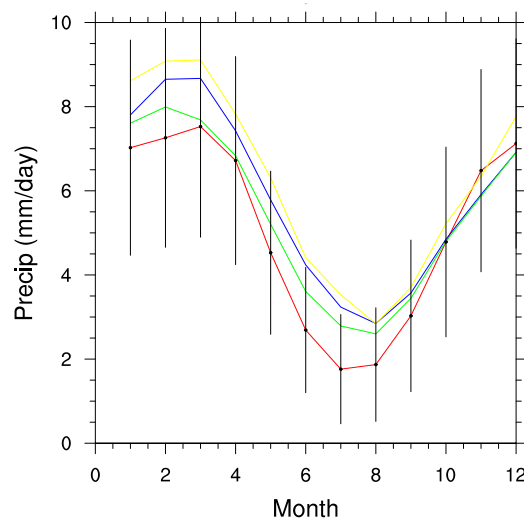


Fig. S1. Seasonal cycle of precipitation in the Amazon, in three different observational datasets, and as simulated by CMIP5 climate models. Red curve, mean and SD of 35 CMIP5 models; blue curve, Princeton observational dataset; green curve, MERRA; yellow curve, TRMM.

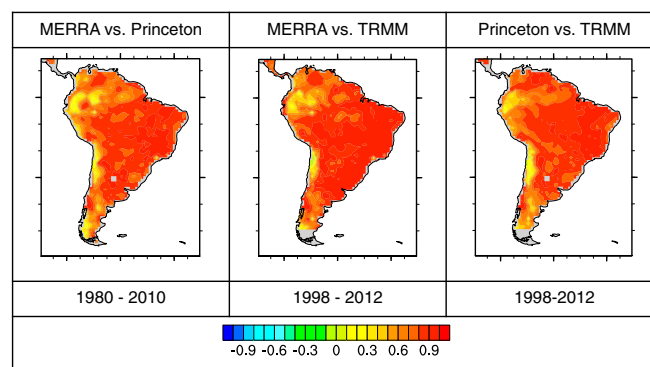
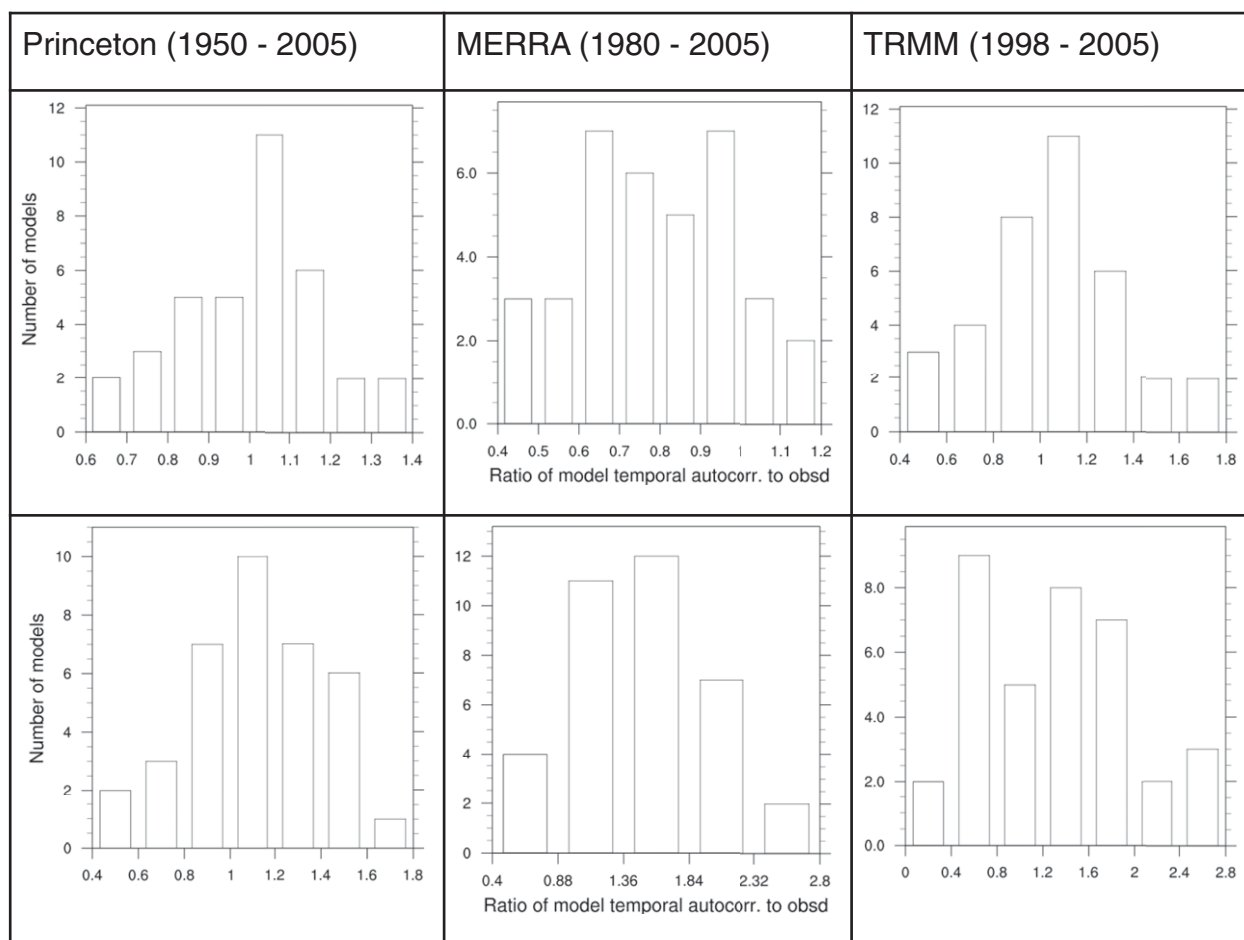


