LLNL-TR-816091

LAWRENCE
LIVERMORE
NATIONAL
LABORATORY

Advancing Measurements and Understanding of the Rate and Structure of Atmospheric Warming

S. Po-Chedley

October 28, 2020

This work performed under the auspices of the U.S. Department of Energy by Lawrence Livermore National Laboratory under Contract DE-AC52-07NA27344.

FULL TECHNICAL FINAL REPORT
Advancing Measurements and Understanding of the Rate and Structure of Atmospheric Warming

Stephen Po-Chedley

LDRD 18-ERD-054

Abstract
The rate and geographic pattern of atmospheric warming are key indicators of historical climate change and play a role in modulating future changes in Earth's climate. The past and future evolution of atmospheric temperature is simulated using global climate models while observational estimates of past warming are derived from satellite microwave measurements. Individual climate models simulate widely varying rates of past and future atmospheric warming and most model simulations exhibit greater tropospheric (lowest ~10 km of atmosphere) temperature change than satellite observations between 1979 and 2020. This project examined intermodel differences in the pattern of atmospheric warming and how these differences influence climate feedbacks that can amplify or damp the rate of global surface warming. A key result is that climate model representation of the current climate can influence climate feedbacks and the simulation of future changes in climate. Another focus of this project was to analyze how models respond to different input datasets, such as volcanic aerosols or sea surface temperature (in atmosphere-only simulations). We find that different prescribed inputs can affect simulated changes in atmospheric temperature, even though "input uncertainty" is often unconsidered in model-observational comparisons. A final focus of this research project was to consider the influence of natural internal climate variability on satellite era changes in climate. Although the Earth is warming substantially due to anthropogenic emissions of greenhouse gases, the observed warming rate can be modulated by natural variations in the Earth's climate. We find that natural climate variability has slowed the rate of tropical tropospheric warming, which explains model-satellite differences in the rate of tropospheric warming.

Background and Research Objectives
It has long been known that human emissions of greenhouse gases result in global surface warming, but the exact sensitivity of the Earth's climate system to greenhouse gas changes is uncertain. The estimated, equilibrium response of global average surface temperature to a doubling of atmospheric carbon dioxide (i.e., equilibrium climate sensitivity, ECS) is 2.3 – 4.7 K (S. C. Sherwood et al. 2020), though global climate models (GCMs) frequently exhibit climate sensitivity values above this range (Zelinka et al. 2020). It is important to further constrain the Earth's sensitivity to atmospheric greenhouse gas changes, in order to better predict climate impacts and to develop appropriate adaptation and mitigation strategies.

One focus of this research project was to better understand individual climate feedback processes, which amplify or damp the surface warming response to greenhouse gas changes (J. Hansen et al. 1984). One specific objective was to use model ensembles from the Coupled Model Intercomparison Project Phase 5 (CMIP5) to determine whether biases in model representation of the current climate (e.g., over the last forty years) influence long-term climate feedback behavior. In particular, we sought to understand how the current distribution of clouds, sea-ice, and humidity affects long-term climate feedback processes. We extended this objective by also exploring how model representation of natural climate variability scales with model ECS and whether observations could be used as an emergent constraint (e.g., Hall et al. 2019).

Another focus of this research was to better understand a longstanding scientific puzzle: GCM simulations of the satellite era (1979 to present) exhibit, on average, two times more tropical tropospheric warming than that derived from microwave sounding unit (MSU) based measurements (Santer, Solomon, et al. 2017). This difference is widespread across CMIP5 models and few model realizations simulate tropospheric temperature changes within the range of satellite-derived trends. Model simulated warming since the 1980s scales with model ECS (Tokarska et al. 2020), suggesting that climate sensitivity may be relatively small (Christy et al. 2018). Other research indicates that observational biases, incorrect model forcing, and internal variability may also contribute to differences in simulated and observed tropical tropospheric temperature trends (Kosaka and Xie 2013; Lu and Bell 2014; Santer et al. 2014; Santer, Fyfe, et al. 2017).

Our research plan included objectives to better understand model-observational differences in the rate of satellite era tropospheric warming including a) determining whether biases exist in microwave-based satellite temperature records and b) assessing the influence of uncertain model inputs on simulated atmospheric temperature trends. In addition to these objectives, we also extended our work to determine if a) model-observational differences from CMIP5 persist in the latest generation of CMIP6 models and b) whether natural climate variability can explain GCM-versus-satellite differences in tropical tropospheric warming.

