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Key Points:
- We propose a multivariate method to conduct an attribution analysis of one variable conditioned on another related climate variable
- We show how this method can be applied to high temperature exceedances given specified precipitation conditions
- Land regions between 60°N and 60°S show increased risk of conditional temperature extremes under dry conditions due to anthropogenic forcing

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

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A Multivariate Conditional Probability Ratio Framework for the Detection and Attribution of Compound Climate Extremes

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Abstract Most attribution studies tend to focus on the impact of anthropogenic forcing on individual variables. However, studies have already established that many climate variables are interrelated, and therefore, multidimensional changes can occur in response to climate change. Here, we propose a multivariate method which uses copula theory to account for underlying climate conditions while attributing the impact of anthropogenic forcing on a given climate variable. This method can be applied to any relevant pair of climate variables; here we apply the methodology to study high temperature exceedances given specified precipitation conditions (e.g., hot droughts). With this method, we introduce a new conditional probability ratio indicator, which communicates the impact of anthropogenic forcing on the likelihood of conditional exceedances. Since changes in temperatures under droughts have already accelerated faster than average climate conditions in many regions, quantifying anthropogenic impacts on conditional climate behavior is important to better understand climate change.

Plain Language Summary Most studies investigating human impacts on climate conditions focus on characterizing changes in individual variables such as precipitation or temperature. However, since many climate conditions are interconnected, these individual variables do not comprehensively represent the many changes that can occur in response to human activity. Here, we introduce a method that takes into account underlying climate conditions while quantifying the impact of human activity on a given climate variable. This method can be used to study pairs of climate variables and here we provide an example application to examine high temperature occurrences during dry precipitation conditions using climate models. For example, we show that regions such as the Amazon have a 4.1 times higher likelihood of experiencing high temperatures under dry climate conditions as a result of human activity. Given our knowledge of future climate change, we anticipate that the relationships between key climate variables may continue to change, which makes the study of human impacts on conditional climate behavior important for a more complete understanding of climate change.

1. Introduction

The detection and attribution of changes in climate to anthropogenic activities serves to deepen our understanding of how humans have externally forced climate change (IPCC, 2013). Detection and attribution studies present evidence of the physical consequences of the presence of anthropogenic forcings, allowing for the characterization and quantification of the many impacts of climate change (Easterling et al., 2016). In recent decades, the field of detection and attribution has begun to investigate changes in individual climate extremes, such as high temperature and heavy precipitation events (Christidis et al., 2005; Easterling et al., 2016; Fischer & Knutti, 2014, 2015; Meehl et al., 2007; Min et al., 2011, 2013). However, due to the interconnected and interactive nature of our climate system, the occurrence of one climate hazard can influence and even trigger the occurrence of associated climate hazards (AghaKouchak et al., 2020). Therefore, traditional studies quantifying the influence of anthropogenic activities on singular (or univariate) climate variables may not capture the full scope of resulting environmental and socioeconomic impacts (AghaKouchak et al., 2020; Leonard et al., 2014; Zscheischler et al., 2018).

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Detection and attribution studies have only recently begun to make progress in evaluating anthropogenic impacts from multivariate perspectives. In 2018, Sarhadi et al. used Coupled Model Intercomparison Project Phase 5 (CMIP5) historical and historical natural-only data to establish that the presence of anthropogenic forcing has significantly impacted the joint probability of concurrent warm and dry years (Sarhadi et al., 2018). Mazdiyasni et al. (2019) recently introduced and applied a novel framework for representing heat wave events, simultaneously incorporating multiple, interdependent features in intensity-duration-frequency curves to highlight the impact of anthropogenic forcing on heat waves. Wang et al. (2020) also attributed increases in the frequency and intensity of summertime compound daytime and nighttime hot extremes to rising anthropogenic emissions. As relatively few attribution studies have examined the impacts of anthropogenic forcing using multivariate approaches, dependencies between interrelated climate variables are still not well-studied or well-represented in detection and attribution literature.

