Geophysical Research Letters

RESEARCH LETTER
10.1029/2019GL086259

Key Points:
- The signal of changes in observed temperature and rainfall due to global warming has clearly emerged in many regions and at mesoscales
- Tropical regions have experienced the largest changes in temperature relative to the amplitude of internal variability
- Signals of increasing extreme rainfall are emerging more quickly than signals in mean rainfall over many parts of the United Kingdom

Supporting Information:
- Supporting Information S1

Correspondence to:
E. Hawkins,
e.hawkins@reading.ac.uk

Citation:
Hawkins, E., Frame, D., Harrington, L., Joshi, M., King, A., Rojas, M., & Sutton, R. (2020). Observed emergence of the climate change signal: From the familiar to the unknown. *Geophysical Research Letters*, *47*, e2019GL086259. https://doi.org/10.1029/2019GL086259

Received 15 NOV 2019
Accepted 28 JAN 2020
Accepted article online 10 MAR 2020

Observed Emergence of the Climate Change Signal: From the Familiar to the Unknown

E. Hawkins[1], D. Frame[2], L. Harrington[2,3], M. Joshi[4], A. King[5], M. Rojas[6], and R. Sutton[1]

[1]National Centre for Atmospheric Science, Department of Meteorology, University of Reading, Reading, UK, [2]New Zealand Climate Change Research Institute, Victoria University of Wellington, Wellington, New Zealand, [3]Environmental Change Institute, University of Oxford, Oxford, UK, [4]Climatic Research Unit, School of Environmental Sciences, University of East Anglia, Norwich, UK, [5]School of Earth Sciences and ARC Centre of Excellence for Climate Extremes, University of Melbourne, Melbourne, Australia, [6]Department of Geophysics and Centre for Climate and Resilience Research, CR2, University of Chile, Santiago, Chile

Abstract Changes in climate are usually considered in terms of trends or differences over time. However, for many impacts requiring adaptation, it is the amplitude of the change relative to the local amplitude of climate variability which is more relevant. Here, we develop the concept of "signal-to-noise" in observations of local temperature, highlighting that many regions are already experiencing a climate which would be "unknown" by late 19th century standards. The emergence of observed temperature changes over both land and ocean is clearest in tropical regions, in contrast to the regions of largest change which are in the northern extratropics—broadly consistent with climate model simulations. Significant increases and decreases in rainfall have also already emerged in different regions with the United Kingdom experiencing a shift toward more extreme rainfall events, a signal which is emerging more clearly in some places than the changes in mean rainfall.

Plain Language Summary Changes in climate are translated into impacts on society not just though the amount of change, but how this change compares to the variations in climate that society is used to. Here we demonstrate that significant changes, when compared to the size of past variations, are present in both temperature and rainfall observations over many parts of the world.

1. Introduction

It was first noted that surface air temperatures were increasing at both local and global scales more than 80 years ago (Callendar, 1938; Kincer, 1933). At the time it was unclear whether the observed changes were part of a longer term trend or a natural fluctuation—the "signal" had not yet clearly emerged from the "noise" of variability—although Callendar (1938) did suggest that the increase in atmospheric carbon dioxide concentrations was partly to blame.

The concept of the emergence of a climate change signal has since been discussed extensively, often linked with the detection and attribution of climatic changes. For example, Madden and Ramanathan (1980) and Wigley and Jones (1981) could not robustly detect the carbon dioxide warming signal, but Hansen et al. (1988) predicted that the ratio of temperature change and the magnitude of interannual variability—the signal-to-noise ratio—would be above 3 in large parts of the tropics by the 2010s, with smaller values over high-latitude land regions. Mahlstein et al. (2011, 2012) subsequently demonstrated that the signal had indeed emerged in the observations, especially in the tropics in boreal summer, and with a similar pattern to that expected from climate model simulations. Lehner et al. (2017) subsequently highlighted emergence of observed temperature changes in both winter and summer in the northern extratropics. Significant changes in precipitation are often harder to detect because both thermodynamic and dynamic factors are crucial (e.g., Zappa & Shepherd, 2017) and because internal variability in precipitation is larger. However, precipitation changes are apparent in some regions (e.g., Zhang et al., 2007) including in extremes (e.g., Min et al., 2011).

Many studies have also considered when further changes in climate will emerge, for both mean temperature (Hawkins & Sutton, 2012; Mahlstein et al., 2011) and precipitation (Fischer et al., 2014; Giorgi & Bi, 2009).

Other studies have considered when changes in climate extremes should have emerged in the past (King et al., 2015) or future (Diffenbaugh & Scherer, 2011; Fischer et al., 2014). However, rather than examine the timing of any climate emergence, we focus here on the related quantity—signal-to-noise.

The clearest emergence of warming—and largest signal-to-noise values—tend to be found in the tropics, which are regions with large and vulnerable populations (Frame et al., 2017; Harrington et al., 2017; Lehner & Stocker, 2015). Signal-to-noise (S/N) is important for climate impacts, especially for ecosystems which have a limited ability to adapt, and so large changes outside past experience could be particularly harmful (Beaumont et al., 2011; Deutsch et al., 2008). Crop growing areas also face unprecedented heat (Battisti & Naylor, 2009) and changes in rainfall which may move outside past experiences (Rojas et al., 2019). The impacts of shifts in snowfall (Diffenbaugh et al., 2013) and Köppen-Geiger zones (Mahlstein et al., 2013) have also been discussed in terms related to the natural variability of the local conditions. Quantifying the changes that have already occurred may help determine which regions are suffering the largest adverse consequences of a warming world.

Here, we revisit the question of where and how the climate change signal is emerging from the background noise of internal variability. In contrast to most previous studies we focus our analysis on observational data sets of temperature and precipitation, with model simulations used only to test the methodology.

2. Observed Emergence and Signal-to-Noise

2.1. Methodology

Our aim is to produce estimates of signal-to-noise (S/N) for changes in observed climate variables without utilizing data from any climate model simulations. The simple approach adopted is to linearly regress local variations in climate onto annual global mean surface temperature change (GMST), that is,

$$L(t) = \alpha G(t) + \beta,$$

where $L(t)$ is the local change (in temperature or precipitation) over time, $G(t)$ is a smoothed version of GMST change over the same period, α defines the linear scaling between L and G, and β is a constant. Sutton et al. (2015) highlighted that a large fraction of variance in local climate changes can be represented by GMST changes, and Fischer et al. (2014) demonstrated that a similar regression approach provided robust estimates of S/N when examining future changes in precipitation in climate model simulations.

