Physical Mechanisms of Tropical Climate Feedbacks Investigated Using Temperature and Moisture Trends*

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ABSTRACT

Tropical climate feedback mechanisms are assessed using satellite-observed and model-simulated trends in tropical tropospheric temperature from the MSU/AMSU instruments and upper-tropospheric humidity from the HIRS instruments. Despite discrepancies in the rates of tropospheric warming between observations and models, both are consistent with constant relative humidity over the period 1979–2008. Because uncertainties in satellite-observed tropical-mean trends preclude a constraint on tropical-mean trends in models regional features of the feedbacks are also explored. The regional pattern of the lapse rate feedback is primarily determined by the regional pattern of surface temperature changes, as tropical atmospheric warming is relatively horizontally uniform. The regional pattern of the water vapor feedback is influenced by the regional pattern of precipitation changes, with variations of $1\text{--}2\text{ W m}^{-2}\text{ K}^{-1}$ across the tropics (compared to a tropical-mean feedback magnitude of $3.3\text{--}4\text{ W m}^{-2}\text{ K}^{-1}$). Thus the geographical patterns of water vapor and lapse rate feedbacks are not correlated, but when the feedbacks are calculated in precipitation percentiles rather than in geographical space they are anticorrelated, with strong positive water vapor feedback associated with strong negative lapse rate feedback. The regional structure of the feedbacks is not related to the strength of the tropical-mean feedback in a subset of the climate models from the CMIP5 archive. Nevertheless the approach constitutes a useful process-based test of climate models and has the potential to be extended to constrain regional climate projections.

1. Introduction

The responses of components of Earth's climate system to surface warming, known as climate feedbacks, act to amplify or damp surface temperature changes. Quantification and understanding of the various climate feedbacks is central to projections of future climate change under increasing concentrations of anthropogenic greenhouse gases.

The water vapor feedback is the largest positive climate feedback (Held and Soden 2000). It operates by increasing atmospheric water vapor concentrations in response to surface warming. Since water vapor is an infrared absorber it drives additional warming. Although climate models simulate a range of different magnitudes of the water vapor feedback, this range decreases when it is combined with the negative lapse rate feedback (Colman 2003; Soden and Held 2006; Colman and Hanson 2013; Vial et al. 2013). The lapse rate feedback arises because the troposphere warms faster than the surface, which increases outgoing longwave radiation compared to the case where the tropospheric warming is the same as surface warming. The partial cancellation between the water vapor and lapse rate feedbacks is a very robust feature of climate models and arises because they tend to maintain tropospheric relative humidity (RH) close to constant under surface warming.

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The two feedbacks also arise from related physical processes. Water vapor is transported into the upper troposphere by vertical motions, which are usually accompanied by condensation and latent heat release (Sherwood et al. 2010b). Upper-tropospheric humidity changes have the greatest impact on the radiative flux at the top of the atmosphere (TOA) and hence are most important for the magnitude of the water vapor feedback (Soden and Held 2006). Latent heating associated with vertical motion also drives the lapse rate feedback by warming the upper troposphere. The physical consistency between the water vapor and lapse rate feedbacks is especially strong in the tropics, where convective motions maintain the atmospheric temperature profile close to moist adiabatic. The magnitudes of these feedbacks are also strongest in the tropics, since that is where most atmospheric water vapor resides and where convection efficiently heats the upper troposphere (Held and Soden 2000). For these reasons we will focus on the tropics in this study.

Since the RH changes under global surface warming are small, Ingram (2010, 2013) and Held and Shell (2012) have proposed using relative, rather than specific, humidity as a state variable in climate feedback analyses. This perspective simplifies analysis of climate model feedbacks by combining the canceling effects of the conventional water vapor and lapse rate feedbacks, and shows that the contribution to climate feedback from changing RH is negligible (Held and Shell 2012; Vial et al. 2013). There is also observational evidence of minimal RH change with surface warming. Soden et al. (2005) showed changes in tropical brightness temperature from the water vapor channel (a wavelength of around $6.7\text{ }\mu\text{m}$) of the High-Resolution Infrared Sounder (HIRS) between 1979 and 2004 are consistent with those expected if RH were constant.

The physical mechanisms underlying both the climatological tropical RH distribution and its changes under global warming have been studied using analytical and numerical models of varying complexity. Sherwood et al. (2006) used the so-called advection–condensation theory to derive a distribution law for tropical free-tropospheric RH. The advection–condensation theory is based on the idea that the specific humidity of an air parcel is set to its saturation value when it is detrained from a convective plume. A detrained parcel then retains this specific humidity, but as it subsides and warms its RH declines. RH is therefore determined by the time scales over which an air parcel entrains into and detrains from convective plumes. The more time that has passed since a parcel has been in contact with a convective plume, the lower its RH will be; those parcels with trajectories avoiding convective plumes for the longest will

have the lowest RH. This theory does not require treatment of cloud microphysics and yet makes accurate predictions of free-tropospheric RH (Sherwood and Meyer 2006; Roca et al. 2012). This may explain why the pattern of RH changes under global warming is rather robust across models (Sherwood et al. 2010a; Vial et al. 2013), despite the different treatments of cloud microphysical processes in models. Romps (2014) derived a related analytical model for tropical RH that predicts that RH is a function of temperature only, which explains the upward shift of the tropical RH profile under global warming (Sherwood et al. 2010a; O’Gorman and Singh 2013).

Recent work has begun to consider the regional pattern of climate feedbacks as a means of studying the physical processes by which they arise. Taylor et al. (2011) noted that although the global-mean water vapor and lapse rate feedbacks among climate models are anticorrelated, there is no such relationship when it comes to regional patterns of these feedbacks in a single model.

Lambert and Taylor (2014) discussed some of the physical reasons for the lack of relationship between regional patterns of tropical water vapor and lapse rate feedbacks in three climate models. They showed the regional pattern of lapse rate feedback is primarily related to the regional pattern in surface temperature change. This is because at low latitudes the Coriolis parameter is small and so horizontal atmospheric temperature gradients also tend to be small (Sobel and Bretherton 2000; Sobel et al. 2001). Tropical tropospheric temperatures are therefore spatially much more uniform than surface temperatures. Since the lapse rate feedback is determined by the difference between temperature change at the surface and in the free troposphere, this means the most negative lapse rate feedback is found over regions with the least surface warming. These regions are typically oceanic because the ocean warms less than the land under global warming (Manabe et al. 1991; Lambert and Chiang 2007; Joshi et al. 2008; Dong et al. 2009). Some land regions actually show a positive lapse rate feedback due to strong surface warming there. On the other hand, water vapor feedback only increases with surface temperature change over the oceans. Over land, water vapor feedback slightly decreases over the regions that warm most since moisture supply in these regions is limited. However, water vapor feedback is not as strongly related to surface temperature change as lapse rate feedback. Lambert and Taylor (2014) show that it is much more strongly related to precipitation changes, with a greater water vapor feedback in regions of heaviest precipitation. This is to be expected since convective

precipitation is associated with vertical moisture transport. These tropical regional feedback structures can provide fingerprints of physical processes operating in climate models and hence a metric of how well they capture real-world processes.

