The observed relationship between Pacific SST variability and Hadley cell extent trends in reanalyses

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ABSTRACT

Reanalysis and other observationally-based estimates suggest the tropical climate has expanded more than simulated by coupled climate models with historical radiative forcing. Previous research has attempted to reconcile this discrepancy by using climate model simulations with constrained tropical Pacific sea surface temperatures (SSTs) to account for the role of internal variability. Here the relationships between Hadley cell extent and internal SST variability and long-term warming are analysed using purely observational techniques. Using linearly independent components of SST variability with reanalysis datasets, the statistical relationship between Pacific variability and Hadley cell extent is quantified by timescale. There is a strong correlation between North Pacific decadal variability and Southern Hemisphere Hadley cell extent. Conversely, there is a weaker observed relation between the El Niño–Southern Oscillation (ENSO) and Hadley cell extent when low-frequency variability is filtered out of the ENSO signal. The observed linear sensitivity of Hadley cell width to long-term warming agrees with coupled general circulation model experiments when accounting for uncertainties, and there is a statistically significant relationship between Northern Hemisphere Hadley cell extent and long-term warming during boreal autumn.

1. Introduction

An expansion of the tropical climate entails a widening of the subtropical dry zones, which is one mechanism underpinning future projections of aridification and water resource stress (Scheff and Frierson 2012; Feng and Fu 2013; Cook et al. 2014; Karnauskas et al. 2016, 2018). Previous studies found a trend of poleward expansion of the tropical climate on the order of 1° latitude per decade for the total tropical belt beginning in 1979 (Seidel et al. 2008; Davis and Rosenlof 2012; Lucas et al. 2014; Quan et al. 2014; Adam et al. 2014), with more recent datasets showing smaller trends of roughly 0.4° per decade (Simpson 2018; Staten et al. 2018; Grise and Davis 2020), which is smaller than the observed trends.

Uncertainty in the role of radiative forcing from GHGs may be constrained or reconciled by assessing the influence of internal climate variability and other forcing mechanisms on tropical width. Stratospheric ozone depletion is suspected to have influenced Southern Hemisphere (SH) Hadley cell extent (HCE) in austral summer (DJF) (Polvani et al. 2011; Min and Son 2013; Garfin et al. 2015; Waugh et al. 2015; Kim et al. 2017), while anthropogenic aerosols, specifically black carbon, have also been shown to affect Northern Hemisphere (NH) HCE in boreal summer (JJA) (Allen et al. 2014; Staten et al. 2018).

Internal climate variability has an important role in recent tropical expansion (Allen and Kovilakam 2017; Grise et al. 2018). First, internal atmosphere-only variability can produce multidecadal tropical width trends in GCM simulations without interannual SST variability (Quan et al. 2014; Garfinkel et al. 2015; Simpson 2018). Second, modelling studies with constrained SSTs in the Pacific have shown better agreement with observed Hadley cell width (HCW) trends when compared with coupled atmosphere-ocean GCM experiments with similar radiative forcing (Allen et al. 2014; Garfinkel et al. 2015; Allen and Kovilakam 2017; Davis and Birner 2017). The periods of most rapid expansion in observations are correlated to changing Pacific SSTs (Allen and Kovilakam 2017; Mantzis et al. 2017; Amaya et al. 2018), suggesting that the Pacific Decadal Oscillation (PDO) and El Niño–Southern Oscillation (ENSO) have enhanced recent expansion trends. Here,
we focus on tropical width in relation to SST variability, intending to isolate the role of Pacific variability in observational datasets.

