When and Where are Long-term Precipitation Trends Reliable Across the Globe?

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Abstract

As global temperatures warm due to human greenhouse gas emissions, there is special interest in how surface water availability has changed across the globe. To investigate this, trends of water-dependent variables such as runoff, soil moisture, and vegetation cover need to be compared to precipitation trends to determine whether non-precipitation trends, like temperature or carbon dioxide, are influencing water availability. Yet, this cannot be done without first determining the reliability of long-term precipitation data. To address this, precipitation data from the Climatic Research Unit Time Series (CRU) and the Global Precipitation Climatology Centre (GPCC) datasets are first filtered only to show observationally constrained data, using a new methodology. Then, standardized trends are mapped and compared with each other to determine when and where they agree, and thus are likely to be reliable. Our findings show that CRU and GPCC trends generally agree over most periods and locations, with some notable exceptions, such as Europe and Russia in the early 20th century and the United States in the early 21st century. These findings will help us determine where and when we can reliably compare precipitation trends to other water-dependent variable trends so that we can answer questions about changes in water availability.

Introduction

In the face of anthropogenic climate change, there is particular interest in how rising global temperatures and carbon dioxide affect surface water availability (Berg and Sheffield 2018; Greve *et al*. 2019; Feng and Fu 2013; Milly and Dunne 2016; Naumann *et al.* 2018; Novick *et al.* 2016; Scheff and Frierson 2014; Swann *et al.* 2016; Zhang *et al*. 2021; Zhao and Dai 2017). This issue is important because society relies heavily on water. Water is required for life and is essential for domestic, industrial, and agricultural operations. Analyzing historical water availability trends can help us understand how future conditions may change under global warming (e.g. Ren *et al*. 2013; Zhao and Dai 2017). Water availability is also very influential on natural ecosystems – changes in water supply can completely transform an ecosystem (e.g. Bernacchi and VanLoocke 2015; McCluney *et al*. 2012). Therefore, our broader research goal is to understand the relationship between local precipitation trends and local trends of other water-dependent variables in as many places as feasible. These other variables include runoff, soil moisture, vegetation cover, and potentially other hydrological variables.

However, before comparing trends between precipitation and other water-dependent variables, the first step in this process is to determine the reliability of long-term global precipitation trends by analyzing observational data from the past century. The Climatic Research Unit Time series (CRU v.4.07; Harris *et al*. 2020) and Global Precipitation Climatology Centre (GPCC v.2022; Schneider *et al*. 2022) gridded monthly precipitation datasets are made up of quality-controlled station data over clearly indicated periods and have been integral in recent IPCC assessments (Gulev *et al*. 2021, Hartmann *et al*. 2013). However, these databases also feature climatologically infilled data in locations where observational data is unavailable. This makes it unclear how reliable these precipitation trends can be if infilled data is used to calculate them. Other studies have analyzed historical precipitation trends, but they only use data from more recent decades (e.g. Adler *et al*. 2017; Gu and Adler 2023; Li *et al.* 2015) and others rely on model simulation (e.g. Li *et al*. 2015; Ren *et al*. 2013). Therefore, in this study, we carefully quantify the reliability of these historical precipitation trends with both the CRU and GPCC databases by removing infilled data points and comparing where and when the trends agree. By determining which locations and periods have reliable long-term precipitation trends, we can more confidently compare them to the trends of other water-dependent variables.

Data and Methods

The CRU dataset consists of monthly data from 1901 to 2022 and covers all land areas, excluding Antarctica, at a 0.5-degree resolution. Observed precipitation anomalies are interpolated using angular distance weighting (ADW) onto the above 0.5-degree grid over land surfaces (Harris *et al.* 2020). CRU's `stn` variable represents the number of stations within a 450 km distance that contribute to each grid box and ranges in value from 0 to 8. When a grid box has a `stn` value equal to zero, observed data doesn't exist within that 450 km distance. When and where this occurs, the CRU interpolates synthetic observations into the gaps by recording the default climatology. To mask these synthetic values in our study, we excluded grid boxes with a `stn` value equal to zero from further analysis.

Similar to CRU, the GPCC v.2022 dataset consists of monthly data from 1891 to 2020, covering all land areas, excluding Antarctica. Although GPCC provides many resolutions of its products, the 0.5-degree resolution product was chosen so that the results of this analysis could be directly compared to those of the CRU dataset. The GPCC monthly precipitation products are based on anomalies from the climatological normal and are spatially interpolated using a modified SPHEREMAP methodology using observed data from a 5-degree by 5-degree area surrounding each grid box (Schneider *et al.* 2022).