Of the many pairs of key climate variables, temperature and precipitation possess a strong negative correlation over much of the global land area during the warm season, which has been widely recognized in the literature (Chang & Wallace, 1987; Huang & van den Dool, 1993; Madden & Williams, 1978; Trenberth & Shea, 2005). In addition, recent studies have highlighted that the dependence between temperature and precipitation may be changing due to increasing temperatures (Cheng et al., 2019; Hao et al., 2019; Zscheischler & Seneviratne, 2017). With CMIP5 projections, Zscheischler and Seneviratne (2017) found that changes in the negative correlation between summertime temperature and precipitation will result in significant increases in concurrently dry and hot summers. Therefore, the attribution of changes in the dependence between temperature and precipitation can provide important insight into the contribution of anthropogenic forcing on fundamental changes in our climate system.

In addition to changes in the dependence of temperature and precipitation, recent studies have also found conditional temperature changes occurring under low precipitation conditions. In the United States, Chiang et al. (2018) used observations to show that drought temperatures have experienced amplified warming relative to average temperatures in southern and eastern regions between the early and late 20th century. The CMIP5 multi-model ensemble average also reflected this pattern of amplified warming under dry conditions in the southern states, indicating that this amplified warming pattern was expressed in both observations and model simulations. With a conditional perspective of temperature change, Chiang et al. (2018) identified regions that are more vulnerable to amplified warming under dry conditions, which differed from regions experiencing the greatest change in average temperatures. This highlights the importance of considering underlying conditions when evaluating emerging changes in climate variables, as conditional analyses can provide different perspectives of changes in climate conditions and climate risks.

Here, we introduce a new approach to attributing climate extremes to anthropogenic forcing by investigating conditional temperature exceedances with the use of copula theory. Copulas are multivariate distribution functions which are useful in modeling the dependence structure between two or more random variables (Madadgar & Moradkhani, 2013; Mazdiyasni et al., 2017; Nelsen, 2006; Zscheischler & Seneviratne, 2017). The use of copulas allows us to better understand the conditional behavior of a given variable, which otherwise may be difficult to study due to the inherent rarity of samples. Using CMIP5 climate models with and without anthropogenic forcing, we examine how the presence of anthropogenic forcing impacts the likelihood of temperature exceedances conditioned on preceding dry meteorological conditions. Anthropogenic forcing refers to the human-driven or anthropogenic impact on Earth's radiative forcing, and includes the emission of heat-trapping greenhouse gases, the industrial release of aerosols, and land use and land cover changes (IPCC, 2013). With a conditional perspective of anthropogenic impacts on our climate, we can gain a better understanding of the changing risks of extremes, which will serve to strengthen future vulnerability and exposure studies. In addition, with this novel approach to evaluating anthropogenic impacts, we can improve our understanding of how extremes have changed and may continue to change in the future.

2. Materials and Methods

2.1. Data

To conduct the study, we used monthly precipitation and temperature from 15 CMIP5 historical and historical natural-only models (see Appendix A for the included models) during the period 1850–2005 (Taylor et al., 2012). The CMIP5 historical models simulate the recent historical past by including anthropogenic (greenhouse gas emissions, anthropogenic aerosol emissions, human-driven land use and land cover change) and natural forcings (solar forcings, volcanic aerosols), while the historical natural-only models only include natural forcings using fixed pre-industrial greenhouse gas and aerosol concentrations (without anthropogenic forcing) (Taylor et al., 2012). We regridded all models to a 1 degree resolution using nearest-neighbor interpolation to examine the multi-model ensemble results.

For our analysis, we used the land regions outlined in the fifth Intergovernmental Panel on Climate Change (IPCC) report (referred to as IPCC regions in the text) to examine conditional differences between historical and historical natural-only conditions across regions (IPCC, 2013). For each climate model, we standardized each IPCC region's median precipitation and temperature time series with each region's historical natural-only 1850–2005 data. We followed the non-parametric standardization methodology introduced in Farahmand and AghaKouchak (2015) to generate each region's 3-month standardized precipitation index (SPI) and standardized temperature conditions on the last month of the SPI time window (Farahmand & AghaKouchak, 2015). Our standardization approach allowed us to uniformly examine a range of dry and warm conditions across different regions and varying climate scenarios. Then, we subsampled the 3-month SPI and monthly standardized temperature values at the end of each season (February, May, August, and November) to create each regional time series used for the analysis outlined in the following section. Due to the autocorrelated nature of our climate variables, we subsampled from our standardized indices in order to reduce the temporal dependence between time points.

