



COMMENTARY

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ENSO Teleconnections More Uncertain in Regions of Lower Socioeconomic Development

Ruby Lieber^{1,2} , Andrew King^{1,2} , Josephine Brown^{1,2} , Linden Ashcroft^{1,2} , Mandy Freund^{1,3,4}, and Celia McMichael¹

¹School of Geography, Earth and Atmospheric Sciences, University of Melbourne, Parkville, VIC, Australia, ²Australian Research Council Centre of Excellence for Climate Extremes, University of Melbourne, Parkville, VIC, Australia, ³CSIRO Ocean and Atmosphere, Melbourne, VIC, Australia, ⁴Climate and Energy College, University of Melbourne, Parkville, VIC, Australia

Key Points:

- Uncertainty in historical El Niño Southern Oscillation teleconnections is examined using an ensemble reanalysis product
- Regional climate responses to El Niño and La Niña are more uncertain in poorer regions
- This inequality in climate information must be addressed to increase resilience to extremes

Supporting Information:

Supporting Information may be found in the online version of this article.

Correspondence to:

R. Lieber,
rlieber@student.unimelb.edu.au

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Author Contributions:

Conceptualization: Ruby Lieber, Andrew King, Josephine Brown
Formal analysis: Ruby Lieber, Andrew King, Josephine Brown, Linden Ashcroft, Mandy Freund, Celia McMichael
Methodology: Ruby Lieber
Supervision: Andrew King, Josephine Brown, Mandy Freund
Writing – original draft: Ruby Lieber
Writing – review & editing: Ruby Lieber, Andrew King, Josephine Brown, Linden Ashcroft, Mandy Freund, Celia McMichael

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Abstract The El Niño Southern Oscillation (ENSO) impacts climate variability globally and can influence extreme climate and weather events. We quantify the uncertainty in ENSO's atmospheric teleconnections with extremes using the Twentieth Century Reanalysis, showing that uncertainty estimates vary regionally over the historical period. Uncertainty is found to be greater in regions of lower socioeconomic development. This can be linked to the limited availability of observational data in these regions as well as difficulties constraining tropical climate dynamics in global gridded atmospheric data sets. Poorer locations face greater challenges due to lack of understanding of past variability limiting confidence in regional projections.

Plain Language Summary Extreme weather events, such as droughts and floods, can be influenced by climate phenomena such as the El Niño Southern Oscillation. El Niño and La Niña events are the biggest drivers of climate variability globally and so it is important to understand their influence on climate extremes. We demonstrate that understanding of how El Niño and La Niña influence extremes is not consistent across the globe. There is the least understanding in the poorest regions of the world. As many of these regions are especially vulnerable to climate change, this has important implications for adapting to the impacts of extremes.

1. Introduction

The El Niño–Southern Oscillation (ENSO) is the world's greatest source of interannual climate variability (McPhaden et al., 2006). ENSO receives widespread scientific and public attention due to the often-damaging nature of its impacts. ENSO has been linked to both environmental and economic impacts including animal population changes (Stenseth et al., 2002), coral bleaching (Zhang et al., 2017), and synchronous crop failure (Anderson et al., 2019). Many studies have suggested that the most devastating impacts of ENSO are felt through climate and weather extremes (Goddard & Gershunov, 2020). ENSO can influence the frequency and intensity of heatwaves (Luo & Lau, 2019), wildfires (Williams & Karoly, 1999), droughts (Singh et al., 2022), and floods (Ward et al., 2014) in many regions of the world. As these extreme events can have devastating consequences for populations and places, it is critical that we have a thorough understanding of the historical relationship between ENSO and extremes. It is also important that we can project and interpret how this relationship may change in the future, as climate change may alter the frequency and intensity of ENSO-related climate and weather extremes (Goddard & Gershunov, 2020).