Scientific Approach and Accomplishments

Climate Feedback Analysis

In order to better understand climate feedback processes, we made use of large ensembles of GCMs to study factors that contribute to intermodel differences in the magnitude of climate feedbacks. In one study, we found that the spatial pattern of surface warming can explain model differences in the magnitude of the lapse rate and water vapor feedbacks (Po-Chedley et al. 2018). We also showed that large model differences in the climatological representation of Antarctic sea ice extent influence polar warming in the Southern hemisphere. As a result, model representation of Antarctic sea ice could explain a significant fraction of intermodel spread of the lapse rate and water vapor feedbacks. This research was consistent with a subsequent study that demonstrated that the Arctic lapse rate and albedo feedbacks are closely coupled, are related to the climatological distribution of Arctic sea ice, and should not be considered independent feedbacks (Feldl et al. 2020). These analyses indicate that model improvements to the representation of historical sea ice extent will reduce model discrepancies in the lapse rate, water vapor, and albedo feedbacks. In turn, this may narrow the range of climate sensitivity values in GCMs.

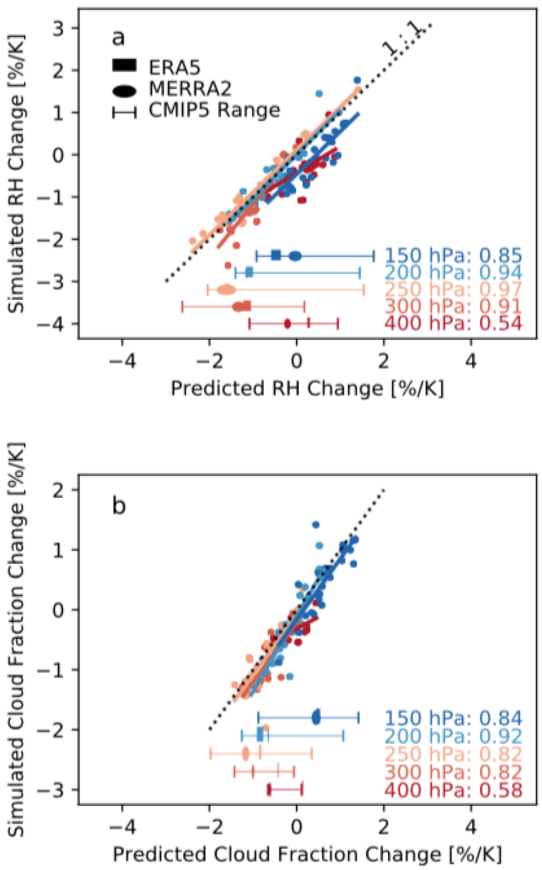

Figure 1 a) Predicted tropical (30ºS – 30ºN) average relative humidity change versus the simulated change for 27 GCMs (dots) at different pressure levels (colors; see legend). The legend provides the correlation coefficient for the predicted-versus-simulated changes. The prediction is based on each model's climatology. The simulated change is computed using the difference between the end-of-century climatology (2061 – 2099) and the satellite era climatology (1980 – 2018). The model range of predicted values is indicated with horizontal lines and the changes inferred from atmospheric reanalyses are displayed as ovals (MERRA2) and rectangles (ERA5). The one-to-one lines is also included (dotted line). Panel b) is the same, but for tropical cloud fraction changes. Adapted from Po-Chedley et al. (2019).

Model biases in the distribution of high clouds and relative humidity can also influence climate feedback processes. Several studies demonstrate that the profiles of tropical clouds and relative humidity shift upward in altitude as the climate warms (Hartmann and Larson 2002; Steven C Sherwood et al. 2010; Singh and O'Gorman 2012; Romps 2014). As a result, models with large vertical gradients in these hydrologic fields are expected to simulate large changes in relative humidity and clouds. Using each model's cloud and relative humidity climatology and simple assumptions about the vertical profile of warming, we found that we could accurately predict simulated changes in tropical upper tropospheric clouds and relative humidity (Figure 1). Using this approach, we were also able to use the climatology from atmospheric reanalysis models to infer future changes in tropical clouds and humidity. This indicates a clear scaling between models' base state and future projections. Improvements to model representation of the observed climate should help constrain model simulations of future changes in climate.