For $G(t)$ we use GMST from the Berkeley Earth temperature data set for 1850–2018 (Rohde et al., 2013), combined with HadSST3 from Kennedy et al. (2011), relative to the mean of 1850–1900, and smoothed with a lowess filter of 41 years to highlight the long-term variations (Figure 1a). The conclusions are insensitive to whether the smoothing parameter is slightly larger or smaller. The "signal" of global temperature change is defined as the value of the smoothed GMST in 2018 ($G_{2018} = 1.19$ K), the "signal" of local climate change described by GMST is αG, and the "noise" is defined as the standard deviation of the residuals ($L - \alpha G$).

Although we do not formally attribute the observed change in GMST, and hence local changes, to particular radiative forcings or feedbacks, applying the method of Haustein et al. (2017) to derive a GMST change that is attributable to human activity gives 1.22 K, similar to G_{2018}. Although 1850–1900 is often considered as a proxy for "pre-industrial" GMST, the Haustein et al. (2017) approach also suggests an additional anthropogenic warming of around 0.05 K occurred between 1750 and 1850–1900, based on radiative forcing estimates back to 1750. Although this plausible pre-1850 attributable warming is not included in our analysis, we refer to the 1850–1900 period as the early-industrial era, rather than pre-industrial.

2.2. Example for Annual Mean Temperatures in Oxford

To demonstrate our approach, we consider a case study of temperature change in Oxford, UK. Burt and Burt (2019) produced an extended temperature record for the Oxford Radcliffe Observatory with annual means available for 1814–2018. The temporal evolution of GMST and temperatures in Oxford are similar, showing that the "fingerprint" of GMST change is clearly visible at the spatial scale of a single continuous weather station, although with more noise at the local scale (Figure 1b, also see Sutton et al., 2015). We

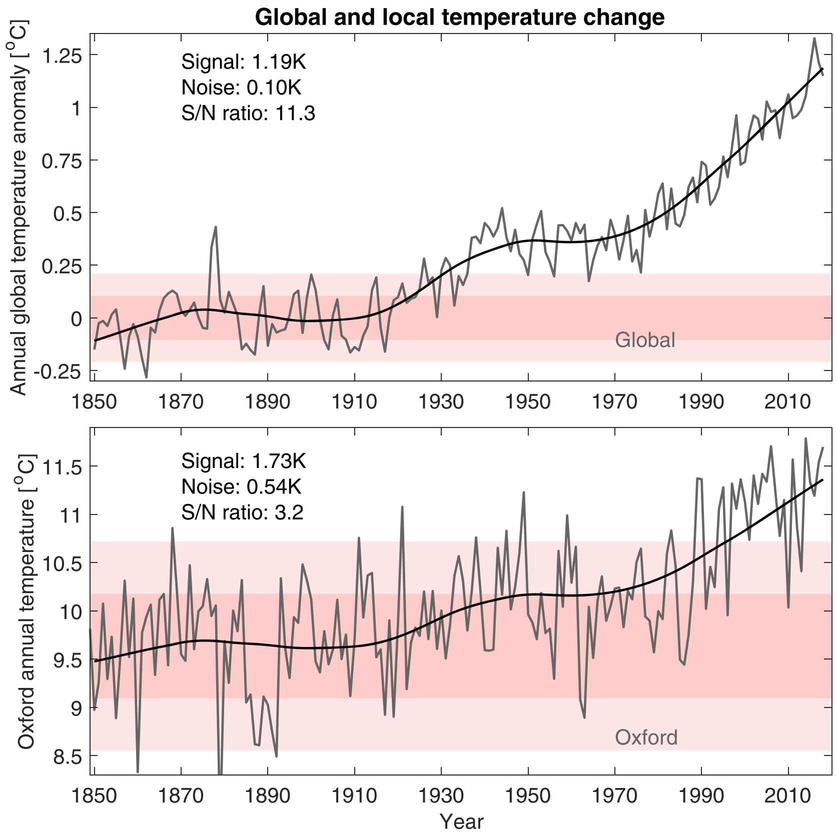

Figure 1. Emergence of global and local temperature change from 1850 to 2018. (top) GMST (gray), smoothed with a 41-year lowess filter (black). (bottom) Oxford annual temperature (gray) and scaled smoothed GMST (black). The correlation between Oxford temperatures and smoothed GMST is 0.67, and if the Oxford data are also smoothed with a 41-year lowess filter, the correlation increases to 0.98. The shaded bands indicate 1 and 2 standard deviations of the noise. Figure S2 shows other regional examples.

note that there is likely an urban heat island influence on temperatures in Oxford of around 0.1–0.2 K (Burt & Burt, 2019).

We regress this local temperature data set onto smoothed GMST and obtain $\alpha = 1.45 \pm 0.25$ (95% confidence interval). The "signal" for Oxford is $\alpha G_{2018} = 1.72 \pm 0.30$ K and the "noise," that is, the local variations that are not explained by GMST variations, is 0.54 K. Oxford therefore exhibits an S/N ratio of 3.2 ± 0.5 (Figure 1b).

We adopt the language of Frame et al. (2017) to describe how the climate has changed from being familiar, to being "unusual" relative to lived experience (S/N > 2), "unknown" (S/N > 3), and here we introduce "inconceivable" for S/N values above 5 (supporting information Figure S1). Using this terminology, temperatures in Oxford have become unknown relative to the early-industrial era. Two other regional examples are illustrated in Figure S2.

2.3. Local Climate Data and Methodological Tests

We perform a similar S/N analysis for each land and ocean grid point in the Berkeley Earth temperature data set (1850–2018) and in the GPCCv2018 land precipitation data set (1891–2016, Schneider et al., 2017). We use the 1° × 1° data sets for both Berkeley Earth and GPCC. We also use the HadUK-Grid data set for the United Kingdom (Hollis et al., 2019) at 25 km spatial resolution for monthly (1862–2017) and daily (1891–2017) precipitation data to examine changes in mean rainfall and extremes. Note that smoothed GMST (1850–2018) is used as G for both local temperature and precipitation analyses.