We have described two robust aspects of climate model behavior that need to be observationally verified. The questions this study seeks to address are the following:

- 1) What changes in both tropical mean and regional free-tropospheric RH have been observed since 1979? Do climate models agree with these observed changes? Answering this question will help assess the constant-RH paradigm of climate feedbacks described above.
- 2) What is the regional structure of tropical water vapor and lapse rate feedbacks in climate models and satellite observational datasets? Answering this question will help assess whether climate models are correctly simulating the physical mechanisms of these feedbacks.
- 3) Do these aspects of climate model behavior in simulations of the past hold information about the magnitude and structure of climate feedbacks operating under long-term global warming?

The paper is organized as follows: [section 2](#) describes observational metrics of climate feedbacks and the climate model output used; [section 3](#) investigates observed and modeled tropical RH trends and regional feedback patterns since 1979; [section 4](#) asks whether these past observations can be used to constrain future climate changes; and [section 5](#) summarizes our results.

2. Data and methods

We use observed changes in the atmospheric state since 1979 as indicators of climate feedback processes. During this period a significant global surface warming trend has been observed ([Hansen et al. 2010](#)). The lapse rate feedback can be described by considering the rate of warming of the middle and upper troposphere relative to the rate of warming of the surface ([section 2a](#)). The water vapor feedback can be described by considering changes in atmospheric humidity with surface warming ([section 2b](#)). Such changes are quantified using ordinary least squares linear fits to monthly anomalies. The uncertainty in these trends is calculated as 1.96 standard errors of the regression slope (i.e., an approximate 95% confidence interval), accounting for temporal autocorrelation.

These changes in the atmospheric state are not exact proxies for climate feedbacks because they do not

directly tell us about changes in the TOA radiative flux. For example, a change in total column water vapor could have a very different impact on TOA radiative flux depending on the vertical structure of the water vapor increase. We can to some extent circumvent this by using remotely sensed brightness temperatures at wavelengths at which water vapor is strongly absorbing. This approach gives information about water vapor concentrations in those parts of the atmosphere most relevant to the TOA radiative flux ([section 2b](#)). The validity of this approach is tested in [section 3](#) ([Fig. 1](#)).

We describe our principal remotely sensed data sources below. We also use observed surface temperature data from the NASA Goddard Institute for Space Studies GISTEMP analysis ([Hansen et al. 2010](#)) and precipitation data from the Global Precipitation Climatology Project (GPCP), version 2.2 ([Adler et al. 2003](#); [Huffman et al. 2009](#)).

a. Tropospheric temperature

Measurements of tropospheric temperature in deep atmospheric layers have been available since 1979 from the Microwave Sounding Unit (MSU) and latterly the Advanced Microwave Sounding Unit (AMSU) instruments. Since these instruments have flown aboard a number of satellites the data must be homogenized to remove nonclimatic influences due to different instrument calibrations, satellite orbital decay, and drift in local sampling time. We use MSU/AMSU temperatures from two datasets using different homogenization methodologies: the University of Alabama Huntsville (UAH) V5.4 ([Christy et al. 2003](#)) and Remote Sensing Systems (RSS) V3.3 ([Mears and Wentz 2009](#); [Mears et al. 2012](#)) datasets.

The MSU/AMSU TMT (middle troposphere) channel has a weighting function that peaks around 600 hPa (approximately 4 km) but includes a contribution from the lower stratosphere. [Fu et al. \(2004\)](#) developed a simple linear combination of the TMT channel with the TLS (lower stratosphere) channel to remove this stratospheric influence. This combination has become known as TTT (total tropospheric temperature). The TTT weighting function peaks around 300 hPa (approximately 9 km). In the tropics TTT can be derived from the following equation ([Fu et al. 2011](#)):

$$TTT = 1.1TMT - 0.1TLS. \quad (1)$$

We calculate TMT, TLS, and TTT from climate model data ([section 2c](#)) for comparison with observations. MSU/AMSU measures emission from atmospheric oxygen. Since spatial variations in atmospheric oxygen concentrations are negligible, we are able to calculate

FIG. 1. (a),(b) Monthly tropical-mean anomalies in (a) tropospheric temperature (TTT) and (b) HIRS channel-12 brightness temperature (T12) against radiative flux anomalies caused by changes in (a) atmospheric lapse rate and (b) relative humidity. (c),(d) Gridpoint anomalies for the month of March in (c) tropospheric temperature (TTT) and (d) HIRS channel-12 brightness temperature (T12) against radiative flux anomalies caused by changes in (c) atmospheric lapse rate and (d) relative humidity. Radiative flux anomalies are positive downward. Solid lines show ordinary least squares fits. The atmospheric state used for the radiation calculations is taken from the HadGEM2-A AMIP simulation. Gridpoint anomalies are calculated by subtracting the local climatology rather than the tropical-mean climatology.

MSU/AMSU temperatures using a static weighting function, supplied by RSS (obtained via FTP from ftp.ssmi.com/msu/weighting_functions), applied to monthly-mean climate model air temperature data.

The structural uncertainty in global-mean trends since 1979 from MSU/AMSU datasets was estimated by Christy (2014) with a standard error of $0.02 \text{ K decade}^{-1}$. Tropical-mean trends have slightly higher structural uncertainty; from the 400 Monte Carlo ensemble members of the RSS dataset (Mears et al. 2011) we estimate a standard error on the tropical-mean trend in TTT since 1979 of $0.03 \text{ K decade}^{-1}$.

b. Tropospheric humidity

Tropospheric humidity measurements have been available since 1979 from the High-Resolution Infrared

Sounder instruments. HIRS channel 12 measures radiance in a spectral band centered at a wavelength of around $6.7 \mu\text{m}$, which is sensitive to the *relative* (rather than specific) humidity of the middle and upper troposphere between approximately 200 and 500 hPa (Soden and Bretherton 1993; Bates and Jackson 2001; Allan et al. 2003; Iacono et al. 2003; Soden et al. 2005). Increasing upper-tropospheric RH (UTRH) increases the atmospheric opacity at these wavelengths, meaning upwelling radiation comes from higher, colder altitudes and the channel-12 brightness temperature T12 is reduced. However, brightness temperatures at these wavelengths are also affected by air temperature (Soden and Bretherton 1993). We quantify the sensitivity of the channel-12 brightness temperature T12 to tropospheric temperature by calculating T12 with RH fixed to a

FIG. 2. Tropical-mean (30°S – 30°N) trend in tropospheric temperature (TTT) against trend in HIRS channel-12 brightness temperature (T12) over the period 1979–2008. Observational data are shown in dark gray. TTT data are from UAH and RSS and T12 data are from NOAA. AMIP model data are shown in colors. “Constant RH (relative humidity)” and “constant SH (specific humidity)” lines are calculated by linear regression of monthly anomalies in TTT against T12 for the HadGEM2-A model data but with relative or specific humidity constrained to a monthly climatology. Ellipses represent 95% (i.e., 2.5%–97.5%) confidence regions, taking into account the covariance between TTT and T12 anomalies.

climatology from a climate model (see section 3 and Fig. 2). We use the HadGEM2-A AMIP simulation (see section 2c) here, but find very similar results when other models are used.

