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Relationship between temperature and precipitable water changes over tropical oceans

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[1] We use observations, climate models and reanalysis output to examine the relationship between changes in temperature and changes in precipitable water. In climate models these variables are highly correlated over the tropical oceans, with a similar scaling ratio for interannual and decadal time scales. This result is consistent with the most recently developed satellite datasets. In contrast, scaling rations based either on an earlier version of the satellite measurements or reanalysis show scaling ratios that are inconsistent with models, and are dependent on time scale. These results demonstrate that climate model output is useful for evaluating differences between divergent observational datasets. **Citation:** Mears, C. A., B. D. Santer, F. J. Wentz, K. E. Taylor, and M. F. Wehner (2007), Relationship between temperature and precipitable water changes over tropical oceans, *Geophys. Res. Lett.*, *34*, L24709, doi:10.1029/2007GL031936.

1. Introduction

[2] Observations from earth orbiting satellites play an important role in monitoring climate change over the past few decades [*Solomon et al.*, 2007]. Secular changes in air temperature, surface temperature, sea-ice and cloud extent, precipitation, water vapor, and Earth's radiation budget have all been studied using satellite measurements. For some climate variables (*e.g.*, surface temperature), it is possible to use in situ data to validate long-term trends in satellite measurements [*Comiso*, 2003; *Reynolds et al.*, 2002]. For other variables, the use of in situ data is severely limited by its low quality or sparse coverage.

[3] Consider, for example, lower tropospheric temperature, which has been monitored since November 1978 by a series of microwave radiometers flown on weather satellites. The confidence with which these measurements can be used to assess decadal scale changes in temperature is reduced by uncertainties in characterizing and adjusting for several sources of calibration error [*Christy et al.*, 2003; *Mears et al.*, 2006; *Mears and Wentz*, 2005]. Independent measurements made by radiosondes have been used to help validate the satellite data [*Christy et al.*, 2007]. Unfortunately, the use of radiosonde-based atmospheric temperatures as an absolute reference is limited by both the paucity of observations over the tropical and southern oceans, and the uncertainty caused by poorly documented changes in instrumentation and observing practice. In a recent study, *Randel and Wu* [2006] used the spatial-temporal structure of the discrepancies between satellite and radiosondes measurements to argue that despite the best efforts of researchers to remove inhomogeneities in the radiosonde data [*Lanzante et al.*, 2003a; *Lanzante et al.*, 2003b; *Thorne et al.*, 2005], substantial errors may remain. Alternatively, *Free and Seidel* [2007] argue that part of these discrepancies may be due to errors in the satellite data. Problems with the radiosonde data may be even worse for measurements of water vapor in the lower atmosphere [*Trenberth et al.*, 2005].

[4] In the future, data from satellite sounders may be validated using a yet-to-be-constructed network of high quality reference radiosonde stations [*World Meteorological Organization*, 2007], or with Global Positioning System (GPS) radio occultation measurements available since 2001 [*Kursinski et al.*, 1997]. Such methods, however, cannot be used to validate satellite data for the pre-GPS era. An alternative approach is to compare satellite derived temperatures to a complementary dataset that is expected to be highly correlated with the measurements in question. *Wentz and Schabel* [2000] compared changes in tropospheric and surface temperatures with changes in total column water vapor or "precipitable water" (W), and found strong correlations between all three variables over tropical oceans. *Fu and Johanson* [2004] evaluated the consistency of temperature trends at the surface and in different atmospheric layers, and *Santer et al.* [2005] compared the tropospheric amplification of surface temperature changes in climate models and observations with the amplification behavior inferred from basic theory. In the latter study, model data were used to estimate the ratio of changes in the surface temperature to changes in lower tropospheric temperature (T_{LT}) across timescales. These ratios were then used to evaluate the divergent T_{LT} trends in different observational datasets.

