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Intensified Likelihood of Concurrent Warm and Dry Months Attributed to Anthropogenic Climate Change

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Key Points:

- Using CMIP6 model output, we attribute large increases in concurrent warm and dry months across the globe to anthropogenic activities
- Due to anthropogenic forcing, the global likelihood of warm-dry months has increased by 2.7 times in land areas between 60°N–60°S
- Warm-dry concurrences show largest increases in the tropics and subtropics (Central and South America, Africa, and East and Southeast Asia)

Supporting Information:

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

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Abstract

Detection and attribution studies generally examine individual climate variables such as temperature and precipitation. Thus, we lack a strong understanding of climate change impacts on correlated climate extremes and compound events, which have become more common in recent years. Here we present a monthly-scale compound warm and dry attribution study, examining CMIP6 climate models with and without the influence of anthropogenic forcing. We show that most regions have experienced large increases in concurrent warm and dry months in historical simulations with human emissions, while no coherent change has occurred in historical natural-only simulations without human emissions. At the global scale, the likelihood of compound warm-dry months has increased 2.7 times due to anthropogenic emissions. With this multivariate perspective, we highlight that anthropogenic emissions have not only impacted individual extremes but also compound extremes. Due to amplified risks from multivariate extremes, our results can provide important insights on the risks of associated climate impacts.

Plain Language Summary

Most climate change studies tend to explore changes in individual climate variables such as temperature or precipitation. Due to this, we currently do not possess a strong understanding of the multiple changes that can occur simultaneously under human-driven climate change. Here we present how the simultaneous occurrence of warm and dry months have increased significantly under modeled climate conditions with human emissions, especially relative to modeled climate conditions without human emissions. We highlight that at the global scale, the occurrence of simultaneously warm and dry months has increased 2.7 times under the presence of human emissions. Since the simultaneous occurrence of extreme climate conditions can produce devastating impacts, this study provides an important perspective on the large-scale multivariate changes that have emerged as a result of human-driven climate change.

1. Introduction

Individual climate hazards such as droughts, floods, heatwaves, and cold spells can cause severe socioeconomic and environmental impacts, and the features of these climate hazards have been well documented (AghaKouchak et al., 2020; Easterling et al., 2000; Field et al., 2012; Heim, 2015; IPCC, 2013; Karl et al., 2008). However, some extreme events are interdependent and can co-occur simultaneously or successively, leading to significant societal impacts (Diffenbaugh, 2020; Diffenbaugh et al., 2017). These co-occurrences can broadly be referred to as compound events, and represent a unique type of event where multiple drivers or hazards influence the risk and magnitude of extreme impacts (Field et al., 2012; Raymond et al., 2020; Zscheischler et al., 2018; Zscheischler, Martius, et al., 2020; Zscheischler & Seneviratne, 2017; Zscheischler, van den Hurk et al., 2020). Recent perspectives highlight that since our climate system is strongly interconnected, traditional assessments of univariate events can seriously underestimate the likelihood of extremes, especially under warming temperatures (AghaKouchak et al., 2014; Zscheischler & Seneviratne, 2017). Therefore, the study of compound events is important to more accurately assess the risks of climate extremes (Leonard et al., 2014; Zscheischler et al., 2018).

Evidence shows that the risk of concurrent events has been increasing due to rising global temperatures (AghaKouchak et al., 2014; Diffenbaugh et al., 2015; Mazdiyasni & AghaKouchak, 2015; M. M. Vogel et al., 2019; Wang et al., 2020). Many studies have observed regional and global increases in the frequency and intensity of concurrent warm and dry conditions in the twentieth century, and project further increases in the 21st century (Diffenbaugh et al., 2015; Hao et al., 2013; Mazdiyasni & AghaKouchak, 2015; Sarhadi et al., 2018).

Compound climate events can be particularly detrimental for climate-sensitive industries such as agriculture and energy, and can produce strong ecological impacts (Moftakhari & AghaKouchak, 2019; Ribeiro et al., 2020; Zhou et al., 2019). Relative to univariate events, the concurrence of climate hazards can amplify impacts on human infrastructure and natural ecosystems (Zscheischler & Seneviratne, 2017). The 2003 European drought and heatwave is a well-known example of the devastating health, economic, and environmental impacts that can occur as a result of compound dry and hot conditions (Ciais et al., 2005; De Bono et al., 2004; García-Herrera et al., 2010; Rouault et al., 2006; van der Velde et al., 2010). In addition, relative to univariate dry conditions, compound dry and hot conditions have been associated with a greater likelihood of crop failure in Spanish provinces due to plant responses to water and heat stress (Ribeiro et al., 2020).

In recent decades, there have been many detection and attribution studies attributing changes in mean or extreme temperature or precipitation events to climate change (Bindoff et al., 2013; Christidis et al., 2005; Easterling et al., 2016; Fischer & Knutti, 2014, 2015; Hegerl et al., 2006; Sarojini et al., 2012; Stott et al., 2001). Previous studies have established that the late twentieth century increase in global mean temperatures can largely be attributed to anthropogenic greenhouse gas emissions (Bindoff et al., 2013). In addition, anthropogenic emissions have been associated with large changes in the likelihood of hot extremes in climate models (Fischer & Knutti, 2015). Recent studies have also highlighted the impacts of human activity on drought events (Chiang, Mazdiyasni et al., 2021; Marvel et al., 2019). Although attribution studies have thoroughly examined the impact of climate change from a univariate perspective, current detection and attribution indices generally focus on one variable at a time, ignoring dependencies between climate variables. In a recent study, Kiriliouk and Naveau proposed and conducted the multivariate extreme event attribution of winter precipitation extremes to human activities (Kiriliouk & Naveau, 2020). Chiang et al. introduced a multivariate detection and attribution framework using conditional probability ratios (Chiang, Greve, et al., 2021). Additionally, Zscheischler and Lehner (2022) proposed an extension to the traditional attribution of extreme events for compound events using the bivariate fraction of attributable risk (Zscheischler & Lehner, 2022). Despite recent progress in this research area, we still lack a comprehensive understanding of the impacts of climate change on compound extremes.