Climate change will not impact people equally; lower-income countries that have contributed the least to greenhouse gas emissions will experience some of the greatest impacts (IPCC, 2022). Climate change can also act to increase socio-political inequalities and inhibit economic development (Diffenbaugh & Burke, 2019), including in agricultural regions where crop yields and associated livelihoods are affected by warming temperatures and extreme weather events (IPCC, 2022). Here, we quantify the uncertainty in the ENSO relationship with weather extremes globally using a state-of-the-art large ensemble reanalysis product. We find there is greater uncertainty in the ENSO-weather extreme relationship in regions of lower socioeconomic development and call for more efforts to reduce the relevant uncertainties in these parts of the world.

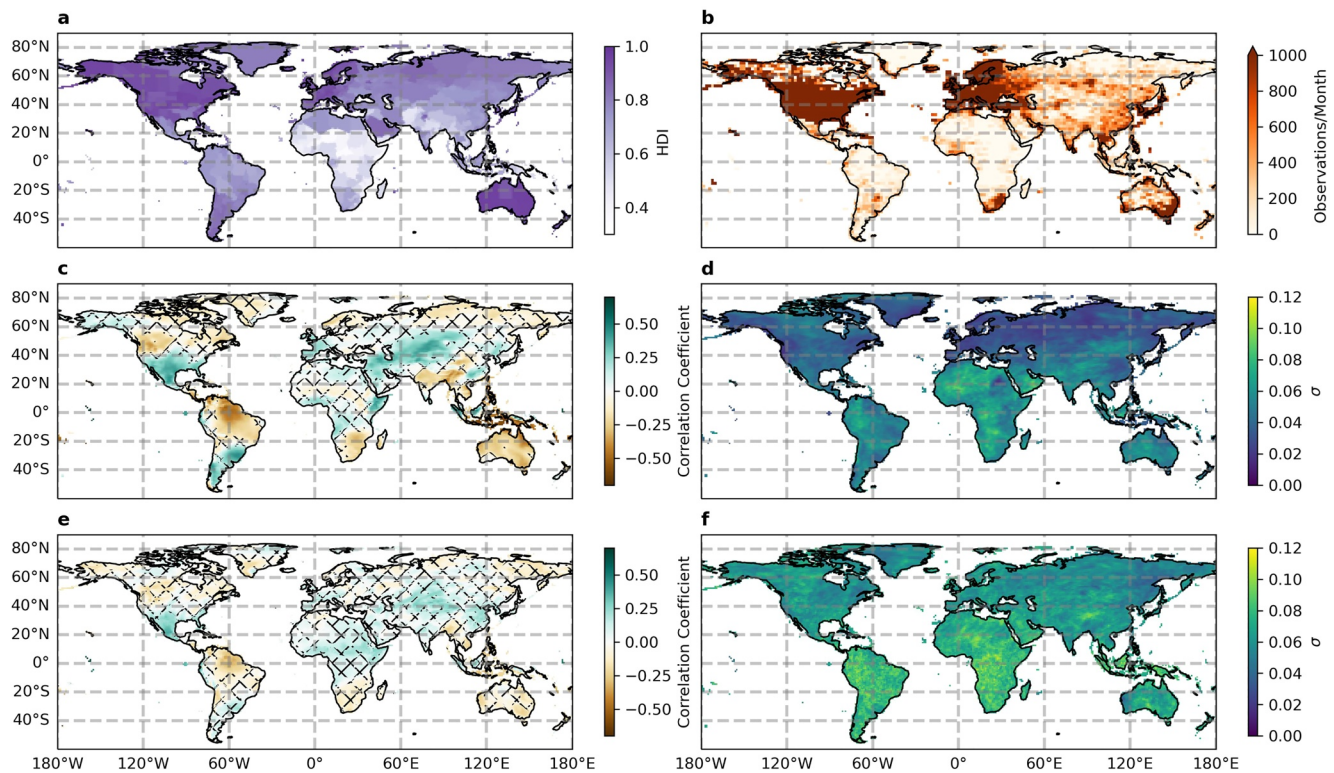


Figure 1. Greatest uncertainty in El Niño–Southern Oscillation relationships in equatorial regions. (a) Map of Human Development Index (2015 values) (Kummu et al., 2018). (b) Map depicting number of station observations used in $2 \times 2^\circ$ bin for 20CR (2015 values) (Compo et al., 2019). (c) 20CR ensemble mean spatial correlation between NDJ Niño3.4 index and seasonal mean precipitation anomalies (1901–2015). Hatching indicates regions of weak teleconnection (correlation coefficient $< |0.2|$). (d) Spatial map of 20CR ensemble spread for the correlation between Niño3.4 index and mean precipitation anomalies as measured by standard deviation. (e) 20CR ensemble mean spatial correlation between NDJ Niño3.4 index and seasonal max Rx1day (1901–2015). Hatching indicates regions of weak teleconnection. (f) Spatial map of 20CR ensemble spread for the correlation between Niño3.4 index and Rx1day as measured by standard deviation. Regions beyond 60°S are cropped out due to low population.

2. Regional Disparities in Understanding Historical ENSO Teleconnection

