NSF Mathematical Sciences Postdoctoral Fellowship Proposal

Introduction

The Earth's climate system is highly variable due to complex non-linear physical processes at various spatial and temporal scales. As a result, while it is well-established that increasing greenhouse gas concentrations will lead to warming surface temperatures and increased atmospheric moisture [1, 2], it is difficult to quantify the extent to which observed climate changes can be attributed to human influence. This issue is addressed in the climate science literature through detection and attribution (D&A) research, where a combination of Global Climate Model (GCM) output and statistical techniques are used to separate the anthropogenic signal from natural variability in the observational record. Detection and attribution techniques have been very successful in establishing that carbon emissions are to a large degree responsible for observed increases in global air surface temperatures. However, given the large spatial variability in global warming impacts, policymakers and the public at large are primarily concerned with the role global warming plays at a local level. There is a particular need to know the extent to which human emissions are contributing to climate extremes, which have a disproportionate impact on infrastructure, the environment, and public health [3, 4, 5, 6]. Detection and attribution of extreme events at the local level is significantly more challenging than doing so for global mean temperatures due to higher levels of natural variability. This challenge presents a pressing need for statistical methodology that can provide robust and reliable detection and attribution conclusions at small scales.

This proposal will develop a Bayesian hierarchical framework for assessing the degree to which local climate changes, and in particular changes in extreme events, can be attributed to anthropogenic greenhouse gases. The methodology that I develop will advance the state-of-the-art of spatio-temporal modeling in order to detect significant causal relationships while controlling for false discoveries. This research will involve the use of cutting-edge computational techniques and resources, as well as recent advancements in the quantity and quality of climate model output, in order to provide robust and reliable conclusions. I will be advised in this project by Dr. Mark Risser of Lawrence Berkeley National Lab, a recognized expert in Bayesian methodology and spatio-temporal statistics who has solved many applied problems in climate change detection and attribution. Throughout the fellowship, I will also collaborate with statisticians at UC Berkeley and climate, atmospheric, and computational scientists at Lawrence Berkeley National Lab. My proposed research will provide for the first time an integrated methodology for making local detection and attribution statements from the perspective of a global framework. This work will provide advancements in our understanding of the role that human actions have on increasingly devastating climate impacts, a topic whose importance will continue to grow in the years to come.

Past Accomplishments

My experience in developing statistical models for complex spatio-temporal climate phenomena and in developing detection and attribution methodology provides me with an ideal background for succeeding in the proposed research. The first portion of my Ph.D. research has focused on building statistical methodology for estimating changes in ocean heat content from dispersed observations. Previous approaches to this problem have focused on statistical models which are only valid locally, and while such approaches can be used to interpolate the heat content field they cannot produce valid uncertainty estimates for the global integral and its trend over time. In my work, I developed a hierarchical model using kernel convolutions to capture the spatially non-stationary and anisotropic covariance properties of the heat content field in order to create a model which can quantify uncertainty in global ocean heat content [7]. As a part of this project, I have developed the **BayesianOHC** R software package that allows statisticians and climate scientists to easily implement sophisticated Bayesian models for the ocean heat content field [8]. Within the topic of non-stationary spatial modeling, I have also published peer-reviewed research on computational techniques for fitting Gaussian process models to large spatial datasets [9].

The second portion of my Ph.D. research has focused on developing an improved hierarchical Bayesian framework for the detection and attribution of the global temperature signal. In particular, I introduce a flexible structure for estimating the climate system's natural variability that allows for the uncertainty induced from estimating the covariance matrix to be propagated to the final result. My approach is able to achieve more accurate coverage rates for detecting the true signal than approaches that do not take this source of uncertainty into account [10]. While my experience with spatio-temporal modeling and detection and attribution will benefit me directly in performing this proposed research, I also have published research in developing Bayesian hierarchical models for psychometric applications [11] and developing algorithms for network optimization [12].