Unlike CRU's `stn` variable, GPCC's `numgauge` variable provides the number of stations physically located within each grid box, but it does not indicate how many stations contributed precipitation data to each grid box. GPCC infills the default climatology to a grid box only when an entire 5-degree by 5-degree area surrounding that grid box does not have a 0.5-degree by 0.5-degree grid box with a `numgauge` value of at least one. Therefore, to exclude synthetic data points from GPCC, we checked the `numgauge` values of all grid boxes within a 5-degree by 5-degree area surrounding each individual grid box. For example, Figure 1(a) shows the grid box of interest (symbol X) and all the surrounding grid boxes within a 5-degree by 5-degree area. Because there are grid boxes with `numgauge` values of at least one (symbol S) located within the 5-degree by 5-degree area, the grid box of interest is constrained by observational data from GPCC stations. In contrast, Figure 1(b) shows that the grid box of interest does not have any grid boxes with a `numgauge` value of at least one within the specified area – we mask and exclude this grid box from our data analysis because it is not constrained by any observational data from a station.

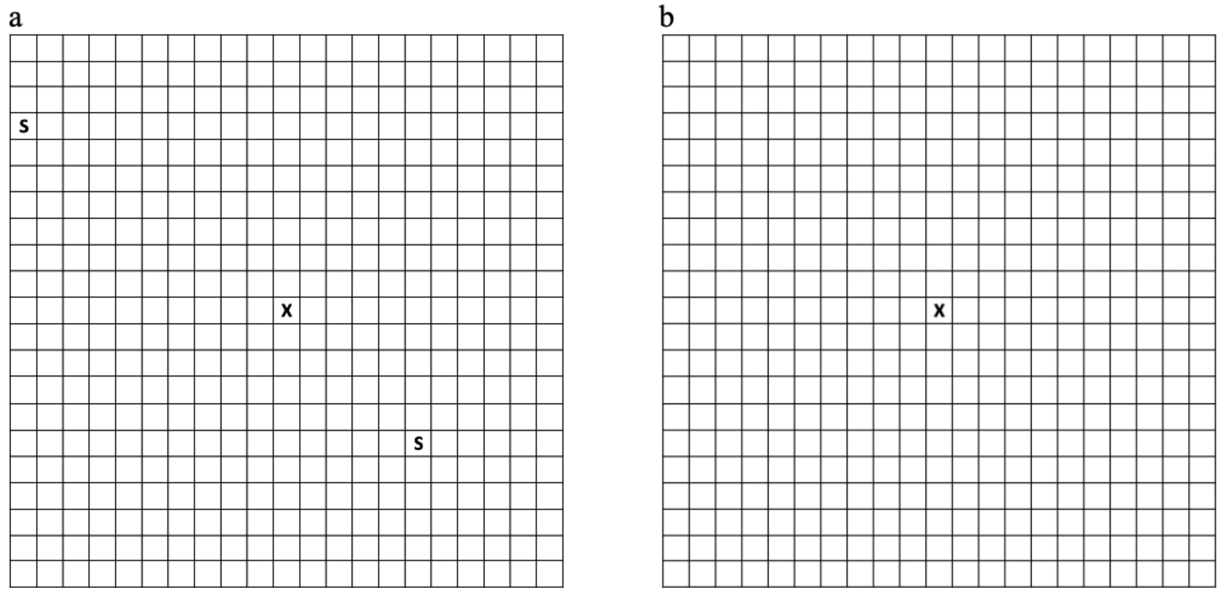

Figure 1: Schematic of GPCC masking procedure by grid box `numgauge` values, where symbol **X** represents the grid box of interest, and symbol **S** represents a `numgauge` value of at least one, that contributes observational data to **X**, within a 5-degree by 5-degree area. (a) This grid box (symbol **X**) has two `numgauge` values of at least one (symbol **S**) within the surrounding area. Therefore, it would not be masked from trend analysis. (b) This grid box of interest (symbol **X**) has no stations within the surrounding area and, therefore, would be masked from further trend analysis.

After both CRU and GPCC data were masked to exclude all synthetic data, the long-term standardized trends of the annual precipitation anomalies were calculated by the following procedure. These trends were standardized so that they could be directly compared to other water-dependent variable trends in future studies. First, the base climatology was calculated by averaging the monthly precipitation values from a 30-year period from 1961 to 1990. Then, monthly anomalies were averaged into annual anomalies, which were then standardized by dividing the annual anomalies by their standard deviations over all years with data for that grid box. Finally, the linear trend rate of the standardized yearly anomalies was calculated and then multiplied by the time interval to represent the total standardized change in precipitation over the entire time period for both datasets (1901-2022 for CRU, 1891-2020 for GPCC).

To refine these results, shorter time periods were also analyzed. To determine which time periods were of interest, an analysis of station data coverage for the CRU and GPCC databases was conducted. The average number of stations that contributed to each grid box and the first and last years of data constrained by station observations for each grid box were calculated and visualized (Figure 2). For CRU, the average number of stations refers to the average `stn` value for each grid box over the time interval. In contrast, the average number of stations for GPCC refers to the sum of all `numgauge` values within a 5-degree by 5-degree area, averaged over the time interval. The first and last year of data constrained by station observations was determined by finding the minimum and maximum years that a grid box had a `stn` value of at least one (for CRU) or had at least one grid box with a `numgauge` value of at least one within a 5-degree by 5-degree area (for GPCC). These findings informed which periods would have more observational data.

