The Spectral Dimension of Modeled Relative Humidity Feedbacks in the CMIP5 Experiments

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ABSTRACT

The spectral radiative kernel technique is used to derive spectrally resolved relative humidity (RH) feedbacks for 16 GCMs that participated in CMIP5. Examining spectral and spatial details of these RH feedbacks leads to three findings. First, while the global average of broadband RH feedbacks is close to zero for all the GCMs, there exist wide discrepancies in the spectral details among the GCMs. Second, the spatial pattern of the RH feedbacks varies with spectral frequency; for a given frequency, the spatial feedback pattern correlates well with the spatial pattern of RH changes over the vertical layer to which the top-of-atmosphere spectral flux at the same frequency is most sensitive. Third, the nearly zero global average of broadband RH feedback is a result of spatial compensation and spectral compensation. Since GCMs have produced consistent RH feedbacks and RH changes to a large extent in the high latitudes, the tropical Atlantic, and the deep tropical Pacific, radiative RH kernels are further used to infer mean changes in RH vertical profiles from spectral RH feedbacks averaged over the three broad regions. Good agreements are demonstrated by comparing such inferences against the actual RH changes in the GCMs. This study suggests that the spectral dimension of RH feedback could provide an additional constraint to climate models and the understanding of vertical features of RH changes when they are obtainable from future observations.

1. Introduction

It is widely known that relative humidity (RH) changes little in the global warming scenario simulated by GCMs (Ingram 2002; Allen and Ingram 2002; Pierrehumbert et al. 2007). Both climate models and observations indicate that global mean specific humidity in the atmosphere will increase with global mean surface temperature by $7\% \text{ K}^{-1}$, leading to “constant RH” in response to surface warming as implied by the Clausius–Clapeyron relation (Wentz and Schabel 2000; Wentz et al. 2007; Trenberth et al. 2005). Additionally, water vapor feedbacks using specific humidity as a state variable in GCMs are also consistent with results that hold RH fixed (Colman and McAvaney 1997; Held and Soden 2000; Soden and Held 2006; Sherwood et al. 2010). Because of the tight coupling of temperature and water vapor changes in models, Held and Shell (2012) found out that it is physically logical to combine lapse-rate feedback

and water vapor feedback together and to use RH as a state variable (hereafter referred to as the RH framework) instead of specific humidity. Thus they proposed RH feedback and calculated RH feedback as well as Planck and lapse-rate feedbacks under the RH framework for 18 models of phase 3 of the Coupled Model Intercomparison Project (CMIP3). These RH feedbacks are all close to zero with much smaller intermodel spread than that for the traditional water vapor feedback (using specific humidity as the state variable). The RH framework also removes most of the cancellation between traditional water vapor feedback and lapse-rate feedback, resulting in little correlation between RH feedback and lapse-rate feedback across the models. Caldwell et al. (2016) confirmed the same benefit of the RH framework when inspecting sources of model spreads for the estimated climate sensitivity. They found that the RH framework can reduce covariance between water vapor and lapse-rate feedbacks, covariance between water vapor and longwave cloud feedbacks, and the intermodel variance in these terms, making it easier

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to understand the feedback mechanisms than the conventional approach using specific humidity as a state variable.

Since last decade, the radiative kernel method has become a popular approach to compute radiative feedbacks from GCM archives. This method was pioneered by Soden and Held (2006), Soden et al. (2008), and Shell et al. (2008). The radiative kernel is the response of top of atmosphere (TOA) broadband flux to a unit perturbation in a given state variable. The radiative feedback for the state variable can then be estimated from the product of the radiative kernel and the change in this variable between two climate states. Traditionally, these radiative feedbacks are studied in terms of broadband flux, but intrinsically the TOA broadband flux is an integration of the spectral flux. Spectral decomposition of the TOA broadband flux has been proven useful in model diagnostics. For example, Huang et al. (2006) and Huang et al. (2007) revealed the compensating biases among spectral bands for the simulated outgoing longwave radiation (OLR). Huang and Ramaswamy (2008) demonstrated that spectral decomposition is useful to help assess the relationship between OLR and sea surface temperature, as well as the impact of water vapor on such relationships. Harries et al. (2001) and Brindley and Bantges (2016) showed how changes in climate variables are manifested across the spectrum and illustrated the advantage of spectral resolution over broadband radiation in the discriminatory power. The spectral dimension of radiative feedbacks can also provide additional insights for understanding feedbacks across the models. Huang et al. (2014) extended the use of radiative kernel approach from broadband to the spectral dimension, and developed and validated a set of longwave spectral radiative kernels. They showed that the broadband feedbacks derived from the spectral radiative kernels are highly consistent with those derived from widely used broadband kernels such as Soden et al. (2008) and Shell et al. (2008). They further showed that the lapse-rate and water vapor feedbacks from different GCMs can have different spectral dependences. To highlight the advantage of spectral diagnostics of the feedbacks, they showed a specific example with two GCMs having identical broadband lapse-rate feedback strength, but the spectral decompositions of the lapse-rate feedbacks from the two models are very different (Fig. S3 in Huang et al. 2014).

Motivated by the potentials of the RH framework in climate feedback studies and useful information contained in the spectral decomposition of broadband feedbacks, in this study we calculate the spectral RH feedbacks for 16 GCMs that participated in CMIP5

(Taylor et al. 2012). Then, based on these spectrally resolved RH feedbacks, a few questions we want to investigate are the following:

- 1) Although the global average of broadband RH feedbacks in all GCMs is close to zero, does such consistency remain throughout the longwave spectrum after spectral decomposition?
- 2) What is the spatial distribution of the RH feedbacks? How does the spatial pattern of RH feedbacks vary from one spectral band to another?
- 3) Over a large climate domain, can spectral decomposition of averaged broadband RH feedbacks qualitatively and quantitatively reveal useful information about actual RH changes at different pressure levels?