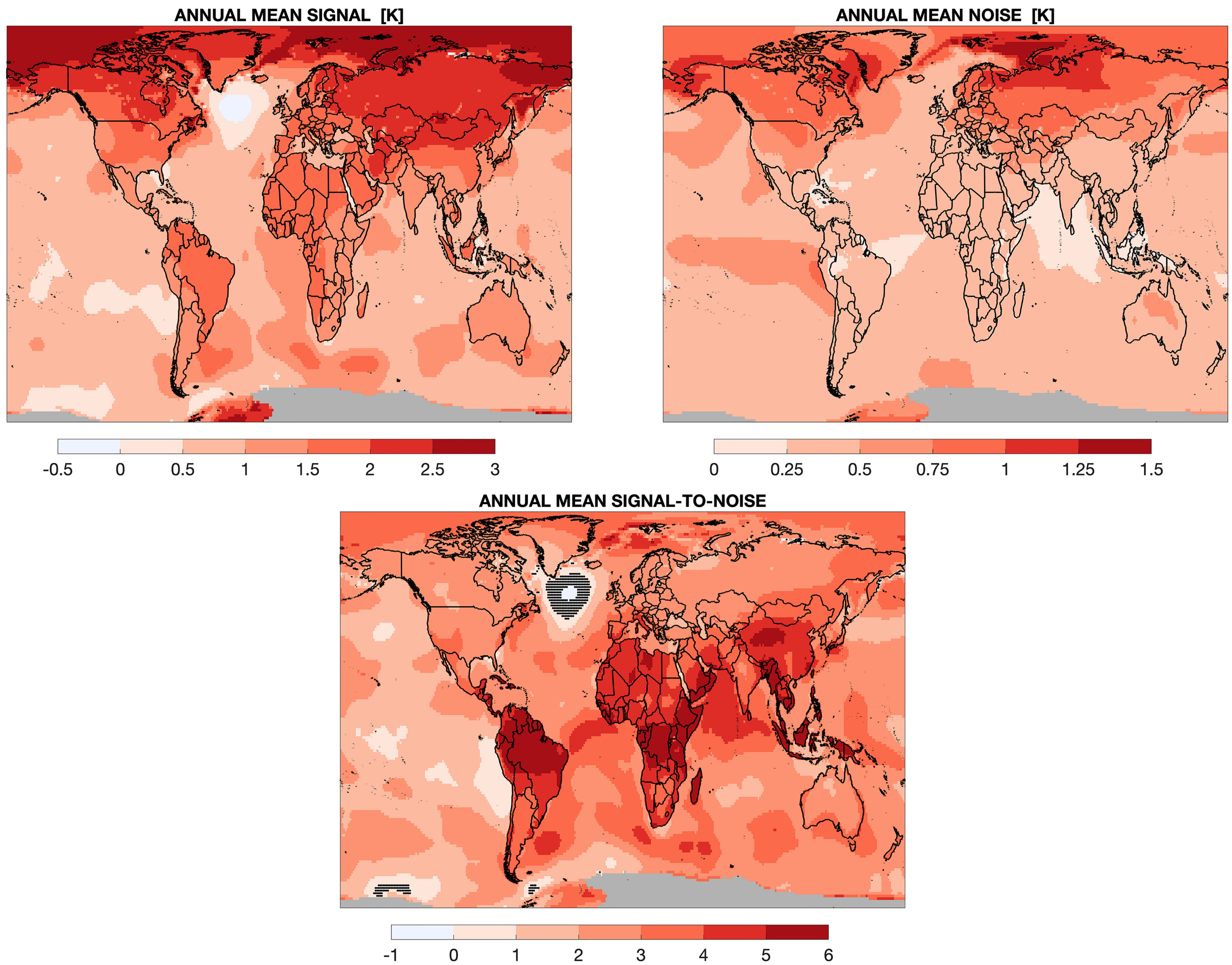

Figure 2. Signal, noise (both in K), and S/N for observed annual mean temperature change in the Berkeley earth data set. Many tropical regions show the smallest signal but also the smallest noise and largest S/N. Gray regions denote lack of sufficient data, that is, less than 100 years. The S/N values in stippled areas are not significantly different from zero.

As the local data are not necessarily available for all years back to 1850, we perform the regression only over the period where local temperatures or precipitation are defined. The signal relative to the early-industrial era can still be calculated assuming that the estimated regression parameter (α) is representative for the whole period, that is, the signal is always αG_{2018}, irrespective of the time period used to calculate α. However, we require that there must be at least 100 years of local climate data available.

We test our methodology using a large ensemble of climate simulations for the historical period (Maher et al., 2019), specifically to examine the uncertainty due to internal variability in derived S/N values for temperature and precipitation. Figures S3 and S4 demonstrate that the methodology produces S/N values with small uncertainties (typically <0.4 over land regions) and robust patterns.

3. Emergence of Unknown Temperatures

The map of the current observed signal of annual temperature change, relative to the early-industrial era, is shown in Figure 2a. It shows the familiar pattern of more warming over land than over the oceans, more warming at high northern latitudes, and less warming in the tropical regions and the southern hemisphere. Virtually all locations have experienced more than 1 K change since the early-industrial era, and many