Fig. S2. Correlation coefficients among monthly precipitation values in different observation-based precipitation datasets used here. Comparisons were made over the full period of overlap (dates below each map) between each pair of datasets.

3 of 7



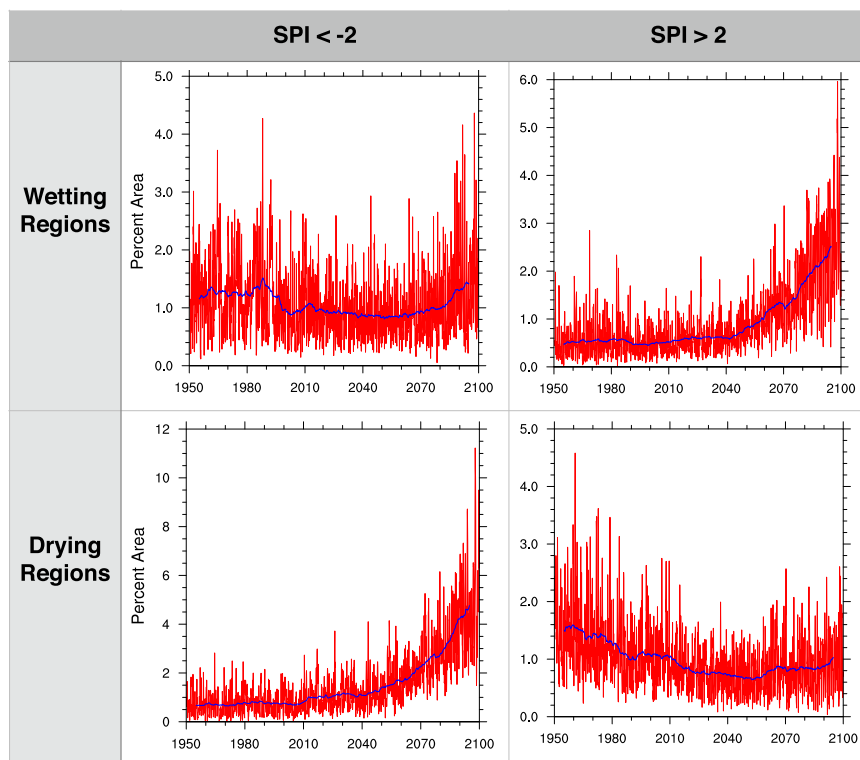


Fig. S6. Same as Fig. 4 except showing results for 3-mo SPI. Multimodel mean projections of percent area in the Amazon affected by severe drought, defined here as $SPI < -2$ (Left) or unusual wetness, defined as $SPI > 2$ (Right). Red curve, monthly results; blue curve, 10-y running mean.

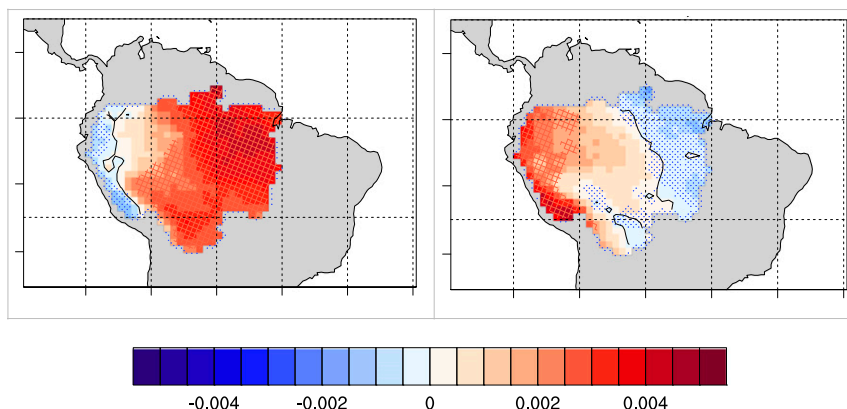


Fig. S7. Same as Fig. 5 except showing results for 3-mo SPI. Linear trends in number of months per year experiencing drought or unusual wetness, 1950–2099. (Left) Months per year experiencing $SPI < -2$; (Right) months per year experiencing $SPI > 2$. Results are the mean of results from 35 CMIP5 models. The black line denotes zero trend; i.e., it separates regions of increasing and decreasing drought frequency. Hatching (dots) indicate regions where $>2/3$ of models have a positive (negative) trend. Units are months per year per year.