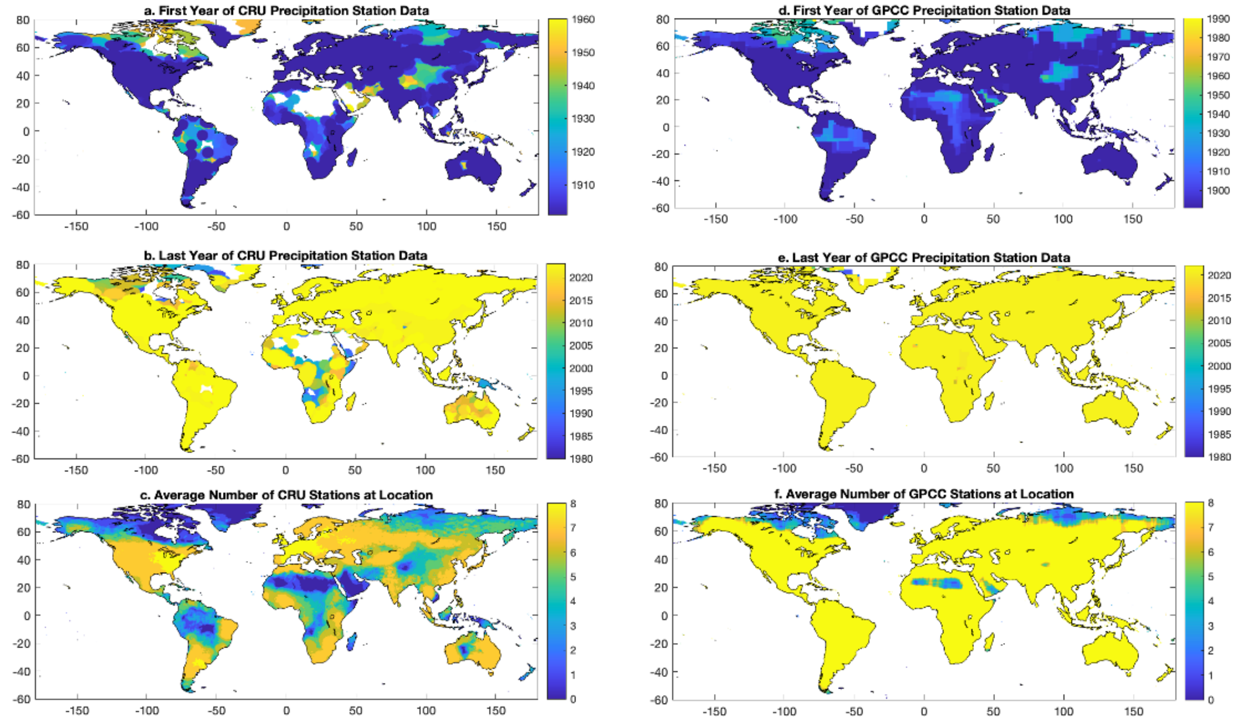

Figure 2: (a) The first year CRU station data is available at each location, (b) the last year CRU station data is available, (c) the average number of CRU stations at each location from 1901 to 2020, (d) the first year GPCC station data is available at each location, (e) the last year GPCC station data is available, (f) the average number of GPCC stations that constrained grid box data at each location from 1891 to 2022.

Then, to confirm the reliability of the trends, global maps of long-term annual standardized precipitation trends were created from both databases for multiple periods with start times ranging from 1901 to 1971 and end times ranging from 1990 to 2020. These global maps only show trends for grid boxes that have data constrained by station observations for every month of every year in the time period. If a grid box even had a single month where data was not constrained by station observations, it is gray on the map. This was done so that every grid box has its trends calculated over the same time interval and therefore can be compared directly with every other grid box.

Additionally, for each period, the standardized linear trend rates of CRU and GPCC were subtracted to find the difference in the total precipitation trends between the GPCC and CRU databases. The difference was then globally mapped to see where the trends in the two databases disagree. The main maps below only show trends of locations that had data coverage from both the GPCC and CRU databases.

Results and Discussion

The results show that the GPCC and CRU trends across the globe are consistent with each other across most periods and areas, especially those that end in 2010 or earlier. For example, Figure 3 depicts maps of GPCC trends, CRU trends, and trend differences from 1901-2010. The GPCC trends are positive (wetting) across most of the map, with the strongest positive trends located in the eastern half of the United States, southern South America, and northern Europe and Asia, in Figure 3(a). Similarly, the CRU trends are also positive in these areas, in Figure 3(b). Indeed, Figure 3(c) shows only slight differences between GPCC and CRU trends, with CRU estimating slightly wetter trends across the United States and southern South America and slightly drier trends across Europe. This demonstrates consistency between the two databases across a long period.