Recent research has demonstrated that historical global surface temperature variability (denoted as psi) closely scales with ECS in climate models (Cox, Huntingford, and Williamson 2018). Using this relationship and an observational estimate of psi, Cox, Huntingford, and Williamson (2018) estimated that the value of ECS is between 1.6 and 4.0 K (95% confidence interval). In subsequent research, we found that psi is influenced by externally forced changes in climate and, as a result, ECS estimates vary considerably depending on the model data used and the time period considered (Figure 2). Further research is needed to determine whether natural internal variability can be separated from externally forced changes in climate and whether estimates of internal climate variability can be used for precise quantification of ECS.

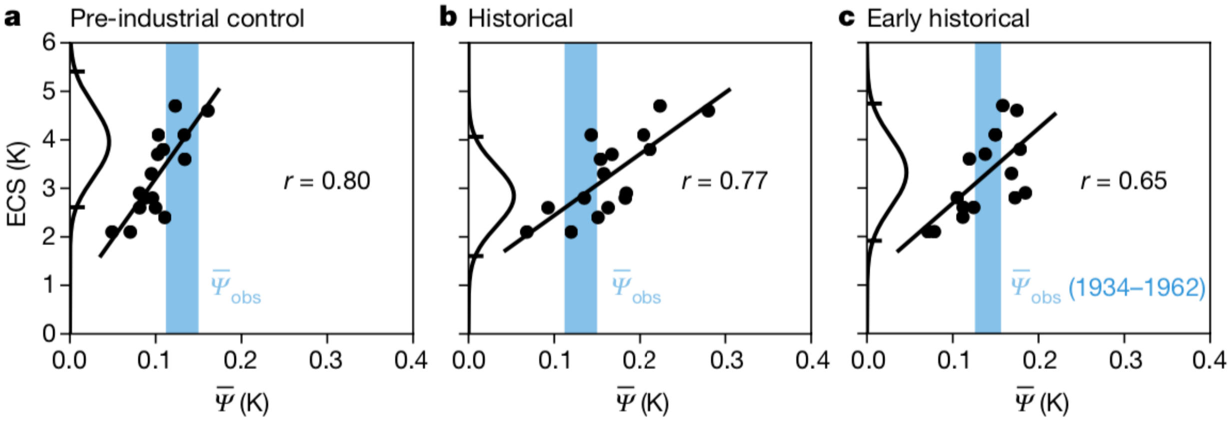

Figure 2 a) Relationship between climate variability (psi) and ECS derived from the entire length of the pre-industrial control simulation available for each model. b) As in **a**, but for simulations of historical climate change over the period 1880–2016. c) As in b, but considering only global temperature data before 1963. The black line is a linear fit and the vertical blue shading is the observational psi value (±1 standard deviation). In panels a and b, the observational range is derived from the entire temperature record (1880–2016), whereas the instrumental record before 1963 is used in panel c. The implied probability distribution of ECS is displayed on the vertical axis. The median ECS value and 95% confidence interval for a–c are 4.0 ± 1.4 K, 2.8 ± 1.2 K and 3.3 ± 1.4 K, respectively. The corresponding 95% confidence interval is denoted by horizontal lines along the *y* axis. Figure from Po-Chedley et al. (2018).

Model-Observational Differences in Satellite-era Tropical Tropospheric Warming

Climate model simulations of tropical tropospheric temperature change from multiple intercomparison projects (CMIP3 and CMIP5) tend to exhibit exaggerated warming relative MSU satellite observations. We undertook several investigations to determine the causes and significance of this apparent model-observational discrepancy.

Recent research suggests that microwave measurements of tropospheric temperature exhibit spurious cooling over the 2000s, which may be a result of an unexpected drift in the measured frequency (Lu and Bell 2014; Christy et al. 2018). We explored this issue by refactoring a line-by-line microwave radiative transfer model so that we could simulate the seasonal and spatial pattern of biases that would result from a shift in the measurement frequency. We then used atmospheric reanalysis data to determine if satellite-versus-reanalysis differences were consistent with a drift in the measurement frequency. Although satellite observations tend to cool relative to reanalysis in the early 21st century, we could not conclusively attribute this drift to shifts in the MSU measurement frequency.

In a subsequent analysis, we were able to show that satellite-derived tropical tropospheric temperature trends are inconsistent with observed changes in column water vapor, indicating that MSU data likely contains residual biases that artificially reduce observational estimates of tropospheric warming (Santer et al. 2020). Such biases, if confirmed, would help explain the gap between satellite observations and model simulations of tropical tropospheric warming.