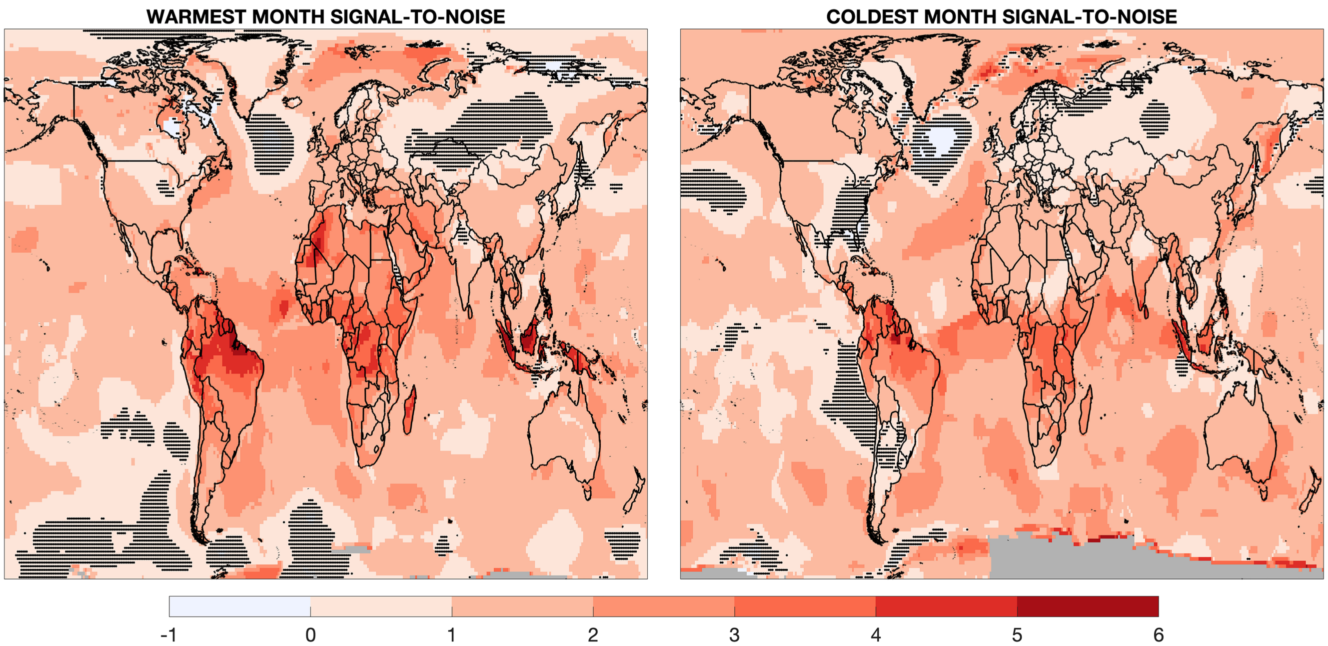

Figure 3. Signal-to-noise ratio for monthly average temperatures, for the climatologically warmest (left) and coldest (right) months at each grid point. Gray regions denote lack of sufficient data, that is, less than 100 years. The S/N values in stippled areas are not significantly different from zero.

regions have exceeded 2 K. The estimated noise shows a similar pattern with larger variability at higher northern latitudes, but the differences between the tropics and extratropics are more pronounced than for the signal (Figure 2b).

The ratio of these two patterns results in a signal-to-noise (S/N) map with the largest values in the tropical regions (Figure 2c). Although these areas generally have smaller signals than higher latitude regions, they have experienced a larger amplitude change relative to the (smaller) background variations in temperature than other regions. This is important as societies, infrastructure, and ecosystems are often adapted for the range of local climate experienced. S/N measures how far the climate is being shifted from that past range; the climate in large parts of the tropics has shifted such that the mean climate would have been inconceivable in the early-industrial era. More than half of the land area has experienced S/N above 3 and so has moved into a climate that is unknown by early-industrial standards (Figure S5).

Over the oceans the largest S/N values are found in the tropical Atlantic and tropical Indian Oceans. Fish species such as tuna have already been seen to be moving away from the tropics to the subtropics, likely to avoid these warmer waters (Monllor-Hurtado et al., 2017). Large parts of the North Atlantic have seen little warming overall, likely due to changes in ocean circulation providing a local cooling influence to offset global warming (e.g., Dima & Lohmann, 2010).

Although there are variations in magnitude, the estimated S/N pattern is relatively robust to the choice of temperature data set (Cowtan & Way, 2014; Lenssen et al., 2019, Morice et al., 2012, Zhang et al., 2019). However, there are notable local differences between data sets over southeast United States and parts of South America (Figure S6). The overall observed emergence pattern is broadly similar to that found in models under future climate change scenarios (Frame et al., 2017) though there are regional-scale differences, especially in the oceans but over some land areas too.

When considering how changes in climate may be experienced, it may in many cases be more relevant to examine seasonal or monthly timescales, depending on the impact being considered. For example, Figure 3 shows that S/N values can still be significant for monthly average temperatures. Again, the largest S/N values are found in the tropics and tend to be larger for the climatologically warmest month than the climatologically coldest month for each location. This is because weather variability tends to be larger in

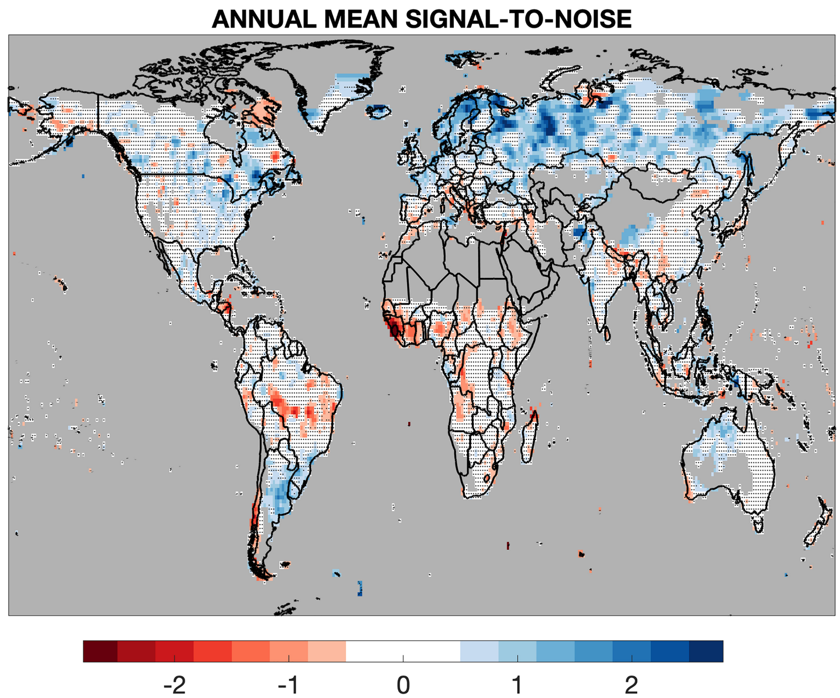

Figure 4. Signal-to-noise ratio for annual mean precipitation over land using the GPCC data set (1891–2016). Blue colors denote regions becoming wetter, and red colors denote regions that are becoming drier. Gray regions are either unobserved (oceans) or deserts (<250 mm/year). Stippling indicates where the regression parameter is not statistically significant from zero.

the colder months. Around 40% of land areas have moved into an unusual climate in their warmest months and 20% in the coldest months (Figure S5). This suggests a comparatively large increase in likelihood of heat-related extreme events in already warm months of already hot countries. One example is southeast Asia where the S/N values are large and the combined effects of El Nino events and climate change on extreme heat in the warmest months of the year have previously been noted (Thirumalai et al., 2017).

