Explaining Differences Between Recent Model and Satellite Tropospheric Warming Rates With Tropical SSTs

A. Tuel

1Ralph M. Parsons Laboratory, Massachusetts Institute of Technology, Cambridge, MA, USA

Abstract Global climate models generally overestimate recent tropospheric warming trends. While a number of explanations have been suggested, their relative impacts have not been quantified. In particular, interannual and long-term variability of tropospheric temperatures (TTT) is known to be strongly constrained by near-surface conditions in ocean regions of deep convection. Here, we analyze the role played by tropical sea surface temperature (SST) variability in recent decades in setting TTT. We find that Coupled Model Intercomparison Project Phase 5 models and observations agree on the interannual relationship between SSTs in regions of deep, tropical convection and TTT. Over the 1979–2018 period, most of the difference between model and satellite-based TTT trends can be explained by respective differences in SST warming trends in regions of deep convection. While large multidecadal patterns of SST variability certainly play a role, notably in the Pacific Ocean, other mechanisms may also contribute to the overestimation of recent SST warming in climate models.

1. Introduction

A prominent feature of climate projections is the strong enhancement of warming aloft in the tropical troposphere (Hartmann et al., 2013; Vallis et al., 2014). Warmer air holds more water vapor, so that it condenses more vapor and releases more heat when lifted vertically. Therefore, temperature decreases with height more slowly in a warmer climate, resulting in larger warming at upper levels compared to the surface. This behavior has in turn major consequences for the global climate. Enhanced tropical upper tropospheric warming increases longwave emissions to space, a negative feedback on the global temperature increase (Po-Chedley et al., 2017). It also acts to steepen the upper-level meridional temperature gradient, which tends to strengthen midlatitude zonal jets and modify the structure of planetary waves, both of which have significant impact for extratropical climate (Simpson et al., 2015; Vallis et al., 2014). Additionally, a warmer tropical troposphere also contains more water vapor, a potent greenhouse gas, which significantly impacts the global radiative balance. Because of those important climate feedbacks, uncertainties in tropical tropospheric warming contribute to uncertainties in the projected response to increasing greenhouse gas concentrations (Po-Chedley et al., 2017). Consequently, the ability of climate models to reproduce this fundamental feature of the tropical troposphere has been the focus of considerable attention. In particular, a debate has erupted over whether global climate model (GCM) simulations exhibited higher rates of tropical middle-to-upper tropospheric temperature (TMT) increase over the last few decades compared to observations (Christy et al., 2007; Christy, 2015; Douglass et al., 2008; Intergovernmental Panel on Climate Change, 2013; Santer et al., 2017). This is an important point, because if models are unable to simulate this robust, zeroth-order behavior, it would have many implications for their ability to correctly simulate the overall climate.

Observed TMT series can be obtained from radiosonde and satellite data. While radiosondes go back a longer time, they suffer from important time-varying biases, particularly in the tropics (Randel & Wu, 2006; Thorne et al., 2011), which may remain even after homogenizing the time series (Thorne et al., 2007). However, since 1979, microwave sounding units (MSUs) onboard satellites have been monitoring emissions from atmospheric oxygen molecules in the microwave band, which are proportional to the temperature of different atmospheric layers. There are two MSU channels frequently used for long-term climate monitoring: channel 2 (approximately surface to 18 km) and channel 4 (lower stratosphere, approximately 15–35 km). MSU channel 2 brightness temperature measurements still include a nonnegligible influence from

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stratospheric temperature changes. Because the stratosphere is cooling in response to increasing concentrations of atmospheric greenhouse gases (Vallis et al., 2014), the stratospheric component of the TMT signal must be removed (Fu et al., 2004; Fu & Johanson, 2004). We refer to the resulting corrected series as tropospheric temperatures (TTT).

While some earlier studies argued that models significantly overestimated tropospheric warming and were consequently not to be trusted for future projections (Christy et al., 2007; Douglass et al., 2008), more recent work has demonstrated that discrepancies were initially overestimated. Instead of a trend ratio of 3–4 between modeled and observed TMT trends, applying the stratospheric correction reduced this ratio to about 2 for the tropics and 1.7 for the global average (Santer et al., 2017). Additionally, once taking observational and statistical uncertainties and natural variability into account, the difference in trends between models and observations did not appear to be significant, at least up to the beginning of the 21st century (Santer et al., 2017; Suárez-Gutiérrez et al., 2017).