We use the HIRS channel-12 climate data record hosted by the U.S. National Oceanic and Atmospheric Administration (Shi et al. 2014). This dataset has been homogenized by Shi and Bates (2011) to remove non-climatic influences, such as intersatellite differences arising from different instrument calibrations. Remaining intersatellite differences are less than 0.08 K (Shi and Bates 2011), indicating that this dataset can provide a long-term stable climate data record.

T12 cannot be calculated from climate model output using a static weighting function because the concentration of water vapor is very spatially variable. Therefore we calculate T12 using the RTTOV V11.2 radiative transfer code (Saunders et al. 2013) on 6-hourly climate model output with the spectral response function for HIRS channel 12.

The HIRS T12 observations are for clear skies. Since the horizontal resolution of a climate model is much lower than a HIRS footprint we cannot simply apply the same cloud-clearing procedure as used in the generation of the HIRS T12 dataset. Instead, we only calculate brightness temperature where the 6-hourly mean cloud fraction is less than 40%. This is the same

approach used by Turner and Tett (2014), who showed the clear-sky bias is very similar whether the threshold fraction is 40% or 10%, and so choose 40% to maximize coverage.

c. Climate model simulations

We use climate model data from phase 5 of the Coupled Model Intercomparison Project (CMIP5; Taylor et al. 2012). Since the calculation of HIRS brightness temperature requires high-frequency cloud data, we choose eight models for which output at subdaily frequency is available. The models used are listed in Table 1. To compare model data with observations we use the AMIP simulations, which are run with sea surface temperatures (SSTs) prescribed to match the real-world and time-varying radiative forcings between 1979 and 2008. We select the first ensemble member for each model. We use the historical simulations, which are run with coupled ocean and time-varying radiative forcings from 1850 to 2005, to compare with AMIP and highlight the role of internal SST variability in determining climatic trends. For the historical simulations, we use all available ensemble members to minimize the effects of internal variability on calculated trends: 1 for BNU-ESM, 5 for CanESM2, 6 for CCSM4, 10 for CNRM-CM5, 5 for HadGEM2-ES, 6 for IPSL-CM5A-LR, 5 for MIROC5, and 3 for NorESM1-M.

TABLE 1. CMIP5 models used in this study. If modeling centers use different names for versions of the model with and without coupled oceans the coupled version is named first, the atmosphere-only version second. The atmospheric resolution is given in terms of the number of points in longitude and latitude and the vertical. If the model is spectral this resolution is the resolution of its geometric transform grid and its spectral resolution is given in brackets. [Expansions of acronyms are available online at <http://www.ametsoc.org/PubsAcronymList>.]

Model name	Institution	Institute ID	Atmospheric resolution	Reference
BNU-ESM	College of Global Change and Earth System Science, Beijing Normal University, China	GCESS	$128 \times 65 \times 26$ (T42)	Ji et al. (2014)
CanESM2/CanAM4	Canadian Centre for Climate Modeling and Analysis, Canada	CCCMA	$128 \times 64 \times 35$ (T63)	von Salzen et al. (2013)
CCSM4	National Center for Atmospheric Research, United States	NCAR	$288 \times 192 \times 27$	Gent et al. (2011)
CNRM-CM5	Centre National de Recherches Meteorologiques/Centre Europeen de Recherche et Formation Avancee en Calcul Scientifique, France	CNRM-CERFACS	$256 \times 128 \times 31$ (T127)	Voldoire et al. (2013)
HadGEM2-ES/HadGEM2-A	Met Office Hadley Centre, United Kingdom	MOHC	$192 \times 144 \times 38$	Martin et al. (2011)
IPSL-CM5A-LR	Institut Pierre-Simon Laplace, France	IPSL	$96 \times 96 \times 39$	Dufresne et al. (2013)
MIROC5	Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology, Japan	MIROC	$256 \times 128 \times 40$ (T85)	Watanabe et al. (2010)
NorESM1-M	Norwegian Climate Centre, Norway	NCC	$144 \times 96 \times 26$	Bentsen et al. (2013)

To link observed climate change with long-term forced climate change under increasing greenhouse gas concentrations, we also use the CMIP5 preindustrial control (piControl) and abrupt carbon dioxide quadrupling (abrupt4xCO₂) simulations. In these simulations the models are run with coupled oceans and constant forcings with carbon dioxide concentrations reflecting either the preindustrial period (287 ppmv) or 4 times this value. We calculate differences between abrupt4xCO₂ and piControl as the difference between the climatological means of the final 30 years of the simulations. In the case of abrupt4xCO₂, which are 150 years long, this means most of the global warming from the increasing CO₂ concentrations will have been realized.

d. Feedback calculations

Here we quantify climate feedbacks using the partial radiative perturbation (PRP) method of [Wetherald and Manabe \(1988\)](#). The TOA radiative flux perturbation associated with a change in climate state is calculated by taking the difference between the TOA radiative flux from the unperturbed state and the TOA radiative flux with only the relevant part of the climate state perturbed. For example, to calculate the water vapor feedback the TOA radiative fluxes are calculated for the

piControl simulation and for the piControl state but with the specific humidity fields from abrupt4xCO₂. The tropical-mean feedback is then calculated by dividing the tropical-mean radiative flux perturbation by the tropical-mean temperature change. We use “two-sided” PRP calculations, after [Colman and McAvaney \(1997\)](#), in which the calculated radiative perturbation is the average of the difference between piControl and the perturbed field from abrupt4xCO₂, and the difference between abrupt4xCO₂ and the perturbed field from piControl. This approach removes errors in the calculated radiative perturbation associated with the substitution of uncorrelated meteorological fields.

The radiative flux calculations are performed with monthly fields from the final 30 years of the piControl and abrupt4xCO₂ simulations using the [Edwards and Slingo \(1996\)](#) radiative transfer code. Since we focus on the water vapor and lapse rate feedbacks in this paper, we perform clear-sky calculations.

We note that the PRP method used here interprets any change in the climate state between the unperturbed and perturbed simulations as being driven by surface temperature change. In fact, components of the climate response unrelated to surface temperature change, so-called adjustments, can be important, especially on

regional scales (Webb et al. 2013; Sherwood et al. 2014). The existence of adjustments is important to consider when interpreting regional climate feedbacks, since in some regions they can exert an important influence on the TOA radiative flux. Clouds make the largest contribution to adjustments in climate models (between 4% and 18% of the total forcing), with water vapor and lapse rate adjustments making relatively small contributions of about 5% and 1% of the total forcing respectively (Vial et al. 2013). Chung and Soden (2015) found local water vapor and lapse rate adjustments of several W m^{-2} in response to a quadrupling of atmospheric CO_2 concentrations. However, they suggest this result is an artifact of their methodology and can be explained in terms of the response of a feedback (with negligible adjustment) to a spatially inhomogeneous warming.