4. Emergence of Unusual Precipitation Amounts

The S/N analysis is repeated for annual mean precipitation using the GPCC data set. In this case, some regions are getting significantly wetter, and others are getting significantly drier (Figure 4), but, unsurprisingly, the signals are less clear than for temperature. Notable emergence of "unfamiliar" (S/N > 1) or unusual precipitation changes are observed in West Africa, Brazil, Chile, and southwest Australia (drier), and the northern high latitudes and Argentina (wetter). The seasonal values of S/N are shown in Figure S7. The changes in several of these regions have been discussed as being consistent with the expected response to increased greenhouse gas forcing, for example, for southwest Australia (Delworth & Zeng, 2014), for Chile (Boisier et al., 2016), and the northern extratropics (Zhang et al., 2007). Using the Center for International Earth Science Information Network (2018) population data set, around 6% of the world's population live in regions with unfamiliar wet conditions and around 2% in unfamiliar dry conditions.

To demonstrate that this framework can be applied to a range of gridded data sets and spatial scales, we consider one small region in more detail. The United Kingdom has a gridded rainfall data set available, covering 1891–2017 (daily) and 1862–2017 (monthly), which is suitable for examining changes in mean and extreme rainfall (Hollis et al., 2019).

Figure 5 shows the signal and S/N for annual mean rainfall, highlighting a tendency for increasing rainfall in large parts of the northern United Kingdom and the western coasts of up to 20% per K of GMST change. The

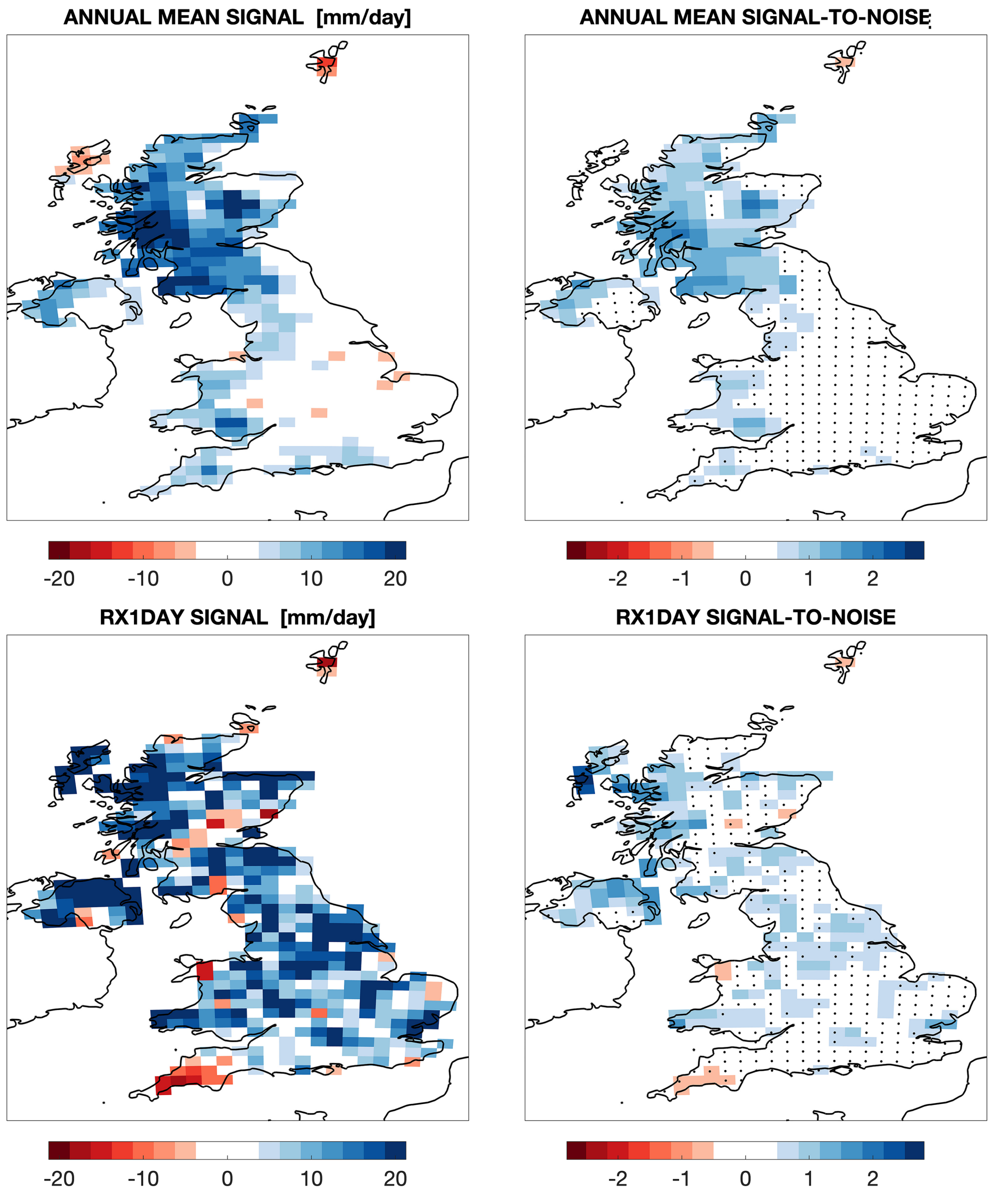

Figure 5. Signal (left) and signal-to-noise ratio (right) for annual mean precipitation over the United Kingdom (top row, 1862–2017) and extreme daily rainfall (RX1day, bottom row, 1891–2017) using the HadUK-grid data set. The signal is presented in units of % per K of GMST change. Blue colors denote regions becoming wetter, and red colors denote regions that are becoming drier. Stippling in the S/N panels indicates where the regression parameter is not statistically significant from zero.

corresponding S/N values exceed 1 in several areas, and these tend to be mountainous regions. Figure S8 shows the seasonal mean S/N values.