Reanalysis products, which combine observations and numerical model simulations to produce a record of historical weather and climate, can be used to inform our understanding of the historical relationship between ENSO and weather extremes. The latest version of the 20th Century Reanalysis (20CR) (Compo et al., 2011), which has been shown to reliably produce atmospheric estimates when compared with other reanalysis products, satellite data, and observations (Slivinski et al., 2021), is unique in having a large 80-member ensemble. This allows us to calculate uncertainty statistics from the range of different realizations of historical climate. By evaluating ENSO teleconnections—the impact of ENSO on climatic conditions in geographically distant areas—at the global scale (Figures 1c and 1e), we can identify regions where there is greater disagreement between ensemble members in their simulation of these relationships. We can then use ensemble spread as a measure of uncertainty in historical ENSO teleconnections and explore the underlying factors contributing to this uncertainty.

In this analysis we investigate links between the country-level Human Development Index (HDI)—as a broad measure of socioeconomic inequality—and uncertainty in ENSO teleconnections. Here we use the most recently available HDI (2015) so that results are relative to present socioeconomic conditions. We are interested in current values as it is the least developed countries now that have the least ability to adapt to future climatic changes. By correlating ensemble spread with the HDI spatially, we find that the agreement on historical ENSO teleconnections between ensemble members is not as well constrained in less developed areas of the world (Figure 2). This is true for both mean climate variables and several measures of climate extremes (Figure 2 and see Figures S1 and S2 in Supporting Information S1 for additional variables). Regions that demonstrate a high uncertainty in the mean rainfall teleconnection also demonstrate a high uncertainty in the teleconnection with Rx1day—an