To address this research gap, we examine the influence of climate change on the compound occurrence of warm and dry months. Droughts and high temperature events negatively impact ecosystem conditions, energy production, public health, and many other sectors (Ciais et al., 2005; De Bono et al., 2004; Hatfield & Prueger, 2015; Mazdiyasni & AghaKouchak, 2015; Tarroja et al., 2018). Depending on local conditions, compound droughts and high temperature events can also increase the risk of local wildfires, which can subsequently trigger other hazards such as debris flows (AghaKouchak et al., 2018).

Many studies have established that precipitation and temperature over land are interconnected through land-atmosphere feedbacks (Alexander, 2011; Hirschi et al., 2011; Koster et al., 2004; Mueller & Seneviratne, 2012; Seneviratne et al., 2010). Precipitation deficits can translate to low soil moisture conditions, which can increase the Bowen ratio and the temperature of the local area (Seneviratne et al., 2010). Preceding precipitation conditions have been shown to impact the subsequent occurrence of hot extremes, especially in transitional soil moisture regimes (Mueller & Seneviratne, 2012). In historical observations and model simulations, regions with more correlated warm-season temperature and precipitation have experienced more frequent concurrent hot and dry summers (Zscheischler & Seneviratne, 2017). Based on 21st century CMIP5 projections, changes in the warm-season relationship between temperature and precipitation are also predicted to translate into significant increases in dry and hot summers (Zscheischler & Seneviratne, 2017). Given these considerations, it's important to study compound warm and dry hazards, especially as our climate continues to warm.

Here we present a monthly-scale concurrent warm and dry detection and attribution study, examining 15 CMIP6 models representing the period between 1850 and 2014 with and without the influence of anthropogenic forcing. We use CMIP6 historical and historical natural-only precipitation and temperature to define warm and dry months (Eyring et al., 2016). The historical scenario imposes anthropogenic forcings (greenhouse gas emissions, aerosols) on climate models to approximate historical observations, while the historical natural-only experiment simulates natural variability with constant pre-industrial atmospheric conditions to represent our historical climate without anthropogenic activity (Eyring et al., 2016). The main objective of the study is to examine the impact of anthropogenic forcing on joint warm and dry months. In addressing this, we can gain a better understanding of the changing likelihood of joint extremes, which can serve to broaden our understanding of vulnerability and exposure due to anthropogenic climate change.

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2. Materials and Methods

2.1. Data Sets

For this study, we use an ensemble of the CMIP6 historical and historical natural-only model output of monthly precipitation (pr) and average temperature (tas) from a total of 15 climate models (see Appendix A for the list of models and specific ensemble members used) and covering the period between 1850 and 2014 (Eyring et al., 2016). The CMIP6 historical experiment imposes anthropogenic and natural forcings that reflect what has been documented in observations (Eyring et al., 2016). Meanwhile, the historical natural-only experiment attempts to represent natural trends and variability with fixed pre-industrial concentrations of greenhouse gases and aerosols to simulate our historical climate without any anthropogenic forcing (Eyring et al., 2016). Both the historical and historical natural-only experiments have been initialized with the same preindustrial-Control data (Eyring et al., 2016). For a uniform multi-model analysis, we regrid all models to a 1° resolution using nearest-neighbor interpolation. We focus on the land area between 60°N and 60°S due to large uncertainties in the representation of polar regions in the models (Block et al., 2020).

2.2. Analysis

To examine the anthropogenic impact on concurrent warm and dry months, we first evaluate the number of individual warm months and dry months across the globe. Since the raw data is subject to seasonal effects, we use monthly percentile thresholds calculated from the historical natural-only 1850–2014 climatology to identify warm and dry month occurrences. For each grid cell from each individual model, we use the tenth percentile of 3-month precipitation sums (e.g., January-March precipitation for March) and the 90th percentile of 1-month average temperature coinciding with the last month of the precipitation time window for each month of the year in order to capture changes relative to the local historical natural-only climatology. With this approach, we easily and consistently compare changes in warm and dry conditions across regions and across climate scenarios. However, we also acknowledge that the chosen percentiles assume, but do not directly refer to specific environmental and socioeconomic impacts. In the main analysis, we use a 3-month time window to examine preceding and concurrent precipitation conditions along with average temperature, although we also present results from 1-month and 6-month time scales for precipitation in the supplemental materials to show the sensitivity of our results to the choice of the time window (Figure S1a in Supporting Information S1).

With the defined thresholds, we conduct a grid cell evaluation of the empirical concurrence of warm and dry months (months simultaneously below the tenth percentile of the 3-month precipitation sum and above the 90th percentile of average temperature), finding the number of concurrent warm and dry months in 1940–2014 and the multi-model median shift in the number of concurrent warm and dry months in 1940–2014 relative to 1851–1925. We acknowledge that due to the serially correlated nature of the climate variables being used, individually identified months may be a part of the same event. However, this does not change the socioeconomic and environmental implications of the study results.

To examine how concurrent months have been changing over time, we also generate a 30-year moving window time series of concurrences for all land grid cells from 60°S to 60°N. Starting at 1850 and shifting the window one year over at a time, we calculate the global median number of historical and historical natural-only concurrent months occurring in each 30-year window, weighting grid cells by land area. In order to quantify the factor by which the likelihood of concurrent months has changed due to the presence of anthropogenic forcing, we also examine the probability ratio—The likelihood of months in historical conditions over the likelihood of months in historical natural-only conditions (Fischer & Knutti, 2015). To calculate the probability ratio of concurrences, we generate the ratio of historical over historical natural-only concurrences in 1940–2014.

We also examine the temporal evolution of warm and dry months on a regional basis with the regions delineated by the fifth Intergovernmental Panel on Climate Change (IPCC) report, which we refer to as IPCC regions (IPCC, 2013). With the IPCC regions, we use each region's median time series based on all land grid cells within the region to generate 30-year moving time series for dry occurrences and warm occurrences as well as warm-dry concurrences.

Additionally, we provide a comparison of the late-twentieth century model results with observations. We use monthly 1° gridded Berkeley Earth Surface Temperatures (BEST) data and 1° gridded Global Precipitation

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Climatology Center (GPCC) Full Data Reanalysis Version 2018 total precipitation data set to identify observed warm-dry concurrences. Due to the lack of reliable observations pre-1950s, we examine the number of months from 1985 to 2014 as well as percent changes in the number of months during 1985–2014 relative to 1950–1979. We identify months using 90th and tenth percentile temperature and precipitation thresholds based on 1950–1979 observations. To provide comparable CMIP6 results, we use 1950–1979 data from the historical models to determine the 90th and tenth percentile thresholds for historical warm-dry occurrences for the same years as the observations.