2.2. Analysis

Recently, copulas have become a popular tool to represent multivariate relationships in climate science (Hao & Singh, 2016; Salvadori et al., 2007). Copulas are multivariate distribution functions, which can model the dependence structure of two or more variables and aid in evaluating compound extremes, that by definition, occur infrequently (Joe, 1997; Nelsen, 2006; Zscheischler & Seneviratne, 2017). Copula theory allows us to examine features such as the joint and conditional behavior of extreme values, which otherwise may be difficult to study (Nelsen, 2006). Copulas are advantageous over other multivariate approaches as the marginal distributions of the individual variables and dependence structure of the variables are evaluated separately, which allows for the flexible application of copula theory to variables with different margins (Grimaldi & Serinaldi, 2006). Due to the interconnected, non-linear nature of our climate system, copulas are a versatile and accessible tool that can be used to describe multivariate climate variables.

Using copula theory, we can express the joint probability distribution of precipitation *(X)* and temperature *(Y)*,

$$F(x,y) = c\left[F_X(x), F_Y(y)\right]$$

where $F(x,y)$ represents the cumulative joint probability of precipitation and temperature, c is the copula cumulative distribution function, and $F_X(x)$ and $F_Y(y)$ represent the marginal probability distribution functions (PDF) of precipitation and temperature, respectively (Sklar, 1959).

For each region, we took the multi-model median subsampled time series and transformed the negative standardized precipitation and standardized temperature data into their uniform marginals, and then isolated the copula family that best represents the bivariate data. To transform the bivariate data into their uniform marginals, we employed this transformation for each pair of datapoints (x_i, y_i):

$$\left(\frac{n - R(x_i) + \frac{1}{2}}{n}, \frac{n - R(y_i) + \frac{1}{2}}{n} \right)$$

where i represents the pair number, n, the total number of pairs, and $R(x_i)$, the rank of x_i.

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We determined the best-fit copula family by using the BiCopSelect function in the R package, VineCopula, employing the Bayesian Information Criteria to select the family (Nagler et al., 2019). We then confirmed the goodness of fit of the best-fit copula family with VineCopula's BiCopGofTest function–which implements a goodness-of-fit test using White's information matrix equality (Nagler et al., 2019).

To highlight the difference between each region's best-fit historical and historical natural-only best-fit copula families and parameters, we constructed two-dimensional kernel density estimates using randomly generated variates from the copula models. We then transformed the variates from uniform marginals back to the negative standardized precipitation and standardized temperature values to visualize historical and historical natural-only variates on the same axes.

Using our fitted copula models, we selected the 10th percentile of precipitation from the historical natural-only scenario and sampled the conditional historical and historical natural-only probability density functions (PDFs) of monthly temperature. From the conditional temperature PDFs, we extracted the probability of temperature exceedances conditioned on the 10th percentile of precipitation. Using the probability ratio concept, we examined a set absolute temperature anomaly (e.g., the 90th percentile of temperature from the historical natural-only scenario) and then found the probability of exceedance for the defined precipitation condition. Finally, for each region, we compared historical and historical natural-only conditional temperature exceedance probabilities to create a "conditional probability ratio," which we abbreviate as CPR, to quantify the difference between the two climate scenarios. Although we chose to use the 10th percentile of precipitation and the 90th percentile of temperature, which are common thresholds used to define climate indices to express dry and hot conditions, any pair of percentiles (and any pair of variables) can be used with this methodology.