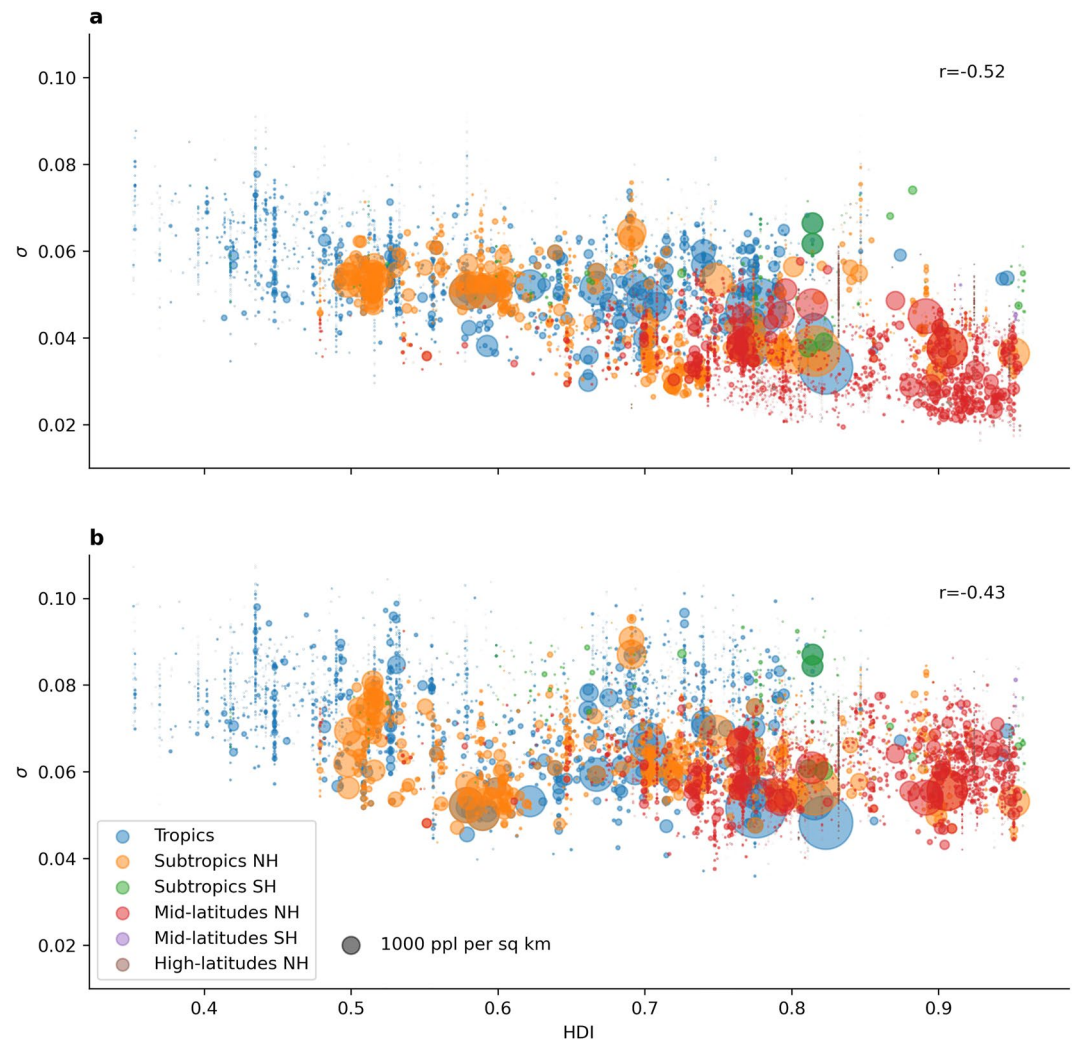


Figure 2. Greater uncertainty in the historical El Niño–Southern Oscillation (ENSO) relationship in less developed regions. 20CR ensemble spread of ENSO teleconnection versus Human Development Index (HDI) for (a) mean precipitation (b) Rx1day. Dot size is weighted by population (Center for International Earth Science Information Network - CIESIN - Columbia University, 2018). Standard deviation is over the period 1901–2015 for NDJ. HDI is 2015 values. Tropics defined as 0°–23.5°, Subtropics as 23.5°–35.5°, Mid-latitudes as 35.5°–60° for both hemispheres, and High-latitudes as 60°–90°. r value represents the Pearson correlation coefficient between the two variables.

index of extreme rainfall representative of the wettest day of the season (Figures 1d and 1f). This suggests that the uncertainty is regionally dependent.

We find that regions that have a higher teleconnection uncertainty are typically located within the tropics and that uncertainty is also typically higher in the southern hemisphere compared to the northern hemisphere (NH, Figures 1d, 1f, and 2). The lowest values of uncertainty are found in the NH mid-latitudes, however ENSO teleconnections are less important for regional climate variability in some of these areas compared to other modes (Rauthe & Paeth, 2004). We note that many of the most developed countries, as measured by HDI, tend to be in the higher latitudes and the least developed countries are predominantly located in the tropics (Figure 1a).

3. Lack of Observations Linked to Lack of Confidence

Our results show that the relationship between socioeconomic development (as measured by the HDI) and uncertainty in the ENSO teleconnection with both mean and extreme rainfall varies regionally. We suggest that local weather dynamics and observation density may both influence confidence in the representations of ENSO