While MSU measurements provide temperature estimates of broad vertical layers, complementary datasets provide temperature on atmospheric levels. We therefore used the radiative transfer capabilities developed as part of this project to simulate the synthetic satellite brightness temperature that would be observed given temperature data at discrete atmospheric levels. Simulated equivalent microwave temperature trends were included in the annual State of the Climate Report (Christy, Mears, and Po-Chedley 2018; Christy et al. 2019).

We also calculated the synthetic tropical tropospheric temperature trends from the most recent generation of climate models (CMIP6, including 361 historical climate simulations from 43 models). Since natural climate variability is stochastic and can enhance or suppress temperature changes that result from greenhouse warming, this large dataset allowed us to better sample model climate variability and its effect on model-observational agreement over 1979 – 2014 (the period simulated by this suite of models). We found that tropical tropospheric warming in models scales with the SST trend in the tropical central Pacific (the Niño 3.4 region; Figure 3). Model simulations that by chance have Pacific multidecadal variability similar to the observations also tend to capture the correct atmospheric warming trend. Climate models with both small and large climate sensitivity values have simulations in accord with the satellite observations, indicating that climate sensitivity is not the only factor determining model-observational agreement. This result indicates that climate variability contributes to model-observational differences in the rate of tropical tropospheric warming over the satellite era and that satellite-model discrepancies are not significant when internal variability is accounted for. In separate work, we found that a similar mode of climate variability also helps to explain societally-relevant climate trends, including the slower-than-expected loss of Western US snowpack since the 1980s (Siler, Proistosescu, and Po-Chedley 2019).

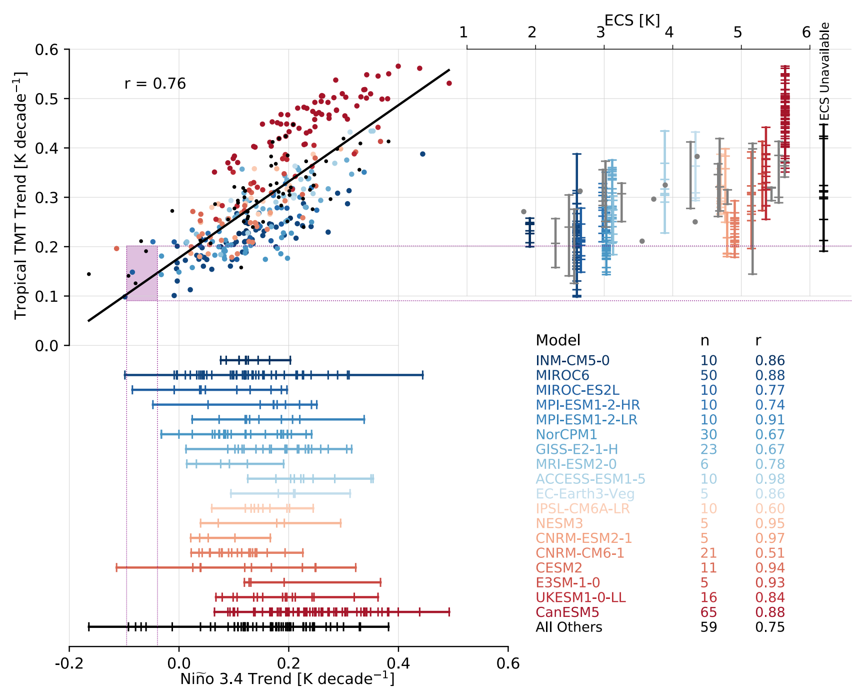

Figure 3 SST trends (1979-2014) in the central Pacific Niño 3.4 region versus the tropical average (20°S – 20°N) mid-tropospheric temperature (TMT) trends for different models (colors; see legend). Models with fewer than five ensemble members are plotted in black. The legend denotes the ensemble size (n) and correlation coefficient between the Niño 3.4 versus tropical TMT trends for each model. The range of each model's Niño 3.4 trends is displayed with horizontal lines in the lower left corner. The range of tropical TMT trends (vertical lines) is plotted against ECS (upper right) with gray dots denoting models with only one ensemble member. From Po-Chedley et al (2020).