3. Results

3.1. Univariate Warm and Dry Hotspots and Shifts

To understand concurrent changes in warm and dry months, we first examine univariate dry occurrences and warm occurrences between 1940 and 2014. In the 1940–2014 time period, the historical natural-only scenario shows relatively uniform dry occurrences across the global land area of interest (Figure 1a). Since our definition of dry months is based on the historical natural-only data from 1850 to 2014, this confirms that there is no evident change between the second and first halves of the time series in the historical natural-only scenario. Under historical natural-only conditions, we also see that very little change can be attributed to natural variability between 1940-2014 and 1851–1925 (Figure 1b). On the other hand, under historical conditions, strong hotspots of dry months occur in parts of Central and South America, East Asia, the Mediterranean region, and West and Southern Africa (Figure 1c). In addition, when examining shifts under historical conditions, we see that dry months have increased in the corresponding regions (Figure 1d). In general, our historical scenario matches 1951–2010 drought frequency trends noted in a previous study examining Global Precipitation Climatology Center precipitation (Spinoni et al., 2014).

Examining univariate warm occurrences, we observe that the number of historical natural-only warm months in the 1940–2014 period is also reflective of the entire study period (Figure 2a). We also see very little naturally driven change between 1940–2014 and 1851–1925 (Figure 2b). In contrast, in the historical scenario, hotspots of warm occurrences are much more widespread across the globe, especially in the tropics and subtropics (Figure 2c). In addition, we see a similar global pattern when examining the change in warm occurrences from 1940 to 2014 relative to 1851–1925 (Figure 2d). This mirrors results from previous studies based on CMIP5 simulations. For example, Fischer and Knutti (2015) found that the tropics had much higher probability ratios of hot extremes (defined as the 99th percentile of pre-industrial model conditions) at present-day (0.85°C) levels of warming (Fischer & Knutti, 2015). We highlight that the tropics experience especially strong increases in warm

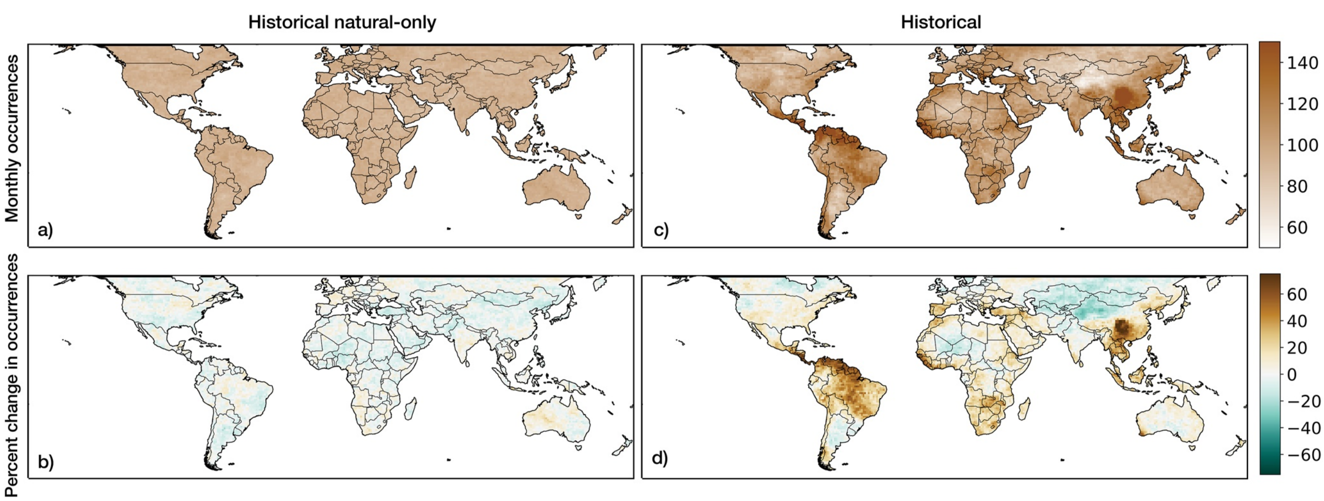

Figure 1. Dry month occurrences (1940–2014) and percent change in occurrences (1940–2014 relative to 1851–1925). (a) Dry month occurrences from the CMIP6 historical natural-only multi-model ensemble median. The value expressed in each grid cell represents the model median number of months with a 3-month precipitation value lower than the tenth percentile of the grid cell's historical natural-only climatology. (b) Percent change in dry month occurrences from the historical natural-only data. (c) Dry month occurrences from the CMIP6 historical ensemble median. (d) Percent change in dry month occurrences from the historical data.

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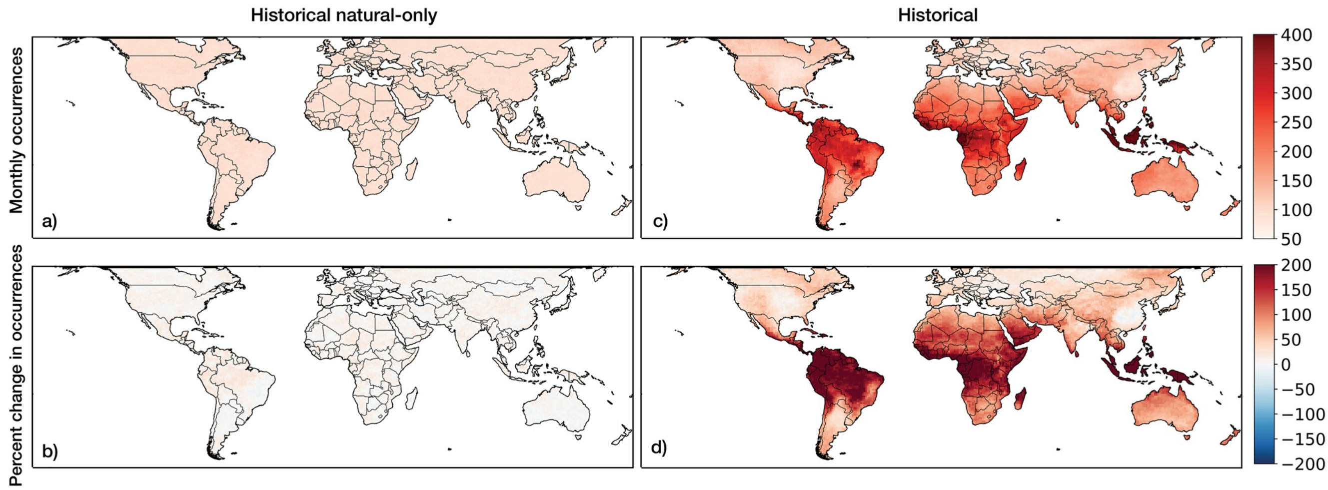