Bearing these questions in mind, we will examine the spatial and spectral details of the RH feedbacks in 16 GCMs and employ inversion techniques to quantitatively relate the vertical profiles of the RH changes with the spectrally resolved RH feedbacks. The rest of this paper is arranged as follows. Section 2 explains the method to calculate the spectral RH feedbacks in 16 GCMs. The spectral and spatial features of RH feedbacks as well as their consistency with actual RH changes are examined in section 3. Section 3 also discusses the relationship between regional spectral RH feedbacks and actual profiles of RH change in several regions. Conclusions and further discussion are presented in section 4.

2. Data and method

a. Calculation of spectral RH feedback

We follow Held and Shell (2012) to replace specific humidity with RH as the state variable to compute radiative feedbacks. Held and Shell (2012) split traditional water vapor feedback λ_Q (using specific humidity as the state variable) into three parts:

$$\lambda_Q = \lambda_{Q_T} + \lambda_{Q_L} + \lambda_{RH}. \quad (1)$$

The first three terms in Eq. (1) are the TOA flux response to a certain amount of humidity perturbation, divided by the global average surface temperature change. In the first term of Eq. (1), the TOA flux responds to the total specific humidity perturbation in the troposphere. In the second term the TOA flux responds to the specific humidity perturbation required by fixing RH while the tropospheric temperature perturbation is uniformly equal to the local surface temperature change. In the third term the TOA flux responds to the specific humidity perturbation required by fixing RH while tropospheric

temperature is perturbed by its difference from the local change of surface temperature. The last term, the RH feedback λ_{RH} we are interested in, is the TOA spectral flux response to the change in RH divided by the global average surface temperature change.

To obtain λ_{RH} , first we need to calculate λ_Q , $\lambda_{Q|_T}$, and $\lambda_{Q|_L}$ and then subtract $\lambda_{Q|_T}$ and $\lambda_{Q|_L}$ from λ_Q ; λ_Q , $\lambda_{Q|_T}$, and $\lambda_{Q|_L}$ are calculated by the spectral radiative kernel approach in Huang et al. (2014). Specifically, the TOA spectral flux change ΔR at a given frequency ν in response to a state variable change Δx on a grid box (lat, lon) at a given time t caused by the increase of surface temperature can be approximated as

$$\begin{aligned} \Delta R(\text{lat}, \text{lon}, \nu; t) &\approx \sum_{p=1}^N \frac{\partial R(\text{lat}, \text{lon}, \nu, t)}{\partial x(\text{lat}, \text{lon}, p, t)} \Delta x(\text{lat}, \text{lon}, p, t) \\ &= \mathbf{K} \cdot \Delta \mathbf{X}, \end{aligned} \quad (2)$$

where the term $\mathbf{K}$ or $\partial R/\partial x$ denotes the spectral radiative feedback kernel (hereafter we refer to the kernel as $\mathbf{K}$ for brevity) for a state variable $x(p)$ (e.g., temperature or logarithm of specific humidity at the p th level, and N is the total number of tropospheric levels). After calculating ΔR due to the change in certain state variable x , the climate feedback λ_x can be derived as

$$\lambda_x = \Delta R(\Delta T_{\text{surf}})^{-1}, \quad (3)$$

where ΔT_{surf} is the global mean surface temperature change. Details about how to construct and validate the spectral radiative kernels can be found in Huang et al. (2014). Specifically, one year of 3-hourly profiles of temperature, specific humidity, cloud fraction, cloud liquid, and ice water content as simulated by the GFDL AM2 model (Anderson et al. 2004) were fed into the principal component-based radiative transfer model (PCRTM; Liu et al. 2006; Chen et al. 2013) to simultaneously compute longwave spectral radiative kernels for temperature and specific humidity at intervals of 10 cm^{-1} .

The kernel for specific humidity considers the TOA spectral flux response to the change of logarithm of specific humidity (i.e., the fractional change in humidity). For this study, we multiply the set of spectral radiative kernels derived in Huang et al. (2014) by atmospheric state perturbations and divide the results by the global average surface temperature change to obtain spectrally resolved λ_Q , $\lambda_{Q|_T}$, and $\lambda_{Q|_L}$. The atmospheric state perturbations are changes of monthly output from years 1–20 to years 61–80 in an 80-yr simulation with a 1% CO_2 increase per year from 16 GCMs that participated in the CMIP5 (Taylor et al. 2012). Information about the 16 GCMs can be found in Table 1. After

longwave spectral feedbacks $\lambda_{Q|_T}$, $\lambda_{Q|_L}$, and λ_Q are computed, we subtract $\lambda_{Q|_T}$ and $\lambda_{Q|_L}$ from λ_Q to obtain the spectral RH feedback λ_{RH} .

b. Spectral RH radiative kernel

The spectral radiative kernel for RH can be shown to be approximately equivalent to the spectral kernel for specific humidity as follows. From Eqs. (1)–(3), on a one grid box we can obtain

$$\begin{aligned} \Delta R_{\text{RH}} &= K_{\log(Q)} \Delta \log(Q) - K_{\log(Q)} \Delta \log(Q|_T) \\ &\quad - K_{\log(Q)} \Delta \log(Q|_L). \end{aligned} \quad (4)$$