Research Objective, Methods, and Significance

In the climate science literature, the detection and attribution problem is commonly formalized as a least-squares regression [13, 14, 15]. In its simplest form this can be written as $\mathbf{y} = \beta\mathbf{x} + \boldsymbol{\epsilon}$, where $\mathbf{y}$ represents the global field of observed trends, $\mathbf{x}$ represents the field of trends that can be attributed to anthropogenic emissions, and the residuals $\boldsymbol{\epsilon} \sim N(0, C)$ represent internal variability with covariance matrix C. Then it can be said that the global warming signal is "detected" in the observations if $\beta > 0$, and that the observed trend can be "attributed" to the anthropogenic signal if β is statistically indistinguishable from one. There are statistical challenges in performing this regression in that the observations (the $\mathbf{y}$ term), the anthropogenic signal (the $\mathbf{x}$ term), and the structure of internal variability (the matrix C) are not exactly known and carry uncertainty in their estimation. Various regression-based detection and attribution approaches have been proposed in the climate literature [16, 17, 18, 19, 20], and in the statistics community recent developments have led to Bayesian hierarchical models that can account for various sources of uncertainty in the final inference [10, 21]. These approaches are limited however in that they only account for making detection and attribution conclusions at large spatial scales.

In this proposal, I will develop a regression-based detection and attribution framework that can make valid statistical conclusions at local scales. This will be done by introducing a stochastic process model for the detection and attribution parameter β, developing improved estimation of the natural variability matrix C, and integrating Bayesian false discovery control techniques into the framework so that the detection and attribution tests can be performed on every grid-cell simultaneously. This framework will be applied to observed changes in mean temperatures as well as to changes in extreme temperatures quantified through quantile regression. The proposed research will provide for the first time an integrated methodology for making local detection and attribution statements from the perspective of a global framework. The work will be structured through the following three aims, which I elaborate on below:

- **Aim 1:** Development of the Local Detection and Attribution Framework
- **Aim 2:** Application to Mean and Extreme Temperatures
- **Aim 3:** Statistical Validation using Climate Model Ensembles

Aim 1: Development of the Local Detection and Attribution Framework

Previous work in the climate literature has extended the regression-based detection and attribution framework to local scales by applying the tests to each location independently [22, 23]. Letting i index over grid-cells, this can be written as $y_i = \beta_i x_i + \epsilon_i$, where $\epsilon_i \sim N(0, \sigma_i)$ represents natural variability at each location. In vector notation, this procedure can be written as $\mathbf{y} = \boldsymbol{\beta} \odot \mathbf{x} + \boldsymbol{\epsilon}$ where $\odot$ signifies pointwise multiplication. While often not used in practice, the application of this methodology to multiple locations independently requires multiple testing correction procedures in

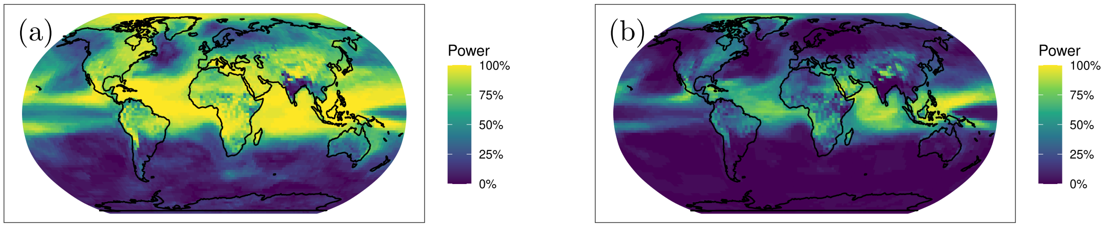

Figure 1: Power of the detection hypothesis test applied independently to each grid-cell without multiple testing correction (a) and using the Benjamini-Yekutieli procedure (b). Power is computed at the 5% level by averaging over the 47-member GISS initial-condition ensemble [31].

order to control for spurious conclusions. These procedures, such as the Benjamini-Yekutieli correction for tests with arbitrary dependence assumptions, can control for the rate of false discoveries [24]. This comes at the cost of decreasing the test's ability to correctly identify true relationships, which in statistics is referred to as the power of the test.