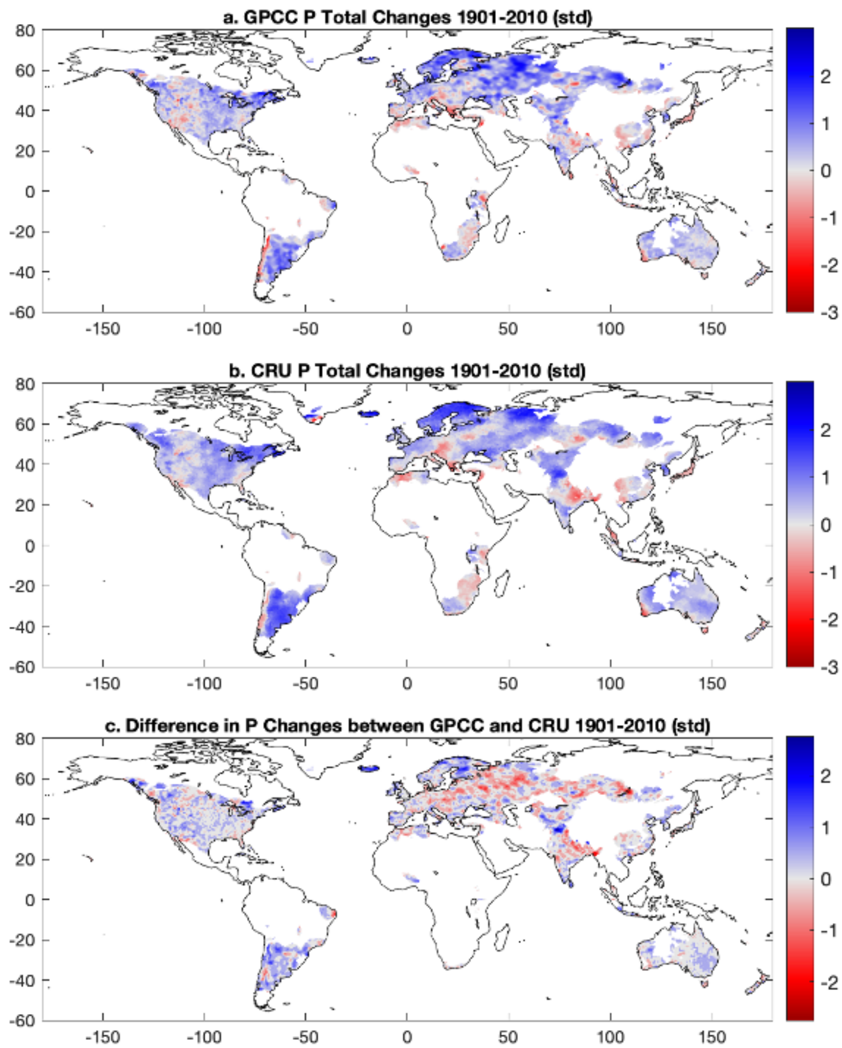

Figure 3: (a) GPCC standardized precipitation trends from 1901-2010, (b) CRU standardized precipitation trends from 1901-2010, and (c) the difference in standardized trends (GPCC minus CRU) from 1901-2010. Total changes represent the precipitation linear trend rate multiplied by the length of the time interval. Trends are shown only where non-synthetic data constrained both GPCC and CRU trends.

GPCC and CRU trends are also consistent across shorter periods. Figure 4 maps similar results from 1961-2010. The GPCC estimates positive trends across the northeastern United States and northern Asia. Negative trends are estimated over the western United States and eastern Brazil, in Figure 4(a). Figure 4(b) depicts the CRU trends, and they strongly agree with GPCC trends. There is strong wetting in the northeastern United States and across northern Europe and Asia and slight drying trends over the western United States and eastern Brazil. Figure 4(c) shows that there are only subtle differences between the trends of the two databases, and the areas that differ are not extensive. GPCC and CRU trends over long and short periods are consistent with each other and can be considered reliable in most areas.