ENSO dominates global interannual SST variability and is thought to be a principal internal mechanism of global atmospheric circulation changes (Seager et al. 2003; Deser et al. 2010; Amaya et al. 2018). An El Niño event increases meridional tropical SST gradients, warms the ascending region of the Hadley cell (HC), and increases energy input into the atmosphere in the deep tropics, invigorating and contracting the circulation (Lu et al. 2008). Like ENSO, the positive phase of the PDO is associated with an HC contraction. The linear trend in the PDO from 1979 to 2011 was negative, which is correlated to the tropical expansion trend during that period, with some studies suggesting that the PDO accounts for up to 50% of the variance in tropical width for specific regions and seasons (Allen et al. 2014; Lucas and Nguyen 2015), especially boreal spring (MAM) and autumn (SON) (Grassi et al. 2012). We must be careful about attributing atmospheric phenomena to the PDO: there is general agreement that the PDO is not an oscillation in the classical sense, it is rather a superposition of SST anomalies stemming from different physical processes, including ENSO and the associated teleconnections that affect the Aleutian low (Pierce 2001; Newman et al. 2003; Schneider and Cornuelle 2005; Newman et al. 2016). The degree to which the PDO is influenced by anthropogenic activity is an open question, and there is some evidence that the PDO contains a signal from anthropogenic aerosol forcing over Asia (Allen et al. 2014; Dong et al. 2014; Wills et al. 2018). That said, we discuss the PDO as low-frequency internal variability here.

While there are many measures of tropical width, we analyse the tropical overturning circulation because it is a dominant feature of the tropical climate with clear impacts on the hydrological cycle (Post et al. 2014; Chen et al. 2014; Karnauskas and Ummenhofer 2014; Lucas and Nguyen 2015; Huang et al. 2018). In particular, the Hadley cell, the zonal-mean representation of the tropical overturning circulation, is assessed here. We refer to the poleward terminus of the Hadley circulation in a particular hemisphere as HCE and the difference in latitude between the NH HCE and SH HCE as HCW. The relationships between tropical width metrics are complex, so generalizing findings from one metric to others must be done with care. For example, there is a disconnect between variability in the subtropical jet and HCE despite previous theories suggesting that they are dynamically linked (Menzel et al. 2019). The subtropical jet is more likely to vary with upper-tropospheric width metrics, while HCE is more likely to vary with the eddy-driven jet, surface wind, sea-level pressure, and precipitation metrics (Davis and Birner 2017; Mbengue and Schneider 2018; Waugh et al. 2018; Davis et al. 2018), and the regional picture is still more complex (Schmidt and Grise 2017; Staten et al. 2019). A common and direct method of measuring HCE is the subtropical zero-crossing of the meridional mass-streamfunction (MMS) at 500hPa (hereafter $\psi_{500}$), however, this metric varies between reanalysis datasets due to departures from mass conservation (Davis and Davis 2018), and it may be preferable to use the subtropical zero crossing of the surface zonal-mean zonal wind (hereafter USFC) as a proxy for HCE in reanalyses (Grise et al. 2019; Grise and Davis 2020). We performed the analysis with both metrics, but USFC results are shown in the supplemental material (Figs. S7–S11) because they are qualitatively similar to results from $\psi_{500}$ (excepting the seasonal relationship to long-term warming), and are less readily compared to existing modelling studies on HCE trends.

It is a challenge to disentangle the signals of long-term warming, multidecadal SST variability, interannua SST variability (Schneider and Held 2001; Wills et al. 2018), and the associated responses of the Hadley circulation (Lu et al. 2008). A strong El-Niño, for example, will increase the global mean temperature but contract the HC, which can obscure the long-term expansion signal in HCW. Nguyen et al. (2015) suggested a significant relationship between SH HCE and global warming in the NOAA Twentieth Century Reanalysis dataset, and Amaya et al. (2018) found that the long-term forced trend in SH HCE may have emerged above internal variability during the last decade using a joint-EOF method on the MERRA-2 reanalysis dataset (with the forced NH HCE signal expected to emerge in the coming decade). Nevertheless, it is thought to be too early to detect a robust global warming signal in HCW across reanalyses because of the influence of natural variability (Staten et al. 2018; Simpson 2018), a question we revisit in the analysis here.