teleconnections in the reanalysis. As spread in reanalysis ensemble members decreases with observation density (Slivinski et al., 2019), the high ensemble spread in countries with a lower HDI may stem from a lower observation count in these regions (Figure 1b). However, some regions with a higher observation count also show high levels of uncertainty (see Figures S3 and S4 in Supporting Information S1), suggesting that this is not the only factor contributing to the disagreement across the ensemble members. The relationship between ENSO teleconnection uncertainty and HDI is also evident in the latter half of the 20th century, despite the overall number of available observations contributing to the reanalysis increasing drastically after the mid 1950s (Slivinski et al., 2019). As most of the identified countries with high levels of ensemble spread are in the tropics, it appears that some uncertainty within the teleconnection can be attributed to the difficulties associated with constraining tropical weather dynamics, often driven by small-scale convective processes, in global gridded atmospheric data sets (Lee & Biasutti, 2014). Convective processes may limit the achievable skill of the reanalysis, which cannot be improved by increasing the number of local observations. Model biases in simulating ENSO's atmospheric teleconnections could also be contributing to the limits of the reanalysis skill, especially in tropical regions where there have been limited improvements in representations of ENSO teleconnections (Lee & Biasutti, 2014). Regional investigations into areas that demonstrated high uncertainty despite having relatively high observation counts support the hypothesis that regional uncertainty can be attributed to a combination of both weather dynamics and observation density (see Figures S3 and S4 in Supporting Information S1).

4. Addressing the Inequality in Climate Information

Our analysis shows a broad trend indicating that in regions and countries with lower HDI we have much less confidence in the relationship between local climate and the world's largest source of climate variability—ENSO. Thus, evaluation of climate models in these regions and confidence in climate projections is more limited (Doblas-Reyes et al., 2021). Model performance has been evaluated in regions such as East Africa where high-quality observational data sets are scarce (Kisembe et al., 2019), however it is important to note that all model evaluations are dependent on the quality of the reference data sets and so underlying uncertainties need to be accounted for (Sillmann et al., 2017). We do not suggest that lack of understanding of ENSO impacts results in poorer socioeconomic conditions. We do however highlight that uncertainty in past climate variability greatly reduces the capacity of regions, countries, and populations to adequately prepare for ENSO-related extremes in our changing climate. This can increase vulnerability of entire populations who work in weather-sensitive industries like agriculture, health, and infrastructure. These findings need to be considered when interpreting model simulations of past and future climate and when analyzing the teleconnection response to global warming.

We need to be particularly wary when interpreting results related to future changes in regions where we have shown there is greater uncertainty in the historical relationship. It is possible that the lack of data in some regions is due to insufficient records, or that data exist but have not been made available for use (Thorne et al., 2017). For example, national data policies and lack of financial investment have been attributed as the main reasons for the limited access to existing climate data in many African countries, and the data that is available is often of poor quality (Dinku et al., 2022). This is likely also the case for many other developing countries. Our results underscore the importance for existing climatological data to be shared more broadly, as it could help increase the certainty of regional climate information and consequently improve certainty of future projections. Data rescue efforts may be useful as increasing the number of observations available in regions with limited data could reduce overall uncertainty when incorporated into reanalysis products (Slivinski et al., 2021). While satellite data has increased the accuracy and spatial coverage of precipitation estimates globally and is useful for analysis over the last few decades (Sun et al., 2018), we still need to pursue data rescue for long range records. Century-long records are essential for assessing the impacts of climate oscillations such as ENSO which can vary over multi-decadal timescales. Availability of climate data remains a key challenge in increasing the scientific understanding of climate, and data recovery is considered a high priority for building climate resilience globally (Hewitt et al., 2020).

If we cannot reduce this uncertainty, it is important to consider the relevant uncertainties in decision making when planning regionally specific climate change adaptation efforts and risk-preparedness for the future. ENSO will continue to exert a profound influence on regional weather extremes and should be recognized as a major risk to populations, including in areas where we have less confidence in its teleconnections. Understanding the

historical teleconnections between ENSO and weather extremes and reducing impact-relevant uncertainties in less developed regions should be a priority for future research.

Data Availability Statement

All data that was used in this study is openly available for download from the following URL/DOIs.