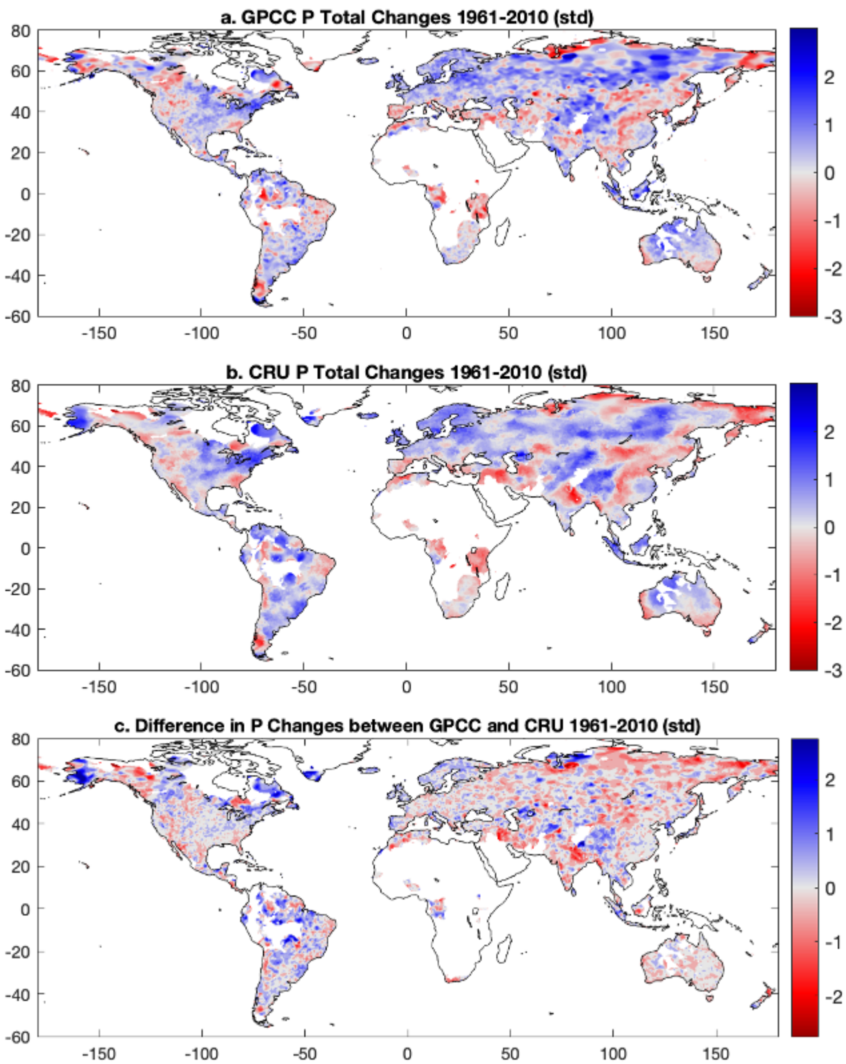

Figure 4: As Figure 3, but using 1961-2010.

Most of these figures do not show any data across most of Africa because they only show locations that had coverage from both databases. Specifically, trend analysis over Africa could only be done with GPCC because only it has sufficient coverage. However, even though we cannot compare GPCC and CRU data in this region, we believe that the GPCC data in this area is reliable, just not as confident as other areas with GPCC and CRU coverage. For example, Figure 5 has almost full global coverage from 1961-2010, and specifically has substantial coverage across the majority of Africa.

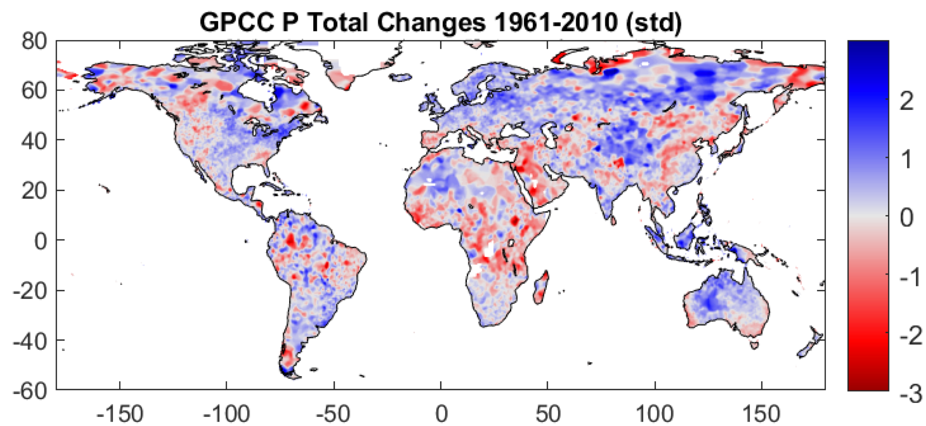

Figure 5: As Figure 4(a), but using only GPCC and using all points where GPCC is available.

However, there are trends in locations during certain periods that stand out as less reliable. One of the most notable discrepancies is shown on GPCC, CRU, and trend differences maps from 1941-2010 (Figure 6). The GPCC estimates wetting trends across Europe and Russia in Figure 6(a), while the CRU estimates much less wetting over the same areas in Figure 6(b). The resulting difference map, Figure 6(c), highlights the contrast between the trends of the two databases. Much of Russia has a negative trend difference, again indicating that the GPCC estimates much wetter trends over this period and area. Other periods that resemble these findings include periods that have beginning years of 1931, 1941, and 1951 (Figures S1, S2, S3, S4, S5). The trends over Russia during this period are not reliable because of the large difference between the trends of these databases.