3. Evidence for consistent feedback structure in models and observations

a. Observed and simulated tropical-mean trends

In this study we use observational data from satellite instruments as proxies for climate feedbacks, on the basis that climate feedbacks are determined by changing atmospheric characteristics in response to surface warming (section 2). The observable quantities are tropospheric temperature (TTT) and the brightness temperature in the HIRS water vapor channel (T12). First we test the relationship between these observable quantities and variations in the TOA radiative flux. To do this we calculate the TOA radiative flux anomalies associated with anomalies in either atmospheric lapse rate or relative humidity. We use the HadGEM2-A AMIP simulation and fix all other atmospheric properties to their monthly climatologies, allowing only lapse rate or relative humidity to vary. We then used the Edwards and Slingo (1996) radiation code to calculate the TOA radiative flux anomaly associated with lapse rate or relative humidity anomalies. The TOA radiative flux anomalies associated with anomalies in atmospheric lapse rate are compared with simulated TTT, and the TOA radiative flux anomalies associated with anomalies in relative humidity are compared with simulated T12.

Figures 1a and 1b show tropical-mean TOA radiative flux anomalies against anomalies in TTT and T12 for the HadGEM2-A AMIP simulation (similar results are obtained for other models). Figure 1a shows there is a strong anticorrelation between TTT and the lapse-rate TOA radiative flux anomaly (these anomalies are positive downward). This is as expected since a cooler atmosphere radiates less energy to space. There is also an anticorrelation between T12 and the water vapor TOA

radiative flux anomaly (Fig. 1b). Again, this is physically expected because a higher T12 is associated with lower relative humidity in the upper troposphere, which means more energy radiates to space. This demonstrates the expected physical relationship that T12 changes can be considered a proxy for changes in the TOA radiative flux caused by water vapor.

These relationships also hold on local scales, as shown in Figs. 1c and 1d, which show gridpoint anomalies in TTT and T12 against gridpoint anomalies in associated TOA radiative flux for a typical month of the HadGEM2-A AMIP simulation. There is a little more scatter in the relationships, but the variance explained (as quantified by the R^2 value) is still over 80% for all months tested. Figure 1d shows that the relationship between T12 anomalies and TOA radiative flux anomalies is different for very large T12 anomalies. This causes a separation of the scatter points into two branches for large positive and negative T12 anomalies. This behavior arises because the relationship between T12 and TOA radiative flux depends on the background atmospheric moisture content (Soden and Fu 1995). If the climatological upper-tropospheric humidity is low, humidity anomalies have a larger impact on the TOA radiative flux, implying a steeper slope on Fig. 1d. If the climatological upper-tropospheric humidity is high, humidity anomalies have a smaller impact on the TOA radiative flux, implying a shallower slope on Fig. 1d. The steeper branches in Fig. 1d represent grid points in the more arid regions of the tropics (which, defined here as 30°S–30°N, include parts of the subtropical dry zones), and the shallower branches represent grid points in the moister regions. Although the differing relationship between T12 and TOA radiative flux at different climatological humidities may affect our results, we note that the relationship is robustly of the same sign everywhere in the tropics and so is still useful for studying patterns of radiative feedbacks over the recent past.

We now turn to the question of whether tropical-mean UTRH trends are consistent between models and observations. Figure 2 presents linear trends between 1979 and 2008 in the tropical-mean T12 and TTT for AMIP simulations and for observations. Models appear to overestimate TTT increases over this period, as reported by Fu et al. (2011) and Po-Chedley and Fu (2012). It remains unclear how much of this discrepancy is due to errors in the homogenization of observations (Po-Chedley et al. 2015), overestimation by the models of the tropospheric temperature sensitivity to surface warming, or other factors such as uncertainties in the SSTs used to drive the AMIP simulations (Flannaghan et al. 2014).

FIG. 3. Gridpoint tropical TTT (a) and T12 (b) trend in deciles of gridpoint surface temperature trend. Black lines show observational datasets and gray shading the 95% confidence interval (estimated as 1.96 standard errors) on the trends in TTT and T12. Dark gray shading indicates overlapping confidence intervals. Colored lines show climate model results. Confidence intervals for the models are omitted for clarity, but are comparable in size to the observational data.

Since the trends presented in Fig. 2 are calculated over a relatively short period of 30 years there is substantial uncertainty, indicated by the shaded 95% confidence regions. All models and observations have a slight positive T12 trend, but for three of the eight models this confidence region overlaps zero. Increasing T12 is consistent with decreasing UTRH or, alternatively, an increase in tropospheric temperature. However, the sensitivity of T12 to TTT is small, as shown by the “constant RH” line in Fig. 2, so the T12 changes are primarily a result of RH changes.

Observed HIRS T12 trends are consistent with constant UTRH, in agreement with the results of Soden et al. (2005), who use a similar method. Most AMIP models also simulate T12 trends that are consistent with constant UTRH. However, uncertainty in the trend calculation over the 30-yr period is very large, so model and observational data are consistent with a broad range of UTRH trends.

b. Regional structure of temperature and humidity trends

The regional structure of tropospheric temperature and T12 trends may provide more information than considering the tropical mean. Lambert and Taylor (2014) identified regional patterns of lapse rate and water vapor feedback in three climate models. These patterns reflect the physical mechanisms by which these feedbacks occur, with the combination of spatially homogeneous tropospheric temperature change and spatially inhomogeneous surface temperature change driving the lapse rate feedback, and convective moistening of the upper troposphere driving the water vapor feedback. Now we investigate whether these same patterns can be discerned

in observed and simulated TTT and T12 trends. If they can, this will suggest that the feedback mechanisms have been operating as expected since 1979.

We first consider the regional structure of TTT and T12 trends as a function of surface temperature trends (Fig. 3). Lambert and Taylor (2014) showed that the regional pattern of lapse rate feedback in three climate models is primarily dependent on the regional surface temperature change pattern, since tropospheric temperature changes are close to uniform across the tropics. Figure 3a shows only a weak dependence of tropospheric temperature trends on surface temperature trends, which is consistent with the conclusions of Lambert and Taylor (2014). Although both observed TTT datasets show less tropical-mean warming than the AMIP models, the regional structure is very similar. The sensitivity of regional TTT trends to regional surface trends can be quantified by a linear regression of the data presented in Fig. 3a (i.e., of TTT trend deciles against surface temperature trend deciles). This analysis shows a slope of approximately $0.2 \pm 0.1 \text{ K K}^{-1}$, with the slopes between all models and observational datasets statistically indistinguishable (see Fig. S1 in the supplemental material, available online at <http://dx.doi.org/10.1175/JCLI-D-15-0253.s1>).

We now turn to the regional pattern of upper-tropospheric moisture trends (Fig. 3b). There is substantial uncertainty in regional T12 trends. There is an indication in the observational data that the lowest T12 trends occur in regions of intermediate surface temperature trends, with higher trends on either side. This “U” shape is also only seen for regions of positive surface temperature trend. Some models, notably CanAM4 and CNRM-CM5, closely follow the “U” shape of the

FIG. 4. Gridpoint tropical TTT (a) and T12 (b) trend in deciles of gridpoint precipitation trend. Black lines show observational datasets and gray shading the 95% confidence interval (estimated as 1.96 standard errors) on the trends in TTT and T12. Dark gray shading indicates overlapping confidence intervals. Colored lines show climate model results. Confidence intervals for the models are omitted for clarity, but are comparable in size to the observational data.

observations for positive surface temperature trends, whereas others, like IPSL-CM5A-LR, have no “U” shape. The observational data do not match the modeled patterns for regions of surface cooling (leftmost points on Fig. 3b), which are mostly in the subsidence region of the eastern Pacific (Fig. S2). Models simulate increasing T12 (decreasing UTRH) over these regions, whereas observations show decreasing T12 (increasing UTRH). This may indicate a bias in the AMIP simulations of upper-tropospheric humidity trends in this region. However, the confidence intervals for the trend calculations are especially broad in these regions, so this difference may be due to chance.