3. Results

Figure 1 depicts selected IPCC regional copula contours as modeled by their best-fit copula families (the best-fit copula families and associated p-values for each IPCC region and climate scenario can be found in Tables S1 and S2, respectively). Here, we have chosen to highlight results from a range of regions across the globe: the Amazon (AMZ), Central Europe (CEU), Central North America (CNA), and South Australia/New Zealand (SAU) (the remaining regions are shown in Figure S1). Each subplot depicts the historical and historical natural-only dependencies between temperature and negative standardized precipitation for the selected region. From these regional plots, we can highlight the impact of anthropogenic forcing on the dependence between temperature and negative precipitation for a given region. The Amazon and South Australia/New Zealand regions show strong shifts in the medians and tails of their distributions, while Central Europe and Central North America show less substantial change in their distribution medians. However, we note that the right tail of the historical Central North America distribution differs substantially from the historical natural-only distribution.

We also note that regions with more significant shifts in their medians do not just shift positions and maintain the same dependence shape, but also experience changes in the structure of the dependence between negative precipitation and temperature. For example, for the Amazon region, between historical and historical natural-only conditions, we highlight that there is significant change occurring in the range of monthly temperature, with very substantial change occurring in the upper tail, and little to no change occurring in the range of monthly precipitation. This translates to very substantial changes in the general dependence structure between temperature and precipitation, since the two variables exhibit different responses to the presence of anthropogenic forcing.

Using the best-fit copula families, we constructed conditional temperature probability density functions (PDFs) by sampling from each region's historical natural-only 90th percentile of negative standardized precipitation, which is approximate to the lower limit of the United States Drought Monitor "moderate drought" category. Figure 2 displays the historical and historical natural-only conditional temperature PDFs for the same regions shown in Figure 1–the Amazon, Central Europe, Central North America, and South Australia/New Zealand (see Figure S2 for the remaining regions). These subplots allow us to directly com-

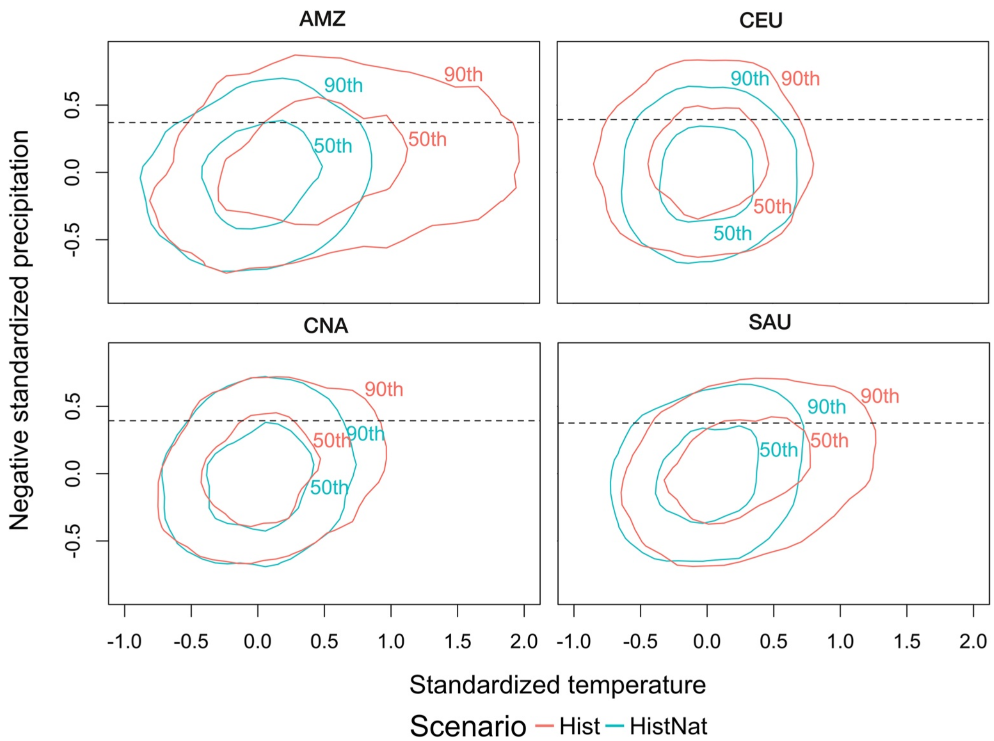

Figure 1. Historical and historical natural-only 50th and 90th percentile contours constructed from best-fit copula families. Each subplot depicts the dependence between negative standardized precipitation and standardized temperature for a given Intergovernmental Panel on Climate Change region. Each subplot contains a dashed line denoting the 90th percentile of negative standardized precipitation from each region's historical natural-only seasonal data. The regions presented are: the Amazon (AMZ), Central Europe (CEU), Central North America (CNA), and South Australia/New Zealand (SAU).