While the power of the detection and attribution framework can be evaluated from a purely statistical perspective, it is more realistic to use climate model output to evaluate the statistical properties under the assumption that the "truth" is known. While climate model output has long been used in the detection and attribution literature, output was historically taken from simulations run under different physical configurations. Recently there have been increases in the availability and size of initial-condition ensembles, which are collections of output from a fixed climate model configuration run under various perturbations of the initial conditions [25, 26, 27]. These initial-condition ensembles imply a statistical distribution over the climate system under the assumption that the physical dynamics are known, which has paved the way for significantly more precise statistical analysis [28, 29, 30].

Using initial condition ensembles, the statistical power of the independent grid-cell detection methodology of [23] can be evaluated against the alternative hypothesis that $\beta_i = 1$ everywhere, which within the context of the historical simulation is known to be true. Figure 1 shows the power values calculated using the ensemble of [31] without multiple-testing correction (Figure 1a) and with the Benjamini-Yekutieli false discovery correction (Figure 1b). As can be seen, the multiple hypothesis testing correction procedure yields a substantial decrease in the power of the detection procedure. While this reduction in power is necessary to control for false discoveries, the power in Figure 1(b) is unrealistically low due to the fact that the substantial spatial correlation between the tests is not taken into account [32].

To address this issue I will model both the internal variability components ϵ_i and the detection and attribution parameters β_i as spatially-correlated processes. As is standard in the literature, internal variability will be modeled as $\boldsymbol{\epsilon} \sim N(0, C)$ where C is largely informed by climate model simulations run under pre-industrial conditions. In order to capture the uncertainty induced from estimating C in the final inference, its estimation will be based on the hierarchical Laplacian parameterization developed in my prior work on detection and attribution of the global signal [10]. This representation will be extended to capture variability at smaller scales, as these components are designed to be filtered out in the framework for the global signal.

The modeling of $\boldsymbol{\beta}$ as a spatial field rather than as a singular parameter will be a novel development, and as this parameter should be inferred from the data its estimation will not involve climate model output directly. Rather, it will be assumed to follow a parameterized stochastic process whose parameters can be estimated within the context of the inference framework. Gaussian processes are widely used to model spatial correlation and would be a natural choice. This parameter is likely to have a correlation structure that varies over the domain, as suggested by Figure 1. As such $\boldsymbol{\beta}$ will be modeled using a non-stationary kernel-convolution Gaussian process using computationally efficient implementations [7, 33].

The overall Bayesian hierarchical framework is summarized in Figure 2. In developing this framework, the specific parameterization of C and the non-stationary Gaussian process parameters denoted as $\boldsymbol{\theta}$ will be designed using climate ensembles as a developmental testbed. The integrated framework will allow for the incorporation of Bayesian false discovery methods to control for spurious conclusions [32, 34, 35, 36]. The power and false discovery rate of the resulting framework will be evaluated using initial condition ensembles from multiple climate model configurations in order to ensure that the conclusions are robust to the physical assumptions.

Aim 2: Application to Mean and Extreme Temperatures

Once the framework described in Aim 1 is developed, I will apply the procedure to observational data in order to produce maps of detection and attribution results at the grid-cell level. The first application will be to mean near-surface air temperatures, for which I will use the HadCRUT observational ensemble which takes into account observational uncertainty [37]. While understanding the relationship between anthropogenic influences and mean temperature changes is important, extremes are of greater general interest due to their disproportionate effect on public health and the environment. I will incorporate extreme temperatures into the detection and attribution framework through quantile regression, which is a statistical method for quantifying trends in the intensity of extremes [38, 39]. The statistical power of extreme detection and attribution will likely differ spatially from the results applied to mean temperatures, due to evidence that in some locations and seasons these aspects of the temperature distribution are changing at different rates [28, 40, 41]. In order to lend insight to this phenomenon, I will compare the results of my framework applied to mean and extreme temperatures in different seasons and evaluate the extent to which observed differences in power agree or disagree with physical intuition and the existing literature.