Lambert and Taylor (2014) found a regional pattern of increasing water vapor feedback with surface temperature change over oceanic regions that warm relatively weakly, and decreasing water vapor feedback with surface temperature change over land regions that warm relatively strongly. This would translate to a “U” shape in our analysis of T12 trends since a negative T12 trend is associated with increasing RH and a stronger water vapor feedback. However, our observational results are inconclusive, with only a subtle “U” shape in the observations and some of the model simulations. Lambert and Taylor (2014) also found a clear difference in the sensitivity of the water vapor feedback to surface temperature change over land and ocean in their strongly forced climate model simulations (a combination of doubled- CO_2 and an A1B scenario of increasing CO_2 concentrations over the twenty-first century; Nakicenovic and Swart 2000). The climate model simulations of the recent past used here are relatively weakly forced. Consequently a strong land–ocean contrast in surface warming does not develop over 1979–2008 and there is no

clear difference between the sensitivity of T12 trends to surface temperature trends over land and ocean (not shown).

In summary, the relationship between regional surface temperature trends and tropospheric temperature change is weak (Fig. 3a), as expected from weak-temperature-gradient theory and previous analysis of the regional lapse rate feedback. This means the regional variation of the lapse rate feedback over this period is principally controlled by the regional variation in surface temperature change. The regional relationship between surface temperature trends and T12 trends is somewhat unclear (Fig. 3b). There is nevertheless some indication that the greatest increases in tropospheric humidity occur in regions of intermediate surface temperature trends, as predicted by Lambert and Taylor (2014). However, regional surface temperature trends have only a weak physical link to regional tropospheric humidity trends, and consequently to the regional pattern of water vapor feedback.

Since the tropical upper troposphere is moistened by deep, precipitating convective plumes, we might expect a stronger relationship between regional humidity trends and regional precipitation trends. Similar connections between T12 and convective activity were demonstrated by Soden and Fu (1995) and Bates and Jackson (2001). Figure 4 shows regional TTT and T12 trends as a function of regional precipitation trends. By using precipitation trends rather than climatological precipitation to sort the T12 trends, we account for the effects of shifting patterns of precipitation on T12 over the instrumental record. Such shifts have been demonstrated in observations by Greve et al. (2014) and in model simulations by Chadwick et al. (2013). TTT is

TABLE 2. Tropical-mean (30°S–30°N) water vapor and lapse rate feedbacks.

Model	Water vapor ($\text{W m}^{-2} \text{K}^{-1}$)	Lapse rate ($\text{W m}^{-2} \text{K}^{-1}$)
BNU-ESM	3.98	−1.45
CanESM2	3.58	−1.24
CCSM4	3.44	−1.25
CNRM-CM5	3.33	−1.14
HadGEM2-ES	3.43	−1.25
IPSL-CM5A-LR	3.85	−1.50
MIROC5	3.56	−1.23
NorESM1-M	3.37	−1.23

fairly insensitive to precipitation (Fig. 4a), as expected from weak-temperature-gradient arguments. T12 is very sensitive to regional precipitation trends (Fig. 4b). Where precipitation decreases, T12 increases, corresponding to a decrease in UTRH. Where precipitation increases, T12 decreases, corresponding to an increase in UTRH. This relationship is robust across models and clearly evident in observations. HadGEM2-A shows only weak sensitivity of T12 to precipitation trend in regions of large positive and negative precipitation trends, but a similar sensitivity to the other models in regions of intermediate precipitation trends. There are still, however, large uncertainties in these regional trends (model confidence intervals in Fig. 4 are omitted for clarity, but are comparable to those for observations).

In this section we have presented the observational and model evidence for two potential constraints on feedback behavior in the tropics: constant UTRH and robust regional structure. We find that modeled and observed T12 trends are consistent with constant (or, for some models, nearly constant) UTRH, but that

uncertainties in the 30-yr trends are large. There is observational evidence for the regional pattern of lapse rate feedback being controlled by the regional pattern of surface temperature changes, and for the regional pattern of water vapor feedback being controlled by the regional pattern of precipitation changes. We will now investigate the mechanisms producing these patterns and whether these robust aspects of feedback behavior can tell us anything about the overall magnitude of climate feedbacks in the future.

4. Linking past and future climate feedbacks

a. Tropical-mean feedback

Tropical-mean climate feedbacks calculated from the difference between piControl and abrupt4xCO₂ simulations (as described in section 2d) are shown in Table 2. We take these calculations to represent the feedbacks occurring in a future, strongly forced, global warming scenario. We might expect that climate models simulating large past humidity trends would simulate large future humidity trends and therefore have a larger water vapor feedback. However, Fig. 5a shows that the tropical-mean T12 trends from the AMIP models do not correlate with the modeled tropical-mean water vapor feedback. For the water vapor feedback in the past to be related to the water vapor feedback in the abrupt4xCO₂ simulations, there would need to be a relationship between the humidity changes in the two sets of simulations. The lack of relationship shown in Fig. 5a suggests this might not be the case. Therefore, our analysis of the observed tropical-mean T12 trend to date cannot provide a constraint on future

FIG. 5. (a) Tropical-mean AMIP T12 trends against tropical-mean water vapor feedback. (b) T12 sensitivity to precipitation against tropical-mean water vapor feedback. The sensitivity of T12 to precipitation is calculated as the slope of a total least squares regression of gridpoint precipitation trends against gridpoint T12 trends. Observational estimates from HIRS data are shown by the vertical black line and their 95% confidence intervals (estimated as 1.96 standard errors) by the gray shading.

FIG. 6. Trend in tropical specific humidity between 1979 and 2005 in AMIP and historical simulations against the change in tropical specific humidity between the final 30 years of piControl and abrupt4xCO₂, normalized by tropical surface temperature trend and surface temperature change respectively. Circles indicate AMIP simulations and diamonds indicate historical simulations. Bars indicate 95% confidence intervals (estimated as 1.96 standard errors). The AMIP trends for a single ensemble member. The historical trends are for the mean of every available ensemble member.

upper-tropospheric changes under continued global warming driven by greenhouse gases. We investigate further by comparing trends in specific humidity since 1979 and the response in the abrupt4xCO₂ simulations in Fig. 6. To make the trends comparable to the abrupt4xCO₂ response, all humidity changes are normalized by the surface temperature response in the abrupt4xCO₂ case and the surface temperature trend in the historical and AMIP cases.