On the right side, $K_{\log(Q)}$ is the spectral radiative kernel for the logarithm of specific humidity. The meanings of Q , $Q|_T$, $Q|_L$, and RH are the same as for Eq. (1). Also, $\Delta \log(Q)$ is the total specific humidity change between two climate states; $\Delta \log(Q|_T)$ is the specific humidity change to hold RH fixed when temperature at each level increases by local surface temperature change; and $\Delta \log(Q|_L)$ is the specific humidity change to hold RH fixed when temperature at each level changes by its difference from the local surface temperature change. Specifically, in this paper regarding humidity perturbation we only consider its fractional change (i.e., the change of logarithm of specific humidity or relative humidity). The term ΔR_{RH} is the spectral flux change responding to RH change between the two climate states. The RH change, if in logarithmic scaling, is

$$\Delta \log(\text{RH}) = \Delta \log(Q) - \Delta \log(Q_s). \quad (5)$$

The term $\Delta \log(Q_s)$ is the change in saturated specific humidity and derived as the function of temperature change ΔT according to the Clausius–Clapeyron relation:

$$\Delta \log(Q_s) = \frac{L}{R_v T^2} \Delta T, \quad (6)$$

where L is specific latent heat and R_v is the gas constant. From Eq. (6) and the definitions of $\Delta \log(Q|_T)$ and $\Delta \log(Q|_L)$, we can get

$$\Delta \log(Q|_T) = \frac{L}{R_v T^2} \Delta T_{\text{surf}}^*, \quad (7)$$

$$\Delta \log(Q|_L) = \frac{L}{R_v T^2} (\Delta T - \Delta T_{\text{surf}}^*), \quad \text{and} \quad (8)$$

$$\Delta \log(Q_s) = \Delta \log(Q|_T) + \Delta \log(Q|_L). \quad (9)$$

Here ΔT_{surf}^* in Eqs. (7) and (8) is the surface temperature change on this individual grid box. Finally combining

TABLE 1. Summary of the 16 GCMs in CMIP5.

Model name and resolution	Modeling center
BCC_CSM1.1 ($\sim 2.8^\circ \times 2.8^\circ$)	Beijing Climate Center, China Meteorological Administration
BNU-ESM ($\sim 2.8^\circ \times 2.8^\circ$)	Beijing Normal University
CanESM2 ($\sim 2.8^\circ \times 2.8^\circ$)	Canadian Centre for Climate Modeling and Analysis
CCSM4 ($0.9^\circ \times 1.25^\circ$)	National Center for Atmospheric Research
CESM1(CAM5) ($0.9^\circ \times 1.25^\circ$)	National Center for Atmospheric Research
CNRM-CM5 ($\sim 1.4^\circ \times 1.4^\circ$)	Centre National de Recherches Meteorologiques
GFDL CM3 ($2^\circ \times 2.5^\circ$)	NOAA Geophysical Fluid Dynamics Laboratory
GISS-E2-H ($2^\circ \times 2.5^\circ$)	NASA/GISS
GISS-ES-R ($2^\circ \times 2.5^\circ$)	NASA/GISS
HadGEM2-ES ($\sim 1.3^\circ \times 1.9^\circ$)	Met Office Hadley Centre
INM-CM4.0 ($1.5^\circ \times 2^\circ$)	Russian Institute for Numerical Mathematics
IPSL-CM5A-LR ($1.9^\circ \times 3.75^\circ$)	Institute Pierre-Simon Laplace
MIROC5 ($1.4^\circ \times 1.4^\circ$)	Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology
MPI-ESM-LR ($1.875^\circ \times 1.875^\circ$)	Max Planck Institute for Meteorology
MRI-CGCM3 ($1.125^\circ \times 1.125^\circ$)	Meteorological Research Institute
NorESM1-M ($1.9^\circ \times 0.5^\circ$)	Norwegian Climate Centre

Eqs. (4), (5), and (9), the spectral flux change responding to RH change can be expressed as

$$\Delta R_{\text{RH}} = K_{\log(Q)} \Delta \log(\text{RH}). \quad (10)$$

Equation (10) clearly reveals that the spectral RH radiative kernel is the same as the one for specific humidity. Thus, we can interpret Fig. 1, which shows the globally averaged specific humidity radiative kernel, as the RH kernel as well. RH changes at different vertical levels contribute differently to TOA flux changes over different spectral bands. Channels in the far-IR water vapor pure rotational band ($10\text{--}600\text{ cm}^{-1}$) and the mid-IR water vapor ν_2 band ($1300\text{--}1900\text{ cm}^{-1}$) are mostly sensitive to relative humidity changes in the upper and middle troposphere, while channels in the window regions ($800\text{--}1200\text{ cm}^{-1}$) are affected most by water vapor continuum absorptions and thus are sensitive to the lower troposphere, especially the planetary boundary layer.

