Observed and Projected Changes to the Precipitation Annual Cycle

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ABSTRACT

Anthropogenic climate change is predicted to cause spatial and temporal shifts in precipitation patterns. These may be apparent in changes to the annual cycle of zonal mean precipitation $P$. Trends in the amplitude and phase of the $P$ annual cycle in two long-term, global satellite datasets are broadly similar. Model-derived fingerprints of externally forced changes to the amplitude and phase of the $P$ seasonal cycle, combined with these observations, enable a formal detection and attribution analysis. Observed amplitude changes are inconsistent with model estimates of internal variability but not attributable to the model-predicted response to external forcing. This mismatch between observed and predicted amplitude changes is consistent with the sustained La Niña–like conditions that characterize the recent slowdown in the rise of the global mean temperature. However, observed changes to the annual cycle phase do not seem to be driven by this recent hiatus. These changes are consistent with model estimates of forced changes, are inconsistent (in one observational dataset) with estimates of internal variability, and may suggest the emergence of an externally forced signal.

1. Introduction

Changes to the amount, distribution, timing, and frequency of precipitation are among the most societally relevant consequences of climate change. A vast body of literature (e.g., Durack et al. 2012; Hegerl et al. 2015; Min et al. 2008; Polson et al. 2013b; Santer et al. 2007; Zhang et al. 2007; Marvel and Bonfils 2013) has begun to identify projected and observed changes to various aspects of the hydrological cycle, but observational uncertainty, model error, large internal variability, and gaps in theoretical understanding hinder progress in detecting precipitation changes in observations and/or attributing them to anthropogenic forcing (Hegerl et al. 2015; Sarojini et al. 2016).

Expected precipitation changes are often partitioned into a thermodynamic component resulting from increased atmospheric water vapor (Allen and Ingram 2002; Held and Soden 2006) and a dynamic component associated with changes to the atmospheric circulation (Chou et al. 2009; Seager et al. 2010; Bony et al. 2013). A fundamental response to a simple, uniform warming can be described as a combination of 1) the convergence of increased moisture by the original circulation, so that wet regions become wetter and dry regions drier, and
2) changes in the zonal mean circulation that shift the locations of these wet and dry regions by expanding the tropical belt and moving the storm tracks poleward. In many places precipitation is tied to the annual cycle, with most rain falling in a distinct wet season. Forced changes in precipitation can therefore also be described as changes in the amplitude (the range between wet and dry season precipitation) and phase (the onset time of the wet season) of the precipitation annual cycle and may be attributed to thermodynamic and dynamic effects. Previous work has indicated that the amplitude of the annual cycle of tropical precipitation will increase under increased greenhouse gas forcing (e.g., Chou and Lan 2012; Dwyer et al. 2014; Tan et al. 2008) and that this change can be explained in terms of the wet-get-wetter response to uniform warming (Dwyer et al. 2014). Models from both phases 3 and 5 of the Coupled Model Intercomparison Project (CMIP3 and CMIP5) also project a delay of the onset of the rainy season in the tropics, particularly in monsoon regions (Biasutti and Sobel 2009; Biasutti 2013; Seth et al. 2011, 2013), but the mechanisms responsible for this signal are less understood, as both local land surface effect and more general changes in circulation have been implied (Dwyer et al. 2014; Seth et al. 2013).

Because the thermodynamic response is relatively robust across models (Chou et al. 2009), signals associated with this mechanism might be expected to emerge sooner in the observational record. Chou et al. (2013) have indicated that, globally, the range between the wet and dry season increased in the 1979–2010 GPCP dataset. However, the signal they identify is especially large in the higher latitudes, where satellite estimates of precipitation are more prone to biases. Moreover, there is little overlap between regions where an intensification of the annual cycle is identified and regions in which the annual cycle is large.