[5] Under the assumption of constant relative humidity, the Clausius-Clapeyron relationship yields a ratio between changes in water vapor and changes in temperature that depends solely on temperature. In order to extend this simple scaling relationship to accurately estimate the ratio between changes in vertically-weighted lower tropospheric temperature (δT_{LT}) and changes in column-integrated value precipitable water anomaly (δW), additional information is required about the vertical profile of relative humidity in both the marine boundary layer, where the bulk of the water vapor resides, and in the free troposphere above. We turn to climate models to obtain this information. Even though the physics that determines these profiles is represented in a

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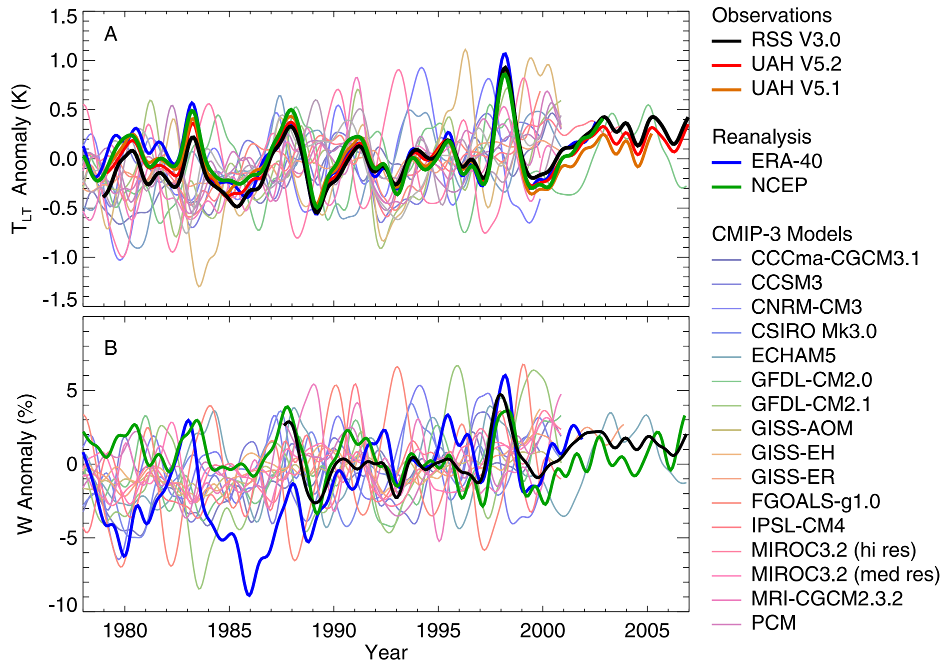

Figure 1. Smoothed time series of (a) T_{LT} and (b) W from satellite observations, reanalysis, and CMIP-3 coupled model results for the tropical oceans (30S to 30N). For six of the models shown here, multiple 20th century simulations were produced, each starting from a different initial condition. Only the first member of each of these ensembles is shown.

number of different ways in different climate models, we find that all models yield essentially the same $\delta W/\delta T_{LT}$ relationship. This allows us to place physically plausible bounds on the $\delta W/\delta T_{LT}$ scaling ratio.

[6] *Wentz and Schabel* [2000] found a tropical oceanic $\delta W/\delta T_{LT}$ scaling ratio of 6.7%/K on interannual time scales, but a significantly larger scaling ratio of 9.5%/K for decadal trends. On interannual time scales, Wentz and Schabel used the ratio of the standard deviations of the time series of W and TLT, $\sigma(W)/\sigma(T_{LT})$, to characterize the scaling ratio, and on decadal time scales they used the ratio of linear trends. Here, we consider whether improved and extended satellite-based W and T_{LT} datasets yield scaling ratios that are more consistent across timescales. We focus on the tropical oceans, where satellite measurements of W are available and seasonal variations are relatively small.

2. Observational Data and Reanalysis Output

[7] The satellite-based water vapor observations analyzed here are microwave measurements of W from the Special Sensor Microwave/Imager (SSM/I) [*Wentz*, 1997; *Wentz et al.*, 2007]. We also examined three different satellite estimates of T_{LT}, each obtained from microwave emissions monitored by the Microwave Sounding Unit (MSU) and the Advanced Microwave Sounding Unit (AMSU). The first two estimates are versions of the T_{LT} dataset constructed by the University of Alabama at Huntsville (UAH V5.1 and V5.2) [*Christy et al.*, 2003]. The third estimate is the latest T_{LT} dataset produced by Remote Sensing Systems (RSS V3.0) [*Mears and Wentz*, 2005]. We include the earlier, outdated version of the UAH data (V5.1) to show the sensitivity of our analysis to small discrepancies between datasets.