Post-2000 data, however, suggest systematic model overestimation of tropospheric warming by Coupled Model Intercomparison Project Phase 5 (CMIP5) models (Gleisner et al., 2015). Observed trends fall too far below model simulated trends for the difference to be statistically indistinguishable from internal variability (Santer et al., 2017). For instance, when considering 1979–2018 trends in the historical and Representative Concentration Pathway 8.5 (RCP8.5) scenarios, there is a clear discrepancy between models and observations (Figure 1). Given that models succeed in reasonably capturing trends up to the late 20th century, divergences in early 21st century TTT trends were argued to follow from the lack of key external forcings in the models, rather than residual observational uncertainties or fundamental deficiencies in model physics (Santer et al., 2017; Suárez-Gutiérrez et al., 2017). A number of factors contribute to amplified tropospheric warming in model simulations compared to observations: stratospheric ozone and water vapor (Solomon et al., 2010, 2012), variability in solar irradiance or volcanic forcing (Santer et al., 2014), or the phasing of interannual climate variability (Gilford et al., 2016; Santer et al., 2017).

In particular, the recent cooling of the tropical Pacific tied to the negative phase of the Pacific Decadal Oscillation (PDO) beginning around 1999 has been proposed as a likely cause of reduced tropospheric warming (Santer et al., 2017). The PDO is an important pattern of multiannual to decadal variability in the Pacific Ocean, whose negative phase is characterized by cool eastern equatorial sea surface temperatures (SSTs) and warm subtropical waters (Trenberth & Fasullo, 2013). Models forced with observed SSTs over the central to eastern tropical Pacific have shown remarkable skill in reproducing the warming pause after 2000.
(Kosaka & Xie, 2013), strongly suggesting that the recent PDO-induced cooling in those regions played an important role in the global warming slowdown observed between 2000 and 2012.

Because deep convection over oceans couples the free troposphere and the boundary layer, near-surface conditions (essentially temperature, given the strong constraints on relative humidity over oceans) strongly impact both the local and average tropical tropospheric moist adiabat since strong temperature gradients cannot be maintained in the tropics. Therefore, it seems logical to consider recent tropical SST trends to understand discrepancies in TTT warming between models and observations. Flannaghan et al. (2014) and Fueglistaler et al. (2015) have shown how a precipitation-weighted tropical SST index, which gives larger weight to regions of deep convection in the tropics, could explain the spread in TTT trends across various models forced with different SST data sets.

Here, we build on the relationship between TTT and SST in regions of deep convection to quantitatively investigate the role played by recent tropical SST trends in models’ overestimation of TTT trends. We find that models and observations agree on the strength of this relationship. Extrapolating to the beginning of the 21st century, reduced TTT trends in models compared to observations can be explained by reduced tropical SST warming, particularly in regions of deep convection from the Indian Ocean to the Eastern Pacific.

2. Data and Methods

Observed TTT series are based on MSU measurements from over a dozen satellites, which have gone through various bias correction and homogenization procedures (Mears & Wentz, 2009; Po-Chedley et al., 2015). This study is restricted to tropical (30°S to 30°N average) TTT series. We use four MSU records: the Remote Sensing Systems version 4.0 (RSS4) (Mears & Wentz, 2016), the Center for Satellite Applications and Research version 4.1 (STR4) (Wang & Zou, 2014), the University of Alabama at Huntsville version 6.0 (UAH6) (Spencer et al., 2017), and the University of Washington (UW; Po-Chedley et al., 2015) data sets. TTT is obtained by a linear combination of MSU channels 2 and 4 following Fu et al. (2004). For UW, which only includes MSU channel 2, the RSS4 MSU channel 4 data are used to remove stratospheric influence. All series span the 1979–2018 period, which we take as our reference to calculate anomalies.