pare differences in the conditional distributions of temperature and quantify the probability of exceeding a specified temperature percentile, which expresses the impact of anthropogenic forcing on high temperature exceedances while accounting for the underlying moisture condition. For the Amazon and South Australia/New Zealand regions, we see very large divergences between the historical and historical natural-only conditional temperature distributions as well as large differences between the temperature exceedances for the two scenarios (historical exceedances are 4.1 and 2.9 times larger than historical natural-only exceedances, respectively). These results correspond well with the copula contours presented for the two regions in Figure 1. In Central Europe and Central North America, the conditional temperature distributions are more similar between the two climate scenarios, which also correspond well with the regional results from Figure 1. However, when comparing the probability of exceedance for Central North America relative to Central Europe, we see that Central North America experiences a relatively larger divergence which is supported by differences in the tails of the dependencies.

Therefore, in general, regions with conditional PDFs which have experienced large changes in location and shape are associated with substantial differences in exceedance probabilities. However, regions with little to no change in the general location or shape of the conditional PDF can still experience large changes at the tail. Overall, we are able to visualize and quantify the impact of anthropogenic forcing on conditional temperature behavior at specified precipitation percentiles using the methodology presented here.

As mentioned earlier, from our conditional temperature PDFs, we are able to compare the historical and historical natural-only likelihood of exceeding a defined temperature threshold under the historical natural-only 90th percentile of negative precipitation for each region. Using the ratio of historical to historical natural-only exceedance probabilities for each region, we can derive conditional probability ratios (CPR)