Figure 2. Warm month occurrences (1940–2014) and percent change in occurrences (1940–2014 relative to 1851–1925). (a) Warm month occurrences from the CMIP6 historical natural-only multi-model median. Each grid cell's value represents the number of months with a temperature value higher than the 90th percentile of the grid cell's historical natural-only climatology. (b) Historical natural-only percent change in warm month occurrences. (c) CMIP6 historical median warm month occurrences. (d) Historical median percent change in warm month occurrences.

months due to weaker interannual variability and seasonal cycles relative to the polar regions, as previously noted by Fischer and Knutti (2015).

3.2. Compound Warm and Dry Hotspots and Shifts

To assess empirical concurrences of warm and dry months, we evaluate the number of months where dry and warm conditions occurred simultaneously in 1940–2014. We also examine the median multi-model shift in the number of concurrent warm and dry months in 1940–2014 relative to 1851–1925. Under historical natural-only conditions, we do not see coherent hotspots or substantial increases in concurrent warm and dry months between the two time periods (Figures 3a and 3b). This indicates that over multi-decadal periods, concurrences are not expected to increase or decrease significantly due to natural variations in climate, which is consistent with what we observed for both warm and dry univariate occurrences from Figures 1a, 1b, 2a and 2b.

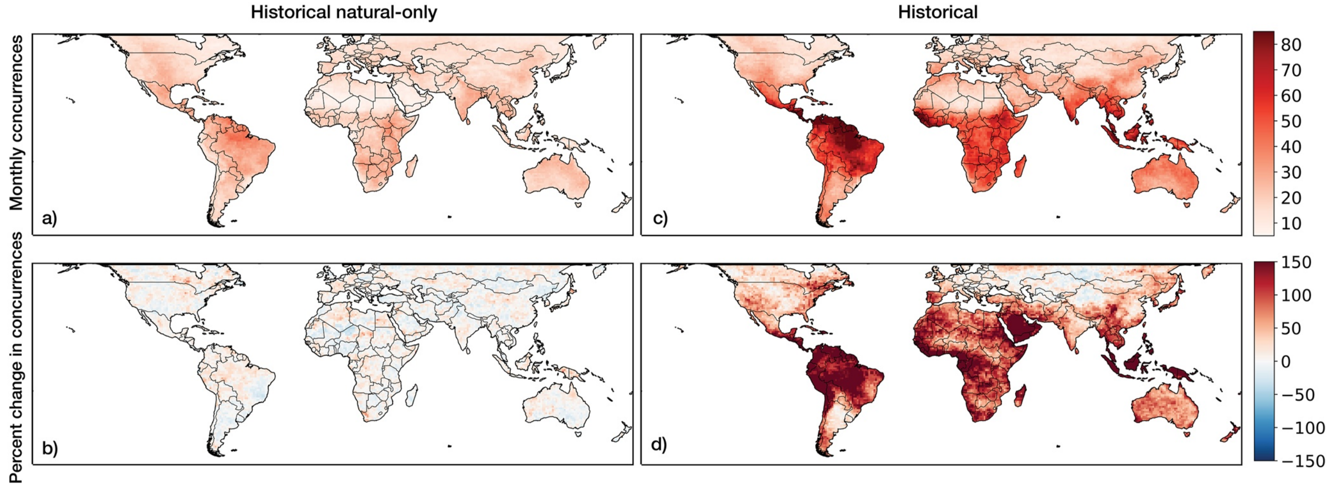

Figure 3. Warm and dry month joint occurrences (1940–2014) and percent change in concurrences (1940–2014 relative to 1851–1925). (a) Warm and dry month concurrences from the CMIP6 historical natural-only multi-model median. Each grid cell's value represents the number of months with a joint occurrence of temperature above the grid cell's historical natural 90th percentile and 3-month precipitation value below the grid cell's historical natural tenth percentile. (b) CMIP6 historical natural-only percent change in concurrences. (c) CMIP6 historical median concurrences. (d) CMIP6 historical median percent change in concurrences.

Under historically forced conditions, we see substantial hotspots of warm and dry concurrences over all land areas between 60°S and 60°N. These increases are particularly large in the tropics and subtropics, which reflect the global pattern of warm occurrences under the historical scenario (Figure 3c). We also see a similar global pattern of percent change in the concurrence of warm and dry months between 1940–2014 and 1851–1925, although regions such as Northern Africa and the Middle East experience large percent increases that are not seen when only examining the total number of concurrences in 1940–2014 (Figure 3d). Overall, it is evident that the general spatial pattern of warm occurrences plays a much larger role relative to dry occurrences in determining the global pattern of joint warm and dry concurrences. This may be due to the fact that the historical temperature distribution experiences a much larger deviation from its historical natural-only distribution relative to the change that precipitation has undergone as a result of anthropogenic forcing (IPCC, 2013). However, although we show that warm occurrences are generally responsible for the global increase in joint warm and dry concurrences, in certain regions (e.g., Southern Europe and parts of East Asia), substantial increases in the occurrence of dry extremes also amplify this joint signal. The results also show that higher latitudes experience relatively smaller changes in warm and dry concurrences, in part due to regional decreases in dry months. Thus, regional changes in drying and wetting also contribute to substantial changes in concurrences.