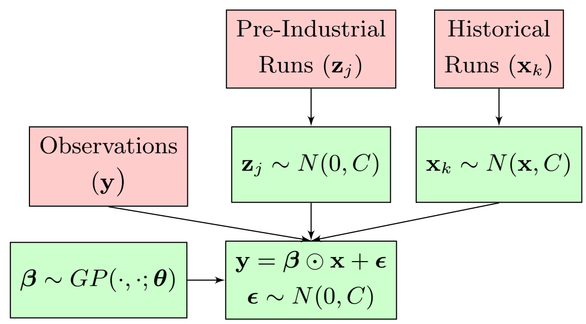

Figure 2: Diagram of the Bayesian hierarchical framework. Data is in red and distributional assumptions are in green. Indices j index over pre-industrial runs $\mathbf{z}_j$ and k index over historical runs $\mathbf{x}_k$. Here the symbol $\odot$ refers to pointwise vector multiplication. The vector $\boldsymbol{\theta}$ represents the non-stationary parameters of the Gaussian process (GP) for $\boldsymbol{\beta}$.

Aim 3: Statistical Validation using Climate Model Ensembles

Recent increases in climate model ensembles have been complemented by inter-comparison projects, which provide collections of ensembles for various scientific purposes [42, 43]. In particular, the Detection and Attribution Model Intercomparison Project (DAMIP) was created for the explicit purpose of evaluating detection and attribution methodology [44]. The historical and pre-industrial scenarios in this collection will be used in the development of the Bayesian framework as described in Figure 2. DAMIP also includes simulations of the historical climate under isolated influences, for example solar radiation or aerosols alone, as well as simulations under shared socio-economic pathways (SSP), which simulate the future climate under various hypothetical emissions scenarios. I will use these simulations for two additional applications. The first will be to split the influence of the signal $\mathbf{x}$ into components representing both greenhouse gas and non-greenhouse gas influences to investigate how well the detection and attribution framework can distinguish between these signals at the local level. The second will be to evaluate the power of the statistical tests under various future warming scenarios. This will allow quantification of the point at which various climate changes will become detectable or attributable as the global warming signal continues to increase in the coming decades.

Career Development

Following the fellowship, I plan to join the faculty at a research university where I will continue to develop statistical methodology for improving our understanding of climate and environmental problems. Through my fellowship appointments at Lawrence Berkeley National Laboratory and the UC Berkeley Department of Statistics, I will establish collaborations with statisticians and climate scientists that I will continue to build throughout my career. I will also develop my scientific writing and communication skills through the publication of my research and through presentations to the statistics and climate science communities.

Choice of Sponsor and Host Institution

Dr. Risser is a recognized expert in spatial, environmental, and Bayesian statistics and has solved many applied problems in climate change detection and attribution. From Dr. Risser, I will deepen my understanding of statistics, climate science, and computational techniques. The research environment at Lawrence Berkeley National Lab will be ideal for conducting my postdoctoral work due to its access to powerful computing resources and collaborative arrangements with eminent climate scientists. I will also be a visiting scholar at the UC Berkeley Department of Statistics where I will build connections in the statistics community, including with Dr. Christopher Paciorek who is a prominent leader in spatio-temporal modeling and statistical computation.

Broader Impacts

This research will be carried out in a way that maximizes its impacts with regard to the statistics and climate communities as well as to the broader public. I plan to present my work at both the annual Joint Statistical Meetings (JSM) and the American Geophysical Union (AGU) fall meeting, which are the main academic conferences for statisticians and climate scientists respectively. I will also develop an R package that will provide accessible functionality for implementing the detection and attribution framework. This package will be made available on the public repository CRAN [45], and I will make all of the code for reproducing my results publicly available through Github.

To make my work more accessible to the general public I will create an online tool through which one can visualize the results of my research. This tool will allow users to select a particular season and quantile level and view the resulting detection and attribution maps. Users will also be able to select a particular location and see the extent to which anthropogenic emissions are responsible for observed changes to their local climate. There will additionally be an option to display the results applied to future simulations under various emission scenarios. This website will be freely accessible via a public web domain, and I will promote the use of this tool through presentations, social media, and news coverage.

