Regional variation of the tropical water vapor and lapse rate feedbacks

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Abstract The global and tropical mean water vapor and lapse rate radiative feedbacks are anticorrelated across contemporary climate models. Hence, despite substantial uncertainty in both, uncertainty in total clear-sky modeled radiative feedback is small compared with other sources of feedback spread. Previous work has demonstrated that no such correlation exists when grid point water vapor and lapse rate feedbacks are considered within one model. Here we show that robust physical processes nevertheless determine significant aspects of both the water vapor and particularly the lapse rate feedbacks within the tropics. The lapse rate feedback increases with surface temperature change because the tropical troposphere cannot maintain strong temperature gradients. The water vapor feedback increases weakly with surface temperature over tropical ocean but slightly decreases over land, associated with moisture availability. Water vapor feedback is more strongly related to precipitation changes, increasing most strongly in the heaviest precipitating regions and least in the weakest.

1. Introduction

The concepts of radiative forcing and feedback are useful for understanding climate change. A small perturbation to the factors that determine mean climate state, such as a change in atmospheric CO2 or insolation, leads to a small change in top of atmosphere (TOA) radiative flux that is approximately related to subsequent climate change via

\[ \Delta N_G = \Delta Q_G - \lambda_G \Delta T_G. \] (1)

Here \( \Delta N_G \), is global mean net downward TOA flux, \( \Delta Q_G \), is the global mean “radiative forcing”—the perturbation in TOA flux caused by changing the factors determining climate state and independent of surface temperature change, \( \lambda_G \) is the global mean climate feedback parameter, which determines the radiative response of climate per Kelvin surface warming, and \( \Delta T_G \) is global mean surface temperature change.

This “forcings and feedbacks” perspective is helpful for several reasons. With some exceptions, different forcings with similar geographical patterns yield similar values of \( \lambda_G \) in the same general circulation model (GCM), but the same forcing applied to different GCMs gives different \( \lambda_G \). Hence, GCMs are associated with a value of \( \lambda_G \) that describes their equilibrium \( \Delta T_G \) to forcing to zeroth order [e.g., Hansen et al., 2005]. If reasons for model disagreement are sought, \( \lambda_G \) may be separated into components. A typical breakdown is \( \lambda = \lambda_P + \lambda_{LR} + \lambda_q + \lambda_{alb} + \lambda_{adi} \), where \( \lambda_P \) is the “Planck” feedback, which is the climate response in the absence of feedbacks, calculated by imposing local surface warming at every vertical level in the atmosphere, \( \lambda_{LR} \) is the lapse rate (LR) feedback, caused by the difference between true GCM atmospheric temperature change and Planck temperature change, \( \lambda_q \) is the water vapor (q) feedback, which occurs in response to changes in water vapor concentration, \( \lambda_{alb} \) is the surface albedo feedback, caused by changes in surface solar shortwave reflection, and \( \lambda_{adi} \) is the cloud feedback, which occurs due to changes in cloud [e.g., Wetherald and Manabe, 1988; Colman, 2003]. Similar forcing components may be defined when processes have effects independent of \( \Delta T_G \) [e.g., Lambert and Faull, 2007; Gregory and Webb, 2008; Colman and McAvaney, 2011], but these are often small for clear-sky processes [e.g., Colman and McAvaney, 2011; Andrews et al., 2012]. Hence, where the xth forcing component is negligible, the xth feedback component may be written \( \lambda_x = \frac{\Delta N_x}{\Delta T_G} \).