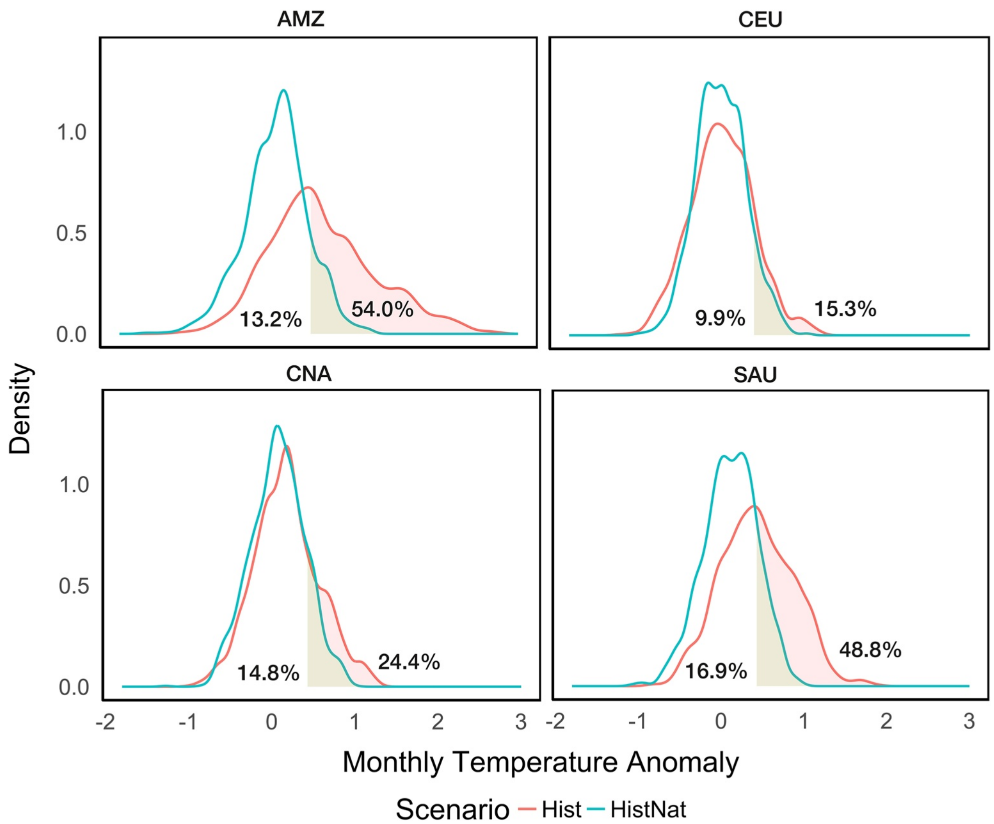

Figure 2. Historical and historical natural-only conditional temperature probability density functions (PDFs). Each subplot shows the historical and historical natural-only conditional temperature PDFs from the historical natural-only 90th percentile of negative precipitation. The area under each distribution exceeding the historical natural-only 90th percentile of temperature is highlighted in the appropriate color. The regions shown are: the Amazon (AMZ), Central Europe (CEU), Central North America (CNA), and South Australia/New Zealand (SAU).

for monthly temperatures exceeding the historical natural-only 90th percentile of temperature (Figure 3). Figure 3 shows that all regions falling between 60°N and 60°S possess CPR scores higher than a value of 1, which indicates that these regions have a higher conditional likelihood of experiencing a high temperature exceedance under the historical scenario relative to the historical natural-only scenario. Essentially, these

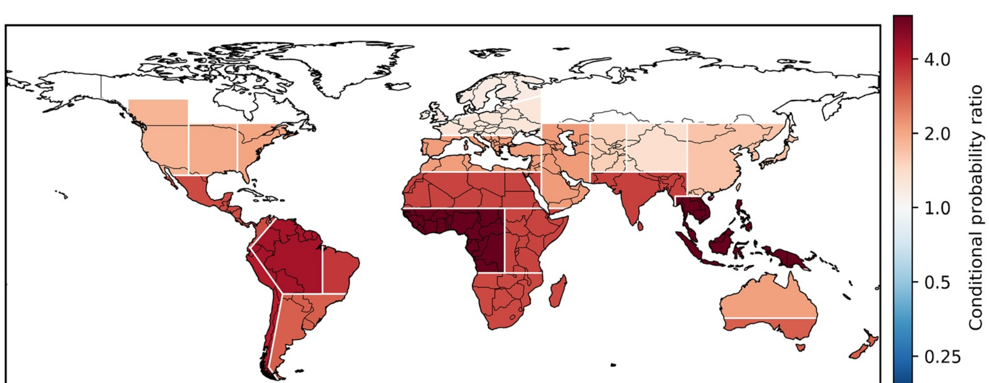

Figure 3. Copula-derived conditional probability ratios (CPR). CPR mapped atop each IPCC region. For all subplots, CPR > 1 represents a higher likelihood of exceeding the defined high temperature threshold in the historical scenario and CPR < 1 represents a higher likelihood of exceeding the defined threshold in the historical natural-only scenario.

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scores communicate that anthropogenic climate change has made conditional high temperature events substantially more likely across the globe.

In addition, CPR scores are also useful in that they can capture large changes in the tail of the distribution, and this methodology allows us to visualize where anthropogenic forcing is impacting extreme event behavior the most. We highlight that regions located in the tropical latitude bands possess higher CPR scores relative to regions located in extratropical bands. These results indicate that anthropogenic forcing has impacted the occurrence of conditional high temperature exceedances in the tropics at a much greater level relative to extratropical regions. This spatial pattern resembles the results from Fischer and Knutti (2015), which investigated the impact of anthropogenic forcing on univariate high temperature exceedances. However, with our CPR scores, we are able to show distinct regional differences not seen when examining univariate temperature extremes. For example, West Africa possesses a much greater CPR score relative to East Africa, which is not conveyed under the previously referenced univariate probability ratio evaluation. Overall, we can see the global impact of anthropogenic emissions on the likelihood of conditional high temperature exceedances, which has already translated into higher concurrences of droughts and heat waves (AghaKouchak et al., 2014; Mazdiyasni & AghaKouchak, 2015).