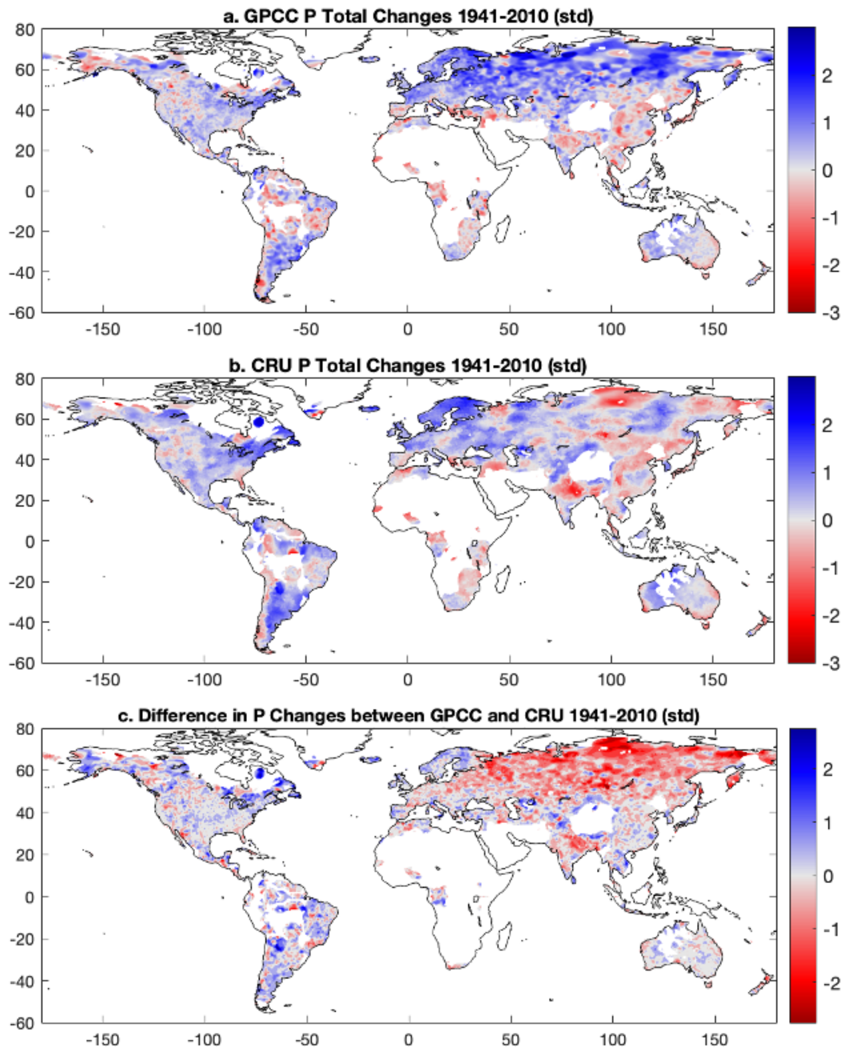

Figure 6: As Figure 3, but using 1941-2010.

In addition, periods ending in 2020 also show inconsistencies, especially in the United States. For example, Figure 7 shows the trends from 1901-2020. The GPCC estimates wetting trends over the eastern United States and slightly drying trends over the western United States in Figure 7(a). In contrast, the CRU estimates wetting trends across almost all of the United States in Figure 7(b). The trend difference map shows that CRU estimates wetter trends than GPCC from 1901-2020 across the entire country, but especially in the Great Lakes region. In contrast, 1901-2010 (Figure 3) does not show nearly as strong a difference. Similarly, Figure 8 shows that CRU trends are wetter than those of GPCC in the northeastern United States from 1961-2020, whereas the trends from 1961-2010 do not show as strong of a difference between the two databases (Figure 4). In general, any trend maps with the end year of 2020 show that CRU predicts wetter trends than GPCC in the United States (Figures S6 and S7).