Forcings and feedbacks have also been defined regionally [e.g., Boer and Yu, 2003a, 2003b]. The approach is necessary for cloud studies, where different cloud regimes show very different behavior [e.g., Senior and...
Mitchell, 1993; Bony and Dufresne, 2005; Webb et al., 2006; Ogura et al., 2008). Recently, Taylor et al. [2011a] examined the regional structure of the tropical $\lambda_q$ and $\lambda_{LR}$ feedbacks in the National Center for Atmospheric Research Community Climate System Model version 3 (CCSM3), motivated by the anticorrelation found between global mean $\lambda_q$ and global mean $\lambda_{LR}$ across GCMs. Global mean anticorrelation occurs because GCMs tend to maintain near constant relative humidity (RH) under climate change [e.g., Ingram, 2010; Held and Shell, 2012]. Models with relatively large tropospheric warming per degree $\Delta T_q$, therefore show not only large negative $\lambda_{LR}$ but also large positive $\lambda_q$. Hence, although ensembles of models frequently show large ranges of $\lambda_q$ and $\lambda_{LR}$, the range of $\lambda_q + \lambda_{LR}$ is smaller, usually leaving clouds as the main source of inter-model difference [e.g., Colman, 2003; Dufresne and Bony, 2008]. Looking at tropical grid point data within one model, Taylor et al. [2011a] found that the anticorrelation between $\lambda_q$ and $\lambda_{LR}$ does not occur. In this paper, we show that modeled tropical $\lambda_q$ and $\lambda_{LR}$ are nevertheless constrained by simple physical processes and discuss the implications for climate feedback studies. We describe the constraints in section 2, the methods and model data we use in section 3, our results in section 4 and present a short discussion and summary in section 5.

2. Causes of Regional Variation of the Tropical Water Vapor and Lapse Rate Feedbacks

Globally, the lapse rate feedback can be thought of as tropospheric amplification of surface warming that occurs because moist processes cause the troposphere to warm more than the surface. The amplification occurs largely in the tropics and is opposed in the global mean by relatively weak atmospheric warming with respect to the surface at high latitudes [e.g., Crook et al., 2011; Taylor et al., 2013].

Within the tropics, however, it is unhelpful to think of regional variations in $\lambda_{LR}$ as regional variations in surface warming amplification. Above about 700 hPa, tropical tropospheric temperatures [e.g., Neelin and Held, 1987; Sobel and Bretherton, 2000] and temperature variability [e.g., Yulaeva and Wallace, 1994; Chiang and Sobel, 2002] are more geographically uniform than at the surface, as the tropical troposphere cannot maintain substantial horizontal pressure and temperature gradients because the local Coriolis parameter is small. The surface, meanwhile, is less affected by this constraint and instead shows a large range of $\Delta T$, as different parts of the surface and atmospheric boundary layer have very different properties. Most notably, the land tends to warm more than the ocean due to processes connected to decreasing RH over land and near constant RH over ocean [Manabe et al., 1991; Joshi et al., 2008; Dong et al., 2009; Fasullo, 2010]. We show these differences for land and ocean surface and midtropospheric warming in CO$_2$-driven climate model simulations, Figure 1a. Taking as our model tropically uniform tropospheric temperature change and strongly varying surface temperature change, we therefore expect grid point lapse rate-driven net downward radiative flux anomalies, $\Delta N_{LR}$, to increase with grid point surface temperature anomalies, $\Delta T$. The most negative values should be found over the least warming ocean regions and the most positive values over the most warming land regions.

Expected behavior of the grid point water vapor feedback, $\lambda_q$, is less clear. Unlike temperature anomalies, tropospheric humidity is not communicated by atmospheric wave activity and significant tropical humidity gradients exist. RH in the tropical oceanic boundary layer is usually around 80% and changes little with warming. Over land, moisture availability can be limited: boundary layer RH may be $< 80\%$ and can decrease further with climate change [Joshi et al., 2008; Byrne and O’Gorman, 2013]. Away from the boundary layer, the humidity of a parcel of tropical air may be approximately determined by the lowest temperature experienced since it was last saturated by deep convection [Sherwood et al., 2006]. This tends to predict fairly uniform upper tropospheric RH but higher midtropospheric RH in regions of convection than in regions of subsidence. Other processes, such as clear-sky mixing of humidity [e.g., Tompkins and Craig, 1998] and hydration of the lower troposphere by shallow convection [e.g., Brient and Bony, 2012] are also important, but the Sherwood prediction of near constant RH under warming is quite successful in a GCM [Sherwood et al., 2009].