This study uses linearly independent modes of SST variability, defined by low-frequency component analysis (LFCA) (Wills et al. 2018), regressed against several modern reanalysis datasets to examine how robustly recent changes in HCE can be attributed to natural Pacific SST variability and long-term warming using an observation-based approach. We also perform the regressions against ‘traditional’ SST variability indices (the global-mean SST anomaly, PDO, and ENSO) for comparison. We find a strong correlation between Pacific decadal variability and SH HCE, and also find the correlation between ENSO and SH HCE is substantially reduced when decadal variability is filtered out of the ENSO signal. We find that the observed linear sensitivity of HCW to the warming signal agrees with the CMIP5 ensemble mean trends and identify boreal autumn (SON) as a season where the linear sensitivity of HCE to the warming signal is statistically significant.
2. Data and methods

a. Data

Monthly data from the four reanalysis datasets listed in Table 1 were used to calculate annual and seasonal means presented here. The SST dataset used was NOAA’s ERSSTv5 (Huang et al. 2017a,b). The NASA GISTEMP version 4 dataset was used for global surface temperature anomalies (Lenssen et al. 2019; GISTEMP 2020), which uses ERSSTv5 for SST anomalies. The NOAA NCEI PDO index was used for the traditional PDO index, which uses ERSSTv4 SST dataset (Mantua et al. 1997; Zhang et al. 1997; NCEI 2019). The ERSSTv4 dataset has been replaced by ERSSTv5 which is used in this study, and small differences in the v4 and v5 datasets may account for some differences between the NCEI PDO index and the LFCA-defined PDO index.

b. Methods

The traditional ENSO index is defined as the 3-month running mean temperature anomaly in the Niño 3.4 region (120°W–170°W, 5°S–5°N), and was detrended using a 30-year running mean climatology, which is the same methodology as NOAA’s Oceanic Niño Index (ONI) except we use an annual running mean instead of one that is updated every 5 years. The PDO is traditionally defined as the leading empirical orthogonal function (EOF) of the North Pacific (Deser et al. 2010). NOAA’s NCEI PDO index instead regresses the ERSSTv4 dataset against the Mantua PDO index (Mantua et al. 1997; Zhang et al. 1997) to keep the historical timeseries fixed. The traditional global-mean temperature increase index (hereafter WARMING), is defined as the global-mean SST anomaly with a base period of 1951 to 1980. SST was used rather than global surface temperature because it is more comparable to the LFCA-derived warming pattern. This index varies closely with the global-mean surface temperature anomaly but the magnitude of oceanic warming is smaller because of enhanced warming over land (cf. Fig. 2 below and Fig. 2 from Adam et al. 2014). The ENSO and WARMING indices are converted to standardized anomalies such that all SST indices have a standard deviation (σ) of 1 and regression sensitivities are comparable.

Similar to Adam et al. (2014), the observed sensitivity of HCW (or HCE) to each SST index is calculated by an ordinary least squares linear regression. The simple linear regression model is

\[ HCW = \beta_0 + \beta X + \epsilon, \]

where \( \beta_0 \) is an intercept, \( X \) is an SST index, \( \beta \) is the sensitivity of HCW to the SST index, and \( \epsilon \) is the residual. The multiple linear regression model is

\[ HCW = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \epsilon, \]

where \( X_1 \) is an SST index for long-term warming, \( X_2 \) is a PDO index representing decadal variability, and \( X_3 \) is an ENSO index representing interannual variability.

Significance tests with a threshold p-value of 0.05 are conducted on the regression coefficients (\( \beta_i \)), with error bars calculated using a t-distribution assuming a true null-hypothesis (\( \beta_i = 0 \)). The error bars do not represent a 95% confidence interval for the true coefficient value, as is often implied (Ambaum 2010). They represent a probability distribution conditioned on the null-hypothesis and offer an indication of the standard error of the regression coefficients. The significance of correlation coefficients is not assessed. When the regression is used across spatial gridpoints (as in Fig. 4) the standard “naïve stippling” approach is used without testing for field significance, which may overestimate the number of significant gridpoints (Wilks 2016). Concerns about the detailed interpretation of the statistical measures used here are overwhelmed by the differences between metrics and reanalyses, with USFC typically showing narrower confidence intervals and less variability between datasets than \( \psi_{SO} \).