3. Results and discussion

a. Features of spectral and spatial distribution of RH feedbacks

Table 2 lists the global average of broadband RH feedbacks for the 16 GCMs. The broadband RH feedback is merely an integration of spectral RH feedbacks against wavenumber over the entire longwave spectrum. All models have broadband RH feedbacks within $\pm 0.1\text{ W m}^{-2}\text{ K}^{-1}$ except the MPI-ESM-LR model. The ensemble mean of broadband RH feedback is only $-0.00085\text{ W m}^{-2}\text{ K}^{-1}$ with a standard deviation of $0.072\text{ W m}^{-2}\text{ K}^{-1}$. Excluding the obvious outlier, $0.21\text{ W m}^{-2}\text{ K}^{-1}$ for the MPI-ESM-LR model, the

ensemble mean of broadband RH feedback becomes $-0.015\text{ W m}^{-2}\text{ K}^{-1}$ with a standard deviation of $0.047\text{ W m}^{-2}\text{ K}^{-1}$, still insignificantly different from zero. Such nearly zero RH feedback is consistent with the well-known “constant RH” scenario. The spectral details of such globally averaged RH feedbacks are shown in Fig. 2a, with the ensemble mean and standard deviation across the 16 GCMs shown in Fig. 2b. The most striking feature in Fig. 2a is that spectral RH feedbacks of different GCMs vary quite differently with the frequency, in spite of their broadband integrations all being so close to zero. As is evident

FIG. 1. Global average of the spectral radiative kernel for specific humidity as well as relative humidity. It is the global average response of TOA spectral flux averaged within spectral bins of 10 cm^{-1} to the change of the logarithm of RH at each pressure level.

TABLE 2. Global average of broadband RH feedbacks ($\text{W m}^{-2} \text{K}^{-1}$) for 16 CMIP5 GCMs.

BCC_CSM1.1	−0.033	GISS-ES-R	0.037
BNU-ESM	0.047	HadGEM2-ES	−0.011
CanESM2	0.059	INM-CM4.0	0.0084
CCSM4	−0.062	IPSL-CM5A-LR	−0.022
CESM1(CAM5)	−0.094	MIROC5	−0.0027
CNRM-CM5	−0.018	MPI-ESM-LR	0.21
GFDL CM3	−0.021	MRI-CGCM3	−0.071
GISS-E2-H	0.036	NorESM1-M	−0.076

from Fig. 2b, for a majority part of the longwave spectrum, the spread of RH feedbacks among GCMs (as measured by the standard deviation) is larger than the model ensemble mean. Another salient feature in Fig. 2a is that, for a model with positive (negative) broadband RH feedback, its spectral decomposition is not necessarily always positive (negative).

Figure 3 shows the global maps of ensemble-mean broadband RH feedbacks as well as the spectral RH feedbacks for three bands, 60–300, 400–600, and 800–1100 cm^{-1} . The three bands are chosen because, as shown in Fig. 1, they are sensitive to the upper, middle, and lower troposphere respectively. Areas with statistically significant nonzero ensemble mean (99% significance level based on the Student's t test) are stippled with dots. Two major findings can be concluded from Fig. 3:

- 1) For the broadband and all spectral bands shown here, the magnitude of local RH feedback is much greater than that of the global average. Some regions exhibit positive RH feedbacks while other regions have negative RH feedbacks with comparable magnitude. Thus, Figs. 2 and 3 indicate that the nearly zero global average of broadband RH feedback is a result of spatial compensation and spectral compensation.
- 2) Spatial patterns of RH feedbacks vary noticeably with the spectral band. For the spectral band of 60–300 cm^{-1} , the most noticeable patterns are significantly positive RH feedbacks at high latitudes (60°–90° for both hemispheres) and comparable negative RH feedbacks in part of tropical Atlantic (5°–20°N and 5°–20°S, 300°–350°E). For the other two spectral bands, the most noticeable spatial pattern is the significantly positive feedback confined in the deep tropical Pacific (5°S–5°N, 200°–250°E). For other geographical regions not mentioned above, like the midlatitudes and the subtropics (20°–40°) in both hemispheres, the ensemble-mean RH feedbacks are not significantly different from zero based on the Student's t test that we performed. In other

words, there is no consensus among the GCMs as to whether the RH feedbacks in such regions are positive or negative under the global warming scenario.

b. Relationships between the mean spectral RH feedbacks and mean RH changes

The three spectral bands examined in the previous section are sensitive to water vapor emission and absorption in different parts of the atmosphere as mentioned above. The 60–300 cm^{-1} band is most sensitive to the upper troposphere, the 400–600 cm^{-1} to the middle troposphere, and the 800–1100 cm^{-1} to the boundary layer (water vapor continuum absorption). Figure 4 then shows ensemble-mean changes in RH at 300, 500, and 850 hPa from years 1–20 to years 61–80 in the 80 years of the 1% CO_2 simulation experiment (the stippled area is statistically significant at the 99% significance level). The similarity between Fig. 3 and Fig. 4 is self-evident. At 300 hPa, the ensemble mean exhibits a significant increase of RH in the high latitudes (60°–90° for both hemispheres) and comparable decrease of RH in part of the tropical Atlantic (5°–20°N and 5°–20°S, 300°–350°E). At 500 hPa, there is little RH change in high latitudes while the most obvious feature is increased RH in the deep tropical Pacific (5°S–5°N, 200°–250°E). At 850 hPa, a statistically significant increase (decrease) of RH is seen in the deep tropical Pacific (part of the subtropics). The spatial features of RH changes at the three pressure levels correlate well with those of spectral RH feedbacks shown in Fig. 3 for the three spectral bands, supporting the advantage of spectral over broadband RH feedbacks for inspecting RH changes.

Within one grid box, RH changes at different levels lead to TOA flux changes at different frequencies, leaving an approximate linear relationship between the spectral RH feedback and vertical profile of RH changes. Regarding mean value averaged over a large climate domain, it is meaningful to examine whether there still exists a relationship between the vertical profile of mean RH change and the spectral decomposition of mean broadband RH feedback. The GCMs examined here have produced consistent RH feedbacks and RH changes to a large extent in the high latitudes, the tropical Atlantic, and the deep tropical Pacific. Thus, we are motivated to further seek quantitative ways to infer regional RH changes from the spectral RH feedbacks averaged in such three broad geographical regions. Since we work with the CMIP5 simulation data, the actual RH change is already known. Thus it gives us an opportunity to examine how well an inversion of mean spectral radiative feedback can render the vertical profile of mean RH change.