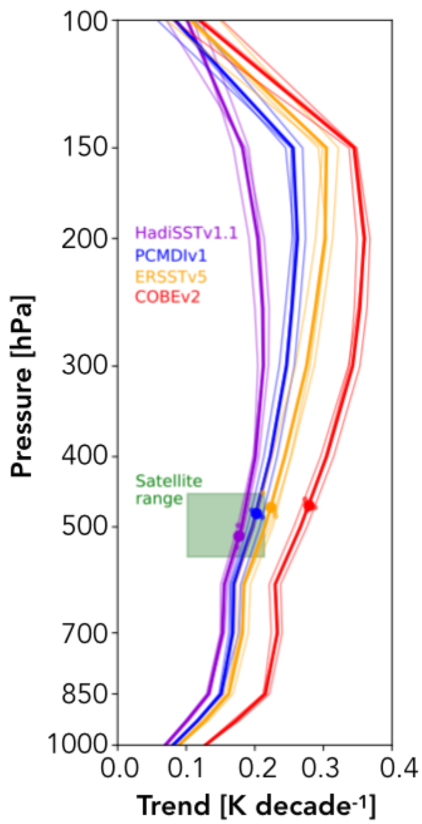

Figure 4 Atmospheric temperature trend (lines) for E3SM atmospheric simulations using different SST boundary conditions (colors; see legend). Also shown is the range of satellite observed mid-tropospheric temperature trends (green box) and the model synthetic equivalent satellite trends (dots).

Another possible factor influencing the agreement between modelled and observed tropical tropospheric temperature trends is the inputs into climate models. GCMs are prescribed changes in climate relevant fields such as greenhouse gases, volcanic and anthropogenic aerosols, and solar irradiance. We considered uncertainty in SST boundary conditions used in atmosphere-only simulations. Using the Department of Energy's Energy, Exascale, Earth System Model (E3SM), we simulated the tropical tropospheric temperature trends for four different SST datasets over 1979 – 2014 (Figure 4). In this sensitivity study, we found that the choice of SST dataset influences the rate of tropical tropospheric warming and that agreement with observations depends on the inputs used for model simulations (Po-Chedley et al. 2020). This is a key point, since model intercomparison projects typically use a particular set of model inputs, which means that input uncertainty is neglected. In a similar study using E3SM, we found minimal impacts between successive versions of the volcanic aerosol dataset used for CMIP6 simulations (Rieger et al. 2020).

Mission Impact

This research has contributed to the Climate Program by improving infrastructure both to analyze a large quantity of climate model simulation output and to compare model data with observations. Several publications also highlighted promising future research directions and contributed to the submission of an early career funding proposal. A number of the published findings involved external researchers, which will lead to continued future collaboration. More broadly, the research findings help advance our understanding of recent and future changes in climate, which advances the Department of Energy's mission to address energy and environmental challenges. Since climate and energy are interrelated, improvements in our ability to understand past and simulate future changes in climate enhances our ability to make confident energy policy decisions.

Conclusion

This research project produced useful tools and uncovered several promising research directions. One finding is that model biases in their representation of the current climate influence future simulations, indicating that improvements to models' ability to simulate the observed record may improve and constrain future projections. Continuing this work to document climatological biases and their impact on future model simulations may contribute to more rapid and targeted model improvements. Our research also indicates that natural climate variability is large enough to explain model-versus-observed differences in satellite era tropospheric warming. Further work isolating and quantifying the magnitude of natural climate variability may help to constrain the value of climate sensitivity. Tools developed to analyze large model datasets and to undertake radiative transfer calculations can be applied to future work. A particularly promising activity may be to compare a larger swath of complementary measurements of the troposphere, which may help to evaluate the accuracy of microwave based tropospheric temperature trends. This work included contributions from several universities and government agencies and plans are underway for further collaboration.

Acknowledgements

This work was performed under the auspices of the U.S. Department of Energy under Contract DE-AC52-07NA27344 with support from LLNL LDRD 18-ERD-054. This is Report number LLNL-TR-816091.

References

Christy, John R., Carl A. Mears, and Stephen Po-Chedley. 2018. "Global Climate: Tropospheric Temperature [in 'State of the Climate in 2017']." *Bulletin of the American Meteorological Society* 99 (8): S16–18.

Christy, John R., Stephen Po-Chedley, Carl A. Mears, and Leopold Haimberger. 2019. "Global Climate: Tropospheric Temperature [in 'State of the Climate in 2018']." *Bulletin of the American Meteorological Society* 100 (9): S17–19. https://doi.org/10.1175/2019BAMSStateoftheClimate.1.

Christy, John R., Roy W. Spencer, William D. Braswell, and Robert Junod. 2018. "Examination of Space-Based Bulk Atmospheric Temperatures Used in Climate Research." *International Journal of Remote Sensing* 39 (11): 3580–3607. https://doi.org/10.1080/01431161.2018.1444293.