When considering the wettest day of the year (RX1day) as $L(t)$, there is a clear signal of increasing extreme rainfall, but the pattern is strikingly different to the mean. This signal is visible across large parts of the United Kingdom, even in regions where there are only small changes in mean rainfall. The signal has only clearly emerged in a few locations (Figure 5), but the spatial average of RX1day across the United Kingdom suggests an increase in extreme rainfall amounts of around 4 mm (or 11%) per K of GMST change (Figure S9), which is around 8% per K of U.K. temperature change, approximately consistent with Clausius-Clapeyron expectations (Pall et al., 2007).

These findings are consistent with Min et al. (2011) who showed that the signal of changes in extreme rainfall was detectable and attributable to human activity over large parts of the northern hemisphere land areas and with Fischer et al. (2014) who used climate model simulations to suggest that emergence of changes in extreme rainfall can occur earlier than changes in mean rainfall. Continued recovery of millions of undigitized weather observations, including for daily rainfall, will improve and lengthen these gridded data sets (e.g., Ashcroft et al., 2018; Hawkins et al., 2019).

5. Summary and Discussion

We have estimated the signal-to-noise ratio (S/N) of observed temperature and precipitation changes since the early-industrial era (1850–1900). Although we do not formally attribute these local changes to specific radiative forcings or feedbacks, the emergence of significantly different climates is related to increases in GMST, which itself is largely due to anthropogenic factors (e.g., Intergovernmental Panel on Climate Change, 2018). Further analysis and adopting techniques to better isolate the forced response, such as "dynamical adjustment" (Deser et al., 2016; Guo et al., 2019; Lehner et al., 2017), could provide improved estimates of observed S/N due to anthropogenic factors.

Consistent with previous studies and expectations from climate model simulations, the largest S/N values for historical temperature changes are seen in the tropical regions, over both land and ocean. Large regions have already experienced a shift to a climate state that is unknown, and even inconceivable, compared to that in the late 19th century. These signals of change are also clear in monthly average temperatures, with warmer months showing more significant changes.

Precipitation signals are emerging in several regions when considering observed rainfall changes, particularly West Africa, parts of South America, and northern Eurasia. Some regions in South America and central Africa exhibit simultaneously high S/N for temperature (S/N > 4) and significantly drier precipitation (S/N < -1) which may compound impacts.

As a demonstration of the methods in a data-rich region, and over a range of spatial scales, our analysis shows that there are clear shifts toward more annual rainfall over the United Kingdom, focused over northern and western areas. Significant increases in extreme heavy rainfall are emerging over large parts of the United Kingdom and are emerging more quickly than changes in mean rainfall in some places. The magnitude of the increase in extreme rainfall (~8% per K of local temperature change) is approximately consistent with expectations from the Clausius-Clapeyron relationship.

Many of the largest global shifts in climate, relative to the background variability, are found in countries with large, vulnerable populations, and this will be exacerbated if policy targets such as those in the Paris Agreement are not met (Frame et al., 2017; King & Harrington, 2018). There are also implications for ecosystems in these regions, which may not be able to adapt to such an unknown climate, especially given the rates of change. The rates of change of signal-to-noise to which societies and ecosystems can adapt are an important topic for future analyses.

Acknowledgments

We thank Nicola Maher for providing the MPI large ensemble data. We also thank the anonymous reviewer, Flavio Lehner, and Richard Betts for useful comments which helped improve the paper. E. H. and R. S. were supported by the National Centre for Atmospheric Science, and E. H. was funded by the ERA4CS INDECIS project with funding from the European Union Grant 690462. A. D. K. was funded by the Australian Research Council (DE180100638). M. J. is funded by UK Natural Environment Research Council Grants NE/S004645/1 and NE/N018486/1. M. R. acknowledges funding from FONDAP-CONICYT 15110009. D. J. F. and L. J. H. were supported by the Whakahura project funded by the Endeavour Fund (Contract RTVU1906). The data sets used in this paper are freely available online: Berkeley Earth (http://berkeleyearth.org), Cowtan & Way (https://www-users.york.ac.uk/~kdc3/papers/coverage2013/series.html), HadCRUT4 (https://www.metoffice.gov.uk/hadobs/hadcrut4/), GISTEMP (https://data.giss.nasa.gov/gistemp/), NOAA GlobTemp (https://www.ncdc.noaa.gov/noaa-merged-land-ocean-global-surface-temperature-analysis-noaaglobaltemp-v5), GPCC (https://www.dwd.de/EN/ourservices/gpcc/gpcc.html), HadUK-Grid (http://catalogue.ceda.ac.uk/uuid/4dc8450d889a491ebb20e724debe2dfb), and MPI Large Ensemble (https://www.mpimet.mpg.de/en/grand-ensemble/). The Oxford Radcliffe Observatory temperature data is available online (https://figshare.com/articles/OXFORD_England_Monthly_and_annual_mean_temperatures_1814_to_date_xlsx/10322015).

References

Ashcroft, L., Coll, J. R., Gilabert, A., Domonkos, P., Brunet, M., Aguilar, E., et al. (2018). A rescued dataset of sub-daily meteorological observations for Europe and the southern Mediterranean region, 1877–2012. *Earth System Science Data*, *10*, 1613–1635. https://doi.org/10.5194/essd-10-1613-2018

Battisti, D. S., & Naylor, R. L. (2009). Historical warnings of future food insecurity with unprecedented seasonal heat. *Science*, *323*(5911), 240–244. https://doi.org/10.1126/science.1164363

Beaumont, L. J., Pitman, A., Perkins, S., Zimmermann, N. E., Yoccoz, N. G., & Thuiller, W. (2011). Impacts of climate change on the world's most exceptional ecoregions. *Proceedings of the National Academy of Sciences*, *108*(6), 2306–2311. https://doi.org/10.1073/pnas.1007217108

Boisier, J. P., Rondanelli, R., Garreaud, R. D., & Munoz, F. (2016). Anthropogenic and natural contributions to the Southeast Pacific precipitation decline and recent megadrought in Central Chile. *Geophysical Research Letters*, *43*, 413–421. https://doi.org/10.1002/2015GL067265

Burt, S., & Burt, T. (2019). *Oxford weather and climate since 1767*. Oxford: Oxford University Press.