FIG. 2. (a) Global average of spectral RH feedbacks for the 16 GCMs in the CMIP5 archive. (b) Model ensemble mean and standard deviation of the global average of spectral RH feedbacks in 16 GCMs.

For the inversion here, we estimate the changes in RH at different pressure levels from the spectral RH feedbacks by inverting the average of spectral radiative kernel K and multiplying by the TOA flux changes in the given region (i.e., the high latitudes, the tropical Atlantic, and the deep tropical Pacific). Two methods are used here for the inversion: the constrained inversion

method (Twomey 1977) and the truncated singular value decomposition (SVD) method (Hansen 1990). Appendix A describes the mathematics of the two methods in detail.

In the following discussion about quantitatively inferring RH changes from the regional-averaged spectral RH feedbacks, we first examine the relationship

FIG. 3. The global map of model-mean RH feedbacks from the 16 GCMs over different spectral bands: (a) broadband (60–2000 cm^{-1}) and (b) 60–300, (c) 400–600, and (d) 800–1100 cm^{-1} . The areas where RH feedbacks are nonzero at the 99% significance level are stippled by dots.

between the spectral feature of multimodel ensemble mean RH feedbacks and the vertical feature of mean RH changes. Then we inspect the standard deviation of model ensembles (measured against the ensemble mean) to examine whether the spread of spectral RH feedbacks among models is consistent with the spread of vertical RH changes. Finally, we use a Taylor diagram approach to explore how well the spectral decomposition of RH feedbacks can render the vertical profile of RH changes.

Before we embark on retrieving the regional RH changes from the spectral RH feedbacks, one implicit linearity assumption needs to be validated: the average of TOA flux changes due to RH perturbations for a given geographical region can be well approximated by the product of the average of spectral RH kernels and the average of RH perturbations over the same region. [Appendix B](#) discusses how to test this assumption and

shows why the linearity assumption is valid for the aforementioned three regions.

1) HIGH LATITUDES (60°–90° FOR BOTH HEMISPHERES)

The left column in [Fig. 5](#) shows the ensemble means of spectral RH feedbacks averaged over the high latitudes for both hemispheres. Two notable spectral features are that 1) RH feedbacks are positive almost across the whole spectrum and 2) two bands, 60–600 cm^{-1} and 1200–2000 cm^{-1} , dominate the broadband RH feedback while the contribution from 800–1200 cm^{-1} is negligible. As mentioned in [section 3b](#), different spectral bands are sensitive to water vapor emission and absorption in different parts of the atmosphere. Based on the spectral features, we can infer two features about the RH changes in the high latitudes: 1) RH changes are positive in almost the whole troposphere and 2) dominant

FIG. 4. The global map of model-mean fractional change of RH among 16 GCMs from years 1–20 to years 60–80 in the experiments with a 1% CO_2 increase per year at (a) 300, (b) 500, and (c) 850 hPa. The areas where the RH changes are nonzero at the 99% significance level are stippled by dots.

changes occur in the upper troposphere. The right column in Fig. 5 shows ensemble-mean profiles of local RH changes in the high latitudes for both hemispheres. The RH changes are obtained by averaging the direct outputs from 16 GCMs (the truth) and retrieved from corresponding spectral RH feedbacks using the two methods introduced in appendix A (the retrievals). Both the retrieved and actual profiles are consistent with the qualitative inference of RH changes from the spectral features mentioned above: in most part of troposphere the RH changes are positive and the RH changes are more prominent in the upper troposphere than in the lower troposphere, with the largest change at around 300 hPa.

Figure 5 also shows the standard deviation of regional spectral RH feedbacks and RH changes among the 16 GCMs. Comparing the magnitude of the standard deviation to the model ensemble mean can help reveal the consistency of RH feedbacks or RH changes among GCMs. From 800 to 1200 cm^{-1} , the ensemble mean of spectral RH feedbacks is larger than the standard

deviation in the Southern Hemisphere high latitudes but this is not the case in the Northern Hemisphere. Correspondingly, between 600 and 700 hPa there is a large spread of RH changes among GCMs in the Northern Hemisphere. This can be seen from the right column of Fig. 5 as the ensemble mean of RH changes is smaller than standard deviation in the Northern Hemisphere.

Figures 6a and 6b, in a Taylor diagram style, summarize how well our inversion of spectral radiative feedback can render the vertical profile of RH changes for each individual GCM. The performances of inversion techniques, measured in a Taylor diagram manner (correlation for pattern matching and standard deviation for magnitude matching), are similar for most GCMs. First, correlations between the retrieved profiles and actual ones range from 0.7 to 0.9, suggesting that our inversion can generally retrieve the vertical distribution of RH changes from the spectral RH feedbacks. Second, the ratio of standard deviations of retrieved RH changes to actual changes is smaller than 1 in all GCMs with one

FIG. 5. (left) Model ensemble mean (black line) and standard deviation (red line) of regional spectral RH feedbacks among 16 GCMs in the high-latitude (a) Southern Hemisphere and (b) Northern Hemisphere. (right) Model-mean profiles of regional RH changes from the years 1–20 to years 60–80 output from the experiments with a 1% CO_2 increase per year in 16 GCMs (red line), retrieved from the regional spectral RH feedbacks by the constrained inversion method (black line) and by the truncated SVD method (blue line) in the regions corresponding to the left column. The standard deviation of actual profiles of regional RH changes among the 16 GCMs (corresponding to the red line) is shown by a red dashed line.

exception. A possible reason is that our inversion tends to overly smooth the vertical variation of RH changes.