Hence, we should expect more strongly warming regions to be associated with larger increases in boundary layer and midtropospheric water vapor and therefore a larger water vapor-driven net downward TOA flux anomaly, $\Delta N_q$. (These changes are not as important to water vapor feedback as upper tropospheric humidity [Randall et al., 2007], but substantial geographical humidity variation is not predicted in the upper troposphere.) However, the effect of warming may be countered over land by decreases in boundary layer
RH that limit the supply of water vapor to the atmosphere aloft. Changes in land and ocean humidity in our climate model experiments are shown in Figure 1b. Because the warmest land regions are not necessarily associated with the strongest convection and because initially colder regions may warm more than initially warmer regions [e.g., Knutson and Manabe, 1995], relating water vapor feedback to ΔT may not work well. An alternative is to track changes in ΔNq as a function of changes in precipitation, as these better reflect changes in the convective processes associated with atmospheric hydration. We expect regions of increasing precipitation to show increases in ΔNq and regions of decreasing precipitation to show decreases in ΔNq.

3. Data and Methods

We take data from the HadSM3 [Pope et al., 2000], Model for Interdisciplinary Research on Climate (MIROC3.2) [Hasumi and Emori, 2004; Yoshimori et al., 2009], and CCSM3 [Collins et al., 2004, 2006] models. For HadSM3 and MIROC3.2, we have stable "control" simulations of preindustrial conditions and "2 × CO₂" simulations, in which CO₂ concentration is instantaneously doubled to twice preindustrial values at the beginning of the run and climate warms to a new equilibrium. HadSM3 and MIROC3.2 are "slab models" that have shallow, thermodynamics-only oceans that must be heat flux corrected at the surface to compensate for the lack of ocean dynamics and hence produce a satisfactory control climate. Evolution to the 2 × CO₂ equilibrium is rapid compared with a full simulation, but aspects of climate response related to changes in ocean dynamics are not captured, which limits the realism of the results, particularly at high latitudes. For HadSM3 we have one 19 year control run and one 18 year 2 × CO₂ run. We also have data for 62 GCM control 2 × CO₂ pairs based on HadSM3 but perturbed in their parameterization of subgrid-scale atmospheric processes to explore modeling uncertainty, taken from the Quantifying Uncertainty in Model Predictions (QUMP) project [Murphy et al., 2004; Webb et al., 2006]. All QUMP runs are 20 years or longer. For MIROC3.2 we have one 30 year control run and one 50 year 2 × CO₂ run. For CCSM3, we take data from a more realistic future A1B scenario run [Nakicenovic et al., 2000]. Climate change is analyzed by comparing 2100–2110 with 2000–2010, following Taylor et al. [2011a, 2011b]. CCSM3 features a full ocean simulation, meaning that changes in climate due to ocean dynamics are captured and that climate evolves on a more realistic timescale. The model is not at equilibrium in either analysis period (TOA flux difference for the two periods is ΔNq = 0.991 W m⁻²). ΔQ for 2100–2110 minus 2000–2010 is 2.28 W m⁻².

We calculate clear-sky ΔNq and ΔNLR using the partial radiative perturbation (PRP) method of Wetherald and Manabe [1988] and Colman and McAvaney [1997]. (All-sky results are similar and therefore not shown.)
Figure 2. Grid point water vapor (blue) and lapse rate (red) ΔN as a function of ΔT for (a) HadSM3, (b) MIROC, and (c) CCSM3. Areas of darker color indicate a higher density of points. Data are normalized to account for the different number of points that arise from different model resolutions. Ninety percent of ocean points lie to the left of the green dashed vertical line; 90% of land points lie to the right of the purple dashed vertical line. The straight lines in Figure 2a are regression fits to the HadSM3 idealized calculations. The blue line is for constant RH; the red line is for uniform atmos ΔT. (d) A summary of water vapor (blue) and lapse rate (red) ΔN in all the GCMs. Tropical means are represented by points: small crosses are QUMP, large squares are HadSM3, large diamonds are MIROC, and large triangles are CCSM3. The straight lines are regression fits to tropical grid point data that span the 10–90% ΔT range for each model. Water vapor results are presented separately for ocean (left-hand increasing lines) and land (right-hand decreasing lines). Lapse rate results are for all tropics. Heavy lines are used for HadSM3, CCSM3, and MIROC and pass through the corresponding tropical mean plotting symbol in each case. Light lines are used for selected QUMP models. Other QUMP models show similar results but are omitted for clarity. All results are last 10 year mean differences for 30°N–30°S apart from CCSM3, which are 2100–2110 minus 2000–2010. Note the different x and y scales on Figure 2d.