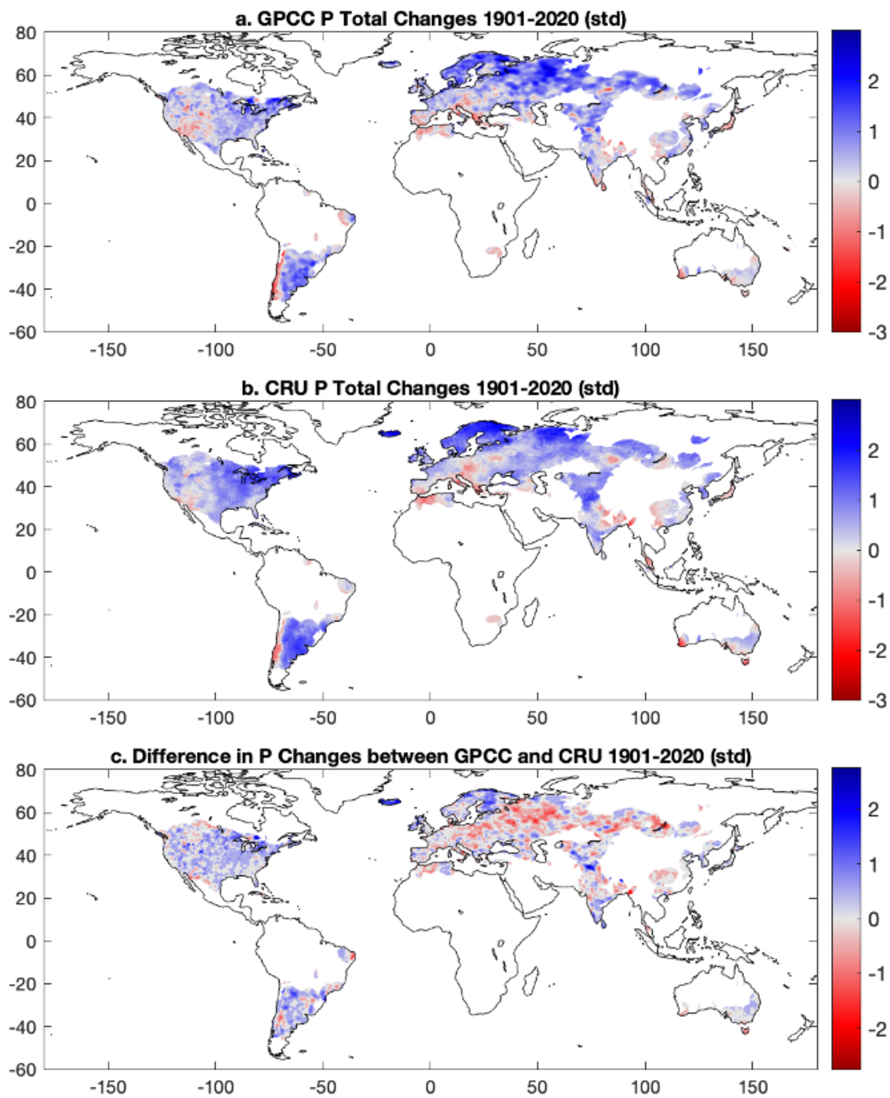

Figure 7: As Figure 3, but using 1901-2020.

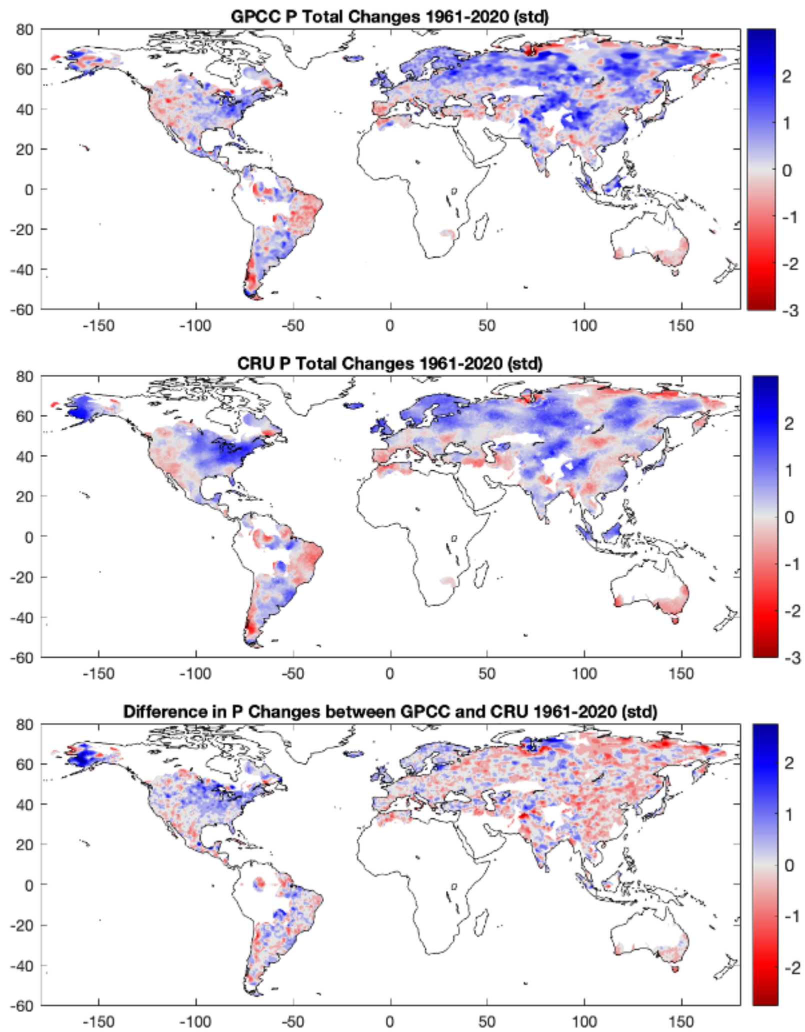

Figure 8: As Figure 3, but using 1961-2020.