[8] The SSM/I-derived W dataset is constructed by intercalibrating the measurements from six different satellites for each channel at the radiance level, and then using a common algorithm to retrieve the precipitable water [*Wentz et al.*, 2007]. The signal to noise ratio for detecting moistening due to increases in tropospheric temperature using microwave-based satellite measurements of W is about 10 times larger than for detecting changes in T_{LT} [*Wentz et al.*, 2007]. We therefore consider W to be more accurate than $T_{LT,}$ despite the difficulty in validating the satellite-derived W data against in situ measurements.

[9] While lower tropospheric temperature data from MSU and AMSU are similarly intercalibrated at the radiance level, the uncertainties mentioned above lead different groups to obtain different results for long-term trends. There are also differences between the T_{LT} trends in the NCEP-50 [*Kalnay et al.*, 1996], and ERA-40 [*Uppala et al.*, 2005] reanalyses.

3. Model Output

[10] We compare the observed data with output from 16 different fully coupled ocean-atmosphere climate models (Table S1 of the auxiliary material).[1] Model results were made available through the World Climate Research Programme's (WCRP's) Coupled Model Intercomparison Project phase 3 (CMIP-3). The simulations considered here are 20th century experiments that include historical changes in anthropogenic and natural forcings [*Santer et al.*, 2007]. All simulations incorporate changes in well-mixed greenhouse gases and in the direct effects of sulfate aerosols. Other forcings, such as other aerosols, ozone, and solar irradiance,

[1]Auxiliary materials are available in the HTML. doi:10.1029/2007GL031936.

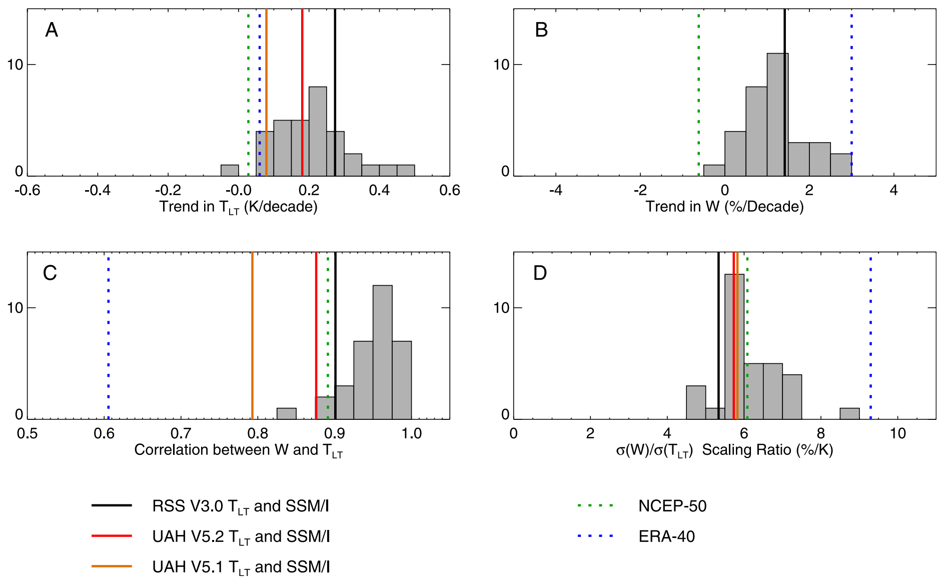

Figure 2. Histograms of T_{LT} and W summary statistics from the CMIP-3 model results over the tropical oceans. (a) Trends (1988–1999) in T_{LT}, (b) trends (1988–1999) in W, (c) correlation coefficient between T_{LT} and W, and (d) interannual scaling ratio $\sigma_W/\sigma_{T_{LT}}$.

vary from model to model. We found that the presence of these forcings has no significant effect on the $\delta W/\delta\ T_{LT}$ scaling that is the focus of this study. In many cases, the same model was run with different initial conditions, yielding separate realizations of the climate "noise" (the unforced variability) that are superimposed on the climate "signal" (the underlying response to the applied forcing). We examined a total of 32 such realizations.

4. Analysis Methods

[11] For each model (or reanalysis) we calculate vertically weighted average temperatures that correspond to the satellite-derived T_{LT} product. We form tropical (30°S to 30°N) oceanic time series of T_{LT} and W for each data source. These time series are smoothed using a low-pass filter [*Lynch and Huang*, 1992] with a cutoff period of 12 months. We express the W anomaly time series in terms of a percent change, because the percent change in W for a given change in temperature varies slowly with temperature For each T_{LT}/W time series pair, we tabulate the correlation coefficient, the overall least-squares linear trends, and the interannual scaling ratio in Table S2.