Previous work (e.g., Durack et al. 2012; Zhang et al. 2007) has identified a human influence on various aspects of the water cycle over the twentieth century. However, the most recent precipitation changes have occurred against a backdrop of the slower-than-expected (compared to models) warming: the much-discussed global warming hiatus (Fyfe and Gillett 2014; Hawkins et al. 2014). This muted global temperature rise has been accompanied by cool temperatures in the equatorial Pacific (Kosaka and Xie 2013) and concomitant intensification of the trade winds (England et al. 2014). There has been vigorous debate over the causes (Huber and Knutti 2014; Kaufmann et al. 2011; Santer et al. 2014; Schmidt et al. 2014), relevance (Johansson et al. 2015), and even statistical existence (Cowtan and Way 2014; Fyfe et al. 2016; Karl et al. 2015) of the hiatus as defined by global mean temperature. However, multiple lines of evidence suggest the recent slowdown in warming resembles a negative phase of the interdecadal Pacific oscillation (IPO; Meehl et al. 2013; Steinman et al. 2015) or sustained La Niña–like conditions (Held 2013). These conditions are attributable to some combination of internal decadal variability, natural forcings (Santer et al. 2014; Schmidt et al. 2014), and anthropogenic warming, and they substantially affect many trends measured over the relatively short satellite era.

How has the seasonality of precipitation changed over the satellite era? How can previous claims of model–observation agreement on a rich-get-richer amplification driven by surface warming be reconciled with the hiatus? These questions require a careful comparison of model-predicted and observed patterns. Here, we perform a formal detection and attribution (D&A) study of the amplitude and phase of the precipitation annual cycle. We consider zonal mean precipitation $P$ because the averaging helps to reduce observational and model uncertainty and, as we shall see, because the zonal mean facilitates physical interpretation of the results.

2. Methods

a. Datasets used

Only two datasets provide long-term measurements of precipitation over both land and ocean. These are the merged satellite–gauge products of the Global Precipitation Climatology Project (GPCP) and the Climate Prediction Center Merged Analysis of Precipitation (CMAP; see below), which provide 2.5° gridded monthly mean data from January 1979 to December 2014. While both datasets provide global coverage, we consider only the region from 50°S to 50°N. The reduced domain eliminates the high latitudes, where the datasets are considered unreliable and will facilitate comparisons (in subsequent work) with the shorter-length TRMM dataset. There are well-known discrepancies between these two satellite datasets, particularly over the oceans (Yin et al. 2004), which result in substantial observational uncertainty. Furthermore, issues with satellite drifts and merging of inhomogeneous data sources may reduce their suitability for long-term trend analysis. Despite these shortcomings, these datasets remain the best global products available. Previous studies have used only GPCP to examine large-scale trends in combined ocean and land precipitation (e.g., Marvel and Bonfils 2013;
c. Amplitude and phase time series

We regrid all CMIP5 simulation output and observations to the GPCP grid and calculate the zonal average \( P(\phi, t) \) of combined land and ocean precipitation, where \( \phi \) is latitude and \( t \) is the monthly time step. To determine the annual cycle at each latitude, we calculate the amplitude and phase of the best-fit sine wave with period 12 months, as in Stine et al. (2009). At each latitude \( \phi \) and for each year \( y \), we calculate the Fourier mode with period 12 months:

\[
F_{12}(\phi, y) = \frac{2}{12} \sum_{t=1/2}^{11/2} e^{2\pi it/12} P(\phi, t + y). \tag{1}
\]

The factor of 2 accounts for positive and negative frequencies. The amplitude is given by

\[
R(\phi, y) = \sqrt{\text{Re}[F_{12}(\phi, y)]^2 + \text{Im}[F_{12}(\phi, y)]^2} \tag{2}
\]

and the phase by

\[
\theta(\phi, y) = \tan^{-1}\left\{ \frac{\text{Im}[F_{12}(\phi, y)]}{\text{Re}[F_{12}(\phi, y)]} \right\} \times \frac{365}{2\pi}. \tag{3}
\]

We also define 1979–2014 multimodel mean (MMM) amplitude and phase climatologies from the real and imaginary components of the annual Fourier mode of the entire 1979–2014 time series. The MMM is calculated first by averaging over ensemble members and then over models. These climatologies are shown in Fig. 1. The black dashed line indicates the multimodel mean 1979–2014 precipitation climatology. Superimposed on this line are circles whose area represents the 1979–2014 zonally averaged, MMM amplitude climatology at each latitude. Colors indicate the 1979–2014 MMM phase.