PRP due to a climate change component is calculated by subtracting control radiative fluxes from fluxes calculated for control run conditions but with the component in question taken from the 2 × CO₂ run. (For CCSM3, 2000–2010 replaces control and 2100–2110 replaces 2 × CO₂.) Our PRP calculations are “two sided” meaning that the PRP found when a component is perturbed from control to 2 × CO₂ conditions, while other components are held at control values is averaged with the PRP found when the component is held at control conditions while the other components are perturbed to 2 × CO₂ conditions, following Colman and McAvaney [1997]. This minimizes biases in our calculations that may occur due to time correlation of meteorological fields. We analyze only longwave fluxes, which account for the entirety of ΔN_{LR} and about 90% of ΔN_{q}. PRP calculations were made using instantaneous input data at each 3-hourly time step for MIROC3.2 and at every fifth time step (15-hourly) for HadSM3 [Edwards and Slingo, 1996]. Because available data for CCSM3 and QUMP are limited, we are forced to use monthly mean input for CCSM3 and annual mean input for QUMP. In the worst case QUMP calculations, the tropical mean error associated with using annual mean data rather than 15-hourly data was estimated to be around 0.05 W m⁻²K⁻¹ for one run where 15-hourly snapshots were available, small compared with the magnitude of results. Grid point errors were up to 10 times bigger in some areas (see section 1 in Text S1 in the supporting information). This limitation must be remembered when interpreting our QUMP results.
Finally, for HadSM3, we have two highly idealized $2 \times CO_2$ calculations that demonstrate responses predicted by simple theory. Each is identical to HadSM3 $2 \times CO_2$, except: (i) “Uniform atmos $\Delta T$” sets tropical tropospheric warming with respect to the control on each vertical level equal to tropical mean tropospheric warming on that level. It therefore provides a lapse rate feedback that is constrained to behave as we anticipated in section 2. (ii) “Constant RH” determines $2 \times CO_2$ scenario specific humidity by maintaining control RH in the warmer climate. It therefore provides the response that occurs due to atmospheric warming in the absence of changes in RH and the distribution of convection.

### 4. Results

We now explore forced changes in GCM-modeled fields for last 10 year mean minus control mean in HadSM3, MIROC, and QUMP, and 2100–2110 minus 2000–2010 in CCSM3. Figure S2 in the supporting information shows that the land surface generally warms more than the ocean surface, with largest increases over arid regions of the Sahara, South Africa, and Australia. HadSM3 also shows large warming over the Amazon basin. Tropical mean warming is 2.7 K in HadSM3, 3.2 K in MIROC, and 2.9 ± 1.5 K in QUMP, where the range is 2 standard deviations about the ensemble mean. Warming in CCSM3 is weak at 1.8 K, as the radiative forcing is less than that for $2 \times CO_2$ and because the model has not yet reached equilibrium. Aloft, changes in tropical temperature are more geographically uniform than at the surface. In HadSM3, for example, mean warming at 500 hPa is 3.5 K, showing amplification compared with the surface overall, but the 10–90% range is 3.1–4.1 K at 500 hPa, around half the 1.9–3.9 K found at the surface.

Maps of $\Delta N_q$ and $\Delta N_{LR}$ in our model runs, Figures S3 and S4 in the supporting information, are similar to those found by other studies [e.g., Soden et al., 2008; Taylor et al., 2011a]. Figure 2 shows $\Delta N_q$ and $\Delta N_{LR}$ against grid point temperature change, $\Delta T$. We label the gradients of these relationships $v_q$ and $v_{LR}$, respectively. Ordinary least squares regression shows that $v_{LR}$ is similar in all our models and slightly more positive over land than ocean, Table 1. Values of the coefficient of determination, $R^2$, are above 0.75 in all cases, apart from in CCSM3 over ocean where the value is 0.48, suggesting that the relationship is quite linear. Results for the uniform atmos $\Delta T$ calculation are comparable, Table 1 and straight red line on Figure 2a, suggesting that uniform tropical tropospheric warming provides a guide to behavior in the GCM experiments. $v_{LR}$ is greater for uniform atmos $\Delta T$ than HadSM3, however, presumably because a weak relationship between surface and 500 hPa warming (correlation = 0.26) reduces spatial variation of the lapse rate feedback in HadSM3.