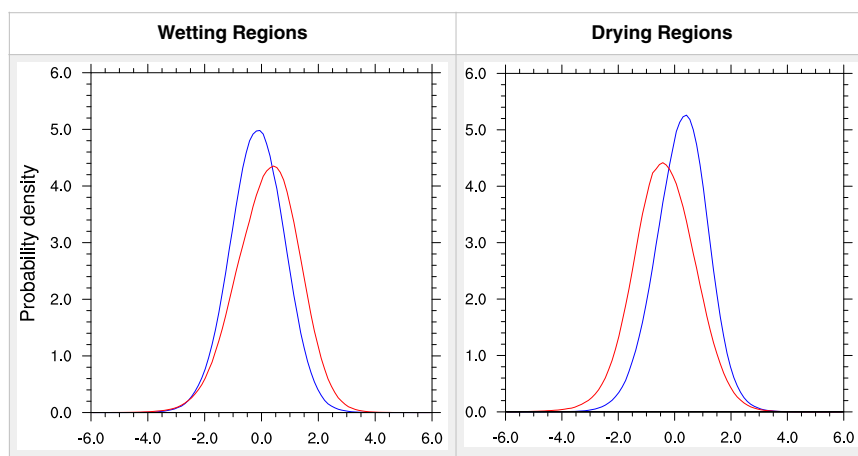


Fig. S8. Same as Fig. 6 except showing results for 3-mo SPI. Probability density functions of simulated 3-mo SPI values, in regions where annual mean precipitation is projected to increase (*Left*) and decrease (*Right*). These regions are shown in Fig. 2. In both wetting and drying and regions, interannual variability in precipitation, as measured by the variance of 3-mo SPI, is projected to increase. Red curves show results for 2071–2100, and blue curves show results for 1950–1979.

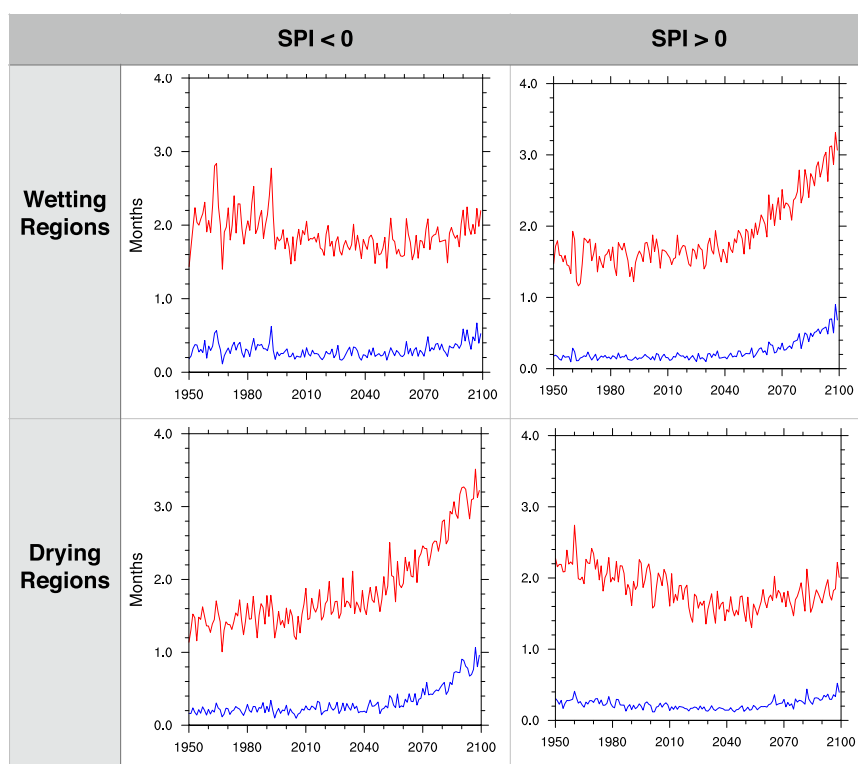


Fig. S9. Same as Fig. 7 except showing results for 3-mo SPI. Simulated frequency of drought or unusual wetness, as measured by months per year when the absolute value of SPI exceeds specified thresholds. Shown are results in locations projected to experience an increase (*Top*) or decrease (*Bottom*) in annual mean precipitation. (*Left*) Results for drought and (*Right*) results for periods of unusual wetness. Red curves show results for SPI < -1 (*Left*) or SPI > 1 (*Right*). Blue curves show results for SPI < -2 (*Left*) or SPI > 2 (*Right*).

Table S1. Observational data products used for evaluation of CMIP5 models

Name	Grid spacing	Years analyzed	References
MERRA-Land	$2/3^\circ$ lon. \times $1/2^\circ$ lat.	1980 through 2012	Reichle et al. (47)
Princeton global meteorological forcing dataset	$1^\circ \times 1^\circ$	1950 through 2010	Sheffield et al. (44)
TRMM 3B43	$0.25^\circ \times 0.25^\circ$	1998 thru 2012	Huffman et al. (48, 49)