Cox, Peter M., Chris Huntingford, and Mark S. Williamson. 2018. "Emergent Constraint on Equilibrium Climate Sensitivity from Global Temperature Variability." *Nature* 553 (7688): 319–22. https://doi.org/10.1038/nature25450.

Feldl, Nicole, Stephen Po-Chedley, Hansi K. A. Singh, Stephanie Hay, and Paul J. Kushner. 2020. "Sea Ice and Atmospheric Circulation Shape the High-Latitude Lapse Rate Feedback." *Npj Climate and Atmospheric Science* 3 (1): 41. https://doi.org/10.1038/s41612-020-00146-7.

Hall, Alex, Peter Cox, Chris Huntingford, and Stephen Klein. 2019. "Progressing Emergent Constraints on Future Climate Change." *Nature Climate Change* 9 (4): 269–78. https://doi.org/10.1038/s41558-019-0436-6.

Hansen, J, A Lacis, D Rind, G Russell, P Stone, I Fung, R Ruedy, and J Lerner. 1984. "Climate Sensitivity: Analysis of Feedback Mechanisms." In *Climate Processes and Climate Sensitivity*, edited by J. E. Hansen and T. Takahashi. American Geophysical Union (AGU). https://doi.org/10.1029/GM029p0130.

Hartmann, Dennis L, and Kristin Larson. 2002. "An Important Constraint on Tropical Cloud -

Climate Feedback.” *Geophysical Research Letters* 29 (20): 10–13. https://doi.org/10.1029/2002GL015835.

Kosaka, Yu, and Shang Ping Xie. 2013. “Recent Global-Warming Hiatus Tied to Equatorial Pacific Surface Cooling.” *Nature* 501 (7467): 403–7. https://doi.org/10.1038/nature12534.

Lu, Qifeng, and William Bell. 2014. “Characterizing Channel Center Frequencies in AMSU-A and MSU Microwave Sounding Instruments.” *Journal of Atmospheric and Oceanic Technology* 31 (8): 1713–32. https://doi.org/10.1175/JTECH-D-13-00136.1.

Po-Chedley, Stephen, Kyle C. Armour, Cecilia M. Bitz, Mark D. Zelinka, and Benjamin D. Santer. 2018. “Sources of Intermodel Spread in the Lapse Rate and Water Vapor Feedbacks.” *Journal of Climate* 31 (8): 3187–3206. https://doi.org/10.1175/JCLI-D-17-0674.1.

Po-Chedley, Stephen, Benjamin D. Santer, Stephan Fueglistaler, Mark D. Zelinka, Philip J. Cameron-Smith, Jeffrey F. Painter, and Qiang Fu. 2020. “Natural Variability Can Explain Model-Satellite Differences in Tropical Tropospheric Warming.” *Proceedings of the National Academy of Sciences* In Review.

Rieger, Landon A., Jason N. S. Cole, John C. Fyfe, Stephen Po-Chedley, Philip J. Cameron-Smith, Paul J. Durack, Nathan P. Gillett, and Qi Tang. 2020. “Quantifying CanESM5 and EAMv1 Sensitivities to Mt. Pinatubo Volcanic Forcing for the CMIP6 Historical Experiment.” *Geoscientific Model Development* 13 (10): 4831–43. https://doi.org/10.5194/gmd-13-4831-2020.

Romps, David M. 2014. “An Analytical Model for Tropical Relative Humidity.” *Journal of Climate* 27 (19): 7432–49. https://doi.org/10.1175/JCLI-D-14-00255.1.

Santer, Benjamin D., John C. Fyfe, Giuliana Pallotta, Gregory M. Flato, Gerald A. Meehl, Matthew H. England, Ed Hawkins, et al. 2017. “Causes of Differences in Model and Satellite Tropospheric Warming Rates.” *Nature Geoscience* 10 (7): 478–85. https://doi.org/10.1038/ngeo2973.

Santer, Benjamin D., Stephen Po-Chedley, Carl A. Mears, John C. Fyfe, Nathan P Gillett, Qiang Fu, Jeffrey F. Painter, et al. 2020. “Using Climate Model Simulations to Constrain Observations.” *Journal of Climate* Submitted.

Santer, Benjamin D., Susan Solomon, Giuliana Pallotta, Carl Mears, Stephen Po-Chedley, Qiang Fu, Frank Wentz, et al. 2017. “Comparing Tropospheric Warming in Climate Models and Satellite Data.” *Journal of Climate* 30 (1): 373–92. https://doi.org/10.1175/JCLI-D-16-0333.1.