The prescribed AMIP SSTs feature a cooling trend over the eastern Pacific between 1979 and 2008 (Fig. S2), which is very different from the pattern of the SST difference between piControl and abrupt4xCO₂ (Fig. S3). Might the particular SST trend pattern be causing a

different humidity response to warming in the AMIP simulations compared to the abrupt4xCO₂ simulation? To test this, we also calculate humidity trends from the CMIP5 historical simulations, which feature coupled oceans with interactive SSTs, and thus feature a range of different patterns of SST trends due to internal variability. Figure 6 shows that the humidity trends in the AMIP and historical simulations are very similar, as indicated by the substantially overlapping confidence intervals. Since the historical simulations have a range of different spatial patterns of SST trends, we can conclude that the specific SST trend pattern prescribed in the AMIP simulations does not bias the trend in atmospheric specific humidity. The spatial pattern of SST

trends is therefore not the cause of the lack of relationship between past and future humidity changes.

The broad confidence intervals on the trends in Fig. 6 also indicate that internal variability plays an important role in the AMIP and historical trends. The trends for the historical simulations were calculated using the mean of all available ensemble members for each model to reduce the uncertainty in the trends, but the confidence intervals remain so broad that there is no clear relationship between the historical trends and the abrupt4xCO₂ response at most pressure levels. The AMIP period is relatively weakly forced, so internal variability plays an important role in humidity trends over this period (Chung et al. 2014). For this reason it is perhaps unsurprising that the AMIP trend does not correlate with the strongly forced response.

There is a notable correlation between the historical trends and the abrupt4xCO₂ response in specific humidity at 200 hPa, where the confidence intervals in the trends are narrower, but this correlation does not manifest itself as a relationship between T12 trends and the abrupt4xCO₂ feedback (Fig. 5a) because 1) the T12 trends were calculated from a single ensemble member and 2) the T12 weighting function covers pressure levels between 200 and 500 hPa, and the correlation between historical trends and the abrupt4xCO₂ response is very weak for lower altitudes.

We also calculate the relationship between the regional variation of T12 trends in the AMIP simulations and the tropical-mean water vapor feedback from the abrupt4xCO₂ simulations (Fig. 5b). The regional variation of T12 trends and water vapor feedback is calculated by a total least squares linear regression fit to the regional trends against regional precipitation trends, thus accounting for uncertainty in both predictor and predictand variables. Each spatial point is assumed to be independent in this analysis. There is little relationship between this metric of regional variation of T12 trends and the tropical-mean water vapor feedback. All models' confidence intervals overlap with those of observational data, although some model pairs' confidence intervals do not overlap. Furthermore, there is no relationship between the slope of water vapor feedback across precipitation percentiles and its tropical-mean magnitude (not shown). This suggests the mean magnitude of upper-tropospheric humidity change under climate change is unrelated to its regional pattern. What, then, produces the regional patterns we observe?

b. Regional feedback patterns

We begin by investigating the structure of humidity changes and relating them to the regional pattern of water vapor feedback. Motivated by our results from

section 3 and Fig. 4, showing strong sensitivity of UTRH trends to precipitation trends, we consider the regional pattern in terms of precipitation changes. Figure 7 shows changes in specific and relative humidity between the abrupt4xCO₂ and piControl model simulations in percentiles of precipitation change, normalized by tropical-mean temperature change. We present fractional specific humidity changes (i.e., as a fraction of the piControl climatology) since this is most strongly related to the TOA radiative perturbation. All models show an increase in tropospheric specific humidity between piControl and abrupt4xCO₂. Specific humidity increases where precipitation increases the most (Fig. 7a), that is, in higher percentiles. This is reflected in the changes in RH: although there are small decreases in RH across most of the upper troposphere, these decreases are smaller where precipitation increases the most (Fig. 7b). This is consistent with our observational analysis (section 3), which showed that, between 1979 and 2008, T12 decreased the most (i.e., RH increased the most) in regions of increasing precipitation (Fig. 4).

Under strongly forced global warming, regional tropical precipitation changes include large shifts in location primarily driven by the spatial pattern of surface warming (Chadwick et al. 2013, 2014). Presenting results in percentiles of precipitation changes conflates two sources of humidity change: first, shifts in location of convection, which can produce large precipitation changes, and second, changes in the vertical moisture transport by convection regardless of its location. Our focus in this paper is to investigate the effect of changing convective moisture transport on the water vapor feedback, so we seek to remove the effects of spatial shifts. To do this we construct precipitation composites by calculating the TOA radiative flux difference between piControl and abrupt4xCO₂ in the same percentiles of precipitation rate rather than at the same geographical location. In geographical coordinates (x, y) the TOA radiative flux difference ΔN is calculated as

$$\Delta N(x, y) = N_2(x, y) - N_1(x, y). \quad (2)$$

More generally, we can define a coordinate system C in which to calculate the TOA radiative flux change. For both piControl and abrupt4xCO₂ simulations C will have a corresponding geographical coordinate, but these coordinates need not be the same between simulations:

$$\Delta N(C) = N_2(C) - N_1(C) \quad (3)$$

$$= N_2(x_2, y_2) - N_1(x_1, y_1). \quad (4)$$

In geographic coordinates $x_1 = x_2$ and $y_1 = y_2$, but this is not the case when regional feedbacks are calculated as

FIG. 7. (a) Fractional change in tropical specific humidity between final 30 years of piControl and abrupt4xCO₂ (i.e., change in specific humidity as a fraction of the piControl climatology) in percentiles of precipitation change, normalized by tropical-mean surface temperature change. (b) Change in tropical relative humidity between final 30 years of piControl and abrupt4xCO₂ (i.e., change in specific humidity as a fraction of the piControl climatology) in percentiles of precipitation change, normalized by tropical-mean surface temperature change.

the difference in radiative flux in the same precipitation percentile. Since the precipitation distribution shifts between piControl and abrupt4xCO₂, the regions of highest precipitation will occupy different geographical coordinates. Therefore the TOA radiative flux change in precipitation percentiles cannot usually be associated with a single point in geographical space because it is function of two pairs of geographical coordinates, (x_1, y_1) and (x_2, y_2). If a precipitation percentile does not shift spatially it can be located in geographical space, but this is not commonly the case. Although the spatial pattern of the TOA radiative flux change is different, the global (or tropical) mean is the same no matter which coordinate system is used.

We present fractional specific humidity changes in precipitation percentiles in Fig. 8, along with the water vapor radiative perturbation. Those models with a greater increase in tropospheric specific humidity (notably IPSL-CM5A-LR) have a larger water vapor feedback. Comparing the specific humidity change using percentiles of the climatological precipitation from piControl and abrupt4xCO₂ (thus accounting for shifts) with the change using percentiles of the precipitation change (i.e., comparing Figs. 8a and 7a), we

see that accounting for shifts in precipitation reduces the horizontal gradient (across precipitation percentiles) in specific humidity changes. This is because precipitation shifts introduce deep convection to areas that might not have been convective in the piControl climate, resulting in large humidity changes; accounting for these shifts removes this effect. Accounting for shifts in precipitation also removes much of the variation in RH change across precipitation percentiles (Fig. S4).