Finally, there are slight inconsistencies in trends in Australia from 1921-1990, 1921-2000, and 1921-2010 (Figure 9). Figure 9 shows trend differences over Australia becoming wetter as the period gets shorter. Figure 9(c) shows little difference between GPCC and CRU trends from 1921-2010. Figure 9(f) shows slightly more wetting trends from CRU than GPCC from 1921-2000. Finally, Figure 9(i) shows the most difference between CRU and GPCC trends in this area, with CRU estimating even wetter trends from 1921-1990. This suggests that the trends over Australia become less reliable as the periods get shorter. This occurs in other periods starting in the early 1900s as well.

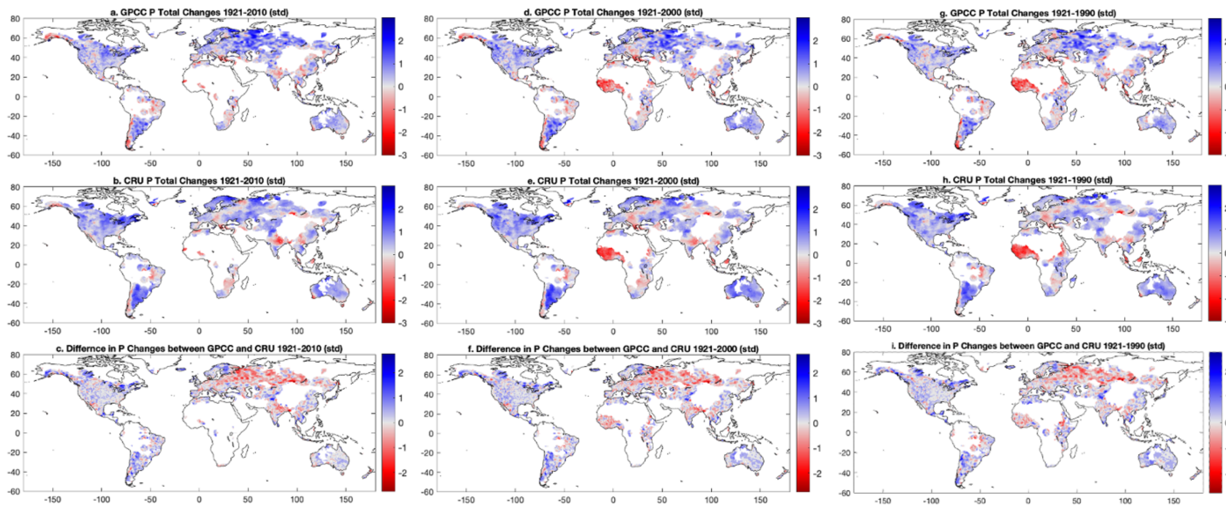

Figure 9: As Figure 3, but using 1921-1990, 1921-2000, and 1921-2010.

Conclusion

This study aimed to analyze and compare historical global precipitation trends to determine where and when they are reliable. Future work will compare these precipitation trends to other water availability trends such as runoff, soil moisture, vegetation cover, and possibly other hydrological variables, so that we can understand whether non-precipitation trends such as temperature or carbon dioxide are affecting water availability. Yet, these comparisons cannot be achieved without a solid understanding of the global precipitation trends. The precipitation data from the GPCC and CRU databases were analyzed by calculating long-term trends in locations that are constrained by real data collected by stations. For the GPCC data, we developed methods that determine which locations are actually constrained in this way, which is not apparent in prior literature.

Overall, we found that GPCC and CRU precipitation trends are consistent with each other across most periods and areas, with some exceptions. GPCC and CRU precipitation trends are consistent over both longer (e.g. 1901-2010) and shorter periods (e.g. 1961-2010). One of the most notable exceptions is across Russia in periods starting from the 1930s to the 1950s, where

CRU trends are much drier than those of GPCC. This inconsistency may be related to the global conflict in this area during this period – perhaps political unrest could have affected the accuracy of observational data during this time (e.g. Schultz and Mankin, 2019). Further data analysis will take this unreliability into account.

Another exception is seen during any period ending in 2020 across the United States – where CRU shows more wetting trends than GPCC. Finally, other inconsistencies regarding the strength of wetting trends in Australia are observed in periods starting in 1920. The shorter periods show wetter CRU trends compared to those of GPCC than longer periods in this location.

These findings are promising for future research into trends of other water-dependent variables. Knowing where and when these precipitation trends are or aren't reliable will help us investigate the difference between trends of water-dependent variables and precipitation trends across the globe in the last century. This will be done by conducting a further analysis of other variables such as runoff, soil moisture, and vegetation cover and comparing those results to the results of this study.

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