GCM atmospheric temperatures are taken from the CMIP5 (Taylor et al., 2012). We analyze output from 22 different models (Table S1 in the supporting information) forced with historical natural and anthropogenic greenhouse gas and aerosol forcings between roughly 1850 and 2005 and the RCP8.5 from 2006 to 2018. RCP8.5 is essentially the trajectory that has been followed until now (Sanford et al., 2014), and results for this study do not differ when considering the RCP4.5 mitigation scenario after 2005. Unforced piControl runs are also used to estimate internal variability in TTT trends within each model. Only one ensemble member per model is retained (r1i1p1). TTT series are computed by applying MSU weighting functions for channels 2 and 4 to GCM data at the grid point level, averaging over the tropics (30°S to 30°N) and removing the stratospheric contamination as in Fu and Johanson (2005). The GPCP data set (Adler et al., 2003) is used to estimate the present distribution of tropical precipitation over oceans, and observed SSTs are taken from the HadISST2 data set (Rayner et al., 2003). While differences exist between various SST data sets (e.g., the Hurrell data set, see Flannaghan et al. (2014)), these are usually minor when compared to model observational SST trend differences.

Following Flannaghan et al. (2014), we define an annual tropical precipitation-weighted SST (PRSST) index by

\[
\langle PRSST \rangle = \frac{\langle SST \cdot P \rangle}{\langle P \rangle}
\]

(1)

where \( \langle \cdot \rangle \) stands for a tropical (30°S to 30°N) average. SST and \( P \) are, respectively, the annual average SST and precipitation fields.

3. Results

Figure 2 shows annual anomalies of detrended TTT and PRSST indices across models and observation data sets. Least squares linear trends are subtracted from each series to remove the influence of long-term trends on interannual variability. Unsurprisingly, the interannual correlation between the two is strong (Flannaghan et al., 2014). Despite differences in SST and precipitation patterns, models and observations
are in good agreement on the interannual amplification of PRSST anomalies in the troposphere (about $1.8 \, ^\circ\text{C}/^\circ\text{C}$), consistent with the results of Santer et al. (2005) who considered monthly data. There remains significant spread in individual model PRSST-TTT slopes (standard deviation about 10% of the mean). While PRSST is not a perfect metric, this also points to intrinsic differences between models, possibly linked to model parametrization of moist convection and cloud radiative effects (Fueglistaler et al., 2015; O’Gorman & Singh, 2013).

As expected from the robustness of the PRSST-TTT relationship, the large differences between modeled and observed TTT trends (Figure 1b) are reflected in PRSST indices. The 1979–2018 PRSST trends based on HadISST and GPCP are only, on average, 55% of that in CMIP5 models (across models, the ratio of the observed PRSST trend to the GCM trends is between 0.32 and 0.94). Similarly, the ratios of observational to GCM average TTT trends are 0.56 for RSS4, 0.65 for STR4, and 0.49 for UW but only 0.36 for UAH6—quite similar values (except for UAH6) consistent with the strong agreement between PRSST-TTT slope magnitudes (Figure 2b). This suggests that overestimated TTT trends are mainly the result of the over-estimation by models of tropical SST trends in regions of deep convection. To put this more quantitatively, for each GCM, we fit a simple linear regression model to the PRSST-TTT relationship over 1850–1978 (historical period excluding our reference period), after removing linear temporal trends in PRSST and TTT, and predict 1979–2018 TTT values based on both model PRSST anomalies (to validate the fit, Figure 3c) and HadISST+GPCP PRSST anomalies during that period (Figure 3a). Predicted trends appear more consistent with MSU observations (Figure 3b). Following Santer, Fyfe et al. (2017) who analyzed the same MSU and CMIP5 data sets, 1979–2018 trends in the difference between modeled and observed TTT series are compared with all possible 40-year trends from each model’s control simulation, an estimate of its TTT internal variability. A p value is calculated as the proportion of control trends exceeding the 1979–2018 trend in model-minus-observed TTT. While original CMIP5 TTT trends are generally significantly larger than what can be expected from pure internal variability (at a 5% level or better), those using predicted TTT series generally fall within each model’s internal noise (Figure 3d). Eight models still exhibit large trends compared to UW and four for RSS4, but six out of those have the largest PRSST-TTT slope values of the group (above $2^\circ\text{C}/^\circ\text{C}$, Figure 2b), which could explain why their predicted TTT trends are still too large. UAH6 is the exception among MSU series: its trend remains systematically too low. A number of homogenization issues...
Figure 3. (a) The 1979–2018 TTT anomalies in CMIP5 models, predicted from observed PRSST anomalies using each model’s pre-1979 PRSST-TTT linear fit and in the four MSU data sets. (b) Distribution of 1979–2018 TTT trends (°C per decade) across CMIP5 models (light gray) and predictions (black). Median and observed values are shown by horizontal dashed lines. (c) Original and predicted 1979–2018 TTT trends in the 22 CMIP5 models estimated by linear regression onto original CMIP5 (black) and HadISST+GPCP (red) PRSST anomalies. Segments indicate 95% confidence intervals. (d) Distribution of p values among CMIP5 models for the difference between original (blue) or predicted (orange) 1979–2018 TTT trends and the four MSU data sets. The 5% rejection region is indicated by a gray rectangle, and numbers below the x axis indicate the number of models (out of 22) in that region. CMIP5 = Coupled Model Intercomparison Project Phase 5; RSS = Remote Sensing Systems; STR = Center for Satellite Applications and Research; UAH = University of Alabama at Huntsville; UW = University of Washington; TTT = tropospheric temperature; SST = sea surface temperature.