d. Relative importance of the annual cycle

Figure 1 clearly shows that the amplitude and phase of the \( P \) annual cycle vary with latitude. At some latitudes the annual cycle is quite strong; at others it is muted or even absent, and in these regions the phase of the fitted sinusoid may vary wildly from year to year. We want to ensure that we track changes in the annual cycle only at those latitudes where it is meaningful. We therefore define a weighting function \( W(m, \phi) \) for each CMIP5 model or observational dataset \( m \) at each latitude \( \phi \) to take into account the relative importance of the annual cycle. We calculate the Fourier mode with period 12 for the entire 36-yr time period 1979–2014 spanned by the observational datasets:

\[
F_{12}^m = \frac{2}{12} \sum_{t=1/2}^{2 \times 36/12} e^{2\pi it/12} P^m(\phi, t), \tag{4}
\]

where \( P^m(\phi, t) \) is the zonal mean precipitation in the CMIP5 model or observational dataset \( m \) at latitude \( \phi \) and time \( t \). From its amplitude \( R_{12}^m \) and phase \( \theta_{12}^m \), we calculate the best-fit sinusoid \( S_{12}^m(t) = R_{12}^m \cos(2\pi t/12 + \theta_{12}^m) \). We define the weighting function as follows:

\[
W(m, \phi) = \left\{ \text{correlation}[S_{12}^m(t), P^m(\phi, t)] \right\}^2. \tag{5}
\]

The weighting function thus measures the total temporal variance in the observed or simulated time series at latitude \( \phi \) in model or observational dataset \( m \) that can be explained by the annual cycle. CMIP5 models contain errors in the location and intensity of the major features of the zonal mean precipitation (Levy et al. 2013; Marvel et al. 2013a). Here, we will show that the two datasets show similar trends in the amplitude and phase of the precipitation annual cycle, enhancing our confidence in the results.

1) GPCP

GPCP (Huffman et al. 1997), version 2.2, begins in 1979 and was last updated in October 2015. It blends retrievals from multiple satellite datasets, sounding observations, and land-based gauges. Post-1988, GPCP incorporates data from the Remote Sensing Systems (RSS) Special Sensor Microwave Imager (SSM/I) over the ocean (Wentz and Spencer 1998).

2) CMAP

NOAA’s CMAP (Xie and Arkin 1997) combines land and low island/atoll gauge data with microwave and infrared observations from polar-orbiting and geostationary satellites. We use the enhanced version, which incorporates the NCEP–NCAR reanalysis to fill gaps in spatial coverage (although this is less relevant for the domain under consideration).

b. Models

We use model simulations from CMIP5 (Taylor et al. 2012). To estimate unforced internal climate variability, we rely on preindustrial (piControl) simulations with no changes in external climate forcings. For comparison with recent observations we use historical simulations with estimated changes in anthropogenic and natural forcings over the period 1860–2005, extended to 2100 by splicing with the corresponding RCP8.5 simulation in which twenty-first-century changes in greenhouse gases and anthropogenic aerosols are prescribed according to the representative concentration pathway 8.5 (ALL+8.5; Van Vuuren et al. 2011).

c. Amplitude and phase time series
and Bonfils 2013; Scheff and Frierson 2012), and defining the weighing function on a model-by-model basis downweights the latitudes in each model where the annual cycle is negligible. Figure 1b shows this weighting function $W(m, f)$ for each CMIP5 model $m$ and the GPCP and CMAP datasets. In the tropics, the annual cycle explains a large fraction of observed and modeled variance because precipitation largely follows the seasonal movement of the ITCZ, which, in the zonal mean, generally moves toward the summer hemisphere (Schneider et al. 2014). The ITCZ crosses the thermal equator twice in a year, resulting in a weak annual cycle (and strong semiannual cycle) and a dip in the weighting function there. Wintertime storms bring precipitation to the midlatitudes, resulting in a strong seasonal cycle [and relatively large values of $W(m, \phi)$] there. The observations and models show sharp decreases in the variance explained by the annual cycle on the equatorward flanks of the storm tracks: regions poleward of the seasonal ITCZ shift, but too far equatorward to be much affected by storm-track precipitation.

e. D&A toolkit

In this paper, we will use a standard set of “fingerprinting” and signal detection methods presented in, for example, Santer et al. (2005, 2011, 2013).

1) FINGERPRINTING

The fingerprint $F(\phi)$ of climate change is the spatial pattern that characterizes the climate system response to external forcing (Allen and Stott 2003; Gillett et al. 2002; Hegerl et al. 1996; Stott et al. 2000; Tett et al. 2002). Following, for example, Hasselmann (1993) and Santer et al. (2011), we define the fingerprint as the model-predicted response to external forcing. We calculate this as follows:

- For each ALL+8.5 model $m$, year $y$, and latitude $\phi$, we calculate the amplitude $R^{m}(\phi, y)$ and phase $\theta^{m}(\phi, y)$.
For each model and latitude, we calculate 1979–2014 amplitude and phase climatologies.