In Supporting Information S1, we show the sensitivity of the results to the length of the precipitation window (Figure S1a in Supporting Information S1), to the thresholds used for average temperature and precipitation (Figure S1b in Supporting Information S1), and to alternative time periods (Figure S1c in Supporting Information S1). Overall, the length of the precipitation window, thresholds used for average temperature, and alternative time periods all do not substantially impact the general spatial patterns of warm and dry month concurrences. However, as shown in Figure S1b in Supporting Information S1, the more restrictive thresholds are associated with greater degrees of change, implying that more extreme compound warm and dry conditions are more sensitive to anthropogenic forcing.

In addition to assessing spatial patterns of warm and dry concurrences, we also examine the temporal evolution of warm and dry concurrences between 1850 and 2014. Using a 30-year moving window, we calculate the global median of concurrences in land grid cells between 60°S and 60°N (Figure 4a). Based on this temporal analysis, we see a clear divergence between historical and historical natural-only concurrences that begins in the mid-twentieth century following a period of relative stasis, roughly reflecting global temperature trends (IPCC, 2013). At the end of the twentieth century, the global median of warm and dry concurrences in the historical scenario is approximately 2.7 times higher than concurrences in the natural-only scenario, indicating that anthropogenic climate change has contributed to making these concurrent months more probable on a global scale. In Figures 4b and 4c, we show how the number of concurrences in large parts of Central and South America, Sub-Saharan Africa, and Southeast Asia contribute to the last 30-year window (1985–2014) of the time series.

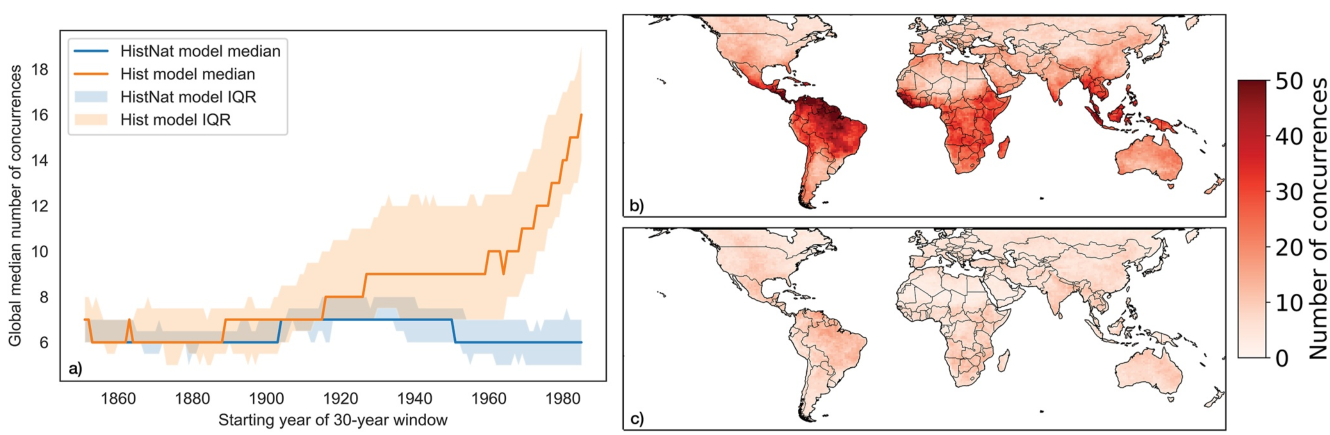

Figure 4. Global median 30-year moving window time series of warm and dry concurrences. (a) The historical (shown in orange) and historical natural-only (shown in blue) time series depicts the multi-model ensemble median and interquartile range. The number of concurrences represents the number of joint warm and dry months within the 30-year moving window. (b) Global concurrences in the last 30-year window (1985–2014) from the historical scenario. (c) Global historical natural-only concurrences in the last 30-year window.

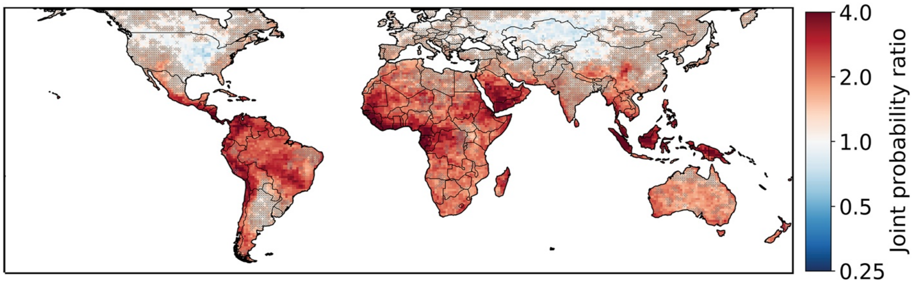

Figure 5. Global probability ratios of warm and dry concurrences in 1940–2014. Values above 1 indicate a higher probability of warm/dry months in the historical multi-model ensemble, while values below 1 indicate a higher probability of warm/dry months in the historical natural-only models. Stippled grid cells represent areas where less than 80% of the models in the ensemble agree on whether the value of the probability ratio exceed or fall below a value of 1.

To evaluate the influence of anthropogenic forcing on the likelihood of warm and dry concurrences, we examine the empirical joint probability ratio—The ratio of historical over historical natural-only concurrences—During 1940–2014 for all grid cells. We observe that anthropogenic forcing has substantially increased the likelihood of warm and dry concurrences for most regions across the globe, especially in Central and northern South America, parts of Africa, Arabia, and Southeast Asia and the Maritime Continent (Figure 5, Figure S2 in Supporting Information S1 for interquartile model range). However, in large parts of North America, Europe, and North and South Asia, the multi-model ensemble does not express high agreement on whether anthropogenic forcing increases or decreases the likelihood of warm and dry concurrences. Notably, we also see probability ratios below 1 in parts of North America and Central Asia, which may be due to a combination of factors stemming from increases in precipitation from large-scale circulation changes as well as decreases in average temperatures due to the presence of anthropogenic aerosols and land use and land cover change (IPCC, 2013). Although historical percent changes in concurrences (Figure 3d) generally correspond well with the warm-dry concurrence likelihoods shown here, differences in probability ratio values in parts of North America and Africa highlight the importance of examining the underlying contributions of natural variability to warm-dry concurrences. With the use of historical natural-only models, we can better understand the varying influence of anthropogenic forcing by region.