The advantage of using the multiple linear regression (Eq. 2) is that the linear sensitivity of HCW to individual indices can be constrained by the sensitivity to other indices. However, difficulties emerge in interpreting individual sensitivities when the independent variables in multiple linear regressions are collinear. Traditional PDO and ENSO indices have strong correlations (Chen and Wallace 2016; Wills et al. 2018) and are generally detrended to remove the warming signal, making them problematic for multiple regression analysis. While ENSO and the PDO may be physically related phenomena, we aim to use Pacific variability indices in Eq. (2) which are uncorrelated. Using LFCA, we generate predictor variables that are linearly independent in time while retaining important

<table>
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<th>Dataset</th>
<th>Resolution (°lon x °lat)</th>
<th>Period</th>
<th>Reference</th>
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</thead>
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<tr>
<td>ERA-1</td>
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<td>Dee et al. (2011); ECMWF (2011)</td>
</tr>
<tr>
<td>ERA5</td>
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<td>1979 - 2018</td>
<td>Hersbach et al. (2019); ECMWF (2019)</td>
</tr>
<tr>
<td>JRA-55</td>
<td>1.25° x 1.25°</td>
<td>1979 - 2018</td>
<td>Kobayashi et al. (2015); JMA (2013)</td>
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<tr>
<td>MERRA-2</td>
<td>0.625° x 0.5°</td>
<td>1980 - 2018</td>
<td>Gelaro et al. (2017); GMAO (2015)</td>
</tr>
</tbody>
</table>

Table 1. Reanalysis datasets used in this study.
properties of their traditional counterparts, and can be used effectively in multiple linear regression.

LFCA is a method of transforming multiple principal components by low-pass filtering and linearly combining EOFs to minimize their low-frequency covariance (Wills et al. 2018). Using methods adapted from discriminant analysis (Schneider and Held 2001), LFCA identifies low-frequency patterns (LFPs) and corresponding indices called low-frequency components (LFCs), which are ordered according to the dominant timescale of variability. The LFCs are not strictly orthogonal, but they are uncorrelated in time. This method gives broadly similar results to the pairwise-rotated EOFs of Chen and Wallace (2016) when applied to Pacific SSTs (cf. Fig. 1 of Chen and Wallace 2016 and Fig. 1 of Wills et al. 2018). The advantage of LFCA over pairwise-rotated EOFs is that LFCA can generate more than two uncorrelated indices.

The LFCA-defined Pacific SST indices used in the multiple linear regression (Eq. 2), ordered from low- to high-frequency variability, are LFC1 (hereafter WARMING*), LFC2 (hereafter PDO*), and LFC3 (hereafter ENSO*). The LFCs are calculated for the period 1900–2018 with the first 3 EOFs of monthly Pacific SSTs from 45°S to 70°N and a 10-year truncation period using the publicly available LFCA code (Wills et al. 2018).

To calculate the MMS (ψ), HCE, and USFC, we use the TropD package (Adam et al. 2018), which was developed to standardize the metrics and methods for calculating tropical width. The MMS is calculated using trapezoidal integration of the zonal-mean meridional velocity from the top of the atmosphere downward in Eq. (3):

$$\psi = \frac{2\pi a \cos\phi}{g} \int_0^p \bar{v} dp,$$

where φ is latitude, a is the radius of the Earth, p denotes pressure, g is the gravitational constant, and \(\bar{v}\) is the meridional component of the zonal-mean wind. HCE is defined as \(\psi_{500}\), which is the latitude, poleward of the MMS extrema (maximum overturning), at which the MMS crosses zero at the 500hPa pressure level in each hemisphere. USFC is defined as the latitude where the 10m zonal-mean zonal wind crosses zero, changing from tropical easterlies to extratropical westerlies.