We subtract these climatologies to get amplitude and phase anomalies for each latitude and model.

Both amplitude and phase time series are weighted by the annual cycle weighting function $W(m, \phi)$.

We then average over ensembles and models to obtain MMM amplitude and phase anomaly time series. The averaging process damps internal variability, revealing the forced response.

The amplitude and phase fingerprints are defined as the leading empirical orthogonal function of the 1860–2100 MMM amplitude and phase anomalies. These fingerprints, which will be discussed further in section 2, are similar to the linear trend at each latitude (not shown).

2) SIGNAL

Given a set of amplitude or phase anomalies from observations $\mathcal{C}(\phi, y)$, the projection $p(y)$ onto the fingerprint is given by $p(y) = \sum_{\phi} \mathcal{C}(\phi, y)F(\phi)$. Physically, this measures the spatial covariance between the searched-for fingerprint and the observational or model data as a function of year. If the fingerprint is increasingly present in the data, then $p(y)$ should increase with time. As in Santer et al. (2011), we define the signal $S(L)$ as the $L$-length trend in $p(y)$, obtained by least squares regression. For GPCP and CMAP observations, $L = 36$ yr.

3) NOISE

To assess the significance of a signal, we need an understanding of how internal climate variability might project onto the fingerprint. To do this, we calculate weighted amplitude and phase anomalies for the CMIP5 preindustrial control runs. By concatenating the first 200 yr of each piControl simulation and projecting the results onto the fingerprints, we obtain a long (4000 yr) time series $p_r(y)$ containing 4000/L nonoverlapping $L$-length segments. Calculating the best-fit trends in these segments results in a distribution whose standard deviation $N(L)$ provides a measure of noise in the trends: the likelihood of observing a given signal purely due to natural internal variability.

4) SIGNAL TO NOISE

If the dimensionless signal-to-noise ratio (SNR) exceeds 1.64, the signal is considered detectable at 90% confidence relative to our best current multimodel estimates of natural internal variability (Bindoff et al. 2013). We use this two-tailed $z$ test throughout to provide a conservative estimate of significance. Similarly, if the signal-to-noise ratio lies within the 5%–95% confidence interval obtained from CMIP5 ALL+8.5 simulations, the signal is considered compatible with the combination of external forcings present in those simulations. Greenhouse gas forcing is dominant over the satellite era, but these simulations also contain estimates of natural (solar and volcanic) and other anthropogenic (aerosols and ozone depletion) forcings. This means that compatibility with the ALL+8.5 distribution does not imply attribution of the signal to any particular forcing. We note that an observed signal can be compatible with external forcing but too weak to emerge from the background of internal variability, or it can be detectable but not compatible with external forcing (if it is incompatible with both unforced and forced model distributions). The latter case is cause for concern and results from some combination of the following: model failure to realistically capture the forced response, uncertainties in the forcings themselves, model underestimation of internal variability, or observational uncertainties.

f. Results

MODELED AND OBSERVED AMPLITUDE AND PHASE CHANGES

In this paper, we argue that the annual cycle of precipitation provides a useful lens through which to examine current and predicted hydroclimate changes. As an additional benefit, this framework also reduces observational uncertainty due to errors in the long-term satellite datasets. Figure 2a shows 1979–2014 observed and simulated $P$ climatologies. Figures 2b–d show 1979–2014 trends in annual mean $P$ (Fig. 2b), $P$ annual cycle amplitude (Fig. 2c), and $P$ annual cycle phase (Fig. 2d). While CMAP and GPCP broadly agree on the overall $P$ climatology (the spatial correlation between the datasets is greater than 0.96 for the 50°S–50°N domain considered here), they show very different trends in annual mean $P$ (spatial correlation $\sim 0.15$). By contrast, the spatial correlation between GPCP and CMAP weighted amplitude trends is 0.77 and between weighted phase trends is 0.68. This is perhaps because factors (such as satellite drift) that lead to spurious long-term trends in a satellite dataset are less likely to affect measures based on seasonal differences if both wet and dry seasons are affected by the same biases.