3.3. Temporal Evolution of Warm and Dry Months by IPCC Region

Using the Intergovernmental Panel on Climate Change (IPCC) regions, we investigate individual and joint median time series to understand how these univariate and bivariate months evolve temporally on a regional basis (See Figures S3a and S3b in Supporting Information S1 for spatially aggregated probability distributions of the regions). For each IPCC region, we quantify the likelihood of dry months, warm months, and warm and dry concurrences in 30-year moving windows under both historical and historical natural-only conditions. Here, we present four of the regions which experienced substantial increases in concurrences under historical conditions (Central America/Mexico (CAM), South Europe/Mediterranean (MED), East Africa (EAF), and Southeast Asia (SEA)) (Figure 6). The remaining regions can be found in the Supporting Information (Figures S4a–S4e in Supporting Information S1).

Of the four regions displayed here, CAM and SEA show moderate increases in the likelihood of dry months as well as very substantial increases in the likelihood of warm months, translating to strong increases in the likelihood of concurrences. On the other hand, MED and EAF show relatively more modest increases in the likelihood of concurrences, which may be due to moderate increases in the likelihood of warm months in MED and little to no change in the likelihood of dry months in EAF. In general, strong changes in the likelihood of warm months dominate the substantial increases expressed in the likelihood of concurrences. However, the likelihood of concurrences can also ultimately be constrained by the likelihood of dry months, as shown in EAF.

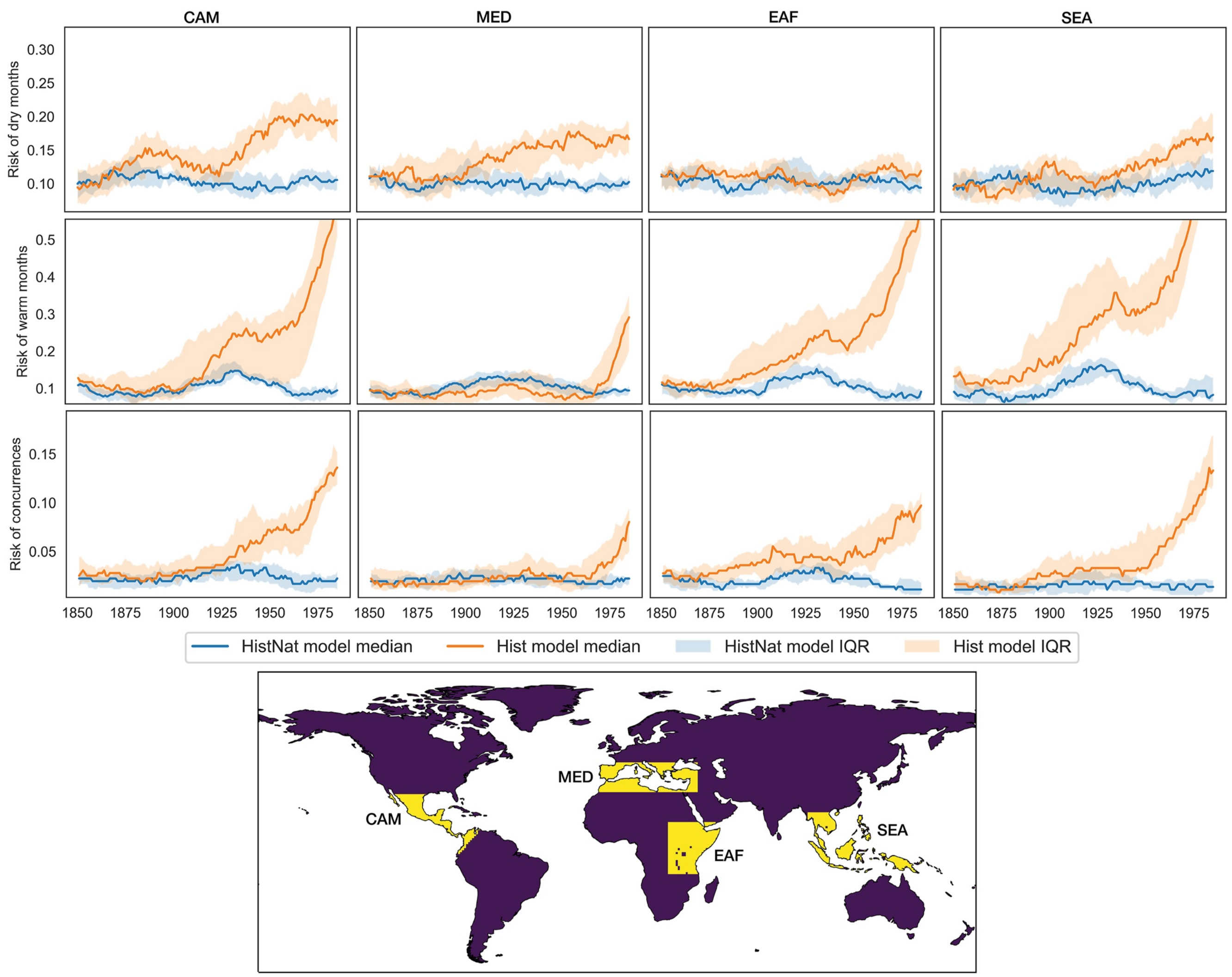

Figure 6. Intergovernmental Panel on Climate Change regional time series of likelihood of dry occurrences, warm occurrences, concurrences. The historical (shown in orange) and historical natural-only (shown in blue) time series depict the multi-model median and interquartile range of values within the 30-year moving window. Regions shown: Central America/Mexico (CAM), South Europe/Mediterranean (MED), Southern Africa (SAF), and Southeast Asia (SEA).

3.4. Observational Validation of the CMIP6 Historical Simulations

Here, we use historical observations to provide a grounding of the key warm and dry concurrence results found with the CMIP6 models. In the supplemental materials, we additionally present the corresponding univariate results from the observations and model simulations (Figure S5 and S56 in Supporting Information S1). In general, we see broad similarities in the global distributions of monthly concurrences and percent change in concurrences in the observations and the CMIP6 model simulations (Figure 7). However, between the periods of 1950–1979 and 1985–2014, we see substantially larger percent changes in warm and dry month concurrences in the observations, which may have implications regarding the magnitudes of changes attributed to anthropogenic forcing. Additionally, there are regional discrepancies between the observations and model simulations in the regions susceptible to warm and dry concurrences and the regions experiencing the largest changes across the late twentieth century. For example, in the observations, large parts of Northern Africa and the Middle East experience a high number of monthly concurrences, while this is not the case in the model simulations. Even so, both observations and model simulations agree that these regions have experienced large increases in concurrences.