2) TROPICAL ATLANTIC (5° – 20°S AND 5° – 20°N , 300° – 350°E)

Similar to Fig. 5, Fig. 7 shows the ensemble mean of regional spectral RH feedbacks for the tropical Atlantic in both hemispheres. Compared to Fig. 5, the spectral features here are noticeably different. In most models, spectral RH feedbacks are negative across the whole spectrum. Moreover, in the tropical Atlantic, the contribution from 800 – 1200 cm^{-1} to the broadband RH feedback strength is comparable to those from 60 – 600 cm^{-1} and 1200 – 2000 cm^{-1} . These spectral features imply that 1) RH changes are negative at almost all levels in most models and 2) the RH changes in the planetary boundary layer and in the free troposphere contribute comparably to the changes of TOA longwave flux. These inferences are quantitatively corroborated by the retrieval results shown in the right column of Fig. 7. The retrievals show that the

ensemble-mean RH change is indeed negative through the entire troposphere and there are two peaks of RH reduction, one in the boundary layer and the other in the upper troposphere above 400 hPa .

Compared to the RH feedbacks in the high latitudes, there is a large spread among GCMs in the tropical Atlantic. In the left column of Fig. 7 the magnitude of the standard deviation is comparable to the model ensemble mean over many frequency regions, noticeably near 60 cm^{-1} (sensitive to emissions from the upper troposphere), near 600 cm^{-1} (sensitive to emissions from 500 – 700 hPa), and at 800 – 1200 cm^{-1} (sensitive to surface emission). These suggest large intermodel spreads for the RH changes in the upper troposphere, in the layer of 500 – 700 hPa , and in the planetary boundary layer for the tropical Atlantic. The actual standard deviations shown in the right column confirm such an inference about the intermodel spread.

The evaluations of our retrieved profiles of RH changes for each GCM are shown in Figs. 6c and 6d.

FIG. 6. (a)–(e) Taylor diagrams to evaluating retrieved profiles of regional RH changes in the 16 GCMs between years 60–80 and years 1–20 of the 1% CO_2 increase per year simulation. The distance between each point and the point labeled “Obs” as illustrated in (a) is a measure of how the retrieved profiles in each model reproduce the true RH changes. The correlation coefficient (similarity between the retrievals and true values) is related to the azimuthal angle; the ratio of standard deviation of retrievals to the true values is proportional to the radial distance from the origin. The retrieved profiles of RH change from regional spectral RH feedbacks are obtained by the constrained inversion method (diamond) and by the truncated SVD method (circle). The color demonstrates the root-mean-square deviation from true RH changes in 16 GCMs.

FIG. 7. As in Fig. 5, but for the tropical Atlantic. In the left column, the standard deviation is multiplied by -1 for the convenience of comparison.

The correlations between our retrieved profiles and actual ones are generally in the range of 0.7–0.9. However, for several models the inversion of spectral RH feedbacks poorly reproduces the actual RH changes when the correlations are smaller than 0.7. Moreover, for most models our inversion overestimates the magnitude of the vertical RH changes (the ratio of retrievals to actual ones is larger than 1). A possible reason for these biases is that the linearity assumption for retrieving mentioned at the beginning of section 3b is not applicable to the tropical Atlantic. Further discussion about this can be found in appendix B. Although the nonlinearity impedes an accurate inversion from mean spectral RH feedback to mean RH changes, Fig. 7 still shows that the spectral decomposition of broadband RH feedback can reveal reasonable information about vertical features of RH changes.

3) DEEP TROPICAL PACIFIC (5°S–5°N, 200°–250°E)

Similar to Fig. 5, Fig. 8 shows the ensemble mean of the spectral RH feedbacks over the deep tropical Pacific. The feedback is positive across the entire spectrum. The

spectral contribution from 800–1200 cm^{-1} to the broadband RH feedback is comparable to that from 60 to 600 cm^{-1} . From 60 to 600 cm^{-1} , the spectral RH feedback monotonically increases with frequency. Note, from 60 to 600 cm^{-1} , the height of maximum sensitivity of TOA spectral flux to RH change monotonically descends from the upper to the middle troposphere (refer to Fig. 1). This is different from the case of the high latitudes, where the peak of spectral RH feedback in the far IR is between 300 and 400 cm^{-1} . These spectral features imply that, in the deep tropical Pacific, the RH changes are positive at almost all levels in the troposphere and there is considerable contribution from the middle-tropospheric RH changes to the broadband RH feedbacks. These inferences are confirmed by the profiles of RH changes in the right column of Fig. 8. The change in RH indeed peaks at 500 hPa, lower than the peak for the high-latitude RH change (Fig. 5).

GCMs agree to a very large extent on the RH feedbacks in the deep tropical Pacific. The ensemble mean of spectral RH feedbacks is larger than the standard deviation over

FIG. 8. As in Fig. 5, but for the deep tropical Pacific.

almost the entire spectrum, especially in $400\text{--}600\text{ cm}^{-1}$ and $800\text{--}1200\text{ cm}^{-1}$. Thus the vertical RH change in the most of troposphere should be consistent among GCMs, which is confirmed by the plots in the right column of Fig. 8.