The orange envelopes in Fig. 2 show the 5%–95% confidence intervals of these variables obtained from ALL+8.5 CMIP5 model ensembles. Figure 2a shows the severity of the double-ITCZ bias in the models but overall good agreement in the northern tropics and in the midlatitudes. Figure 2b shows that simulated trends in annual mean precipitation are more consistent with
GPCP than CMAP, as the latter lies within the model envelope only in the dry subtropics. Figures 2c,d indicate that, while the observed amplitude and phase trends lie within the model envelopes at most latitudes, there are notable areas of model–observation disagreement: observed amplitude trends in the tropics are more negative than in models, and observed phase trends are more positive than in the models at certain subtropical latitudes. To assess the significance of these discrepancies, understand the physical mechanisms that dictate the model trends, and evaluate the performance of climate models over the satellite era, we require a formal comparison using the framework of detection and attribution.

g. Model-derived fingerprints

Figure 3a shows the fingerprint of externally forced changes to the amplitude of the precipitation annual cycle. We note that prior to calculating the multimodel mean, the amplitude time series has been weighted by $W(m, \phi)$ (Fig. 1b). This pattern explains 89% of the variance in the 1860–2100 MMM amplitude time series. Corroborating previous findings (Chou et al. 2013), the annual cycle amplitude increases almost everywhere, with the largest anomalies in the deep tropics where the base state precipitation is also large. The exceptions to this overall increase are on the equatorward flanks of the storm tracks in both hemispheres. Here, the decrease in amplitude likely reflects the predicted poleward shift of the storm tracks and subsequent reduction in wintertime precipitation on their equatorward edges (Hu and Fu 2007; Previdi and Liepert 2007; Scheff and Frierson 2012). Figure 3b shows the fingerprint of externally forced changes to the phase of the precipitation annual cycle, weighted by $W(m, \phi)$. This mode explains 72% of the variance in the 1860–2100 MMM phase time series. The fingerprint is characterized by little change or phase delays (later onset of the wet season) at most latitudes, with the exception of advances (earlier wet season onset) on the equatorward flanks of the storm tracks, particularly in the Southern Hemisphere. The phase delays are strongest around 15°N (at the longitude of the African Sahel) and around 45°N and 45°S (the poleward flank of the storm tracks). These results are consistent with the prediction that climate change will result in shorter, more-intense wet seasons in many monsoon regions and hence delay the monsoon onset (Biasutti and Sobel 2009; Biasutti 2013; Seth et al. 2011, 2013).
Earlier wet season onsets poleward of 30°N and 30°S (red circles) are likely to be associated with forced circulation shifts that push the storm tracks toward the poles (Scheff and Frierson 2012; Marvel and Bonfils 2013).

h. La Niña composites

Recent studies (e.g., Fyfe and Gillett 2014) have suggested that the global mean temperature trend from circa 1998–2014 may be smaller than predicted by CMIP5 models. This so-called global warming hiatus has been characterized by protracted La Niña–like cooling of the eastern equatorial Pacific (Kosaka and Xie 2013), stronger-than-normal trade winds (England et al. 2014), and distinctive precipitation and SLP patterns (Trenberth et al. 2014). This pattern has been deemed consistent with the IPO (Deser et al. 2004; Kosaka and Xie 2013; Meehl et al. 2013). Naturally occurring La Niña conditions affect the amplitude and phase of zonal mean precipitation. To characterize these effects, we compute La Niña composite patterns as follows: For every 200-yr piControl simulation, we calculate boreal winter (DJF) mean sea surface temperatures averaged over the Niño-3.4 region. We identify years in which this quantity is more than one standard deviation below the mean and designate these as La Niña years. We then calculate amplitude and phase anomalies relative to the piControl temporal mean amplitude and phase at each latitude. Averaging these anomalies over all La Niña years and over all models yields the amplitude and phase composite patterns shown in Figs. 3c and 3d, respectively. The amplitude signal is mostly restricted to the equatorial region and the northern tropics, where it indicates a reduction of the annual cycle amplitude, consistent with a reduction of austral summer and increase in boreal winter zonal mean tropical precipitation during the dry season (Lu et al. 2008). Amplitude weakly increases in the southern subtropics, and changes are negligible elsewhere. Phase changes associated with La Niña, by contrast, are not confined to the tropics. They are positive (earlier) in the latitudes of the southern ITCZ and of the northern monsoons and negative (delayed) in a narrow latitudinal band on the poleward flank of the storm tracks and may be associated with the poleward shifts of the Hadley cell and jets during a La Niña event (Lu et al. 2008).