When examining the global median number of concurrences in land grid cells between 60°S and 60°N over time, we see comparable changes across time, as shown by Figure 8. However, we also note that over time, the

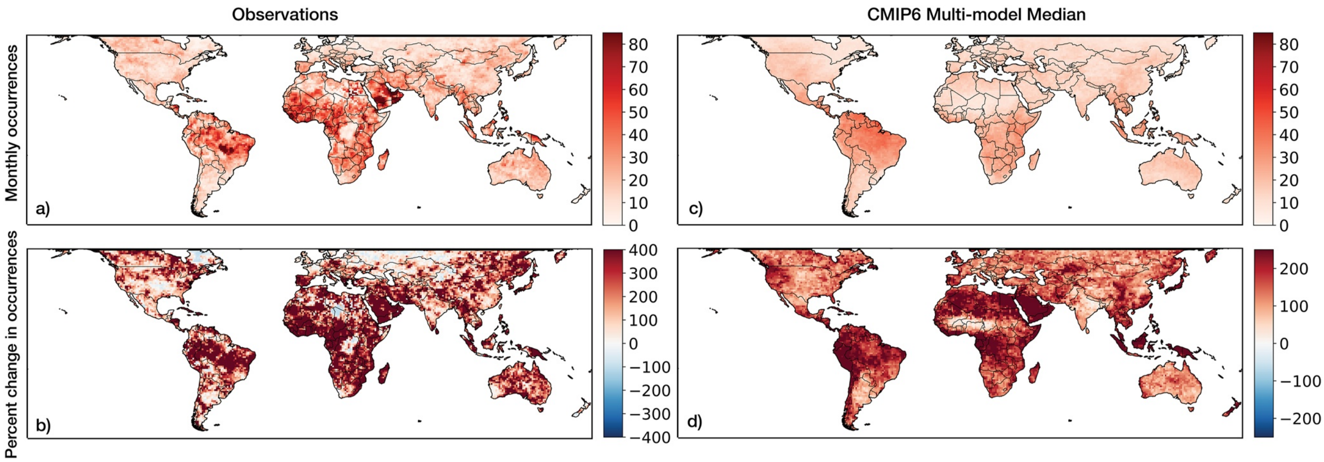

Figure 7. Warm and dry month joint occurrences (1985–2014) and percent change in concurrences (1985–2014 relative to 1950–1979). (a) Observed warm and dry month concurrences for 1985–2014. (b) Observed percent change in concurrences from 1985 to 2014 relative to 1950–1979. (c) CMIP6 historical median concurrences. (d) Historical median percent change in concurrences.

historical model simulations underestimate the global median number of concurrences in comparison to the observations, which may also have implications on the magnitude of the impact of anthropogenic forcing on the concurrence of these conditions.

4. Discussion

4.1. Underlying Mechanisms and Drivers of Compound Warm and Dry Conditions

Although changes in univariate dry occurrences are not widespread across the globe, with our results, we find that significant increases in warm-dry concurrences can be attributed to anthropogenic forcing at both regional and global scales. At the global scale, compound warm and dry months occur approximately 2.7 times more in historical conditions relative to historical natural-only conditions at the start of the 21st century. We highlight that increases in the likelihood of warm and dry concurrences are especially pronounced in the tropics and subtropics,

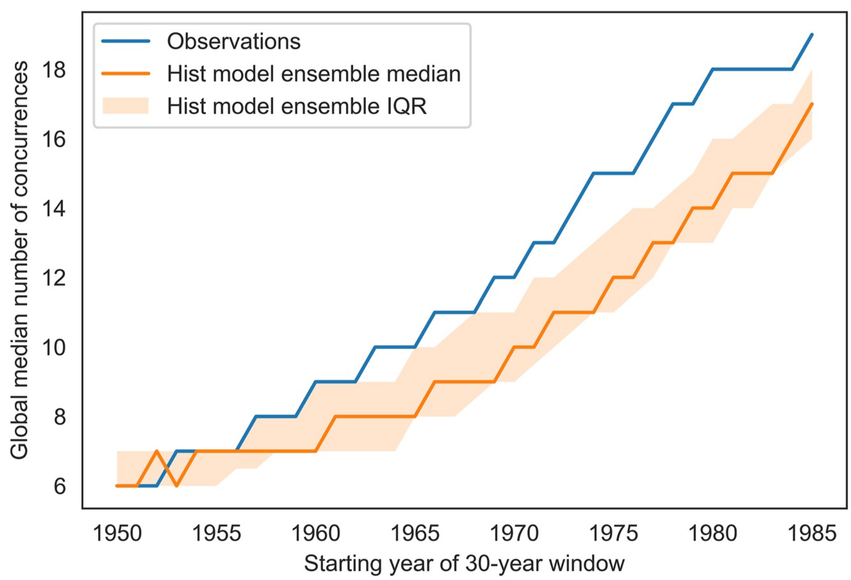

Figure 8. Global median 30-year moving window time series of warm and dry concurrences. (a) The observations are shown in blue and the historical multi-model median and interquartile range of values are shown in orange. The number of concurrences represents the global median number of warm-dry months within the 30-year moving window.

(e.g., large parts of Central and South America, Africa, and East and Southeast Asia). Notably, warm-dry concurrences have increased most in regions such as Western and Central Africa as well as Southeast Asia which possess lower adaptive capacities to address these concurrent events. Overall, the global pattern of the probability ratio of joint warm and dry months shows that land areas across the globe have been clearly impacted by the presence of anthropogenic activities. This highlights a clear impact of anthropogenic climate change on compound warm-dry conditions.