3. Results

a. Trends in Hadley cell extent

Figure 1 shows the annual-mean time series and linear trends of HCE and HCW for the period 1979–2011 and the trends for the period 1979–2018 (with MERRA-2 and the ensemble mean starting in 1980). The magnitude and significance of the trends are sensitive to the reanalysis dataset and period (Mantsis et al. 2017; Grise and Davis 2020). For the period 1979–2011, all datasets show larger poleward expansion trends, especially in the SH, but this is not universally true for earlier end dates. For example, ERA5 shows no SH HC expansion trend for the period 1979–2005 (Fig. S1). With more recent datasets (excluding ERA-Interim) and now 4 decades of data, the linear trend in each hemisphere is nominally poleward but not significant. The central estimate for the HCW trend across these reanalyses is roughly 0.2° per decade, which is lower than earlier estimates.

Annual-mean HCW trends are compared to coupled GCM trends found in previous studies using historical radiative forcing scenarios, which have some sensitivity to model selection and initial conditions. The historical HCW trend estimate in the CMIP5 ensemble is 0.1–0.2° per decade (Hu et al. 2013; Adam et al. 2014; Quan et al. 2014; Tao et al. 2016; Allen and Kovalkam 2017). There is some difficulty in comparing trends because the historical forcing period ends in 2005 for the CMIP5 experiments while the regressions performed here extend to 2018. However, the estimate is validated by the RCP8.5 scenario in the CMIP5 and CESM large ensemble experiments (Staten et al. 2018; Simpson 2018), and also by the CMIP6 experiments with a historical forcing period extending to 2014 (Grise and Davis 2020), all showing similar trends. It is also likely that the HCE response to GHG forcing is 2–3 times larger in the SH than in the NH (Watt-Meyer et al. 2019; Grise and Davis 2020). Thus, hereafter we take the historical GCM trends to be roughly 0.15°, 0.05°, and 0.10° per decade for HCW, NH HCE, and SH HCE respectively.

The smaller HC expansion trends for the period 1979–2018 compared to earlier end dates indicate that low-frequency variability of HCW is substantial and that 3 decades of observations are likely not enough to identify the long-term warming signal in this aspect of the general circulation (Allen and Kovalkam 2017; Davis and Birner 2017; Mantsis et al. 2017; Amaya et al. 2018; Staten et al. 2018; Simpson 2018; Grise and Davis 2019). The addition of recent data has reduced the uncertainty in the trends, and they now agree in magnitude with the expansion trends of ~0.15° per decade in the CMIP5 experiments with historical radiative forcing. This may indicate that we are closer to observing the response to long-term radiative forcing in the Hadley circulation, though it is preferable to explicitly assess the role of internal variability, rather than assume it is small over this longer period. We next attempt to constrain the observed linear relationship between HCW and SST variability, including its long-term warming trend.

b. Hadley cell extent and Pacific sea surface temperatures

Figure 2 shows the annual-mean time series and linear trends of three LFCs (WARMING*, PDO*, and ENSO*) defined using 3 EOFs and a 10-year truncation period as in Wills et al. (2018) for the period 1900–2018. The time series of Pacific LFCs closely follow the traditional SST indices—the global-mean SST anomaly (WARMING), the NCEI PDO
Fig. 1. Timeseries of (a) Hadley cell width (HCW), (d) NH Hadley cell extent (HCE), and (g) SH HCE from 1979 to 2018 for 4 different reanalysis datasets (colours) and the mean of all datasets (black). The MERRA-2 and mean timeseries start from 1980. Plots on the right-hand side show corresponding trends in ° latitude per decade from the start of the timeseries to end year of (b),(e),(h) 2018 and (c),(f),(i) 2011, with the error bars representing the t-distribution interval with $p = 0.05/2$ in either direction.

Table 2. Correlation coefficients for monthly SST index timeseries for 1900–2018.