- Population density: <https://sedac.ciesin.columbia.edu/data/set/gpw-v4-population-density-rev11/data-download>.
- HDI: <https://datadryad.org/stash/dataset/doi:10.5061/dryad.dk1j0>.
- Number of station observations: https://psl.noaa.gov/data/20CRv3_ISPD_obscounts_bymonth/.
- 20CRv3: https://portal.nersc.gov/archive/home/projects/incite11/www/20C_Reanalysis_version_3/everymember_anal_netcdf/subdaily.
- HadISST: <https://www.metoffice.gov.uk/hadobs/hadisst/>.
- The Jupyter Notebooks to execute the analysis in the paper are preserved at: <http://doi.org/10.5281/zenodo.7187466>.

References

- Anderson, W., Seager, R., Baethgen, W., Cane, M., & You, L. (2019). Synchronous crop failures and climate-forced production variability. *Science Advances*, 5(7), eaaw1976. <https://doi.org/10.1126/sciadv.aaw1976>
- Center for International Earth Science Information Network - CIESIN - Columbia University. (2018). *Gridded population of the world, version 4 (GPWv4): Population density, revision 11*. NASA Socioeconomic Data and Applications Center (SEDAC). <https://doi.org/10.7927/H49C6VHW>
- Compo, G. P., Slivinski, L. C., Whitaker, J. S., Sardeshmukh, P. D., McColl, C., Brohan, P., et al. (2019). *The international surface pressure data-bank version 4*. Research Data Archive at the National Center for Atmospheric Research, Computational and Information Systems Laboratory. <https://doi.org/10.5065/9EYR-TY90>
- Compo, G. P., Whitaker, J. S., Sardeshmukh, P. D., Matsui, N., Allan, R. J., Yin, X., et al. (2011). The twentieth century reanalysis project. *Quarterly Journal of the Royal Meteorological Society*, 137(654), 1–28. <https://doi.org/10.1002/qj.776>
- Diffenbaugh, N. S., & Burke, M. (2019). Global warming has increased global economic inequality. *Proceedings of the National Academy of Sciences of the United States of America*, 116(20), 9808–9813. <https://doi.org/10.1073/pnas.1816020116>
- Dinku, T., Faniriantsoa, R., Islam, S., Nsengiyumva, G., & Grossi, A. (2022). The climate data tool: Enhancing climate services across Africa. *Frontiers in Climate*, 3, 185. <https://doi.org/10.3389/fclim.2021.787519>
- Doblas-Reyes, F., Sorensson, A., Almazroui, M., Dosio, A., Gutowski, W., Haarsma, R., et al. (2021). Linking global to regional climate change. In *Climate change 2021: The physical science basis. Contribution of working group I to the sixth assessment report of the intergovernmental panel on climate change* (pp. 1363–1512). Cambridge University Press.
- Goddard, L., & Gershunov, A. (2020). Impact of El Niño on weather and climate extremes. In *El Niño Southern Oscillation in a changing climate* (pp. 361–375).
- Hewitt, C., Allis, E., Mason, S. J., Muth, M., Pulwarty, R., Shumake-Guillemot, J., et al. (2020). Making society climate resilient: International progress under the global framework for climate services. *Bulletin of the American Meteorological Society*, 101(2), E237–E252. <https://doi.org/10.1175/bams-d-18-0211.1>
- IPCC. (2022). Summary for policymakers. In H.-O. Pörtner, D. C. Roberts, M. Tignor, E. S. Poloczanska, K. Mintenbeck, A. Alegría, et al. (Eds.), *Climate change 2022: Impacts, adaptation, and vulnerability. Contribution of working group II to the sixth assessment report of the intergovernmental panel on climate change*. C. U. Press.
- Kisembe, J., Favre, A., Dosio, A., Lennard, C., Sabiiti, G., & Nimusiima, A. (2019). Evaluation of rainfall simulations over Uganda in CORDEX regional climate models. *Theoretical and Applied Climatology*, 137(1), 1117–1134. <https://doi.org/10.1007/s00704-018-2643-x>
- Kummu, M., Taka, M., & Guillaume, J. H. (2018). Gridded global datasets for gross domestic product and Human Development Index over 1990–2015. *Scientific Data*, 5(1), 1–15. <https://doi.org/10.1038/sdata.2018.4>
- Lee, D. E., & Biasutti, M. (2014). Climatology and variability of precipitation in the twentieth-century reanalysis. *Journal of Climate*, 27(15), 5964–5981. <https://doi.org/10.1175/jcli-d-13-00630.1>
- Luo, M., & Lau, N. C. (2019). Amplifying effect of ENSO on heat waves in China. *Climate Dynamics*, 52(5–6), 3277–3289. <https://doi.org/10.1007/s00382-018-4322-0>
- McPhaden, M. J., Zebiak, S. E., & Glantz, M. H. (2006). ENSO as an integrating concept in Earth science. *Science*, 314(5806), 1740–1745. <https://doi.org/10.1126/science.1132588>
- Rauthe, M., & Paeth, H. (2004). Relative importance of Northern Hemisphere circulation modes in predicting regional climate change. *Journal of Climate*, 17(21), 4180–4189. <https://doi.org/10.1175/jcli3140.1>
- Sillmann, J., Thorarinnsson, T., Keenlyside, N., Schaller, N., Alexander, L. V., Hegerl, G., et al. (2017). Understanding, modeling and predicting weather and climate extremes: Challenges and opportunities. *Weather and Climate Extremes*, 18, 65–74. <https://doi.org/10.1016/j.wace.2017.10.003>
- Singh, J., Ashfaq, M., Skinner, C. B., Anderson, W. B., Mishra, V., & Singh, D. (2022). Enhanced risk of concurrent regional droughts with increased ENSO variability and warming. *Nature Climate Change*, 12(2), 163–170. <https://doi.org/10.1038/s41558-021-01276-3>
- Slivinski, L. C., Compo, G. P., Sardeshmukh, P. D., Whitaker, J. S., McColl, C., Allan, R. J., et al. (2021). An evaluation of the performance of the twentieth century reanalysis version 3. *Journal of Climate*, 34(4), 1417–1438. <https://doi.org/10.1175/JCLI-D-20-0505.1>
- Slivinski, L. C., Compo, G. P., Whitaker, J. S., Sardeshmukh, P. D., Giese, B. S., McColl, C., et al. (2019). Towards a more reliable historical reanalysis: Improvements for version 3 of the Twentieth century reanalysis system. *Quarterly Journal of the Royal Meteorological Society*, 145(724), 2876–2908. <https://doi.org/10.1002/qj.3598>