Turning to the water vapor feedback, $v_q$ is positive over ocean and slightly negative over land in all models, Table 1. $R^2$ is near 0.2 in all cases, suggesting that regional variation of $\Delta N_q$ depends on more than $\Delta T$. GCM behavior is not captured by the constant RH calculation, which shows only weak differences in water vapor feedback as a function of temperature, Table 1 and straight blue line in Figure 2a. The near time invariance

| Table 1. Gradients in Last 10 Year Mean Grid Point Tropical (30°N–30°S) Net Downward Radiative Fluxes, $\Delta N$, as a Function of Tropical Grid Point Temperature Changes in W m$^{-2}$ K$^{-1}$, v, and as a Function of Tropical Grid Point Precipitation Change in W m$^{-2}$ mm$^{-1}$ d$^{-1}$, $\xi$ | Model | $v$ (W m$^{-2}$ K$^{-1}$) | $\xi$ (W m$^{-2}$ mm$^{-1}$ d$^{-1}$) |
|---|---|---|---|
| HadSM3 | $2.52 \pm 0.24$ | $1.90 \pm 0.08$ |
| HadSM3 (constant RH) | $0.55 \pm 0.11$ | $1.24 \pm 0.04$ |
| HadSM3 (uniform atmos $\Delta T$) | $3.23 \pm 0.13$ | $2.06 \pm 0.08$ |
| CCSM3 | $3.53 \pm 1.48$ | $2.19 \pm 0.44$ |
| MIROC | $2.58 \pm 0.26$ | $1.58 \pm 0.16$ |
| QUMP | $-0.96 \pm 0.59$ | $1.85 \pm 0.84$ |

$^a$Errors are two standard deviations based on residual variance, apart from QUMP where they are two standard deviations of the range of central estimates.
Figure 3. (a–c) Grid point $\Delta N_q$ as a function of grid point $\Delta P$. Last 10 year mean for 30°N–30°S for HadSM3 in Figure 3 and MIROC in Figure 3b and 2100–2110 – 2000–2010 for CCSM3 in Figure 3c. Areas of darker color indicate a higher density of points. Data are normalized to account for the different number of points that arise from different model resolutions. (d) $\Delta N$ composite on precipitation percentile normalized by $\Delta T_T$, for comparability across models. Large black squares and black solid line are HadSM3, large black crosses and dashed line are HadSM3 constant RH, large red diamonds and line are MIROC, large blue triangles and line are CCSM3, and thin grey lines are QUMP. (e) Changes in RH as a function of pressure composited on precipitation percentile. Changes in RH, $\Delta RH$ on 21°3% are red, $-1.5% < \Delta RH < -0.5%$ are yellow, $-0.5% < \Delta RH < 0.5%$ are white, $0.5% < \Delta RH < 1.5%$ are pale blue, and $1.5% < \Delta RH$ are dark blue.

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Precipitation features change their location in addition to their intensity under climate change [e.g., Chadwick et al., 2013], meaning that $\xi_q$ measures shifts in the location as well as the strength of the water vapor radiative effect. We therefore prepare “precipitation composites” of $\Delta N_q$ by finding the difference between $2 \times CO_2$ and control states for the same percentiles of precipitation intensity. Figure 3d shows the composites for our models where grid points are averaged across 10 equal population bins whose mean precipitation climbs from left to right. We find that $\Delta N_q$ is greater in general for more strongly precipitating bins and that behavior across models is quite similar per K tropical mean temperature change, $\Delta T_T$. Gradients are 0.010 ± 0.004 W m⁻² K⁻¹%⁻¹ in HadSM3, 0.010 ± 0.003 W m⁻² K⁻¹%⁻¹ in MIROC, 0.015 ± 0.003 W m⁻² K⁻¹%⁻¹ in CCSM3, and 0.013 ± 0.007 W m⁻² K⁻¹%⁻¹ across the QUMP ensemble. Errors are

of the land-sea surface warming ratio [e.g., Lambert et al., 2011] and the troposphere surface warming ratio, Figure 1, means that similar slab model results are found at equilibrium and during warming from control to $2 \times CO_2$ conditions (see section 5 in Text S1 in the supporting information).