The detection and attribution of climate impacts is a high-profile topic that is relevant to climate scientists and statisticians as well as to policymakers and the public at large. Most prior detection and attribution studies have focused on either the global signal, which has little relevance to particular communities, or to individual newsworthy events, which while informative is less reliable due to selection bias and multiple testing issues. My proposed research will provide for the first time an integrated methodology for making local detection and attribution statements from the perspective of a global framework. As the global warming signal continues to grow in the coming years, it will be increasingly important to have a well-understood methodology for establishing the causal link between anthropogenic greenhouse gas emissions and damaging impacts.

References

[1] Svante Arrhenius. On the influence of carbonic acid in the air upon the temperature of the ground. *The London, Edinburgh, and Dublin Philosophical Magazine and Journal of Science*, 41(251):237–276, 1896.

[2] V Masson-Delmotte, P Zhai, A Priani, SL Connors, C Péan, S Berger, et al. Ipcc, 2021: Climate change 2021: The physical science basis. contribution of working group i to the sixth assessment report of the intergovernmental panel on climate change, 2021.

[3] P. A. Stott, D. A. Stone, and M. R. Allen. Human contribution to the European heatwave of 2003. *Nature*, 432:610–614, 2004.

[4] Pardeep Pall, Christina M Patricola, Michael F Wehner, Dáithí A Stone, Christopher J Paciorek, and William D Collins. Diagnosing conditional anthropogenic contributions to heavy colorado rainfall in september 2013. *Weather and Climate Extremes*, 17:1–6, 2017.

[5] Michael Wehner, Dáithí Stone, Hari Krishnan, Krishna AchutaRao, and Federico Castillo. The deadly combination of heat and humidity in india and pakistan in summer 2015. *Bulletin of the American meteorological society*, 97(12):S81–S86, 2016.

[6] David J Frame, Michael F Wehner, Ilan Noy, and Suzanne M Rosier. The economic costs of Hurricane Harvey attributable to climate change. *Climatic Change*, 160(2):271–281, 2020.

[7] Samuel Baugh and Karen McKinnon. Hierarchical bayesian modeling of ocean heat content and its uncertainty. *arXiv*, 2021. URL `https://arxiv.org/abs/2110.09717`.

[8] Samuel Baugh. *BayesianOHC: Non-stationary Gaussian Processes for Modeling Ocean Heat Content*, 2021. URL `https://github.com/samjbaugh/BayesianHeatContentCode`. R package version 0.1.0.

[9] Samuel Baugh and Michael L Stein. Computationally efficient spatial modeling using recursive skeletonization factorizations. *Spatial Statistics*, 27:18–30, 2018.

[10] Samuel Baugh and Karen McKinnon. Achieving more accurate uncertainty quantification in climate change detection and attribution through hierarchical bayesian modeling of the internal variability covariance matrix. In *AGU Fall Meeting Abstracts*, volume 2021, 2021.

[11] Minjeong Jeon, Ick Hoon Jin, Michael Schweinberger, and Samuel Baugh. Mapping unobserved item–respondent interactions: A latent space item response model with interaction map. *Psychometrika*, pages 1–26, 2021.

[12] Samuel Baugh, Gruia Calinescu, David Rincon-Cruz, and Kan Qiao. Improved algorithms for two energy-optimal routing problems in ad-hoc wireless networks. In *2016 IEEE International Conferences on Big Data and Cloud Computing (BDCloud), Social Computing and Networking (SocialCom), Sustainable Computing and Communications (SustainCom)(BDCloud-SocialCom-SustainCom)*, pages 509–516. IEEE, 2016.

[13] Gabriele C Hegerl, Hans von Storch, Klaus Hasselmann, Benjamin D Santer, Ulrich Cubasch, and Philip D Jones. Detecting greenhouse-gas-induced climate change with an optimal fingerprint method. *Journal of Climate*, 9(10):2281–2306, 1996.