i. Signal detection results

Figure 4a shows the projections of GPCP and CMAP zonal mean data onto the amplitude fingerprint. The interannual variability is similar in both datasets, and the overall trend is negative. Evidently the similarity between the searched-for fingerprint and the observations has decreased over the satellite era. By contrast, Fig. 4b shows the observed projections onto the phase fingerprint. Here, both GPCP and CMAP increasingly resemble the model-derived fingerprint over time. To
To assess the significance of these trends, we compare them to the distribution of 36-yr unforced trends that result from the projection of the preindustrial control data onto the fingerprint. We also calculate 1979–2014 trends in the individual ALL:\textsuperscript{18.5} ensemble members. Figure 5a shows the unforced and ALL+8.5 amplitude signal distributions along with the GPCP and CMAP amplitude signals and the regression slope errors. All have been normalized by the standard deviation of the noise distributions. The ALL+8.5 distribution is shifted to the right of the preindustrial control distribution, and a signal of external forcing is detectable at 90% confidence in approximately 30% of the ALL+8.5 1979–2014 simulations. This, however, is not reflected in the observations. The CMAP signal is detectable at 90% confidence (SNR = \(-1.8 \pm 1.1\)): it lies in the far-left tail of the noise distribution (Fig. 5a, green bars; see also Table 1). The GPCP signal is negative but not detectable.
(SNR = \(-0.2 \pm 1.0\)). However, both GPCP and CMAP amplitude signals are incompatible with the 5%–95% range of the ALL + 8.5 distributions, indicating that the recent change in observed precipitation annual cycle amplitude is fundamentally different from the expected responses predicted by the CMIP5 models over the observational period. Figure 5b shows the noise, forced model, and observed phase signals. Again, the ALL + 8.5 model distribution is shifted to the right, and the signal is detectable at 90% confidence in 21% of these simulations. Both GPCP (SNR = 2.2 \pm 0.8) and CMAP (SNR = 1.3 \pm 0.9) show positive signals, but only GPCP is detectable at 90% confidence. The GPCP signal is also consistent with forced CMIP5 models: it lies within the 5%–95% interval calculated from CMIP5 ALL + 8.5 distributions (orange bars).

1) A Protracted La Niña?

Our detection and attribution analysis has revealed that observations over the satellite era increasingly resemble the expected phase fingerprint but are increasingly dissimilar to the expected amplitude fingerprint (in fact, they increasingly resemble the inverse of the expected pattern). To what extent may these behaviors be explained by increasing similarity to a La Niña–like mode of variability?

To gauge the resemblance between the observations and La Niña, we project the observations onto the La Niña composites derived from the piControl simulations (Figs. 3c,d). Figure 6a shows the projection onto the La Niña composite amplitude pattern; Fig. 6b shows the projection onto the composite phase pattern. Both datasets indicate upward trends in both variables, indicating increasing similarity to the La Niña–like patterns.

The relationships between the observed projections onto the fingerprint (Figs. 4a,b) and onto the La Niña composites (Figs. 6a,b) are shown by the scatterplots in Figs. 6c,d. In both CMAP and GPCP, over 90% of the temporal variance in the projection onto the amplitude fingerprint is explained by the projection onto the La Niña composite. This suggests that the observations look less like the model-predicted anthropogenic forcing fingerprint because they look more like a La Niña–type mode of variability. This aligns with previous studies that have characterized the recent global mean temperature slowdown or hiatus as compatible with sustained La Niña–like conditions. We note that this analysis does not address the source of this model–observation mismatch but merely confirms that the observed trends in P amplitude increasingly resemble La Niña.

Figure 6d indicates a very weak relationship between the observed projections onto the phase fingerprint and projections onto the phase La Niña composite. Less than 5% of the variance in phase projection onto the fingerprint is explained by the projection onto La Niña. In this case, similarity to the fingerprint does not appear to result from similarity to a La Niña–like mode of variability.