Evaluations of our retrieved RH changes for individual GCMs are shown in Fig. 6e. Inversion performance is generally satisfactory. For most GCMs, the correlation between our retrieved profiles and actual ones is around 0.9 with the ratio of standard deviations being close to one. Among three regions examined here, the inversion technique performs the best for the deep tropical Pacific. In other words, in the deep tropical Pacific the spectral decomposition of broadband RH feedbacks is most linearly proportional to the changes in RH vertical profile.

4. Conclusions and discussion

We use the spectral radiative kernel technique to derive spectrally resolved RH feedbacks for 16 GCMs in the CMIP5 archives. As expected, globally averaged broadband RH feedback is nearly zero for the GCMs. However, after spectral decomposition of broadband RH feedback, wide discrepancies are revealed among GCMs. Further spatial decomposition shows that regional broadband RH feedbacks are no longer nearly zero as is the global average. Spatial patterns of broadband RH feedbacks vary noticeably with the spectral region. A part of the far-IR band, $60\text{--}300\text{ cm}^{-1}$, exhibits positive RH feedbacks in the high latitudes and the deep tropical Pacific but negative RH feedbacks in the tropical Atlantic. The other part of the far-IR band ($400\text{--}600\text{ cm}^{-1}$) and the window region ($800\text{--}1200\text{ cm}^{-1}$) show statistically significant positive RH feedbacks in the deep tropical Pacific. The nearly zero global broadband RH feedback is a result of spatial compensation and spectral compensation.

We further utilize regional-averaged RH radiative kernels to analyze regional spectral RH feedbacks in the high latitudes, the tropical Atlantic, and the deep tropical Pacific, regions where GCMs produce RH feedbacks significantly different from zero. This exercise is used to further explore whether useful information about vertical feature of RH changes can be extracted from the spectral decomposition of heavily averaged fluxes. We retrieve profiles of RH changes using two approaches and check the consistency of retrievals with the actual ones from the GCM output. Although our retrieving methods do not take nonlinearity error into account, the results from both methods are consistent and demonstrate that RH changes in different parts of the troposphere can be attributed from the spectral decomposition of RH fluxes. Such additional information cannot be gleaned from broadband RH feedback studies alone. Further study on improving retrieving method possibly provides more accurate vertical profiles of mean RH changes.

Spectral decomposition of RH feedbacks reveals considerable intermodel differences that may be cancelled in the integration over broadband. The spectral feature of RH feedbacks is tightly related to the vertical feature of RH changes even averaged over a large climate domain. These advantages permit stricter evaluation of feedbacks in GCMs against observations. If we can separate the spectral signal of RH changes combined with changes in other feedback variables from observed TOA longwave spectral flux (Huang et al. 2010a,b; Kato et al. 2014), it is possible to provide an additional constraint, that is, a spectral constraint to climate models given the recent accumulation of high-quality spectral radiance observations by the Atmospheric Infrared Sounder (AIRS; Chahine et al. 2006), the Infrared

FIG. A1. The first six components of left singular vectors from the SVD of globally averaged RH radiative kernels, with their corresponding eigenvalues indicated.

Atmospheric Sounding Interferometer (IASI; Hilton et al. 2012), and the Cross-track Infrared Sounder (CrIS; Han et al. 2013).

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APPENDIX A

Two Linear Inversion Methods

To infer $\mathbf{x}$ from $\mathbf{y}$ when $\mathbf{y}$ is approximated by $\mathbf{K}\mathbf{x}$, we implement two methods to invert $\mathbf{K}$ in this paper. First is the constrained inversion method (Twomey 1977). By this method,

$$\mathbf{x} = (\mathbf{K}^T \mathbf{K} + \lambda \mathbf{I})^{-1} \mathbf{K}^T \mathbf{y}, \quad (\text{A1})$$

where $\mathbf{I}$ is the identity matrix, and λ can be obtained by minimizing the root-mean-square (RMS) deviation after calculating the RMS between the retrieved $\mathbf{x}$ and

FIG. A2. The first six components of right singular vectors from the SVD of globally averaged RH radiative kernels, with their corresponding eigenvalues indicated.

true values as a function of λ . In this paper, the $\mathbf{K}$ is the spectral RH radiative kernel that relates the TOA flux change $\mathbf{y}$ to the change of RH profile $\mathbf{x}$.

Another method is the truncated singular value decomposition (SVD) method (Hansen 1990). In SVD decomposition, we express the RH Jacobian $\mathbf{K}$ in the form

$$\mathbf{K} = \mathbf{U}\mathbf{\Lambda}\mathbf{V}^T, \quad (\text{A2})$$

where $\mathbf{\Lambda}$ is the diagonal matrix of singular values and $\mathbf{U}$ and $\mathbf{V}$ are orthogonal matrices of its left and right singular vectors. Using this eigenvector basis, the $\mathbf{K}^{-1}$ can be approximately by

$$\mathbf{K}^{-1} = \mathbf{V}_t \mathbf{\Lambda}_t^{-1} \mathbf{U}_t^T, \quad (\text{A3})$$

where the subscript t means that only the t largest eigenvalues and their corresponding eigenvectors are remained. The dropped eigenvalues and eigenvectors

would greatly contribute to error terms. The term $\mathbf{K}^{-1}$ can relate the RH spectral feedbacks to profiles of RH changes by multiplying $\mathbf{K}^{-1}$ with RH spectral feedbacks and surface temperature change. Figures A1 and A2 show the first six left singular vectors in $\mathbf{U}$ and right singular vectors in $\mathbf{V}$ when their corresponding eigenvalues are in descending order. From the first singular vector in $\mathbf{U}$ and $\mathbf{V}$, negative RH changes through the whole troposphere can be inferred from negative radiation changes across the whole spectrum when contributions in the far-IR (60–600 cm^{-1}) and window regions (800–1200 cm^{-1}) are comparable to each other. From the second singular vector in $\mathbf{U}$ and $\mathbf{V}$, an increase of RH in the lower troposphere can be inferred from positive radiation changes in the far IR, while a decrease in upper-troposphere RH can be inferred from negative radiation changes in window regions. For the inversion in this paper, we use first five singular vectors as well as eigenvalues in the high latitudes and six in the other regions.