5. Trends in Precipitable Water and Temperature

[12] The smoothed T_{LT} time series from satellites and reanalysis show relatively small differences in decadal-scale trends (Figure 1a). Because the simulated results are from fully coupled models, W and T_{LT} fluctuations associated with modes of internal variability, such as the El Niño/Southern Oscillation (ENSO), do not occur at the same time as the observed events, except by chance. For W, there are noticeable differences between the satellite and reanalysis data, particularly for ERA-40 (Figure 1b). These discrepancies are largest in regions where the reanalyses are poorly constrained by radiosonde measurements, such as the tropical oceans that are of interest here [*Trenberth et al.*, 2005].

[13] We computed the trends over the 1988–1999 period, for which both satellite and model W and T_{LT} results are available. The satellite and reanalysis T_{LT} trends are all within the range predicted by the models (Figure 2a). In contrast, *Santer et al.* [2005] found that over a longer period

Table 1. Trends in δW and δT_{LT}, Scaling Ratios, and Correlations Between δW and δT_{LT} Found in Climate Models, Satellite Data, and Reanalyses for the Tropical Oceans[a]

	Trend(δW), %/decade	Trend(δT_{LT}), K/decade	Trend Ratio, %/K	Interannual Ratio, %/K	Corr.
CMIP-3 models (median values and standard deviation)	1.13 (0.73)	0.20 (0.11)	5.68 (1.5)	5.98 (0.82)	0.958 (0.036)
SSM/I-RSS V3.0 T_{LT}	1.46	0.28	5.23	5.36	0.901
SSM/I-UAH V5.2 T_{LT}	1.46	0.19	7.87	5.78	**0.876**
SSM/I-UAH V5.1 T_{LT}	1.67	0.08	**22.2**	5.97	**0.790**
NCEP-50	−0.57	0.03	**−18.6**	6.12	0.891
ERA-40	3.03	0.06	**47.1**	**10.5**	**0.606**

[a]Statistics that lie more than 2-σ from the mean of the model distribution are shown in bold. The climate model and reanalysis results are for the 1981–1999 period, while the satellite results are for the 1988–2006 period, so the trend results from the satellite data and the models and reanalysis cannot be directly compared. Also, for UAH V5.1, the calculations are performed over the 1988–2005 period when both SSM/I and UAH 5.1 data are available.

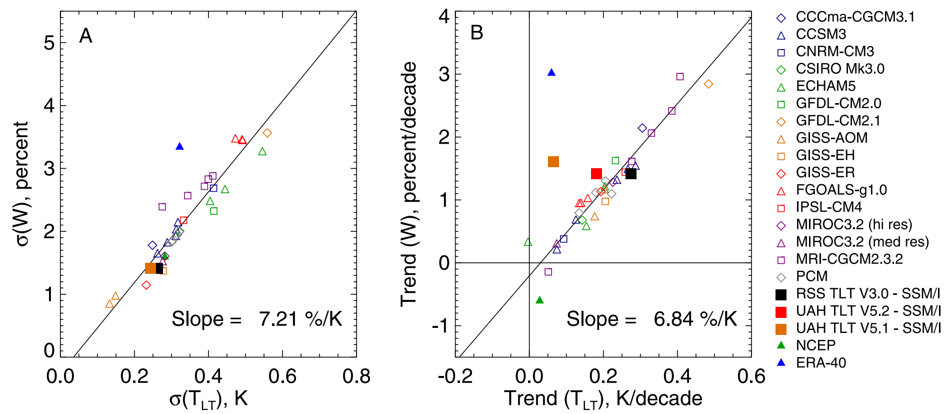

Figure 3. Scatter plot of the variability of W as a function of (a) the variability in T_{LT}, and (b) the trend in W as a function of the T_{LT} trend for the tropical oceans. Trends are calculated over the periods given in Table 1. In Figure 3a, UAH V5.2 and UAH V5.1 yield nearly identical results, so the UAH V5.2 data point is hidden. The lines shown bisect the two different linear fits obtained with first W, then T_{LT} assumed to be the dependent variable. *Isobe et al.* [1990] show that this is a good method for finding an estimate of an underlying relationship in the presence of unknown measurement errors and/or scatter that is not strictly related to measurement error, as is the case here.