<table>
<thead>
<tr>
<th></th>
<th>WARMING</th>
<th>PDO</th>
<th>ENSO</th>
<th>WARMING*</th>
<th>PDO*</th>
<th>ENSO*</th>
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<tr>
<td>WARMING</td>
<td>1</td>
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<td>0.23</td>
<td>0.95</td>
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<td>0.17</td>
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<tr>
<td>PDO</td>
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<td>1</td>
<td>0.44</td>
<td>-0.10</td>
<td>0.91</td>
<td>0.10</td>
</tr>
<tr>
<td>ENSO</td>
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<td>0.44</td>
<td>1</td>
<td>0.07</td>
<td>0.43</td>
<td>0.83</td>
</tr>
<tr>
<td>WARMING*</td>
<td>0.95</td>
<td>-0.10</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>PDO*</td>
<td>0.12</td>
<td>0.91</td>
<td>0.43</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>ENSO*</td>
<td>0.17</td>
<td>0.10</td>
<td>0.83</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

index (PDO), and the Niño3.4 anomaly (ENSO)—with correlation coefficients of $R = 0.95$, $R = 0.91$, and $R = 0.83$ respectively for monthly values (Table 2). The correlations between the LFCA SST indices are zero, while the correlations between traditional SST indices are non-zero (Table 2). The linear trends in monthly warming indices for the period 1979–2018 are $0.44 \pm 0.03 \sigma$ per decade for WARMING, $0.50 \pm 0.03 \sigma$ per decade for WARMING*, and $0.18 \pm 0.01$ kelvin per decade for the global-mean surface temperature anomaly. The period of maximum tropical expansion during this time was likely 1990–2012 (Mantsis et al. 2017), which coincides with a negative PDO trend: for the period 1979–2011, the trends are $-0.56 \pm 0.10 \sigma$ per decade and $-0.51 \pm 0.09 \sigma$ per decade for the traditional PDO and PDO*, respectively.

Figure 3 shows the absolute value of correlation coefficients for a simple linear regression (Eq. 1) between annual means of SST indices and HCW. The correlation between WARMING and HCW is weak ($R < 0.2$), while the correlation to traditional PDO and ENSO indices are comparable and strong ($0.3 < R < 0.7$, depending on the hemisphere and reanalysis). When the warming signal is defined as independent of internal Pacific SST variability, as in WARMING*, the correlations to HCW typically increase, but not substantially or universally across reanalyses.
Fig. 2. Annual-mean timeseries of traditional Pacific SST indices (black) and the indices defined by low-frequency component analysis (LFCA) (red) for the period 1900–2018. (a) Warming indices including the global-mean SST anomaly (WARMING), low-frequency component 1 (LFC1, WARMING*), and the global-mean surface temperature anomaly (Surface Warming, blue). (b) The NCEI PDO index and LFC-2 (PDO*). (c) Mean anomalies in the Niño 3.4 region (ENSO) and LFC-3 (ENSO*). Annual-means are averaged from monthly values and anomalies are all in reference to the 1951-1980 base period. Units are in standard deviations ($\sigma$), except for the global-mean surface temperature anomaly which is expressed in Kelvins.

Notably, when ENSO is defined using LFCA, with decadal variability removed, the correlation to the SH HCE drops by roughly 0.2 for all datasets, such that less than 10% of SH HCE variability is accounted for in ENSO*. Conversely, the SH HCE correlation to the PDO rises such that 20–50% of the variability in SH HCE is accounted for in the PDO* signal. This suggests that there is an element of the traditional ENSO signal which is covariant with the PDO and varies on decadal timescales, and that this low-frequency element of the traditional ENSO signal is the part that interacts with the descending branch of the SH HC.

Figure 4 shows the observed linear sensitivity of the MMS to the SST indices at each zonal-mean point in the latitude–pressure plane for ERA5. The sensitivity is obtained from annual-mean values with a simple linear regression (Eq. 1) for the traditional SST indices and obtained using a multiple linear regression (Eq. 2) for the LFCs. Both of the traditional ENSO and PDO indices are associated with an HC contraction and the descending branch of the SH HC is strongly sensitive to each. Notably, the descending branch of the SH HC has almost no statistical relation to ENSO* but has a strong relation to PDO* (Figs. 4d,f).