Even after accounting for shifts the specific humidity change is still greater in regions of higher precipitation. Convective activity is strongest in these regions, so vertical transport of water is most efficient. At lower precipitation percentiles convective activity is limited, so the humidity changes will be more strongly influenced by lateral transport of water vapor at the altitude of convective outflow. The regional variation of humidity changes (Fig. 8a) is reflected in the regional variation of the water vapor feedback (Fig. 8b).

Models can have very different magnitudes of tropical-mean humidity changes but have similar regional variation of the humidity changes, which means they can have very different magnitudes of tropical-mean

FIG. 8. (a) Fractional change in tropical specific humidity between final 30 years of piControl and abrupt4xCO₂ (i.e., change in specific humidity as a fraction of the piControl climatology) in percentiles of climatological precipitation from each simulation, normalized by tropical-mean surface temperature change. (b) Tropical water vapor radiative perturbation in percentiles of climatological precipitation from each simulation, normalized by tropical-mean surface temperature change.

water vapor feedback but similar regional variation. For example, NorESM1-M and IPSL-CM5A-LR have similar regional feedback patterns—as indicated by the variation of the water vapor feedback over precipitation percentiles—but different tropical-mean magnitudes: NorESM1-M has a tropical-mean water vapor feedback of $3.36 W m^{-2} K^{-1}$ and IPSL-CM5A-LR has a tropical-mean water vapor feedback of $3.85 W m^{-2} K^{-1}$ (Table 2).

Despite the robustness of the regional variation of the water vapor feedback, it appears to arise from different altitudes in different models. For example, CanESM2 has the largest gradient in upper-tropospheric (100–250 hPa) specific humidity change, but has an opposing gradient in midtropospheric (250–400 hPa) specific humidity change (Fig. 9). Considering all models, the regional variation of the water vapor feedback is partly accounted for by upper-tropospheric specific humidity response regional variation ($R^2 = 0.45$) but it is much better explained by the sum of the regional variations of the upper and midtropospheric specific humidity response ($R^2 = 0.87$). Water vapor anomalies at different altitudes have different influences on the TOA radiative flux (Soden and Held 2006), so the majority of the regional variation of the water vapor feedback is explained by humidity changes in the upper troposphere, but a full explanation also needs to take account of humidity changes in the middle troposphere.

The robustness of the regional variation of the water vapor feedback is therefore the result of compensation between the regional variation in upper and midtropospheric humidity changes. This might be expected since moisture detrained by convective plumes in the midtroposphere and advected away from the convective region will not be available to be detrained in the upper troposphere. A strong gradient across precipitation percentiles in upper-tropospheric specific humidity changes is therefore achieved by having a weak gradient in midtropospheric specific humidity (as seen especially for CanESM2 in Figs. 8 and 9). Likewise a weak gradient in upper-tropospheric humidity results when more of the water vapor anomaly is detrained in the midtroposphere (see, e.g., NorESM1-M in Figs. 8 and 9).

We now turn to the regional variation of the lapse rate feedback. We showed in section 3 that the regional variation of the lapse rate feedback is principally determined by surface temperature changes. However, given the physical relationships between the two feedbacks it seems unlikely that their regional patterns would be unrelated. Figure 10 shows changes in air temperature, normalized by tropical-mean surface temperature change, in precipitation percentiles alongside the lapse rate feedback in precipitation percentiles. Higher precipitation percentiles, where convective heating is stronger, have more upper-tropospheric warming than the lower percentiles. At higher precipitation percentiles

FIG. 9. Regional slope of tropical specific humidity change between piControl and abrupt4xCO₂ across precipitation percentiles against regional slope of tropical water vapor feedback across precipitation percentiles in CMIP5 models for specific humidity averaged over (a) 250–100 hPa and (b) 400–250 hPa, and (c) the sum of specific humidity changes between 250–100 and 400–250 hPa. Gray lines show ordinary least squares linear fits.

convective activity is high, so convection maintains the large-scale temperature profile close to moist adiabatic. Further away from the deep convective regions, at lower precipitation percentiles, the atmospheric warming is weaker. Although the Coriolis parameter is small in the tropics it is not zero, meaning that some horizontal atmospheric temperature gradient can be sustained. This is consistent with our observational evidence showing a weak dependence of TTT trends on surface temperature trends (Fig. 3). When the tropical region is constrained to 20°S–20°N rather than 30°S–30°N, horizontal gradients in temperature change get smaller but are still present.

Since there is some weak horizontal gradient in upper-tropospheric warming, there is a corresponding gradient in the lapse rate feedback. It is most negative in regions where the upper troposphere warms most relative to the surface and lower troposphere. As Fig. 10 shows, this happens in the highest precipitation percentiles.

We can now see that, although there is no correlation between the water vapor and lapse rate feedbacks on a geographical basis, there is a correlation when the two feedbacks are considered in precipitation percentiles, which accounts for precipitation shifts by calculating the change in TOA radiative flux in a separate coordinate system. This is consistent with our physical ideas about how these feedbacks operate. Since humidity changes in the upper troposphere have

the greatest impact on TOA radiative flux, convective transport of moisture from the boundary layer to the upper troposphere would be expected to play a key role in determining the magnitude of the water vapor feedback. Our analysis of the regional variation of the water vapor feedback also suggests that this convection drives a pattern with stronger water vapor feedback in strongly precipitating regions. Similarly, the lapse rate feedback, a result of the upper troposphere warming relative to the surface, is a result of convective activity. Condensation of water vapor in convective plumes releases latent heat; this process is enhanced in a warmer, more humid atmosphere, such that the tropical troposphere tends to maintain a moist adiabatic lapse rate, resulting in the negative lapse rate feedback. Thus, both these feedbacks are intimately related to convection and precipitation in the tropics. By considering the feedbacks in precipitation percentiles rather than geographical coordinates we most closely align our analysis with these physical principles.

The precipitation framework also shows the regional pattern of water vapor feedback is partly related to the horizontal gradients in temperature change shown in Fig. 10. The horizontal gradient in RH changes is minimal (Fig. S4), consistent with the results of the advection-condensation theory which predicts tropical tropospheric RH changes under surface warming to be mainly vertical shifts (Sherwood et al. 2006, 2010b;

FIG. 10. (a) Fractional change in tropical air temperature between final 30 years of piControl and abrupt4xCO₂ in percentiles of climatological precipitation from each simulation, normalized by tropical-mean surface temperature change. (b) Tropical lapse rate radiative perturbation in percentiles of climatological precipitation from each simulation, normalized by tropical-mean surface temperature change.

Romps 2014). Since horizontal gradients in RH changes are small (Fig. S4) but there is a notable horizontal gradient in temperature change (Fig. 10) a horizontal gradient in specific humidity change is to be expected.

As a consequence of the relationship between temperature and specific humidity in the advection/condensation framework, we see an anticorrelation between regional patterns of water vapor and lapse rate feedbacks in terms of precipitation percentiles (cf. Figs. 8b and 10b). However, the relationship between water vapor and lapse rate feedbacks in precipitation percentiles is only statistically significant from zero (as calculated from an ordinary least squares fit, assuming each percentile is independent) in three of the eight climate models analyzed here (Fig. S5). In some models (e.g., NorESM1-M) the anticorrelation is weak. This is to be expected since there are additional factors that determine the spatial distribution of feedbacks, especially surface temperature change in the case of the lapse rate feedback (as demonstrated earlier).