Santer, Benjamin D, Céline Bonfils, Je F Painter, Mark D Zelinka, Carl Mears, Susan Solomon, Gavin a Schmidt, et al. 2014. “Volcanic Contribution to Decadal Changes in Tropospheric Temperature.” *Nature Geoscience* 7 (3): 185–89. https://doi.org/10.1038/NGEO2098.

Sherwood, S. C., M. J. Webb, J. D. Annan, K. C. Armour, P. M. Forster, J. C. Hargreaves, G. Hegerl, et al. 2020. “An Assessment of Earth’s Climate Sensitivity Using Multiple Lines of Evidence.” *Reviews of Geophysics* 58 (4): 1–92. https://doi.org/10.1029/2019RG000678.

Sherwood, Steven C, William Ingram, Yoko Tsushima, Masaki Satoh, Malcolm Roberts, Pier Luigi

Vidale, and Paul A O'Gorman. 2010. "Relative Humidity Changes in a Warmer Climate." *Journal of Geophysical Research: Atmospheres* 115 (D9). https://doi.org/10.1029/2009JD012585.

Siler, Nicholas, Cristian Proistosescu, and Stephen Po-Chedley. 2019. "Natural Variability Has Slowed the Decline in Western U.S. Snowpack Since the 1980s." *Geophysical Research Letters* 46 (1): 346–55. https://doi.org/10.1029/2018GL081080.

Singh, Martin S., and Paul A. O'Gorman. 2012. "Upward Shift of the Atmospheric General Circulation under Global Warming: Theory and Simulations." *Journal of Climate* 25 (23): 8259–76. https://doi.org/10.1175/JCLI-D-11-00699.1.

Tokarska, Katarzyna B., Martin B. Stolpe, Sebastian Sippel, Erich M. Fischer, Christopher J. Smith, Flavio Lehner, and Reto Knutti. 2020. "Past Warming Trend Constrains Future Warming in CMIP6 Models." *Science Advances* 6 (12): 1–14. https://doi.org/10.1126/sciadv.aaz9549.

Zelinka, Mark D., Timothy A. Myers, Daniel T. McCoy, Stephen Po-Chedley, Peter M. Caldwell, Paulo Ceppi, Stephen A. Klein, and Karl E. Taylor. 2020. "Causes of Higher Climate Sensitivity in CMIP6 Models." *Geophysical Research Letters* 47 (1): 1–12. https://doi.org/10.1029/2019GL085782.

Publications and Presentations

Christy, John R., Carl A. Mears, and Stephen Po-Chedley. "Global Climate: Tropospheric Temperature [in 'State of the Climate in 2017']." *Bulletin of the American Meteorological Society* 99, no. 8 (2018): S16–18. https://doi.org/10.1175/2018BAMSStateoftheClimate.1. LLNL-JRNL-746708.

Christy, John R., Stephen Po-Chedley, Carl A. Mears, and Leopold Haimberger. "Global Climate: Tropospheric Temperature [in 'State of the Climate in 2018']." *Bulletin of the American Meteorological Society* 100, no. 9 (2019): S17–19. https://doi.org/10.1175/2019BAMSStateoftheClimate.1. LLNL-JRNL-772017.

Christy, John R., Carl A. Mears, Stephen Po-Chedley, and Leopold Haimberger. "Global Climate: Tropospheric Temperature [in 'State of the Climate in 2019']." *Bulletin of the American Meteorological Society* 101, no. 8 (2020): S30–32. https://doi.org/10.1175/2020BAMSStateoftheClimate.1. LLNL-JRNL-811903.

Feldl, N., S. Po-Chedley, H. K. A. Singh, S. Hay, P. J. Kushner, *npj Climate and Atmospheric Science* 3, no. 1 (2020): 1–9. https://doi.org/10.1038/s41612-020-00146-7. LLNL-JRNL-783239.

Rieger, Landon A., Jason N. S. Cole, John C. Fyfe, Stephen Po-Chedley, Philip J. Cameron-Smith, Paul J. Durack, Nathan P. Gillett, and Qi Tang. "Quantifying CanESM5 and EAMv1

Sensitivities to Mt. Pinatubo Volcanic Forcing for the CMIP6 Historical Experiment." *Geoscientific Model Development* 13, no. 10 (October 9, 2020): 4831–43. https://doi.org/10.5194/gmd-13-4831-2020. LLNL-JRNL-800287.