In both of the warming regressions (Figs. 4a,b), there is a strengthening of the descending HC branches, which leads to tropical expansion and is consistent with the response of GCMs to longwave radiative forcing. There is also a non-
prescribed PDO-like SST anomalies and found that the PDO can produce some of the observed changes in tropical width, but primarily in the NH, underestimating the total tropical expansion trends and finding little influence in the SH (Grassi et al. 2012; Allen et al. 2014; Garfinkel et al. 2015; Allen and Kovilakam 2017). Zhou et al. (2020) also found that SST anomalies in the North Pacific are unlikely to influence SH HCE in a GCM. These studies are not a quantitative comparison of HCE sensitivity to the results presented here, but it remains likely that there is a discrepancy between the observed strong PDO–SH HCE correlation and the ability of PDO-like SST anomalies to force an SH HCE response in atmospheric GCMs.

c. Seasonal analysis

Studies using GCM experiments have found that stratospheric ozone depletion is a principal driver of changes in the SH general circulation during DJF (Polvani et al. 2011; Min and Son 2013; Waugh et al. 2015; Garfinkel et al. 2015). If the PDO is correlated to the stratospheric ozone depletion signal, then the SH PDO–HCE relation could be an artifact. We would expect to see a strong SH PDO–HCE relation in DJF if this were the case. Fig. 6 shows the correlation of the LFCA SST indices to HCE by season and hemisphere. We find that the average correlation between SH HCE and the PDO in DJF (Fig. 6d) is not meaningfully different or stronger than other seasons and is unlikely to be conflated with the stratospheric ozone depletion signal.

Grassi et al. (2012) found the strongest observed relationship between PDO and tropical width during MAM and SON. Fig. 7d shows that the SH HCE sensitivity to PDO is indeed strongest during the equinoctial seasons, but the relationship appears to be borderline significant for all seasons and datasets (the same is true for the USFC metric in Fig. S9d).

Interestingly, the strongest NH HCE–ENSO correlation is during JJA (Fig. 6e), and JJA is the only season where there is a significant NH HCE–ENSO sensitivity for all datasets (Fig. 7e). This is not the case for the traditional ENSO index (Figs. S12e and S13e) where there are several significant sensitivities across datasets that are not present when low-frequency variability is filtered out of the ENSO signal.

WARMING* has the strongest correlation to NH HCE in SON (Fig. 6a) and there is a significant NH HCE–WARMING* sensitivity in Fig. 7a for all datasets in SON, marking a robust emergence of the warming signal in the Hadley circulation during boreal autumn. It is noteworthy that Tao et al. (2016) and Watt-Meyer et al. (2019) found larger HC expansion rates during SON in the NH compared to other seasons in radiatively forced GCM experiments. The correlation between WARMING* and SH
HCE is also strong for JJA, and there is a borderline significant WARMING*–SH HCE sensitivity during JJA for all datasets (Figs. 6b and 7b). When HCE is measured with the USFC metric, there is no statistically significant NH USFC–WARMING* relationship during SON, or in any season, for any dataset (Fig. S11a). This marks the only difference between the USFC and $\psi_{500}$ metrics that could meaningfully alter the conclusions outlined here, and may indicate a fundamental difference between the two metrics in SON or could alternatively indicate an artifact in the $\psi_{500}$ metric that is consistent across reanalyses.

4. Conclusions

The historical disparity between large tropical expansion rates in observations or reanalyses and smaller expansion rates in radiatively forced GCM experiments has been explained by accounting for the effects of natural variability,
stratospheric ozone depletion, aerosols, and discrepancies in tropical width metrics and older reanalyses (Davis and Davis 2018; Staten et al. 2018; Grise et al. 2019). The observed expansion rate remains larger than in GHG-forced GCM experiments, and decadal Pacific SST trends are likely responsible for some of the observed expansion rate, especially in the NH (Allen et al. 2014; Allen and Kovalam 2017; Amaya et al. 2018; Simpson 2018). Here, we quantified the observed sensitivity of HCW to long-term warming while accounting for natural SST variability by using multiple linear regressions with linearly-independent modes of SST variability defined by LFCA. It is still too early to see a robust warming-related expansion signal in the annual-mean Hadley circulation, but the observed annual-mean sensitivity of HCW to warming agrees with the trends in GCM experiments. A statistically significant relationship between NH HCE and long-term warming has emerged in boreal autumn across reanalyses, but this may be exclusive to the $\psi_{500}$ metric as it is not apparent in the USFC metric.