Callendar, G. S. (1938). The artificial production of carbon dioxide and its influence on temperature. *Quarterly Journal of the Royal Meteorological Society*, *64*(275), 223–240. https://doi.org/10.1002/qj.49706427503

Center for International Earth Science Information Network - Columbia University (2018). Gridded population of the world, version 4 (GPWv4): Population count, revision 11. Palisades, NY: NASA Socioeconomic Data and Applications Center (SEDAC). https://doi.org/10.7927/H4JW8BX5. Accessed 18th November 2019.

Cowtan, K., & Way, R. G. (2014). Coverage bias in the HadCRUT4 temperature series and its impact on recent temperature trends. *Quarterly Journal of the Royal Meteorological Society*, *140*(683), 2014. https://doi.org/10.1002/qj.2297

Delworth, T. L., & Zeng, F. (2014). Regional rainfall decline in Australia attributed to anthropogenic greenhouse gases and ozone levels. *Nature Geoscience*, *7*(8), 583–587. https://doi.org/10.1038/ngeo2201

Deser, C., Terray, L., & Phillips, A. S. (2016). Forced and internal components of winter air temperature trends over North America during the past 50 years: Mechanisms and implications. *Journal of Climate*, *29*, 2237–2258. https://doi.org/10.1175/JCLI-D-15-0304.1

Deutsch, C. A., Tewksbury, J. J., Huey, R. B., Sheldon, K. S., Ghalambor, C. K., Haak, D. C., & Martin, P. R. (2008). Impacts of climate warming on terrestrial ectotherms across latitude. *Proceedings of the National Academy of Sciences*, *105*(18), 6668–6672. https://doi.org/10.1073/pnas.0709472105

Diffenbaugh, N. S., & Scherer, M. (2011). Observational and model evidence of global emergence of permanent, unprecedented heat in the 20th and 21st centuries. *Climatic Change*, *107*(3–4), 615–624. https://doi.org/10.1007/s10584-011-0112-y

Diffenbaugh, N. S., Scherer, M., & Ashfaq, M. (2013). Response of snow-dependent hydrologic extremes to continued global warming. *Nature Climate Change*, *3*, 379–384. https://doi.org/10.1038/nclimate1732

Dima, M., & Lohmann, G. (2010). Evidence for two distinct modes of large-scale ocean circulation changes over the last century. *Journal of Climate*, *23*, 5. https://doi.org/10.1175/2009JCLI2867.1

Fischer, E. M., Sedlacek, J., Hawkins, E., & Knutti, R. (2014). Models agree on forced response pattern of precipitation and temperature extremes. *Geophysical Research Letters*, *41*, 8554–8562. https://doi.org/10.1002/2014GL062018

Frame, D., Joshi, M., Hawkins, E., Harrington, L. J., & de Roiste, M. (2017). Population-based emergence of unfamiliar climates. *Nature Climate Change*, *7*(6), 407–411. https://doi.org/10.1038/nclimate3297

Giorgi, F., & Bi, X. (2009). Time of emergence (TOE) of GHG-forced precipitation change hot-spots. *Geophysical Research Letters*, *36*, L06709. https://doi.org/10.1029/2009GL037593

Guo, R., Deser, C., Terray, L., & Lehner, F. (2019). Human influence on winter precipitation trends (1921–2015) over North America and Eurasia revealed by dynamical adjustment. *Geophysical Research Letters*, *46*, 3426–3434. https://doi.org/10.1029/2018GL081316

Hansen, J., Fung, I., Lacis, A., Rind, D., Lebedeff, S., Ruedy, R., et al. (1988). Global climate changes as forecast by Goddard Institute for Space Studies three-dimensional model. *Journal of Geophysical Research*, *93*(D8), 9341. https://doi.org/10.1029/JD093id08p09341

Harrington, L., Frame, D., Hawkins, E., & Joshi, M. (2017). Seasonal cycles enhance disparities between low- and high-income countries in exposure to monthly temperature emergence with future warming. *Environmental Research Letters*, *12*, 114039. https://doi.org/10.1088/1748-9326/aa95ae

Haustein, K., Allen, M. R., Forster, P. M., Otto, F. E. L., Mitchell, D. M., Matthews, H. D., & Frame, D. J. (2017). A real-time global warming index. *Scientific Reports*, *7*(1), 1–6. https://doi.org/10.1038/s41598-017-14828-5

Hawkins, E., Burt, S., Brohan, P., Lockwood, M., Richardson, H., Roy, M., & Thomas, S. (2019). Hourly weather observations from the Scottish Highlands (1883–1904) rescued by volunteer citizen scientists. *Geoscience Data Journal*. https://doi.org/10.1002/gdj3.79

Hawkins, E., & Sutton, R. (2012). Time of emergence of climate signals. *Geophysical Research Letters*, *39*, L01702. https://doi.org/10.1029/2011GL050087

Hollis, D., McCarthy, M., Kendon, M., Legg, T., & Simpson, I. (2019). HadUK-Grid—A new UK dataset of gridded climate observations. *Geoscience Data Journal*. https://doi.org/10.1002/gdj3.78

Intergovernmental Panel on Climate Change (2018). Summary for policymakers. In Masson-Delmotte, V, et al. (Eds). *Global warming of 1.5°C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty* (pp. 32). Geneva, Switzerland: World Meteorological Organization.