[14] Myles R Allen and Simon FB Tett. Checking for model consistency in optimal fingerprinting. *Climate Dynamics*, 15(6):419–434, 1999.

[15] Dorit Hammerling, Matthias Katzfuss, and Richard Smith. Climate change detection and attribution. In *Handbook of Environmental and Ecological Statistics*, pages 789–817. Chapman and Hall/CRC, 2019.

[16] Tim Barnett, Francis Zwiers, Gabriele Hengerl, Myles Allen, Tom Crowly, Nathan Gillett, Klaus Hasselmann, Phil Jones, Ben Santer, Reiner Schnur, et al. Detecting and attributing external influences on the climate system: A review of recent advances. *Journal of Climate*, 18(9):1291–1314, 2005.

[17] Xuebin Zhang, Francis W Zwiers, Gabriele C Hegerl, F Hugo Lambert, Nathan P Gillett, Susan Solomon, Peter A Stott, and Toru Nozawa. Detection of human influence on twentieth-century precipitation trends. *Nature*, 448(7152):461–465, 2007.

[18] Benjamin D Santer, Jeffrey F Painter, Carl A Mears, Charles Doutriaux, Peter Caldwell, Julie M Arblaster, Philip J Cameron-Smith, Nathan P Gillett, Peter J Gleckler, John Lanzante, et al. Identifying human influences on atmospheric temperature. *Proceedings of the National Academy of Sciences*, 110(1):26–33, 2013.

[19] Alexis Hannart, Aurélien Ribes, and Philippe Naveau. Optimal fingerprinting under multiple sources of uncertainty. *Geophysical Research Letters*, 41(4):1261–1268, 2014.

[20] Alexis Hannart. Integrated optimal fingerprinting: Method description and illustration. *Journal of Climate*, 29(6):1977–1998, 2016.

[21] Matthias Katzfuss, Dorit Hammerling, and Richard L Smith. A bayesian hierarchical model for climate change detection and attribution. *Geophysical Research Letters*, 44(11):5720–5728, 2017.

[22] Thomas R Knutson, Fanrong Zeng, and Andrew T Wittenberg. Multimodel assessment of regional surface temperature trends: Cmip3 and cmip5 twentieth-century simulations. *Journal of Climate*, 26(22):8709–8743, 2013.

[23] Thomas R Knutson and Fanrong Zeng. Model assessment of observed precipitation trends over land regions: Detectable human influences and possible low bias in model trends. *Journal of Climate*, 31(12):4617–4637, 2018.

[24] Yoav Benjamini and Daniel Yekutieli. The control of the false discovery rate in multiple testing under dependency. *Annals of statistics*, pages 1165–1188, 2001.

[25] Brian C O'Neill, Claudia Tebaldi, Detlef P van Vuuren, Veronika Eyring, Pierre Friedlingstein, George Hurtt, Reto Knutti, Elmar Kriegler, Jean-Francois Lamarque, Jason Lowe, et al. The scenario model intercomparison project (scenariomip) for cmip6. *Geoscientific Model Development*, 9(9):3461–3482, 2016.

[26] Jennifer E Kay, Clara Deser, A Phillips, A Mai, Cecile Hannay, Gary Strand, Julie Michelle Arblaster, SC Bates, Gokhan Danabasoglu, James Edwards, et al. The community earth system model (cesm) large ensemble project: A community resource for studying climate change in the presence of internal climate variability. *Bulletin of the American Meteorological Society*, 96(8):1333–1349, 2015.

[27] Ryan L Sriver, Chris E Forest, and Klaus Keller. Effects of initial conditions uncertainty on regional climate variability: An analysis using a low-resolution cesm ensemble. *Geophysical Research Letters*, 42(13):5468–5476, 2015.

[28] Matz A Haugen, Michael L Stein, Elisabeth J Moyer, and Ryan L Sriver. Estimating changes in temperature distributions in a large ensemble of climate simulations using quantile regression. *Journal of CLIMATE*, 31(20):8573–8588, 2018.