Figures 3a–3c show $\Delta N_q$ against grid point precipitation change, $\Delta P$, in HadSM3, MIROC, and CCSM3. The gradients of these relationships, which we label $\xi_q$, are positive and similar for land and ocean and similar across models apart from in CCSM3, where values are smaller, Table 1. $R^2$ is larger than for $\Delta N_q$ against $\Delta T$ in every case. Over ocean it is always above 0.4, apart from in CCSM3 and in one QUMP run; over land $R^2$ values are smaller, typically around 0.3, but still slightly improved compared with the $\Delta T$ case.

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two standard deviations. Results for constant RH show a similar structure but a smaller increase across precipitation percentiles of 0.006 ± 0.001 W m⁻² K⁻¹ %. This behavior makes sense when we inspect a composite of RH changes on vertical levels in HadSM3, Figure 3e. Increases in midtropospheric and feedback-crucial upper tropospheric RH are found in the more intense precipitating bins, associated with increases in convective outflow height and increases in midtropospheric RH. Overall, a ΔP based analysis provides a cleaner picture than a ΔT based picture for water vapor feedback. Nevertheless, substantial spread of individual grid points remains unexplained.

5. Conclusion

Associating the climate change-driven grid point tropical water vapor and lapse rate TOA radiative flux anomalies, ΔN_q and ΔN_qR, with their corresponding grid point temperature changes, ΔT, in the HadSM3, MIROC3.2, CCSM3, and QUMP models, explains significant aspects of regional feedback structure. ΔN_q tends to increase with increasing ΔT over oceanic areas and tends to slightly decrease with increasing ΔT over more strongly warming land areas, where moisture supply is limited. ΔN_qR increases robustly with increasing ΔT across the tropics. This is because variations in ΔN_qR are largely due to surface and boundary layer temperature variations rather than free tropospheric temperature variations, which are constrained to be quite uniform by the inability of the tropical atmosphere to maintain strong temperature gradients [e.g., Neelin and Held, 1987; Sobel and Bretherton, 2000]. Hence, more strongly warming surfaces see less negative ΔN_qR. Over the most strongly warming land areas, ΔN_qR may even be positive. As a result, over ocean, variations in ΔN_q and ΔN_qR are weakly correlated (average correlation = 0.18 for HadSM3, MIROC, and CCSM3), and over land they are anticorrelated (average correlation = −0.58). The same is true of the corresponding feedback terms, Δq ≈ ΔN_q/ΔT_R and ΔqR ≈ ΔN_qR/ΔT_R, where ΔT_R is tropical mean surface temperature.

We estimated the gradients of the flux anomaly-surface temperature relationships for ΔN_q and ΔN_qR, termed ν_q and ν_qR, and found them to be similar across models and fairly independent of ΔT_R. ν_q provides a robust description of lapse rate feedback, but ν_q points to a weaker relationship between ΔT and ΔN_q. An improved relationship is obtained if ΔN_q is instead related to changes in precipitation, ΔP. We find that ΔN_q increases more strongly in regions of heavier precipitation, partly explainable if relative humidity remains constant in the warmer climate, but also associated with increases in free tropospheric RH that occur in regions of heaviest precipitation.

Our results do not explain directly the differences between global or tropical mean clear-sky feedbacks in GCMs. Nonetheless, the simple, quite model-independent spatial structures we find are signatures of the physical processes that produce the simulated tropical water vapor and lapse rate feedbacks. These may be simpler to detect with current observing systems than spatial means, because the absolute value of anomalies is less important [Wielicki et al., 2013]. Thus, the focus of our future work is testing whether or not satellite observations yield regional feedbacks that work in the same way.

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