(1979–1999) the T_{LT} trend for the now outdated version of the UAH data (UAH V5.1) was outside the range of model predictions. Our present use of the shorter trend period 1988–1999 results in a larger spread in modeled trends and omits the poorly-calibrated December 1986–February 1987 overlap between the NOAA-09 and NOAA-10 satellites.

[14] Both the SSM/I W trend (Figure 2b) and the RSS T_{LT} trend are toward the high end of the model distribution. This is partly due to the influence of the large 1997–1998 El Nino event, which inflates the observed T_{LT} and W trends [*Santer et al.*, 2007]. The reanalysis W trends are near opposite tails of the modeled distribution.

6. Co-Variability of Precipitable Water and Temperature Anomalies

[15] In the model data, the variability of tropically-averaged T_{LT} and W anomalies is highly correlated on interannual timescales, with a median correlation of 0.96 (Figure 2c). The correlations between δW and δT_{LT} for UAH V5.1-SSM/I and ERA-40 are both well outside the modeled distribution. Those for the newer versions of the satellite data are consistent with the model results, though at the lower end. This is due in part to short-term sampling-induced errors in the satellite measurements, but we cannot rule out the possibility that the models analyzed over constrain the monthly covariability between T_{LT} and W.

[16] In order to obtain reliable estimates of the correlation coefficient and scaling ratio, we analyzed slightly different periods for different datasets (see Table 1). This slight inconsistency is not important to our conclusions, because the correlations and scaling are relatively insensitive to the small changes in forcing between these two time periods.

[17] The histogram of the model-derived $\sigma(W)/\sigma(T_{LT})$ scaling ratio (Figure 2d) peaks around 6%/K (median value 5.97). Scaling ratios for the satellite observations and NCEP-50 lie well within the modeled distribution, while the ERA-40 value is significantly different from the model results (Table 1).

[18] To investigate behavior on longer timescales, we show a scatter plot of T_{LT} and W trends (Figure 3b). The modeled trends scatter closely around a straight line with a slope of 6.84 ± 0.47 %/K. Within the uncertainty estimates, the slope of this line agrees with the slope of the fit to the variability scatter plot (Figure 3a, slope = 7.21 ± 0.41 %/K), demonstrating that the scaling ratio is close to being timescale invariant.

7. Discussion

[19] We have established that a nearly constant, timescale-invariant ratio between δT_{LT} and δW is a robust feature of 16 fully coupled climate models, consistent with physical expectations. This similarity occurs despite large structural differences between models, in such aspects as their spatial resolution, external forcings included, and parameterization schemes for sub-grid-scale phenomena.

[20] While both reanalyses have tropical oceanic T_{LT} time series that are very similar to satellite observations (but with slightly less decadal warming), the W time series differ substantially in observations and reanalyses. The ERA-40 results show markedly lower correlations between W and T_{LT} than the models or the latest satellite observations. On decadal timescales, the reanalyses differ significantly from the model expectations (Figure 3, Table 1). We conclude that there are large errors in W in both reanalyses. These may be due to some combination of uncorrected long-term drifts in the assimilated observations and discontinuities that arise when an observing system (*e.g.*, microwave observations by satellites) starts or stops providing data to the reanalysis system [*Bengtsson et al.*, 2004; *Uppala et al.*, 2005].

[21] The SSM/I W data and the now outdated UAH V5.1 T_{LT} data also form an inconsistent pair, since both the interannual timescale correlation (Figure 2c, Table 1) and the decadal-trend scaling ratio (Figure 3b, Table 1) are far from those simulated by models. In contrast, the two combinations that contain the newer versions of the satellite T_{LT} dataset (RSS V3.0 and UAH V5.2) are both broadly

consistent with the model results on both interannual and decadal time scales. The consistency of two most recent T_{LT} datasets with the less noisy and more reliable SSM/I-derived W dataset greatly increases our confidence in the reality of lower tropospheric warming over the SSM/I period analyzed here. Our results demonstrate the use of climate model output for evaluating observational datasets, particularly in cases where there is agreement across models, timescales, and with basic physical principles.

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