[29] Michael L Stein. Some statistical issues in climate science. *Statistical Science*, 35(1):31–41, 2020.

[30] Nathan JL Lenssen, Alexis Hannart, and Dorit M Hammerling. Simulation testbed for trend detection and attribution methods.

[31] Ron L Miller, Gavin A Schmidt, Larissa S Nazarenko, Susanne E Bauer, Maxwell Kelley, Reto Ruedy, Gary L Russell, Andrew S Ackerman, Igor Aleinov, Michael Bauer, et al. Cmip6 historical simulations (1850–2014) with giss-e2. 1. *Journal of Advances in Modeling Earth Systems*, 13(1):e2019MS002034, 2021.

[32] Mark D Risser, Christopher J Paciorek, and Dáithí A Stone. Spatially dependent multiple testing under model misspecification, with application to detection of anthropogenic influence on extreme climate events. *Journal of the American Statistical Association*, 114(525):61–78, 2019.

[33] Mark D Risser and Daniel Turek. Bayesian inference for high-dimensional nonstationary gaussian processes. *Journal of Statistical Computation and Simulation*, 90(16):2902–2928, 2020.

[34] John D Storey. The positive false discovery rate: a bayesian interpretation and the q-value. *The Annals of Statistics*, 31(6):2013–2035, 2003.

[35] Peter Müller, Giovanni Parmigiani, Christian Robert, and Judith Rousseau. Optimal sample size for multiple testing: the case of gene expression microarrays. *Journal of the American Statistical Association*, 99(468):990–1001, 2004.

[36] Bradley Efron. Size, power and false discovery rates. *The Annals of Statistics*, 35(4):1351–1377, 2007.

[37] Colin P Morice, John J Kennedy, Nick A Rayner, and Phil D Jones. Quantifying uncertainties in global and regional temperature change using an ensemble of observational estimates: The hadcrut4 data set. *Journal of Geophysical Research: Atmospheres*, 117(D8), 2012.

[38] Roger Koenker and Kevin F Hallock. Quantile regression. *Journal of economic perspectives*, 15(4):143–156, 2001.

[39] Masha Kocherginsky, Xuming He, and Yunming Mu. Practical confidence intervals for regression quantiles. *Journal of Computational and Graphical Statistics*, 14(1):41–55, 2005.

[40] Karen A McKinnon, Andrew Rhines, Martin P Tingley, and Peter Huybers. The changing shape of northern hemisphere summer temperature distributions. *Journal of Geophysical Research: Atmospheres*, 121(15):8849–8868, 2016.

[41] Andrew Rhines, Karen A McKinnon, Martin P Tingley, and Peter Huybers. Seasonally resolved distributional trends of north american temperatures show contraction of winter variability. *Journal of Climate*, 30(3):1139–1157, 2017.

[42] Gerald A Meehl, George J Boer, Curt Covey, Mojib Latif, and Ronald J Stouffer. The coupled model intercomparison project (cmip). *Bulletin of the American Meteorological Society*, 81(2): 313–318, 2000.

[43] Veronika Eyring, Sandrine Bony, Gerald A Meehl, Catherine A Senior, Bjorn Stevens, Ronald J Stouffer, and Karl E Taylor. Overview of the coupled model intercomparison project phase 6 (cmip6) experimental design and organization. *Geoscientific Model Development*, 9(5):1937–1958, 2016.

[44] Nathan P Gillett, Hideo Shiogama, Bernd Funke, Gabriele Hegerl, Reto Knutti, Katja Matthes, Benjamin D Santer, Daithi Stone, and Claudia Tebaldi. The detection and attribution model intercomparison project (DAMIP v1. 0) contribution to CMIP6. *Geoscientific Model Development*, 9(10):3685–3697, 2016. doi: 10.5194/gmd-9-3685-2016.

[45] Kurt Hornik. R FAQ, 2020. URL `https://CRAN.R-project.org/doc/FAQ/R-FAQ.html`.