4. Conclusions

In this study, we have introduced a conditional framework which allows us to account for underlying precipitation conditions when assessing the impact of climate change on temperature extremes. Through our framework, we have directly compared how conditional temperature distributions have diverged under historical and historical natural-only conditions and shown how different regions across the globe have responded to the presence of anthropogenic forcing. With our results, we have shown that regions such as the Amazon and South Australia/New Zealand have a 4.1 and 2.9 times higher likelihood of exceeding a high temperature threshold under dry conditions in the historical relative to the historical natural-only climate scenario. In a global analysis, we also demonstrated that conditional high temperature exceedances in tropical regions experienced the greatest change in likelihood due to anthropogenic forcing. We also highlight that with our introduced metric, we are able to see differences between historical and historical natural-only conditions that are not shown when only examining univariate extremes. As we have seen previously, average temperatures under drought conditions are accelerating in many regions in the United States, and if we do not account for conditional risks, we may misrepresent how often temperature and related concurrent extremes occur. By understanding how preceding precipitation conditions may inform the risk of high temperature extremes, we can also be better prepared for future extreme events.

Here, the methodology introduced can be easily applied to different spatial resolutions and regions across the globe and is complementary to existing univariate attribution indices. In addition, this framework provides a non-linear representation of changes in temperature distributions based on different underlying moisture conditions. Our findings are also relevant in other fields of study that are impacted by climate conditions. Climate-sensitive sectors (such as agriculture and energy production) have and will continue to experience strong ramifications from the increased likelihood of high temperature exceedances due to anthropogenic forcing, and thus will benefit from acknowledging the impact of climate change on conditional temperature extremes. The copula-derived conditional probability ratio index introduced here also provides a novel view of the impacts of anthropogenic forcing on climate extremes given specified climate conditions. With current climate change projections, we expect that the relationships between key climate variables will continue to evolve, which makes the study of the impacts of anthropogenic forcing on conditional behavior crucial for a more comprehensive view on climate change impacts.

Appendix A

Modeling center	Institute ID	Model name	Latitude	Longitude
Commonwealth Scientific and Industrial Research Organization (CSIRO) and Bureau of Meteorology (BOM), Australia	CSIRO-BOM	ACCESS1.3	1.25	1.875
Beijing Normal University (BNU)	BNU	BNU-ESM	2.7906	2.8125
Canadian Centre for Climate Modeling and Analysis	CCCMA	CanESM2	2.7906	2.8125
National Center for Atmospheric Research	NCAR	CCSM4	0.9424	1.25
Centre National de Recherches Météorologiques/Centre Européen de Recherche et Formation Avancée en Calcul Scientifique	CNRM-CERFACS	CNRM-CM5	1.4008	1.40625
Commonwealth Scientific and Industrial Research Organization in collaboration with Queensland Climate Change Centre of Excellence	CSIRO-QCCCE	CSIRO-Mk3-6-0	1.8653	1.875
LASG, Institute of Atmospheric Physics, Chinese Academy of Sciences and CESS, Tsinghua University	LASG-CESS	FGOALS-g2	2.7906	2.8125
NASA Goddard Institute for Space Studies	NASA GISS	GISS-E2-H GISS-E2-R	2	2.5
Institut Pierre-Simon Laplace	IPSL	IPSL-CM5A-LR IPSL-CM5A-MR	1.8947 1.2676	3.75 2.5
Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), and National Institute for Environmental Studies	MIROC	MIROC-ESM MIROC-ESM-CHEM	2.7906	2.8125
Meteorological Research Institute	MRI	MRI-CGCM3	1.12148	1.125
Norwegian Climate Centre	NCC	NorESM1-M	1.8947	2.5

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

The CMIP5 data used in this study can be accessed online through the Earth System Grid Federation system. This study used the local node: https://esgf-node.llnl.gov/search/cmip5/.

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