in the UAH series have been pointed out that could underestimate the recent TTT increase (Po-Chedley & Fu, 2012; Po-Chedley et al., 2015). Although those results were based on older versions of the data set, version 6 may still contain a systematic cooling bias. Issues with the three other MSU series cannot be excluded, but a more thorough investigation would be required to account for the discrepancy.

Trend maps help highlight the origins of SST differences. Large-scale cooling in the eastern tropical Pacific and enhanced warming in the central parts of the Pacific subtropics, a clear signature of the PDO, are evident in HadISST but absent from CMIP5 (Figures 4a and 4b). More generally, however, tropical SSTs, notably in regions of deep convection, have not warmed as much over the last few decades as in model projections. The contribution of two specific regions, the Indian Ocean (45–110° E) and the Eastern Pacific (180–80° W), is estimated by replacing 1979–2018 SST in each CMIP5 model by the corresponding HadISST data and calculating resulting PRSST trends (Figure 4). The relative weight of each in total tropical precipitation is well estimated by the models (Figure S1), a fact also reflected in the agreement between CMIP5+HadISST and GPCP+HadISST PRSST trends (Figure 4b, “Obs”). Reduced tropical SST warming in observations compared to models, particularly in deep convection regions of the eastern Pacific and Indian Oceans, strongly contributes to the overestimation of PRSST trends.
It remains unclear whether the CMIP5 overestimation of tropical PRSST trends is only due to a dephasing of internal variability between climate simulations and observations or results from systematic model biases. Excluding the Eastern Pacific (180°–80°W), average tropical SSTs have increased by 0.12 °C per decade since 1979, compared to a median rate of 0.18 °C per decade in CMIP5 models. Over the whole twentieth century, however, CMIP5 and HadISST trends are in close agreement (roughly +0.04 °C per decade for both the whole tropics and deep convection zones). Important tropical SST biases have previously been noted in CMIP5 models due, among others, to variability in models' representation of cloud cover and thermocline depth, which have substantial impact on the SST threshold for convection (Li & Xie, 2012). The ability of models to correctly reproduce interannual and multidecadal tropical SST variability is also still disputed (Jha et al., 2014; Kosaka & Xie, 2013; Li & Xie, 2012; Wang et al., 2015), questioning the aptitude of GCMs to accurately simulate the ocean heat budget, with implications for long-term SST trends. The task is made harder by the fact that relatively limited ocean regions (20–25% of tropical oceans) have a disproportionate effect on the whole tropical troposphere and global climate in general.

4. Conclusions

In conclusion, using the simple framework of precipitation-weighted tropical SST indices, we find that discrepancies in TTT trends between CMIP5 models and observations over the last few decades are essentially a consequence of differences in SST trends in regions of deep convection. Although the transition to a negative PDO regime and the associated Eastern Pacific cooling played a major role, reduced tropical SST warming in other regions like the Indian Ocean cannot be neglected. While observational biases in MSU series cannot be excluded, it appears that the key to explaining recent TTT trends lies in understanding why tropical SST trends are smaller in models than observations. Dephasing of interannual variability is undoubtedly part of the answer, but systematic model errors, like biases in the Pacific cold tongue (Seager et al., 2019) or incorrect forcing (e.g., volcanic, Santer et al., 2014), may also contribute. Looking ahead, this would have profound implications for long-term tropospheric warming trends and the global climate. Given that the tropical SST-TTT relationship is correctly reproduced by GCMs, explaining the spread in TTT trends will require understanding why models differ in their SST projections within deep convection zones. Developing models that correctly simulate tropical precipitation, ocean circulation, and heat uptake is vital for making reliable projections for the troposphere.
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