This apparent discrepancy can be understood by comparing the spatial structure of the amplitude and phase fingerprints (Figs. 3a,b) to the spatial structure of the observed changes (Figs. 2c,d). The observed amplitude changes are large in the tropics, where both the fingerprint and La Niña pattern show large changes (of opposite sign). The observed phase changes, by contrast, are largest outside the tropics, as is the fingerprint. If we exclude latitudes between 10° S and 10° N from the analysis (Table 1), the amplitude signal-to-noise ratios in both GPCP and CMAP are positive (Table 1), and a much smaller percentage (55% for GPCP, 27% for CMAP) of the signal variance is explained by similarity to La Niña. This suggests a hint of forced changes to the amplitude in the extratropics, and Fig. 2c indeed shows that the observed amplitude increases in the subtropics and decreases on the equatorward flanks of the storm tracks, as in the fingerprint. The phase signal-to-noise ratios in the extratropics are also positive (Table 1), and only 10% (GPCP) and 16% (CMAP) of the signal variance is explained by similarity to La Niña. If, by contrast, we consider only the deep tropics (latitudes between 10° S and 10° N, Table 1), the amplitude SNR for GPCP and CMAP are strongly negative. The tropical amplitude trends strongly resemble protracted La Niña conditions, with 98% and 85% of the signal variance explained by projection onto the La Niña composites. The tropics-only phase signals are positive but undetectable above internal variability and largely explained by projection onto La Niña (68% for CMAP, 73% for GPCP).

2) Placing Annual Cycle D&A Results in Context

Observed changes to the amplitude of the annual cycle are large in the tropics, do not resemble the
fingerprint of external forcing, and are not compatible with model-simulated internal variability at 90% confidence. However, they do resemble the La Niña composite pattern. This suggests that differences between modeled and observed trends during the warming slowdown are not confined to temperature changes. Instead, a signature of the warming hiatus is also expressed in zonal mean precipitation and is congruent with other studies identifying differences between modeled and observed trends in trade wind anomalies (England et al. 2014) and Pacific SSTs (Kosaka and Xie 2013). In other words, while the models and observations do not agree on changes to the precipitation amplitude, this mismatch is consistent with a wide and increasing body of literature on the warming hiatus.

Observed changes to the phase of the annual cycle, by contrast, are not dominated by the tropics and may suggest the emergence of a forced signal. Thus, we obtain categorically different results depending on whether we consider changes to the amplitude or phase of the annual cycle. This difference highlights an important consideration for detection and attribution studies. Precipitation is affected by multiple interlinked physical processes on multiple spatial and temporal scales, and the observations will always reflect some combination of externally forced response and internal climate variability. This means that results will necessarily depend on the analysis method and that a comprehensive understanding of observed and simulated precipitation changes must synthesize multiple analysis frameworks. For example, Marvel and Bonfils (2013) examined changes in zonal mean precipitation, attributing the observed combination of thermodynamic and dynamic precipitation changes to external forcing. Likewise, Polson et al. (2013a) identified an externally forced signal in the contrast between wet and dry regions but allowed the location of such regions to change from season to season and year to year. Using this method, observed drying trends, for example, may result from changes in the location of the dry regions, reductions in water vapor availability, or some combination of the two. Our results are consistent with the conclusions of Lintner et al. (2012), who attributed the mismatch between CMIP3 projections and recent changes in the contrast between wet and dry occurrences to ENSO-related variability.

3. Conclusions

Changes to the amplitude of the precipitation annual cycle have implications for hydrological extremes like droughts and floods (Chou and Lan 2012); changes to the phase can affect growing seasons and crop yields.
We show that, in addition to their clear societal importance, trends in these quantities are similar in two long-term satellite datasets. A focus on seasonality changes rather than trends in the annual mean therefore reduces observational uncertainty and enhances confidence in the results.

The zonal mean fingerprints used in this study identify changes that are both thermodynamic and dynamic in origin. Increases in the amplitude at most latitudes likely reflect the rich-get-richer mechanism that is prominent over the oceans. The decreases of the amplitude in the subtropics may result from the (dynamical) poleward expansion of the Hadley circulation. Changes in the annual cycle phase are similarly affected by the availability of water vapor [possibly through a temporal variant of the upped-ante mechanism of Neelin et al. (2003)] and changes in atmospheric circulation that affect the position and movement of the storm tracks and ITCZ.

We expect some combination of forced change and the recent climate hiatus to manifest in the observations, but responses to external forcing can be obscured by internal variability. Contrary to previous work, we find no evidence of an observed increase in the range between wet and dry season precipitation that could be attributed to anthropogenic forcing. In fact, our results show that observed changes to the amplitude of the precipitation annual cycle are nearly opposite to those projected by CMIP5 models. These signals are incompatible with CMIP5 forced trends and (in one dataset) incompatible with internal variability. Thus it is the particular latitudinal amplitude and phase dependence of the annual hydrological cycle that exposed the mix of internal variability and external, anthropogenic, and natural forcing that has shaped precipitation seasonality over the satellite era.

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