We find that the PDO is strongly correlated to SH HCE across reanalyses for multiple PDO definitions and that ENSO is less correlated to SH HCE when decadal variability is removed from the ENSO signal. This does not rule out ENSO as a principal driver of HCW variability because we have somewhat arbitrarily restricted the signal so that ENSO* and the PDO* are separated by timescale. The key point is that it is the low-frequency component of ENSO, if any, that is covariant with SH HCE, and this component of ENSO, in turn, covaries with the PDO.

Previous studies have also documented a strong observed correlation between the PDO and tropical width but primarily for the equinoctial seasons (Grassi et al. 2012) or using different tropical width metrics (Lucas and Nguyen 2015; Mantsis et al. 2017), which may not be covariant with HCE (Waugh et al. 2018). A new finding in our analysis, in contrast, is the evidence of a strong relationship between the SH HCE and PDO for all seasons (Figs. 6d and 7d).

Importantly, most modelling studies indicate that the PDO is more strongly related to NH HCE than SH HCE (Allen et al. 2014; Garfinkel et al. 2015; Allen and Kovalam 2017; Mantsis et al. 2017), our analysis agrees with the modelled sensitivity in the NH, but we document a stronger observed relationship to SH HCE. Thus there may be a discrepancy between the observed SH PDO–HCE relation and the ability of PDO-like SST anomalies to force variability in SH HCE in GCMs.

The spread in regression values across reanalyses highlights the difficulty in assessing the contribution of SST.
variability and warming to tropical expansion. These findings indicate that the PDO accounts for ~20–50% of annual SH HCE variability and long-term warming accounts for ~0–10% of annual HCW variability, depending on the reanalysis dataset. Much of the variability is unaccounted for, but the analysis was conducted based on Pacific SSTs alone and recent GCM analyses suggest internal atmospheric variability can also give rise to decadal variability trends (Quan et al. 2014; Garfinkel et al. 2015; Simpson 2018). Anthropogenic aerosols, stratospheric ozone depletion, and internal atmospheric variability have all been shown to influence tropical width, at least seasonally (Grise et al. 2019), and have been omitted from the analysis technique of this study.

Furthermore, the analysis was conducted on two zonal-mean tropical width metrics and could be extended to other metrics to generalize or refine the findings. HCE predominantly varies with sea level pressure and precipitation over ocean basins rather than land, so to increase relevance to populated areas, future studies should focus on the regional variability of tropical circulations (Schmidt and Grise 2017; Staten et al. 2019).

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Data availability statement. ERA-Interim data were accessed from the ECMWF (https://www.ecmwf.int/en/forecasts/datasets/reanalysis-datasets/era-interim). ERA-5 were accessed from the Copernicus Climate Change Service (C3S; https://cds.climate.copernicus.eu/cdsapp#!/home). MERRA-2 data were accessed from NASA’s GMAO (https://gmao.gsfc.nasa.gov/reanalysis/MERRA-2/). JRA-55 data were accessed with permission from the JRA project (https://jra.kishou.go.jp/JRA-55/index_en.html#download). ERSSTv5 data were accessed from NOAA’s Physical Sciences Laboratory (https://psl.noaa.gov/data/gridded/data.noaa.ersst.v5.html). NOAA’s NCEI PDO index can be accessed at https://www.ncdc.noaa.gov/teleconnections/pdo/. GISTEMP v4 can be accessed at https://data.giss.nasa.gov/gistemp/.

References
Fig. 7. As in Fig. 5 for each season and hemisphere with LFCA-defined SST indices only. Plots show the observed linear sensitivities of Hadley cell extent to each SST index for the (left) NH and (right) SH, calculated using a multiple linear regression.