Generally, both meteorological droughts and heat events are associated with long-lasting, large-scale anticyclonic circulation anomalies (Alizadeh et al., 2020; Chang & Wallace, 1987; Miralles et al., 2019), producing natural concurrences of these extremes. In addition, land-atmosphere feedbacks have been shown to connect preceding dry meteorological conditions with the occurrence of heat extremes (Mueller & Seneviratne, 2012). However, the strong presence of anthropogenic forcing has driven changes in warm and dry conditions in a number of ways. The univariate occurrence of warm months has significantly increased due to the ubiquitous influence of greenhouse gases, although temperatures have been moderated through Northern Hemisphere aerosol emissions (IPCC, 2013). Meanwhile, greenhouse gases and aerosols have contributed to substantial drying in Central and South America, the Mediterranean, East and Southeast Asia, and large parts of Africa through a combination of dynamic and thermodynamic mechanisms (Chiang, Mazdiyasni, et al., 2021; Marvel & Bonfils, 2013). The combination of these anthropogenic forcings have resulted in the patterns seen here in our results. As aerosol emissions are expected to decline in the 21st century, we may expect to see changes in warming and drying patterns accordingly.

In addition to the univariate impacts of anthropogenic forcing on temperature and precipitation, recent studies have suggested that future anthropogenic warming will impact the strength of land-atmosphere feedbacks, influencing the dependencies between warm and dry conditions and the frequency of warm-dry events (Zscheischler & Seneviratne, 2017). Therefore, the results shown here may be a result of univariate changes in temperature and precipitation extremes as well as changes in the dependence between warm and dry conditions resulting from the presence of anthropogenic emissions.

4.2. Study Limitations

We acknowledge that there are limitations associated with the use of model simulations, as we have shown in the observational validation. Here, we highlight the deficiencies of the model simulations that are specific to the study. The CMIP models provide a good representation of the dependence between temperature and precipitation over land area (Zscheischler & Seneviratne, 2017). However, in some regions, such as Central and northern South America, eastern Africa, and western Australia, the models depict a stronger relationship between temperature and precipitation than observations, which may be due to model biases or due to observational uncertainties (Zscheischler & Seneviratne, 2017). Biases may stem from climate models failing to consistently represent land-atmosphere feedbacks in a uniform fashion (Sippel et al., 2017). In addition, biases may come from climate models producing conditions that are too dry in relation to observations, which may cause extremes to be hotter than observed (Vogel et al., 2018). These model deficiencies may ultimately contribute to the misrepresentation of the vulnerability of specific regions to warm and dry concurrences, and further study is needed to better characterize and understand how specific regions have and will continue to experience these conditions.

Separately, our study operates under the assumption that historical natural-only climate simulations produce reasonable representations of a natural world without anthropogenic greenhouse gases and aerosol emissions. Climate models can reasonably reproduce proxy paleoclimatic data, indicating the ability of models to approximate natural conditions (Braconnot et al., 2012). However, climate models do suffer from biases with respect to changes in regional temperature and precipitation patterns (Braconnot et al., 2012). In addition, there are still uncertainties related to comparisons between historical and historical natural-only simulations. For example, model drift may influence differences in historical and historical natural-only simulations (Gupta et al., 2013) and consequentially, may impact the results presented here. Future studies may examine how local climatology may play a role in regional concurrent warm-dry changes in response to anthropogenic forcing. For example, regionally focused studies examining changes in warm-dry months in wet or dry seasons may improve our understanding of seasonal anthropogenic impacts. In addition, valuable insights

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may be gained by studying how the presence of anthropogenic forcing influences changes in the magnitudes of concurrent warm-dry conditions. We also acknowledge that the results of our analysis are dependent on our representation of dryness through precipitation as opposed to measures which incorporate factors such as evaporative demand which have been shown to be more sensitive to rising global temperatures (Cook et al., 2014).

5. Conclusions

Our results aid in developing a better understanding of the widespread nature of the climate change impacts on concurrent warm and dry spells. This work directly shows the influence of anthropogenic climate change on compound monthly-scale occurrences of temperature and precipitation extremes. Gaining a better understanding of regional and global changes in concurrent events and the underlying drivers of these changes is important for improving local management practices and preparedness for future climate extremes. Global increases in compound warm-dry events have far-reaching implications on a multitude of sectors, including water availability, energy production, agricultural productivity, and wildfires, which can further impact local and regional hydrological conditions. Notably, compound warm-dry events may substantially impact water availability through concurrent impacts on evaporative demand and low precipitation, as well as through impacts on decreased snowpack. Due to this, the methods and results presented here can be utilized in risk assessment studies to more accurately capture environmental, socioeconomic, and infrastructural vulnerability and exposure to future compound extremes.

Appendix A: List of CMIP6 Models

Modeling center	Institute ID	Model name	Ensemble member
Commonwealth Scientific and Industrial Research Organization, Australian Research Council Centre of Excellence for Climate System Science, Australia	CSIRO-ARCCSS	ACCESS-CM2	r1i1p1f1
Commonwealth Scientific and Industrial Research Organization, Australia	CSIRO	ACCESS-ESM1-5	r1i1p1f1
Beijing Climate Center, China	BCC	BCC-CSM2-MR	r1i1p1f1
Canadian Centre for Climate Modeling and Analysis, Canada	CCCMA	CanESM5	r1i1p1f1
National Center for Atmospheric Research, United States	NCAR	CESM2	r1i1p1f1
Centre National de Recherches Météorologiques, Centre Européen de Recherche et de Formation Avancée en Calcul Scientifique, France	CNRM-CERFACS	CNRM-CM6-1	r1i1p1f2
Chinese Academy of Sciences, China	CAS	FGOALS-g3	r1i1p1f1
Geophysical Fluid Dynamics Laboratory, United States	GFDL	GFDL-CM4	r1i1p1f1
		GFDL-ESM4	r1i1p1f1
NASA Goddard Institute for Space Studies, United States	NASA GISS	GISS-E2-1-G	r1i1p1f2
Met Office Hadley Centre, United Kingdom	MOHC	HadGEM3-GC31-LL	r1i1p1f3
Institut Pierre Simon Laplace, France	IPSL	IPSL-CM6A-LR	r1i1p1f1
Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies, RIKEN Center for Computational Science, Japan	MIROC	MIROC6	r1i1p1f1
Meteorological Research Institute, Japan	MRI	MRI-ESM2-0	r1i1p1f1
Norwegian Climate Centre, Norway	NCC	NorESM2-LM	r1i1p1f1

Conflict of Interest

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

Data Availability Statement

The CMIP6 data used in this study can be accessed online through the Earth System Grid Federation (ESGF) system. This study used the local node: https://esgf-node.llnl.gov/search/cmip6/.

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