Santer, Benjamin D., Céline J. W. Bonfils, Qiang Fu, John C. Fyfe, Gabriele C. Hegerl, Carl Mears, Jeffrey F. Painter, et al. "Celebrating the Anniversary of Three Key Events in Climate Change Science." *Nature Climate Change* 9, no. 3 (March 25, 2019): 180–82. https://doi.org/10.1038/s41558-019-0424-x. LLNL-JRNL-758507.

Santer, Benjamin D., Stephen Po-Chedley, Carl Mears, John C. Fyfe, Nathan Gillett, Qiang Fu, Jeffrey F. Painter, et al. "Using climate model simulations to constrain observations." *Journal of Climate* submitted. LLNL-JRNL-816149.

Siler, Nicholas, Cristian Proistosescu, and Stephen Po-Chedley. "Natural Variability Has Slowed the Decline in Western U.S. Snowpack Since the 1980s." *Geophysical Research Letters* 46, no. 1 (January 16, 2019): 346–55. https://doi.org/10.1029/2018GL081080. LLNL-JRNL-758571.

Po-Chedley, S., K.C. Armour, C.M. Bitz, M.D. Zelinka, and B.D. Santer. "Sources of Intermodel Spread in the Lapse Rate and Water Vapor Feedbacks." *Journal of Climate* 31, no. 8 (2018). https://doi.org/10.1175/JCLI-D-17-0674.1. LLNL-JRNL-739332.

Po-Chedley, S., K.C. Armour, C.M. Bitz, M.D. Zelinka, and B.D. Santer. "On the Intermodel Spread of the Lapse Rate and Water Vapor Feedbacks." Oregon State University, Corvallis, OR, USA, September, 2018. LLNL-PRES-758891.

Po-Chedley, Stephen, Cristian Proistosescu, Kyle C Armour, and Benjamin D Santer. "Climate Constraint Reflects Forced Signal." *Nature* 563, no. 7729 (2018): E6–9. https://doi.org/10.1038/s41586-018-0640-y. LLNL-JRNL-748281.

Po-Chedley, Stephen, Mark D. Zelinka, and Benjamin D. Santer. "The Influence of Climatology on Model Feedbacks." NASA Langley Seminar, Langley, VA, USA, March, 2019. LLNL-PRES-758949.

Po-Chedley, Stephen, Mark D. Zelinka, Nadir Jeevanjee, Tyler J. Thorsen, and Benjamin D. Santer. "Climatological Controls on the Response of Tropical Clouds and Relative Humidity to Greenhouse Gas Forcing." Naval Postgraduate School Department of Meteorology Colloquium, Monterey, California, USA, March, 2019. LLNL-PRES-769519.

Po-Chedley, Stephen, Mark D. Zelinka, Nadir Jeevanjee, Tyler J. Thorsen, and Benjamin D. Santer. "Climatology Explains Intermodel Spread in Tropical Upper Tropospheric Cloud and Relative Humidity Response to Greenhouse Warming." *Geophysical Research Letters* 46, no. 22 (2019): 13399–409. https://doi.org/10.1029/2019GL084786. LLNL-JRNL-783140.

Po-Chedley, Stephen, Mark D. Zelinka, Nadir Jeevanjee, Tyler J. Thorsen, and Benjamin D. Santer. " Climatological controls on the response of tropical clouds and relative humidity to greenhouse gas forcing." CFMIP, Mykonos, Greece, October, 2019. LLNL-PRES-793026.

Po-Chedley, Stephen, Benjamin D. Santer, Stephan Fueglistaler, Mark D. Zelinka, Philip J. Cameron-Smith, Jeffrey F. Painter, and Qiang Fu. "Natural Variability Can Explain Model-Satellite Differences in Tropical Tropospheric Warming." *Proceedings of the National Academy of Sciences* (2020): Under Review. LLNL-JRNL-811875.

Zelinka, Mark D., Timothy A. Myers, Daniel T. McCoy, Stephen Po-Chedley, Peter M. Caldwell, Paulo Ceppi, Stephen A. Klein, and Karl E. Taylor. "Causes of Higher Climate Sensitivity in CMIP6 Models." *Geophysical Research Letters* 47, no. 1 (2020): 1–12. https://doi.org/10.1029/2019GL085782. LLNL-JRNL-791582.

Notes to the Editors

- We use psi in the text (and the symbol in the figures).
- There are superscripts and ascii symbols (plus or minus and percent) in the caption for Figure 2. We write out psi (but the figure has the appropriate symbol).