Kennedy, J. J., Rayner, N. A., Smith, R. O., Parker, D. E., & Saunby, M. (2011). Reassessing biases and other uncertainties in sea surface temperature observations measured in situ since 1850: 1. Measurement and sampling uncertainties. *Journal of Geophysical Research*, *116*, D14103. https://doi.org/10.1029/2010JD015218

Kincer, J. B. (1933). Is our climate changing? A study of long-time temperature trends. *Monthly Weather Review*, *61*(9), 251–259. https://doi.org/10.1175/1520-0493(1933)61<251:ioccas>2.0.co;2

King, A. D., Donat, M. G., Fischer, E. M., Hawkins, E., Alexander, L. V., Karoly, D. J., et al. (2015). The timing of anthropogenic emergence in simulated climate extremes. *Environmental Research Letters*, *10*(9), 094015. https://doi.org/10.1088/1748-9326/10/9/094015

King, A. D., & Harrington, L. J. (2018). The inequality of climate change from 1.5 to 2°C of global warming. *Geophysical Research Letters*, *45*, 5030–5033. https://doi.org/10.1029/2018GL078430

Lehner, F., Deser, C., & Terray, L. (2017). Toward a new estimate of "time of emergence" of anthropogenic warming: Insights from dynamical adjustment and a large initial-condition model ensemble. *Journal of Climate*, *30*(19), 7739–7756. https://doi.org/10.1175/jcli-d-16-0792.1

Lehner, F., & Stocker, T. (2015). From local perception to global perspective. *Nature Climate Change*, *5*, 731–734. https://doi.org/10.1038/nclimate2660

Lenssen, N. J. L., Schmidt, G. A., Hansen, J. E., Menne, M. J., Persin, A., Ruedy, R., & Zyss, D. (2019). Improvements in the GISTEMP uncertainty model. *Journal of Geophysical Research: Atmospheres*, *124*, 6307–6326. https://doi.org/10.1029/2018JD029522

Madden, R. A., & Ramanathan, V. (1980). Detecting climate change due to in- creasing carbon dioxide. *Science*, *209*(4458), 763–768. https://doi.org/10.1126/science.209.4458.763

Maher, N., Milinski, S., Suarez-Gutierrez, L., Botzet, M., Dobrynin, M., Kornblueh, L., et al. (2019). The Max Planck Institute grand ensemble: Enabling the exploration of climate system variability. *Journal of Advances in Modeling Earth Systems*, *11*, 2050–2069. https://doi.org/10.1029/2019MS001639

Mahlstein, I., Daniel, J. S., & Solomon, S. (2013). Pace of shifts in climate regions increases with global temperature. *Nature Climate Change*, *3*, 739–743. https://doi.org/10.1038/nclimate1876

Mahlstein, I., Hegerl, G., & Solomon, S. (2012). Emerging local warming signals in observational data. *Geophysical Research Letters*, *39*, L21711. https://doi.org/10.1029/2012GL053952

Mahlstein, I., Knutti, R., Solomon, S., & Portmann, R. W. (2011). Early onset of significant local warming in low latitude countries. *Environmental Research Letters*, *6*(3), 034009. https://doi.org/10.1088/1748-9326/6/3/034009

Min, S.-K., Zhang, X., Zwiers, F. W., & Hegerl, G. C. (2011). Human contribution to more-intense precipitation extremes. *Nature*, *470*(7334), 378–381. https://doi.org/10.1038/nature09763

Monllor-Hurtado, A., Pennino, M. G., & Sanchez-Lizaso, J. L. (2017). Shift in tuna catches due to ocean warming. *PLoS ONE*, *12*(6), e0178,196. https://doi.org/10.1371/journal.pone.0178196

Morice, C. P., Kennedy, J. J., Rayner, N. A., & Jones, P. D. (2012). Quantifying uncertainties in global and regional temperature change using an ensemble of observational estimates: The HadCRUT4 data set. *Journal of Geophysical Research*, *117*, D08101. https://doi.org/10.1029/2011JD017187

Pall, P., Allen, M. R., & Stone, D. A. (2007). Testing the Clausius–Clapeyron constraint on changes in extreme precipitation under CO_2 warming. *Climate Dynamics*, *28*, 351. https://doi.org/10.1007/s00382-006-0180-2

Rohde, R., Muller, R. A., Jacobsen, R., Muller, E., Perlmutter, S., Rosenfeld, A., et al. (2013). A new estimate of the average earth surface land temperature spanning 1753 to 2011. *Geoinformatics & Geostatistics*, *1*, 1. https://doi.org/10.4172/2327-4581.1000101

Rojas, M., Lambert, F., Ramirez-Villegas, J., & Challinor, A. J. (2019). Emergence of robust precipitation changes across crop production areas in the 21st century. *Proceedings of the National Academy of Sciences*, *116*(14), 6673–6678. https://doi.org/10.1073/pnas.1811463116

Schneider, U., Finger, P., Meyer-Christoffer, A., Rustemeier, E., Ziese, M., & Becker, A. (2017). Evaluating the hydrological cycle over land using the newly-corrected precipitation climatology from the Global Precipitation Climatology Centre (GPCC). *Atmosphere*, *8*(12), 52. https://doi.org/10.3390/atmos8030052

Sutton, R., Suckling, E., & Hawkins, E. (2015). What does global mean temperature tell us about local climate? *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, *373*(2054), 20140426. https://doi.org/10.1098/rsta.2014.0426

Thirumalai, K., DiNezio, P. N., Okumura, Y., & Deser, C. (2017). Extreme temperatures in Southeast Asia caused by El Niño and worsened by global warming. *Nature Communications*, *8*(1), 1–8. https://doi.org/10.1038/ncomms15531

Wigley, T. M. L., & Jones, P. D. (1981). Detecting CO_2-induced climatic change. *Nature*, *292*, 205.

Zappa, G., & Shepherd, T. G. (2017). Storylines of atmospheric circulation change for European regional climate impact assessment. *Journal of Climate*, *30*, 6561–6577. https://doi.org/10.1175/JCLI-D-16-0807.1

Zhang, H.-M., Lawrimore, J., Huang, B., Menne, M., Yin, X., Sanchez-Lugo, A., et al. (2019). Updated temperature data give a sharper view of climate trends. *Eos*, *100*. https://doi.org/10.1029/2019eo128229

Zhang, X., Zwiers, F. W., Hegerl, G. C., Lambert, F. H., Gillett, N. P., Solomon, S., et al. (2007). Detection of human influence on twentieth-century precipitation trends. *Nature*, *448*(7152), 461–465. https://doi.org/10.1038/nature06025