FIG. B1. The spatial average of TOA radiance changes due to RH perturbations, i.e., $\overline{\mathbf{K}} \times \Delta \mathbf{RH}$ and $\overline{\mathbf{K}} \times \overline{\Delta \mathbf{RH}}$, in the (a) high latitudes in the Southern Hemisphere (60° – 90° S), (b) high latitudes in the Northern Hemisphere (60° – 90° N), (c) the tropical Atlantic in the Southern Hemisphere (5° – 20° S, 300° – 350° E), (d) the tropical Atlantic in the Northern Hemisphere (5° – 20° N, 300° – 350° E), and (e) the deep tropical Pacific (5° S– 5° N, 200° – 250° E).

FIG. B2. The temporal average of TOA radiance changes due to RH perturbations, i.e., $\overline{K \times \Delta RH}$ and $\overline{K \times R H}$, in the five regions explained in Fig. B1.

APPENDIX B

An Assumption in Retrieving the Average Changes of RH Profiles from the Average Changes of TOA Fluxes

In section 3b we try to retrieve the regional 20-yr average of RH changes $\overline{\Delta RH}(\text{lat}, \text{lon}, \text{time})$ from the regional average of TOA flux changes $\overline{\Delta R}(\text{lat}, \text{lon}, \text{time})$ due to the RH perturbations. (An overbar represents averaging over all variables in the parentheses.) The retrieval is performed through the inversion of regional average of spectral RH kernel $\overline{K}(\text{lat}, \text{lon}, \text{time})$. The regional average of TOA flux changes $\overline{\Delta R}(\text{lat}, \text{lon}, \text{time})$ is obtained in two steps: first we multiply the RH kernel $K(\text{lat}, \text{lon}, \text{time})$ by the RH perturbation $\Delta RH(\text{lat}, \text{lon}, \text{time})$ to get the TOA flux changes $\Delta R(\text{lat}, \text{lon}, \text{time})$ on each grid box (lat, lon) for every month (time) in 20 years; second we spatially and temporally average $\Delta R(\text{lat}, \text{lon}, \text{time})$ to get the $\overline{\Delta R}(\text{lat}, \text{lon}, \text{time})$. Thus one assumption must be valid before the retrieval:

$$\overline{\Delta R} = \overline{K \times \Delta RH} \cong \overline{K} \times \overline{\Delta RH}. \quad (\text{B1})$$

The two left sides are the average TOA flux changes $\overline{\Delta R}(\text{lat}, \text{lon}, \text{time})$ on which we would perform inversion, and $\overline{\Delta RH}$ on the right side is the average change of RH profiles that we would like to obtain. The assumption for retrievals is that the order of multiplying and averaging would affect little the ultimate results. The averages of TOA flux changes due to RH perturbations for a given geographical region are well approximated by the product of the average of spectral RH kernels and the average of RH perturbations over the same region.

To test the assumption, we perform the following experiments based on the RH output from GFDL CM3 in each of the five regions in section 3b. First, we test whether Eq. (B1) is valid for spatial average. We calculate the annual mean perturbations of RH profiles $\overline{\Delta RH}(\text{lat}, \text{lon})$ in one year and the annual mean spectral RH kernel $\overline{K}(\text{lat}, \text{lon})$ on each grid box. Then we perform averaging $\overline{K}(\text{lat}, \text{lon})$, $\overline{\Delta RH}(\text{lat}, \text{lon})$, and $\overline{K(\text{lat}, \text{lon}) \Delta RH(\text{lat}, \text{lon})}$ over all grid boxes in the chosen region. Second, we test whether Eq. (B1) is valid for the temporal average in a similar way. We calculate the monthly regional average of perturbations of RH profiles in one year $\overline{\Delta RH}(\text{mon})$ and the monthly regional average of spectral RH kernel $\overline{K}(\text{mon})$. Then we calculate the annual mean $\overline{K}(\text{mon})$, $\overline{\Delta RH}(\text{mon})$, and $\overline{K(\text{mon}) \Delta RH(\text{mon})}$ over the 12 months. The average TOA flux changes due to RH perturbations in two calculation orders, that is, $\overline{K \times \Delta RH}$ (first multiply K and ΔRH and then average) and $\overline{K} \times \overline{\Delta RH}$ (first average K

and ΔRH and then multiply) for spatial average and temporal average, are separately shown in Figs. B1 and B2 in the five regions. Over the tropical Pacific Ocean, whatever the operation order, the two lines almost overlap each other. In the high latitudes on both hemispheres, to a large degree, Eq. (B1) is valid. However, over the tropical Atlantic Ocean, the operation order matters. The average TOA flux changes by $\overline{K \times \Delta RH}$ and $\overline{K} \times \overline{\Delta RH}$ are not consistent with each other, which means that our retrieved regional average of RH changes are probably deviated from the true changes.

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