It must be noted that our feedback calculations were performed under clear-sky conditions. As noted by Held and Soden (2000), the sensitivity of the OLR to water vapor depends on whether clouds are included in the calculations. In the convective regions of the tropics OLR is heavily influenced by deep convective cloud. An analysis of all-sky water vapor and lapse rate feedbacks

in precipitation percentiles may reveal a muted feedback effect in the highest percentiles, since clouds act to mask the effects of humidity and temperature changes.

5. Conclusions

In this study we assess the potential for satellite observational data to provide information about long-term tropical water vapor and lapse rate climate feedbacks. We focus on two aspects of these feedbacks. First, we ask to what extent the tropical upper-tropospheric relative humidity remains constant under climate change. This constitutes a useful constraint on the water vapor and lapse rate feedbacks since it implies a level of cancellation between the two, with strong positive water vapor feedback implying strong negative lapse rate feedback. Second, we ask whether the novel approach to describing the regional patterns of these feedbacks introduced by Lambert and Taylor (2014) could be used to constrain the feedbacks arising from long-term climate change.

By considering the observed trend in tropospheric temperature as a proxy for the lapse rate feedback and the observed trend in T12 (HIRS channel-12 brightness temperature) as a proxy for the water vapor feedback, we find it more likely than not that tropical-mean upper-tropospheric specific humidity increased over the period

1979–2008 (section 3, Fig. 2), in agreement with previous studies (Soden et al. 2005; Chung et al. 2014). Despite discrepancies between the rates of tropospheric warming between models and MSU/AMSU observations (Fu et al. 2011; Po-Chedley and Fu 2012), observational and model data are consistent with constant upper-tropospheric relative humidity during this period. The uncertainty in the T12 trends is comparable in magnitude to the intermodel spread in these trends, so it remains difficult to distinguish between different climate models simulations of the past and the observations. The large uncertainties in trends between 1979 and 2008 also make it impossible to draw connections between past and future trends in tropical-mean tropospheric humidity (section 4a, Fig. 5a). This is perhaps unsurprising given the important role internal variability plays in 30-yr trends in T12 (Chung et al. 2014). Future research might be able to draw connections between past and future trends if this influence of internal variability is accounted for. However, in addition to the uncertainty in trends associated with internal variability, there is also uncertainty in the MSU/AMSU and HIRS datasets associated with the homogenization methods used in their construction. This uncertainty is not accounted for in this study, so it would further inflate the total uncertainty in estimated trends. The structural uncertainty in the MSU/AMSU datasets could be further evaluated using additional datasets, such as the intercalibrated MSU/AMSU temperatures from NOAA's Center for Satellite Applications and Research (STAR) (Zou and Wang 2011).

We also consider observational evidence for regional patterns of tropospheric temperature and humidity changes as proxies for climate feedbacks. We find much greater spatial variation in surface temperature trends than upper-tropospheric temperature trends, as expected since the tropical atmosphere can maintain only weak temperature gradients. This is evidence that the spatial pattern of the lapse rate feedback is primarily determined by the spatial pattern of surface temperature change. We find the spatial pattern of T12 trends is strongly related to the spatial pattern of precipitation trends, with positive T12 trends (negative upper-tropospheric relative humidity trends) in regions of negative precipitation trends, and negative T12 trends (positive upper-tropospheric relative humidity trends) in regions of positive precipitation trends. This is evidence that the spatial pattern of the water vapor feedback is primarily determined by the spatial pattern of precipitation change. This is a clear signature of the physical mechanism of the water vapor feedback, which is primarily driven by transport of water vapor into the free troposphere. These vertical moisture

transports are greater in regions of greater precipitation (i.e., more convective activity).

The simulated sensitivity of tropospheric temperature trends to surface temperature trends and of upper-tropospheric humidity trends to precipitation trends are consistent with observational data within uncertainty bounds. We find the regional sensitivities of these feedbacks to be unrelated to the strength of the mean feedback (section 4b, Fig. 5b).

In conventional geographic coordinates the spatial patterns of tropical lapse rate and water vapor feedbacks are not correlated (Taylor et al. 2011; Lambert and Taylor 2014). Here we show that the physically expected anticorrelation is partially recovered if the regional pattern of feedbacks is calculated in precipitation space rather than geographic space. That is, higher percentiles of precipitation are associated with strong positive water vapor feedback and strong negative lapse rate feedback. This regional pattern is robust among the eight climate models analyzed here and there is strong observational evidence for it from HIRS T12 observations. The water vapor feedback varies by 1 to 2 $\text{W m}^{-2} \text{K}^{-1}$ across the tropics (compared to a tropical-mean feedback magnitude of 3.3 to 4 $\text{W m}^{-2} \text{K}^{-1}$), and the lapse rate feedback varies by 0.5 to 1 $\text{W m}^{-2} \text{K}^{-1}$ across the tropics (compared to a tropical-mean feedback magnitude of -1.1 to $-1.5 \text{ W m}^{-2} \text{K}^{-1}$). Thus, although we do not find a strong relationship between tropical-mean humidity changes over 1979–2008 and in the quadrupled- CO_2 model simulations, we show that the two periods share common regional patterns of these humidity changes, suggesting common regional patterns of the water vapor feedback.

Our decomposition of the water vapor and lapse rate feedback according to precipitation percentiles is similar to the approach of decomposing cloud feedbacks according to percentiles of tropospheric vertical velocity (Bony et al. 2004; Wyant et al. 2006). This allows the feedback to be analyzed separately in convective and subsidence regimes. Our proposed precipitation decomposition is similar, but has the advantage that the precipitation rate is more readily observed in the tropics than the vertical velocity (vertical velocity for the real world is usually taken from reanalyses). Chadwick et al. (2013) showed that tropical precipitation rates are strongly related to convective mass flux and mean vertical velocity, indicating that our results should be very similar if the water vapor feedback were decomposed according to vertical velocity. One distinction is that the precipitation decomposition does not distinguish as clearly between different subsiding regimes. This is because regions of the tropics with different subsidence strength tend to have similarly low precipitation.

Although we find the regional patterns to be unrelated to the overall tropical-mean feedback strength, it is important to describe and understand the regional patterns of feedbacks because they play a key role in regional climate predictability via their impact on energy transport by the atmospheric circulation (Zelinka and Hartmann 2012; Huang and Zhang 2014; Roe et al. 2015; Voigt and Shaw 2015). Furthermore, the observational evidence presented here suggests models capture the physical processes determining regional feedbacks quite well. Although this is not related to the mean feedback strength, it is encouraging to see climate models behaving as physically expected and consistent with observations. Our results also suggest changes in precipitation play an important role in the regional water vapor feedback. In the tropics, much of the intermodel spread in precipitation changes comes from spatial shifts (Chadwick et al. 2013; Bony et al. 2013). The relationships between dynamical precipitation changes, water vapor feedback, and circulation changes due to changes in energy transport indicate that the topic of radiation–dynamics coupling is an important area of future research.

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