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- Stenseth, N. C., Mysterud, A., Ottersen, G., Hurrell, J. W., Chan, K.-S., & Lima, M. (2002). Ecological effects of climate fluctuations. *Science*, 297(5585), 1292–1296. <https://doi.org/10.1126/science.1071281>
- Sun, Q., Miao, C., Duan, Q., Ashouri, H., Sorooshian, S., & Hsu, K. L. (2018). A review of global precipitation data sets: Data sources, estimation, and intercomparisons. *Reviews of Geophysics*, 56(1), 79–107. <https://doi.org/10.1002/2017rg000574>
- Thorne, P., Allan, R. J., Ashcroft, L., Brohan, P., Dunn, R. H., Menne, M., et al. (2017). Toward an integrated set of surface meteorological observations for climate science and applications. *Bulletin of the American Meteorological Society*, 98(12), 2689–2702. <https://doi.org/10.1175/bams-d-16-0165.1>
- Ward, P. J., Jongman, B., Kummu, M., Dettinger, M. D., Weiland, F. C. S., & Winsemius, H. C. (2014). Strong influence of El Niño Southern Oscillation on flood risk around the world. *Proceedings of the National Academy of Sciences of the United States of America*, 111(44), 15659–15664. <https://doi.org/10.1073/pnas.1409822111>
- Williams, A. A., & Karoly, D. J. (1999). Extreme fire weather in Australia and the impact of the El Niño-Southern Oscillation. *Australian Meteorological Magazine*, 48(1), 15–22.
- Zhang, N., Feng, M., Hendon, H. H., Hobday, A. J., & Zinke, J. (2017). Opposite polarities of ENSO drive distinct patterns of coral bleaching potentials in the southeast Indian Ocean. *Scientific Reports*, 7(1), 1–10. <https://doi.org/10.1038/s41598-017-02688-y>